The Sustainability Index: A new tool to breed for reduced greenhouse gas emissions intensity in Australian dairy cattle

T.T.T. Nguyen[1], C.M. Richardson[2], M Post[3], P.R. Amer[3], G.J. Nieuwhof[1], P. Thurn[1] and M. Shaffer[1]

[1]DataGene Ltd., AgriBio, 5 Ring Road, Bundoora, VIC 3083, Australia
[2]AbacusBio International Ltd, Edinburgh, UK
[3]AbacusBio Ltd, Dunedin, New Zealand
Corresponding author: tnguyen@datagene.com.au

Abstract

The Australian dairy industry has set a target to reduce greenhouse gas (GHG) emissions intensity by 30% by 2030 compared to the 2015 level. At the animal level, apart from nutritional modifications and other management practices, selecting animals which emit less GHG can be a cost-effective and long-term strategy. Given the world's demand for protein is increasing, selecting for animals with lower GHG emissions per unit of production (aka emissions intensity) is a realistic approach that addresses the key issue of emissions reduction while maintaining farm productivity. In August 2022, DataGene released the Sustainability Index which can be used by dairy farmers to select bulls and cows with lower environmental footprints. The index was built based on the existing Balanced Performance Index (BPI) but placed greater emphasis on production, survival, health and feed efficiency. Compared to BPI, the weightings for protein, fat, survival, mastitis resistance and feed efficiency are increased by 2.6, 1.4, 2.8, 1.3 and 3.8-fold; respectively. It is expected that with the use of the Sustainability Index, emissions intensity will be reduced by 6.3%, 7.3% and 4.4% in Holstein, Jersey and Red breeds by 2050 compared to the current level; respectively. By comparison, the corresponding values for BPI were 5.0%, 6.2% and 4.1%; respectively. However, the trade-off in BPI when using the Sustainability Index will be \$1.50, \$1.05 and \$0.27 per year for Holstein, Jersey and Red breeds; respectively. The Sustainability Index is published on DataVat and the Good Bulls App.

Keywords: emissions intensity, sustainability, selection index.

Introduction

Improving environmental sustainability through reduced greenhouse gas (GHG) emissions is a global priority. In Australia, the agriculture sector produces 67 Mt carbon dioxide equivalents (CO_2-e), accounting for 13% of the country's total emissions in 2020 (Australian Government Climate Change Authority 2021). The dairy sector accounts for 12.5% of agriculture emissions, or about 2% of national emissions (Dairy Australia 2021). Emissions intensity per cow and per kg of fat protein corrected milk were estimated 6.9 ± 1.46 t CO_2-e and 1.04 kg CO_2-e, respectively (Christie *et al.*, 2011) Although the carbon footprint of Australian dairying is one of the lowest internationally (Mazzetto *et al.*, 2022), there is still scope for further reduction. The Australian dairy industry has made a commitment to minimising its environmental footprint, including reducing GHG emission intensity by 30% by 2030 across the whole industry compared to the 2015 level (Dairy Australia 2020).

Enteric methane accounts for about 57% of emissions on an average Australian dairy farm (Dairy Australia 2021). While recognising that management and dietary solutions can be used to reduce enteric methane, selective breeding can provide a complementary solution which is cost-effective, permanent, and cumulative (de Haas *et al.,* 2021; Manzanilla-Pech *et al.,* 2021), while potentially benefiting both emissions intensity and total emissions. One solution for the latter is to produce a breeding value for enteric methane, which requires a large number of records and good quality methane phenotypes or predictors on individual animals. In Australia, the current number of records on methane data is still limited, which impedes the implementation of genomic selection for the trait (Richardson *et al.,* 2021b). While the long-term goal is to have a breeding value for methane, increased emphasis on improved milk production, survival, fertility and feed efficiency could be a short-term approach (Løvendahl *et al.,* 2018) as breeding values for these traits are readily available in the national genetic evaluation. Richardson *et al.* (2021b) used this approach and developed a GHG subindex of milk yield, fat yield, protein yield, survival and feed saved with an accuracy of ~0.50. The subindex was expressed in CO_2-e gross emissions per cow.

There are two philosophical approaches that can be taken to reduce greenhouse gas emissions associated with livestock production. Broadly these are targeting reductions in emissions either with or without consideration of the animal's productive output.

The first approach is to target a reduction in gross agricultural emissions from the livestock sector. When considering this approach, geneticists tend to focus on measuring the total GHG output per animal per day and apply downward selection pressure to this measure. One consequence of this is that because more productive, higher milk yielding animals tend to eat more feed than lower producing animals, and because GHG output is tightly linked to feed intake (Pickering *et al.,* 2013), selection for reduced gross per animal GHG emissions is likely to be highly antagonistic to the current selection direction for productive performance. Selection on any index predicting GHG output per animal per day, will penalise high milk producing animals.

A second approach is to focus on emissions intensity in the breeding goal. Emissions intensity measures gross GHG output per animal per day against their productive output. High milk producing animals and farming systems tend to have lower emissions intensity than lower producing animals and systems because their proportional superiority in milk yield is only partly offset by the higher GHG output associated with the feed required for higher milk production (Gerber *et al.,* 2011; Pryce and Bell 2017). This perspective is consistent with the dilution of maintenance principal, whereby high yielding animals have only slightly higher feed requirements for maintenance and/or for rearing their replacements while the extra feed required for milk production is proportionally offset by the additional milk production resulting in a net gain in overall efficiency. This approach aligns well with farmers' objectives, that is to maximise profit through efficiency, increased cow fertility and longevity (Lovett *et al.,* 2006; Waghorn and Hegarty 2011; Richardson *et al.,* 2021a). Most of the trait changes being driven by current Australian dairy indexes (i.e. the Balanced Performance Index or BPI, and to a more modest extent the Health Weighted Index or HWI) are already improving emissions intensity, as they are simultaneously improving milk yield and fertility, which are both favourably associated with emissions intensity.

