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THE APPLICATION OF A SUB-INDEX WEIGHTED PERCENT EMPHASIS METHOD TO AUSTRALIAN DAIRY SELECTION INDEXES

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SUMMARY

Percent trait emphasis is a concept used to interpret the selection effort of a trait in a selection index. Zhang and Amer (2021) published a sub-index weighted percent emphasis and demonstrated its advantage over the traditional method. The objective of this study is to apply this method to a current selection index and compare that with the traditional method. The results showed that 1) the new methods for calculating trait percent emphasis outperform conventional methods, 2) differences in trait accuracy of prediction impact their real percent emphasis, and 3) unfavourable correlations among traits reduce their effective emphasis in indexes.

INTRODUCTION

Percent trait emphasis is commonly used to describe selection indexes used in national genetic evaluations to help farmers and other users to interpret the selection effort being applied to competing traits. The currently accepted and widely used methods to calculate trait percent emphasis use the product of trait mean EBV and genetic SD as the base measurement, and the summation over all traits as the scaling factor (VanRaden 2002; Miglior *et al.* 2005, 2017). The sub-index weighted method (Zhang and Amer 2021) also accounts for accuracy of trait evaluation and correlations among traits. This method has been applied to USDA net merit of young bulls with lower accuracies compared to proven bulls (VanRaden *et al.* 2021). The aim of this study is to apply both methods to Australian HWI index and compare their results and impacts.

MATERIALS AND METHODS

Selection index emphasis methods. The method is described in Zhang and Amer (2021). In short, the traits in the selection indexes are clustered based on their genetic correlations or accuracy adjusted EBV correlations. Then traits relative emphases are weighted by the corresponding cluster weights calculated as the percentage of the cluster variance over the sum of variances of all clusters.

Materials. We used the Australian dairy Health Weighted Index (HWI) and Balanced Performance Index (BPI) in 2020 to test the emphasis methods. We used a set of genomic Australian Breeding Value (ABV) predictions of 9,283 Holstein-Friesian cows with a minimum single trait evaluation accuracy of 60% except the trait feed saved (AUS HWI, DataGene 2020a; Axford *et al.* 2021). Table 1 shows the trait economic weights, Australian Breeding Values (ABV) SD and mean trait accuracies. The ABV correlations are shown in Appendix 3, Table 7 of DataGene (2020b).

RESULTS AND DISCUSSION

The hierarchical clustering grouped traits with high within-cluster and low between-cluster absolute genetic or (G)EBV correlation traits together (Figure 1). Most of the sub-index groups were also consistent with their trait function groups, except FAT had been grouped separately from MILK and PROT, and PINSET and OTYPE were also separated, indicating that trait functions may not be an ideal way to group traits.

Table 1. Summary statistics of 2020 Australian HWI selection index[1]

Trait	Trait abbreviation	Unit	Economic Weight ($)		ABV SD	Mean accuracy (%)
			HWI	BPI		
Milk protein	PROT	kg	4.36	6.67	8.02	NA
Milk fat	FAT	kg	1.35	2.08	12.1	NA
Milk volume	MILK	L	-0.07	-0.11	365	76.0
Survival	SURV	% surv one parity to next	7.20	7.2	3.16	61.8
Fertility	FERT	42d calving%	14.1	6.94	5.14	69.0
SCC	SCC	count/ml	0.69	0.69	21.3	76.4
Mastitis Resistance	MAS	resistance ABV unit	6.75	6.75	3.19	71.3
Milking speed	MSPEED	ABV unit	5.02	5.02	2.13	68.5
Temperament	TEMP	ABV unit	3.60	3.6	1.75	NA
Mammary system	MAMM	ABV unit	3.59	2.76	4.18	NA
Overall type	OTYPE	% increase in score	1.36	1.36	3.97	68.1
Pin set	PINSET	% increase in score	0.78	0.78	4.78	NA
Feed saved	FEEDEF	kg DM saved	0.3853	0.1927	74.8	34.8
Udder depth	UDDEP	ABV unit	0	0.82	4.09	NA

[1]Axford *et al.* (2021)

Compared to the emphasis calculated by the traditional method, the sub-index emphasis of group 1 traits increased 10% in both HWI and BPI, whereas emphasis of group 2 traits decreased 8% in HWI and decreased 11% in BPI (Table 2). Group 1 was a favourable trait combination, because both their covariances and economic weights were positive, resulting in a higher cluster weight, w_k, i.e. $[a_k' G_{kk} a_k]^{\frac{1}{2}}$, compared to the cluster weight using the traditional method, which is a simple summation of relative economic weight without considering the covariances, i.e. $[a_k' I_k \sigma^2_{g_{kk}} a_k]^{\frac{1}{2}}$. Group 2 traits MILK and PROT formed an unfavourable trait combination, because their covariance was positive (137,249) but their economic weights were in opposite directions (HWI: $4.36 for PROT and $-0.07 for MILK; BPI: $6.67 for PROT and $-0.11 for MILK), resulting in a lower cluster weight, w_k, compared to that using traditional method.