In this study, we aimed to:

1. Quantify improvement in emissions intensity made since the implementation of the BPI,
2. Describe the development and implementation of the Sustainability Index which can be used as a tool to reduce emissions intensity in Australian dairy cattle, and
3. Predict the effect of alternative indexes on emissions and economics.

Material and methods

This study will utilise kg of CO_2-e per kg of protein equivalent (kg CO_2-e/kg prot-e) as a measure of expressing emissions intensity rather than kg of CO_2-e per kg of fat protein corrected milk or kg of CO_2-e per kg of energy corrected milk. This choice is based on protein's higher economic value ($6.76/kg) compared to fat ($2.08/kg) in the Australian context.

For this analysis, the impacts of variations of a 'sustainability index' were estimated and compared to the existing BPI and HWI indexes. Three possible sustainability selection indexes were considered. These sustainability indexes were developed by including three variations of a GHG subindex at three carbon values within the BPI to produce the Sustainability Index, based on methodology adapted from Richardson *et al.* (2022). The three carbon prices were $500/kg CO_2-e, $1000/kg CO_2-e and extreme high or infinite. Acknowledging that these prices are high in the current Australian context, the index we aimed to develop, however, is a desired gains index and high assumed carbon prices are necessary to invoke meaningful change. Initial consultations with Australian farmers indicated their willingness to sacrifice economic gains to reduce environmental impacts, which allows the adjustment of BPI for this purpose, similar to the way the HWI was developed with major emphasis on health and fertility (Axford *et al.,* 2021).

As the traits included in the GHG subindex are currently included in the breeding objective, the additional emphasis received by each trait within the GHG subindex was applied to its economic weight to present the total relative emphasis of each trait, as opposed to the emphasis of a subindex. Richardson *et al.* (2021a) used methodology adapted from Amer *et al*. (2018) to calculate coefficients that express the kg of CO_2-e associated with a unit change in index traits. These coefficients were used as weights and applied to Australian breeding values (ABVs) commonly used in selection and most strongly associated with emissions to derive three possible subindexes aimed to rank the environmental impact of individual animals based on their genetic merit. The environmental and economic impact of the three index scenarios were measured and compared to the two current national indexes.

Genetic bull data

Genotypes for 5,499 registered bulls (n=4,382 registered Holstein, n=734 registered Jersey, n=383 registered Red Breeds including Aussie Red, Ayrshire, Illawarra and Dairy Shorthorn) used in this study were provided by DataGene Ltd., with processing and genotyping methods being consistent with the national genetic evaluation dataset. Bulls were born between 2010 and 2015. The ABVs used in this analysis included milk yield, protein yield, fat yield, survival and feed saved, as well as other traits of interest such as heat tolerance and liveweight and were accessed from the August 2021 official genetic evaluation run.

Calculating relative weights

Emission intensity coefficients were previously calculated by Richardson *et al.* (2021a) based on the approach used by Amer *et al.* (2018) and adapted to calculate the effect of a unit change in milk yield, fat yield, protein yield, feed saved, and survival traits on CO2-e emissions per kg kilogram of protein equivalents (Table 6). Protein equivalents are a weighted aggregate of the product outputs from protein yield, fat yield, and milk yield weighted on the component value ratio relative to protein. Briefly, this method estimates the change in total emissions and product output caused by a 1 unit change in each index trait, resulting from either a direct emissions trait (GHG yield), changes in herd structure (fewer replacements), or the dilution effects of higher yields (milk production) and proliferation (more offspring/dam). As fertility is a primary reason for culling, the environmental impact of fertility is largely accounted for by the survival ABV, with minimal additional effects applying to extended lactations observed in seasonal calving systems (Richardson *et al.*, 2021a; Workie *et al.,* 2021). Therefore, the survival GHG coefficient is considered in the index, with no coefficient directly for fertility. The model was used in the current study to dynamically represent an Australian dairy herd and assess effects of changes in traits.

Developing the sustainability index

Multiple variations of an environmentally focused national selection index were previously developed using gross GHG coefficients as described by Richardson *et al.* (2022). However, these indexes only explored the application of developing a GHG subindex targeting gross emissions. The variations of sustainability index investigated in this paper were developed using the methodology described in Richardson *et al.* (2022), adapted to generate intensity coefficients. Briefly, the component traits used in the development of the index are the same as those in the BPI, namely milk yield, fat yield, protein yield, survival, fertility, somatic cell count, mastitis resistance, temperament, mammary system, udder depth, overall type, pin set and feed saved (Axford *et al.,* 2021). Emissions intensity coefficients/values (IV) were estimated that describe the change in enteric methane per unit of output attributed to traits currently under selection in Australian dairy cattle (expressed in kg carbon dioxide equivalents per kg protein-equivalents). Since these IV coefficients were estimated to be independent, they can be used as weights within an index to place non-economic emphasis on traits with environmental impact. The calculated IV coefficients were applied to existing ABVs shown to have an independent effect on enteric methane emissions and used to develop a GHG subindex. As the GHG subindex contains traits already include in the breeding objective, the additional weight of each trait within the GHG subindex was directly applied to the trait within the sustainability subindex. The investigated index scenarios were as follows:

$$SI_j = \sum \left(EW_n + \left(IV_n * CP_j\right)\right) * ABV_n$$

Where *SIj* is the sustainability index calculated using j^{th} carbon price, EW_n is the economic weight of the n^{th} trait (milk yield, fat yield, protein yield, survival, fertility, somatic cell count, mastitis resistance, temperament, mammary system, udder depth, overall type, pin set and feed saved), IV_n is the emissions intensity coefficient (kg CO_2-e/kg protein-e changed in 1 cow per unit change in the trait ABV) for the n^{th} trait (milk yield, fat yield, protein yield, survival and feed saved), ABV_n is the Australian Breeding Value for the n^{th} trait (milk yield, fat yield, protein yield, survival, fertility, somatic cell count, mastitis resistance, temperament, mammary system, udder depth, overall type, pin set and feed saved), and CP_i is the j^{th} carbon price (AUD$500, AUD$1000 and extreme or infinite/tonne CO_2-e).

Relative emphasis

The relative emphasis of each trait and subindexes for every variant of the BPI was calculated using the approach of Zhang and Amer (2021), which accounts for the accuracy of the ABVs as well as the (favourable or antagonistic) relationships between traits in contrast to traditional approaches that are often a simple multiplication of the relative contribution of each trait's economic value (converted to absolute value) by its genetic standard deviation. Here, we applied the method of Zhang and Amer (2021) using correlations between the ABVs. The resulting trait emphasis values more accurately present the true selection pressure each trait receives within the given index.

Correlations between traits

Pearson correlation coefficients among all indexes and ABVs were calculated. The method for computing correlations in the presence of missing values that was used is 'pairwise.complete.obs' in R (R Core Team 2022). In this methods, each correlation can be based on a different number of observations as all complete pairs of observations on two ABVs/indexes are used to calculate the correlation between these ABVs/indexes. Pearson correlation coefficients between ABVs and indexes used the same number of observations, as indexes are only calculated for bulls without any missing values for ABVs in the breeding goal.

Estimating trait responses

The response of a trait (*R*) to a particular index *j* was calculated using the following formula:

$$R = \frac{\rho(ABV, Index\_j) \times SD(ABV)}{SD(Index\_ref)} \times \Delta(Index\_ref)$$

Where ρ*(ABV, Index_j)* denotes the correlation between the trait ABV and *Index_j* (i.e. SI, BPI and HWI), *SD(ABV)* and *SD(Index_ref)* are the standard deviation of each ABV and selected *SD(Index_ref)* (BPI and HWI) respectively, Δ*(Index_ref)* is the amount of unit change in the *Index_ref*, used as a baseline to compare responses across traits and indexes.

Environmental and economic response

Geneflow modelling was used to assess the economic and environmental impact of implementing the three variations of the sustainability index in the national breeding objective. The geneflow model utilises selection index theory combined with capital budgeting methodologies to quantify the industry level impacts of genetic selection for reduced GHG, and conventional production traits (i.e., milk yield, fat yield, protein yield) on key national metrics of GHG emissions in Australian dairy cattle. The model was used to quantify any trade-offs required between increasing genetic gain in traditional production traits versus GHG mitigation. Scott *et al.* (2021) reported that the annual rate of genetic gain in BPI since 2013 ranged between 0.11 and 0.22 genetic SD per year for Holstein cows and bulls, respectively. Consequently, it was assumed that a 1-SD improvement in BPI (AUD$84.06; Axford *et al.* (2021)) would be achieved over around 10 years of selection. The responses in BPI units achieved by selection on each of the considered indexes, as well as the total CO_2-e reduction achieved by selection for each index, are presented.

Results

Historic changes in Australian dairy industry emissions intensity (kg CO2-e/kg prot-e) from 2015 to 2022 have resulted in improvements of 1.3%, 1.4% and 0.8% in Holstein, Jersey and Red Breeds, respectively (Table 1). This is equivalent to the reduction of 0.25, 0.27 and 0.15 kg CO2-e/kg prot-e in the three breeds, respectively. That is, most of the trait changes being driven by the BPI, and to a more modest extent the HWI, are already improving emissions intensity. This is because they are simultaneously improving production and survival, which are both favourably associated with emissions intensity.

The future changes to be expected in emissions intensity with deployment of the new indexes considered, particularly by 2030 are modest. It is important to note that the trajectory of genetic change between now and 2026 has already been set by historic selection decision. Figure 1 shows the improvements made by each of the indexes for Holstein, Jersey and Red Breeds. Among the indexes, HWI showed the least improvement with a reduction of 5.39%, 6.74% and 4.94% in emissions intensity in Holstein, Jersey and Red Breeds, respectively, by 2050 compared to the 2015 levels. The SI_extreme index showed the most improvement with a percent reduction in emissions intensity were 8.02%, 9.20% and 5.59% in the three breeds, respectively.

We predicted future changes in emissions intensity using three indexes with different carbon pricing, namely SI_500, SI_1000 and SI_extreme, which had the carbon price of AUD 500/t CO2-e, AUD 1000/t CO2-e, and AUD infinite/t CO2-e, respectively, applied as a weight to the carbon emissions associated with subindex component traits (milk yield, fat yield, protein yield, survival and feed saved). When considering the changes in BPI (AUD per cow) over time for different indexes, SI_extreme resulted in the largest loss in profit relative to selection based on BPI with a BPI loss of 18.12%, 12.80% and 6.16% by 2050 in Holstein, Jersey and Red breeds, respectively (Figure 2). That is a reduction of AUD 90.5, 55.5 and 16.1 per cow per year in the three breeds. SI_500 showed the least sacrifice in BPI with a reduction of AUD 12.5 (2.5%), AUD 8.8 (2.0%) and AUD 2.4 (0.9%) per cow in Holstein, Jersey and Red breeds, respectively, but achieved the least gain in emissions intensity. When comparing SI_1000 and SI_extreme, the gain in emissions intensity made by SI_extreme was moderate (e.g., 8.02% vs. 7.64% in Holstein) but the relative negative impact on BPI gain was much higher (e.g. AUD 90.5 vs. AUD 27.5 per cow).

For these reasons, SI_1000 was chosen as the Sustainability Index (SI), which was predicted to result in a reduction of emissions intensity by 7.64%, 8.96% and 5.52% in Holstein, Jersey and Red breeds, respectively, by 2050 relative to the 2015 level. Using SI_1000 also resulted in expected slower gain in BPI compared to the use BPI itself by AUD 27.5 (6.87%), AUD 19.0 (5.49%) and AUD 5.1 (2.42%) per cow in Holstein, Jersey and Red breeds, respectively, in the same time period. That is equivalent to AUD 0.79, AUD 0.54 and AUD 0.15 per cow per year. From this point forward, SI refers to the index SI_1000 as it was chosen by industry for implementation.

Table 1. Changes in emissions intensity (kg CO2-e/kg prot-e) from 2015 to 2022 as a result of implementation of the Balanced Performance Index (BPI)

Breed	Unit gain (kg CO2-e/kg prot-e)	Percent change (%)
Holstein	-0.25	-1.3
Jersey	-0.27	-1.4
Red breeds	-0.15	-0.8

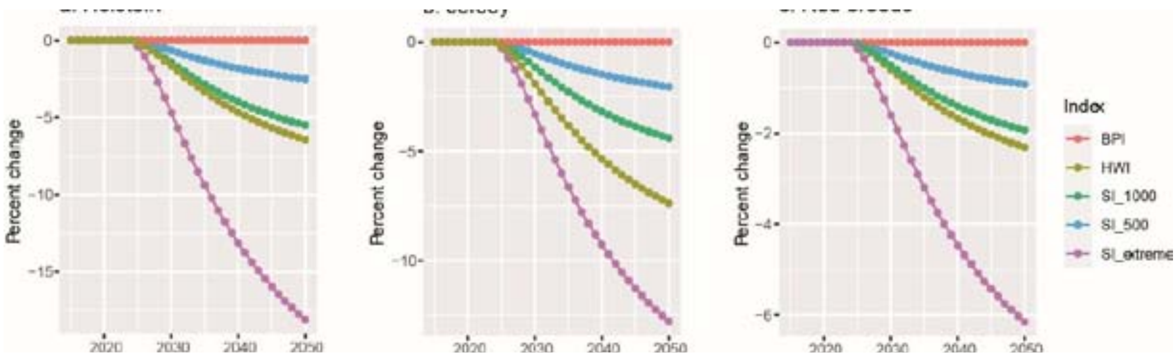

Figure 1. Percent change in emissions intensity (kg CO2-e/kg prot-e) in a) Holstein, b) Jersey and c) Red Breeds with different indexes (BPI = Balanced Performance Index, HWI = Health Weighted Index, SI_500, SI_1000, SI_extreme = Sustainability Index with carbon price per tonne CO2-e = AUD 500, 1000 and infinite, respectively).

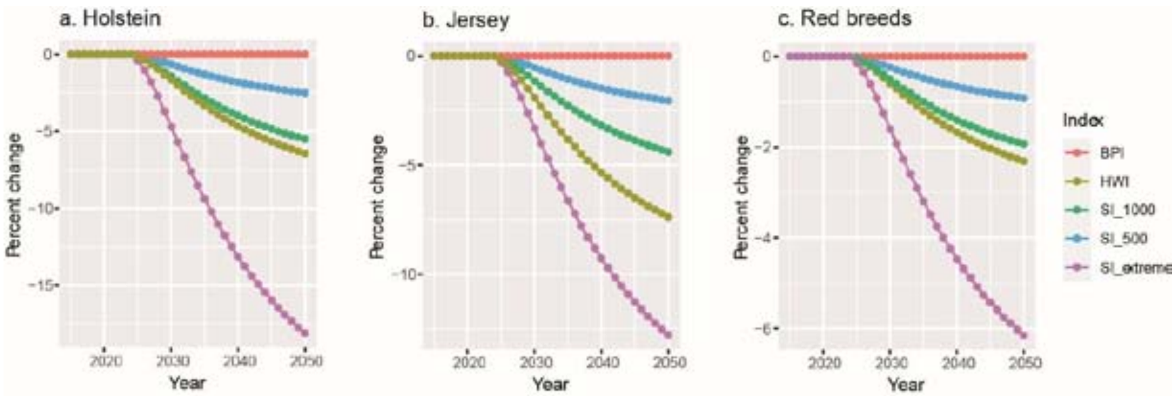

Figure 2. Percent change in units of Balanced Performance Index in a) Holstein, b) Jersey and c) Red Breeds with different indexes (BPI = Balanced Performance Index, HWI = Health Weighted Index, SI_500, SI_1000, SI_extreme = Sustainability Index with carbon price per tonne CO2-e = AUD 500, 1000 and infinite, respectively).