The new emphasis methods results are more realistic because they will better reflect the selection response in practice. Using the traditional method, the emphasis of group 1 was likely underestimated whereas emphasis of group 2 was likely exaggerated. With the adjustment in the sub-index weight method, traits with small weights were given slightly higher weights.

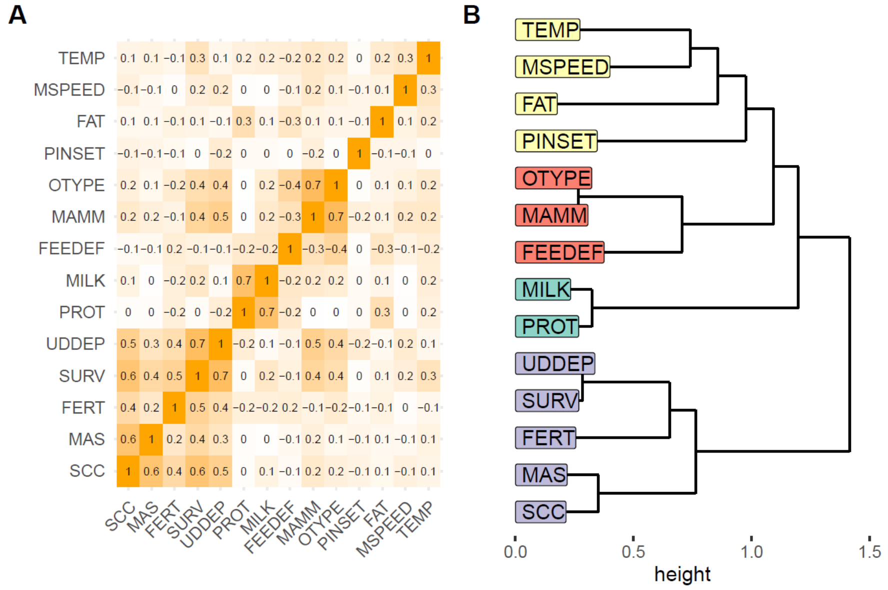

Figure 1. Correlation and hierarchical clustering of the main estimated breeding value traits included in the Australian BPI and HWI indexes

Table 2. Sub-index total percent emphases across methods and datasets and changes of the 3 new methods compared to the traditional method

Sub-index group	**Traits**	**HWI** Percent emphasis by method (%)		**BPI** Percent emphasis by method (%)	
		Traditional	Sub-index weighted	Traditional	Sub-index weighted
1	FERT, SURV, SCC, MAS, UDDEP	47	57	36	46
2	MILK, PROT	22	14	35	24
3	OTYPE, MAMM, FEEDEF	18	16	12	10
4	TEMP, MSPEED, FAT, PINSET	13	13	17	19
Total changes compared to Traditional			20		25

A common argument against the percent emphasis method is that selection response solely can be enough to describe the selection pressure in practice. This is not true when the trait undergoes genetic change due to effects other than selection, such as natural selection, drifts, or correlations with other preselected traits. We often see traits with no economic weightings undergo genetic changes and some traits with positive economic weightings undergo negative genetic changes due to correlated responses. In the current study, in HWI, the predicted selection response for SCC and FERT are 0.6 and 0.8 SD units (Datagene 2020b), respectively, very similar in value. Whereas the emphases for these two traits are 6.44% and 32% (Table 2), indicating that FERT is undergoing a much higher selection pressure than SCC to achieve similar selection response. It is also very hard to express trait responses in a way that makes them add up to 100%, making interpretation difficult for practical breeders and farmers.

CONCLUSIONS

This study compared sub-index weight and traditional emphasis methods for defining the relevant importance of traits in a selection index. The sub-index weight method generated more realistic results than the traditional method when within-sub-index trait correlations were relatively larger than those of between-sub-index, and when genetic evaluation accuracies were relatively variant across all EBVs. The new method provides convenient deployment options where pre-defined genetic (co)variance matrices are replaced by alternatives calculated from sets of estimated breeding values for defined groups of selection candidates.

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