Table 2. Economic weights of traits included in the Sustainability Index (SI). Economic weights of the same traits for the Balanced Performance Index (BPI) the Health Weighted Index (HWI) are also included for comparative purposes.

	Holstein		Jersey		Red Breeds		
Trait	SI	BPI*	SI	BPI*	SI	BPI*	HHWI*
Protein yield	17.49	6.76	17.49	6.76	17.49	6.76	4.36
Fat yield	2.82	2.08	2.82	2.08	2.82	2.08	1.35
Milk yield	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.07
Survival	20.21	7.20	20.21	7.20	20.21	7.20	7.20
Daughter fertility	6.94	6.94	6.94	6.94	6.94	6.94	14.11
Somatic cell count	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Mastitis resistance	8.70	6.75	8.70	6.75	8.70	6.75	6.75
Milking speed	5.02	5.02	5.02	5.02	5.02	5.02	5.02
Temperament	3.60	3.60	3.60	3.60	3.60	3.60	3.60
Mammary system	2.76	2.76	2.76	2.76	2.76	2.76	3.59
Udder depth	0.82	0.82	0.82	0.82	0.82	0.82	0.00
Overall type	1.36	1.36	1.36	1.36	1.36	1.36	1.36
Pin set	0.78	0.78	0.78	0.78	0.78	0.78	0.78
Feed saved	0.7227	0.1927	0.5300	0	0.7227	0.1927	0.3853

*Axford et al. (2021). Economic weights for HWI component traits are the same in three breeds.

Economic weights for index traits calculated for the SI are summarised in Table 2. Compared to BPI, more emphasis was placed on protein yield, survival, mastitis resistance and feed saved. Compared to BPI, the weightings for protein, fat, survival, mastitis resistance and feed efficiency are increased by 2.6, 1.4, 2.8, 1.3 and 3.8-fold; respectively.

Correlations between the August 2022 breeding values between SI, BPI and HWI for bulls born in 1990 or later are presented in Table 3. Correlations with SI were higher for BPI than for HWI (0.96 vs 0.89 in Holstein, 0.95 vs 0.86 in Jersey and 0.94 vs 0.82 in Red breeds). This means although there was some level of reranking, majority of bulls which are ranked highly in BPI also have high SI breeding values.

Table 3. Correlations between August 2022 breeding values of the Sustainability Index (SI) and the Balanced Performance Index (BPI) and the Health Weighted Index (HWI) for a) Holstein, b) Jersey and c) Red bulls born in 1990 or later.

	SI	BPI	HWI
Holstein			
SI	1		
BPI	0.96	1	
HWI	0.89	0.96	1
Jersey			
SI	1		
BPI	0.95	1	
HWI	0.86	0.93	1
Red bulls			
SI	1		
BPI	0.94	1	
HWI	0.82	0.92	1

Table 4. Relative emphasis (%) of traits within the Sustainability Index (SI) in Holstein, Jersey and Red bulls. Relative emphasis of the same traits for the Balanced Performance Index (BPI) and the Health Weighted Index (HWI) are also included for comparative purposes.

	Holstein			Jersey			Red Breeds		
Trait	SI	BPI*	HWI*	SI	BPI*	HWI*	SI	BPI*	HWI*
Protein yield	32.3	20.1	12.6	39.9	24.3	15.4	55.6	25.1	16.4
Fat yield	11.0	9.3	5.9	7.9	9.8	6.3	10.4	9.7	6.4
Milk yield	8.2	14.9	9.2	9.9	16.7	10.5	8.4	13.8	8.9
Survival	11.8	8.4	8.2	13.7	8.8	8.7	7.6	5.1	5.1
Daughter fertility	9.3	13.2	26.0	4.9	9.9	19.8	4.2	0.0	0.0
Somatic cell count	2.4	5.5	5.3	2.8	5.6	5.5	2.5	11.0	22.5
Mastitis resistance	5.5	8.0	7.7	5.8	7.4	7.3	2.4	6.2	6.3
Milking speed	1.7	4.0	3.8	1.7	3.1	3.1	0.7	7.0	7.1
Temperament	1.2	2.3	2.3	1.7	3.0	3.0	0.9	5.2	5.3
Mammary system	2.9	4.3	5.4	3.5	6.0	7.6	1.7	2.8	2.8
Udder depth	0.6	1.2	0.0	0.7	1.5	0.0	0.3	4.4	5.8
Overall type	1.3	2.0	1.9	1.7	2.7	2.6	0.9	1.4	0.0
Pin set	1.0	1.4	1.3	0.7	1.3	1.3	0.4	2.0	2.1
Feed saved	11.7	5.3	10.4	5.0	0.0	9.1	3.9	5.0	10.1

*Axford et al. (2021)

Table 5. Predicted responses to selection (SD unit response to 1 SD change in the Sustainability Index (SI), the Balanced Performance Index (BPI) and the Health Weighted Index (HWI)) for Holstein, Jersey and Red bulls.

	Holstein			Jersey			Red Breeds		
Trait	SI	BPI	HWI	SI	BPI	HWI	SI	BPI	HWI
Protein yield	0.68	0.42	0.18	0.83	0.63	0.35	0.91	0.80	0.70
Fat yield	0.50	0.55	0.28	0.64	0.67	0.39	0.68	0.67	0.52
Milk yield	0.32	0.05	-0.07	0.45	0.18	0.07	0.43	0.22	0.12
Survival	0.48	0.50	0.42	0.50	0.48	0.50	0.57	0.54	0.47
Daughter fertility	0.16	0.32	0.63	-0.14	0.01	0.40	0.63	0.71	0.85
Somatic cell count	0.42	0.50	0.45	0.02	0.10	0.22	0.35	0.41	0.45
Mastitis resistance	0.34	0.46	0.49	0.08	0.24	0.33	0.11	0.21	0.26
Milking speed	0.06	0.11	0.06	0.37	0.39	0.28	0.09	0.11	0.11
Temperament	0.25	0.25	0.14	0.46	0.46	0.36	0.13	0.12	0.01
Mammary system	0.16	0.18	0.05	0.40	0.40	0.35	-0.34	-0.37	-0.45
Udder depth	0.14	0.21	0.19	-0.37	-0.27	-0.10	-0.07	0.00	-0.02
Overall type	0.18	0.19	0.05	0.44	0.42	0.29	-0.31	-0.37	-0.51
Pin set	0.03	0.02	0.04	0.37	0.34	0.31	0.28	0.33	0.40
Feed saved	-0.02	-0.05	0.19	-0.17	-0.19	0.11	-0.06	0.03	0.23

Relative emphasis of traits in SI is shown in Table 4. The SI has major emphasis on production (52% in Holstein, 58% in Jersey and 74% in Red breeds), followed by health and fertility (29% in Holstein, 27% in Jersey and 17% in Red breeds), feed saved (12% in Holstein, 5% in Jersey and 4% in Red breeds), type (6% in Holstein, 7% in Jersey and 3% in Red breeds), and workability (3% in Holstein, 3% in Jersey and 2% in Red breeds).

Predicted responses to selection with the SI are summarised in Table 5 for Holstein, Jersey and Red bulls. Reponses in other traits were also predicted but not presented in this paper. Compared to BPI, in general SI was predicted to accelerate the rates of reductions in emissions intensity and increase the rate of gain in production. These results confirmed that production traits are closely linked to GHG emissions. Using SI is also expected to reduce gains in mastitis resistance, cell count and fertility in Holstein and Red breeds. In Jersey, selection on SI versus BPI would diminish gains in mastitis resistance and cell count, with slight declines in fertility and udder depth. However, natural genetic variation in the breed populations means that there are many Jersey bulls that have both a high SI and a high fertility ABV or a high SI and a high udder depth ABV to choose from (DataGene 2022).

Discussion

In this study, we have presented realised historic and predicted future genetic gains in both environmental emissions variables and familiar genetic traits and indexes when selecting Holsteins, Jerseys and Red Breeds for current and novel future industry indexes. The results indicate that the current selection indexes have reduced emissions intensity but have scope for further improvement. Among the potential indexes which were modelled based on the current index BPI with different emphasis on production, fertility, survival, health and feed saved with different carbon prices, SI_1000 or the Sustainability Index (SI) was implemented as it would lead to a reduction in emissions intensity with minimal sacrifice in profit.

This study is an extension of the work undertaken by Richardson *et al.* (2021a) and Richardson *et al.* (2022). The former estimated the independent effects of traits in the Australian National Breeding Objective on the gross GHG production and GHG intensity. The latter investigated options to reduce GHG emissions in the Australian dairy industry by including environmental component in the national breeding program. Richardson *et al.* (2022) focussed on prediction of changes in gross per-animal GHG production. Selection on a gross emissions index in the Australian dairy context is

Table 6. Intensity coefficients, defined as the independent change is emissions intensity due to a unit change in each trait, used in the derivation of weights applied to traits within the sustainability indexes.

Trait	Intensity Coefficients, kg CO_2-e/ kg prot-e
Protein yield, kg	-0.032
Fat yield, kg	-0.002
Milk yield, L	0.001
Survival, %	-0.029
Feed Saved, kg	-0.002
Mastitis Resistance, %	0.006

*Previously calculated by Richardson et al 2021a expected to favour high fertility but at the same time penalise animals with high milk yield potential. The extent of the swing from milk yield to fertility then depends on how much weight is given to direct economic profit versus achieving gross emissions reductions in the formulation of the index. The Australian dairy industry, however, has set target to reduce emissions intensity (Dairy Australia 2020).

The SI placed more emphasis on protein yield, survival, mastitis resistance and feed saved compared to the BPI. For the Australian dairy situation, the main trait of current commercial interest to farmers which also reduces emissions is fertility. Improving genetic merit for fertility reduces culling of infertile cows, and thereby reduces the number of GHG emitting replacements required on a dairy farm which reduces gross emissions. Selection for reduced emissions intensity swings the balance of selection effort towards milk production and away from fertility. In the SI, the economic weight for fertility remains the same as BPI (6.94) but relative emphasis has reduced from 13.2% to 9.3% in the case of Holstein, largely as a result of the selection emphasis moving to milk production traits.

Expected future changes in emissions intensity through the SI predicted in this study from shifting selection from the BPI to SI are modest when compared to the gains in emissions intensity already being achieved through selection on the BPI. This is partially due to the approach which only uses existing ABVs which reduce feed intake per unit of production and therefore not capturing the variation in GHG emissions per unit of feed consumed among animals (Richardson *et al.,* 2022). Recently, Agriculture and Horticulture Development Board (UK) has implemented its EnviroCow Index which also aims to reduce emissions intensity. It was predicted that EnviroCow reduces emissions intensity over 1% each year when direct and indirect effects due to genetic improvements are taken into account. It is noted that the reductions reported in our study did not include indirect effects. In Ireland, the Economic Breeding Index (EBI) for dairy cattle has recently been updated to include a Carbon Subindex (https://www.icbf.com/?p=18914). This subindex penalises traits which increase feed intake and therefore increase gross per cow emissions. This approach targeting a reduction in gross emissions results in more selection emphasis on fertility, and less selection emphasis on milk production.

Richardson *et al.* (2022) reported that a reduction of approximately 21% in emissions intensity can be achieved after 30 years of genetic selection if a residual methane trait is available at the prediction accuracy of 0.54. In the absence of a novel methane trait with adequate reliability for industry implementation, the most practical approach is to take advantage of existing traits as shown in the present study. It provides an alternative that does not require the infrastructure needed for new trait recording. However, to further accelerate reduction of GHG emissions intensity, a large number of records of direct or indirect measures of methane may be required. There are several methods to measure enteric methane for dairy cows. Australia has methane records for ~400 animals measured using the sulfur hexafluoride (SF6) tracer method (Deighton *et al.* 2014) which is costly to implement on a large scale. Other systems such as GreenFeed® (Zimmerman and Zimmerman 2012) or 'sniffer' (Garnsworthy *et al.,* 2012) are increasingly being used to collect methane related data, especially the latter can be used on-farm conditions and on a large number of animals. Other proxies for methane could also be used in addition to direct measures of methane, such as milk mid-infrared spectroscopy (Vanlierde *et al.,* 2018; Shadpour *et al.,* 2022), microbiome (Zhang *et al.,* 2020), or volatile fatty acids in ruminal fluids (Williams *et al.,* 2019).

This study focusses on reducing emissions intensity as it is aligned with the current industry goal. However, we also recognise that the goal is to reduce gross emissions when considered at an industry, national or global level. This can be achieved by targeting other aspects of livestock production. Combination of additional measures such as management of diet, adjustment to animal numbers, management of stored manure, and appropriate use of carbon neutral fertiliser, renewable fuels and energy, will need to be adopted on farms. With more explicit methane records, direct selection for a trait which reduces methane emissions per unit of feed consumed should become possible and be a more effective option.

Conclusions

The results from the present study indicate that the current Australian selection indexes for dairy cattle have contributed to lower emissions intensity and it is possible to further improve by using a new Sustainability Index although with modest marginal additional reduction. It is predicted that the Sustainability Index will reduce emissions intensity by 7.64%, 8.96% and 5.52% in Holstein, Jersey and Red breeds by 2050 compared to the 2015 level; respectively and the corresponding sacrifice in profit will be AUD 0.79, AUD 0.83, AUD 0.22 per cow per year. The Sustainability Index has been implemented by DataGene since August 2022 and the results on bulls and cows can be accessed on DataVat (datavat.com.au) and Good Bulls App. While the Sustainability Index is a practical and cost-effective approach to breed for the reduction in emissions intensity at this point in time, faster genetic gain can be achieved by selecting directly on methane trait or its proxy. Many countries endeavour to collect methane and related data, an international collaborative effort in sharing these data would be beneficial to all in achieving our common goal.

Acknowledgements

This research has been conducted by AbacusBio, DairyBio, and DataGene and funded by DataGene. DairyBio is co-funded by Agriculture Victoria, Dairy Australia and Gardiner Foundation. The authors would like to acknowledge the contributions from members of the DataGene Genetic Evaluation Standing Committee, dairy farmers and DataGene staff who participate in the consultations and implementation of the Sustainability Index.

References

Amer, P.R., F.S. Hely, C.D. Quinton and A.R. Cromie, 2018. A methodology framework for weighting genetic traits that impact greenhouse gas emission intensities in selection indexes. Animal 12, 5-11.

Australian Government Climate Change Authority, 2021. Agriculture. Factsheet 7. https://www.climatechangeauthority.gov.au/sites/default/files/2021-03/2021Factsheet%20-%20Agriculture.pdf

Axford, M., B. Santos, K. Stachowicz, C. Quinton, J.E. Pryce and P. Amer, 2021. Impact of a multiple-test strategy on breeding index development for the Australian dairy industry. Animal Production Science 61, 1940-1950.

Christie, K.M., R.P. Rawnsley and R.J. Eckard, 2011. A whole farm systems analysis of greenhouse gas emissions of 60 Tasmanian dairy farms. Animal Feed Science and Technology 166-167, 653-662.

Dairy Australia, 2020. Australian Dairy Industry Sustainability Report 2019 Towards our 2030 Goals. Dairy Australia, Melbourne, Australia.

Dairy Australia, 2021. Emission sources in dairy. https://www.dairyaustralia.com.au/dairysa/land-water-and-climate/climate/preserve#.Y3XB73ZBxD8. Accessed 17 November 2022

DataGene, 2022. TechNote 29: Sustainability Index. https://datagene.com.au/sites/default/files/Upload%20Files/Technote%2029%20Sustainability%20Index.pdf

de Haas, Y., R.F. Veerkamp, G. de Jong and M.N. Aldridge, 2021. Selective breeding as a mitigation tool for methane emissions from dairy cattle. Animal 15, 100294.

Deighton, M.H., S.R.O. Williams, M.C. Hannah, R.J. Eckard, T.M. Boland, W.J. Wales and P.J. Moate, 2014. A modified sulphur hexafluoride tracer technique enables accurate determination of enteric methane emissions from ruminants. Animal Feed Science and Technology 197, 47-63.

Garnsworthy, P.C., J. Craigon, J.H. Hernandez-Medrano and N. Saunders, 2012. On-farm methane measurements during milking correlate with total methane production by individual dairy cows. Journal of Dairy Science. 95, 3166–3180.

Gerber, P., T. Vellinga, C. Opio and H. Steinfeld, 2011. Productivity gains and greenhouse gas emissions intensity in dairy systems. Livestock Science 139, 100-108.

Løvendahl, P., G.F. Difford, B. Li, M.G.G. Chagunda, P. Huhtanen, M.H. Lidauer, J. Lassen and P. Lund, 2018. Review: Selecting for improved feed efficiency and reduced methane emissions in dairy cattle. Animal 12, s336-s349.

Lovett, D.K., L. Shalloo, P. Dillon and F.P. O'Mara, 2006. A systems approach to quantify greenhouse gas fluxes from pastoral dairy production as affected by management regime. Agricultural Systems 88, 156-179.

Manzanilla-Pech, C.I.V., P. Loevendahl, D. Mansan Gordo, G.F. Difford, J.E. Pryce, F. Schenkel, S. Wegmann, F. Miglior, T.C. Chud, P.J. Moate, S.R.O. Williams, C.M. Richardson, P. Stothard and J. Lassen, 2021. Breeding for reduced methane emission and feed-efficient Holstein cows: An international response. Journal of Dairy Science 104, 8983-9001.

Mazzetto, A.M., S. Falconer and S. Ledgard, 2022. Mapping the carbon footprint of milk production from cattle: A systematic review. Journal of Dairy Science 105, 9713-9725.

Pickering, N., Y. de Haas, J. Basarab, K. Cammack, B. Hayes, R. Hegarty, J. Lassen, J.C. McEwan, S. Miller, C.S. Pinares-Patiño, G. Shackell, P. Vercoe and V.H. Oddy, 2013. Consensus methods for breeding low methane emitting animals. A White Paper prepared by the Animal Selection, genetics and genomics network of the livestock research group of global research alliance for reducing greenhouse gases from agriculture. 57 pp. The Animal Selection, Genetics and Genomics Network

Pryce, J.E. and M.J. Bell, 2017. The impact of genetic selection on greenhouse-gas emissions in Australian dairy cattle. Animal Production Science 57, 1451-1456.

R Core Team, 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Richardson, C.M., P.R. Amer, F.S. Hely, I. van den Berg and J.E. Pryce, 2021a. Estimating methane coefficients to predict the environmental impact of traits in the Australian dairy breeding program. Journal of Dairy Science 104, 10979-10990.

Richardson, C.M., P.R. Amer, C. Quinton, J. Crowley, F.S. Hely, I. van den Berg and J.E. Pryce, 2022. Reducing greenhouse gas emissions through genetic selection in the Australian dairy industry. Journal of Dairy Science 105, 4272-4288.

Richardson, C.M., B. Sunduimijid, P. Amer, I. van den Berg and J.E. Pryce, 2021b. A method for implementing methane breeding values in Australian dairy cattle. Animal Production Science 61, 1781-1787.

Scott, B.A., M. Haile-Mariam, I.M. MacLeod and J.E. Pryce, 2021. Does selecting for the a2 alfa-casein allele increase inbreeding? Proc. Assoc. Advmt. Anim. Breed. Genet. 24, 361-364.

Shadpour, S., T.C.S. Chud, D. Hailemariam, G. Plastow, H.R. Oliveira, P. Stothard, J. Lassen, F. Miglior, C.F. Baes, D. Tulpan and F.S. Schenkel, 2022. Predicting methane emission in Canadian Holstein dairy cattle using milk mid-infrared reflectance spectroscopy and other commonly available predictors via artificial neural networks. Journal of Dairy Science 105, 8272-8285.

Vanlierde, A., H. Soyeurt, N. Gengler, F.G. Colinet, E. Froidmont, M. Kreuzer, F. Grandl, M. Bell, P. Lund, D.W. Olijhoek, M. Eugène, C. Martin, B. Kuhla and F. Dehareng, 2018. Short communication: Development of an equation for estimating methane emissions of dairy cows from milk Fourier transform mid-infrared spectra by using reference data obtained exclusively from respiration chambers. Journal of Dairy Science 101, 7618-7624.

Waghorn, G.C. and R.S. Hegarty, 2011. Lowering ruminant methane emissions through improved feed conversion efficiency. Animal Feed Science and Technology 166-167, 291-301.

Williams, S.R.O., M.C. Hannah, J.L. Jacobs, W.J. Wales and P.J. Moate, 2019. Volatile Fatty Acids in Ruminal Fluid Can Be Used to Predict Methane Yield of Dairy Cows. Animals 9,

Workie, Z.W., J.P. Gibson and J.H.J. van der Werf, 2021. Analysis of culling reasons and age at culling in Australian dairy cattle. Animal Production Science 61, 680-689.

Zhang, Q., G. Difford, G. Sahana, P. Løvendahl, J. Lassen, M.S. Lund, B. Guldbrandtsen and L. Janss, 2020. Bayesian modeling reveals host genetics associated with rumen microbiota jointly influence methane emission in dairy cows. The ISME Journal 14, 2019-2033.

Zhang, X. and P. Amer, 2021. A new selection index percent emphasis method using subindex weights and genetic evaluation accuracy. Journal of Dairy Science 104, 5827-5842.

Zimmerman, P.R. and R.S. Zimmerman, 2012. U.S. Patent and Trademark Office, Pat. No. US20090288606. Method and system for monitoring and reducing ruminant methane production.