Contributed paper

INVESTIGATION OF METHODS FOR INCLUSION OF FIXED EFFECTS FOR ULTRASOUND SCAN CARCASS TRAITS IN LARGE SCALE SHEEP GENETIC EVALUATION

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SUMMARY

Australian sheep genetic evaluation is conducted routinely for millions of animals for many traits. In the current analysis implemented by the OVIS software, phenotypes are pre-adjusted for systematic fixed effects to make fair genetic comparison between animals. This study assessed whether correction factors used in OVIS remain valid, and to explore whether the pre-adjustment method is still suitable and is comparable with a linear model. Furthermore, importance of interactions between body weight and sex, or body weight and flock were estimated. Regression slopes were calculated from forward prediction, using eye muscle depth data on 234,810 White Suffolk and 249,136 Poll Dorset sheep and fat depth data on 246,149 White Suffolk and 268,002 Poll Dorset sheep. Updated pre-adjustment factors produced regression slopes of progeny performance on their sire's estimated breeding values (EBVs) equal to 0.67 and 0.62 (averaged over breeds) for eye muscle depth and fat depth, respectively. Regression slopes were same for eye muscle depth and slightly better for fat depth than OVIS (0.66 and 0.64 respectively). A linear model produced significant improvements in regression slopes (0.60 and 0.50 respectively). Including interaction effects between fixed effects did not significantly influence the accuracy of prediction of progeny performance. A linear model will be implemented in future OVIS evaluation for ultrasound scan carcass traits.

INTRODUCTION

Genetic evaluation is conducted to provide information to breeders about the genetic merit of their animals in the form of estimated breeding values (EBVs) and selection index values. EBVs are calculated by correcting observed phenotypes for systematic environmental effects to allow fair genetic comparisons between animals. There are two common approaches to correct for the environmental effects: 1) pre-adjustment of phenotypes for environmental effects before genetic evaluation (Brown and Reverter 2002; Schaeffer 2019) or 2) fitting environmental effects in the mixed model equations to estimate them jointly with the breeding values (Laird and Ware 1982; Meyer 2004). The analytical software that implements the Australian genetic evaluation for sheep (OVIS) uses a pre-correction method, including correction of scanned carcass traits for the animal weight at scanning animal via linear and quadratic regression coefficients. The only fixed effect that is directly fitted in an animal model in OVIS is the contemporary group (CG) which includes breed, flock, management group, sex, and year of measurement subclass (Brown *et al.* 2016).

Theoretically, fixed effects such as the weight of animals and interaction effects between fixed effects should be included directly into the mixed model equation because the linear model corrects for the systematic environmental effects and gives an unbiased estimate of breeding value directly from the model (Laird and Ware 1982; Henderson 1984; Meyer 1998). However, estimating all effects jointly in the routine analysis increases the computational burden which can be prohibitive for large-scale genetic evaluation with millions of animals for many traits. With increasing computing power and further advances in analysis algorithms, this is becoming less problematic. Another consideration in potentially changing adjustment methods is that pre-adjustment factors are multiplicative and hence non-linear, and such corrections cannot always be implemented in a linear mixed model in the same manner. The current adjustment factors were estimated many years ago and they may need to be updated.

Given these considerations, this paper aims to determine whether the adjustment factors currently used by OVIS are still appropriate, and to propose updated adjustment factors if required. Furthermore, we examined whether correcting scanned carcass traits for body weight differs significantly between sexes or flocks. Finally, we compared the effectiveness of a linear model in the evaluation compared to using pre-correction factors.

MATERIALS AND METHODS

Data were retrieved from the LAMBPLAN database, comprising ultrasound measurements of eye muscle depth (EMD) and fat depths (FD) and associated body weight recorded at post-weaning in Australian and New Zealand sheep. A subset of the terminal dataset was extracted including animals born from 2009 onwards. Data were filtered according to the guidelines of OVIS (Brown *et al.* 2000). There were 234,810 and 249,136 animals for eye muscle depth and 246,149 and 268,002 animals for fat depth for the White Suffolk (WS) and Poll Dorset (PD) breeds, respectively. Estimated variance components were estimated for the scanned traits using the following mixed model equation:

$$y = \boldsymbol{X_1}b + \boldsymbol{Z_1}\,a + \boldsymbol{Z_2}m + \boldsymbol{Z_3}mp + \boldsymbol{Z_4}sfy + e$$

Where y is the vector of observations, b is a vector of fixed effects, a is a vector of breeding values of animals, m is a vector of maternal breeding values, mp is a vector of maternal permanent environmental effects, *sfy* is a vector of sire by flock year interaction effects, and e is a vector of random residuals. $\mathbf{X_1}$ is an incidence matrix relating b to y and $\mathbf{Z_1}$, $\mathbf{Z_2}$, $\mathbf{Z_3}$ and $\mathbf{Z_4}$ are incidence matrices relating *a, m, mp* and *sfy* to y. Then, variance components were used to estimate BLUP EBVs using the above mixed model equation. Contemporary group was only fitted as the fixed effect component, b, when EBVs were estimated from pre-adjustment because phenotypes were already adjusted for other fixed effects.

Estimating fixed effects and their interactions. The fixed effects currently included in OVIS for scanned carcass traits are contemporary group and a linear and quadratic regression on body weight of the animal and these effects were fitted in a complete linear mixed model that was used as a reference model. The reference linear model was expanded by adding interaction effects, one at a time, including sex by body weight, year of birth by body weight, flock by body weight and flock by sex by body weight. A complete mixed model was fitted and the significance of extra interaction effects was evaluated. Significant interaction effects were then tested for their effect on the EBVs through forward prediction(Huisman *et al.* 2015; Legarra and Reverter 2017).

Regression of progeny performance on sire EBVs. Forward prediction was conducted to test the predictive ability of the EBVs from the various models and their effectiveness in predicting progeny performance. The breeding values of sires for post-weaning body weight were estimated from the training data by different mixed models and by pre-adjustment of the phenotype. The training data included animals born before 2017. EBVs of sires were validated only if they had progeny born after 2016. Progeny performance was corrected for all of the fixed effects using solutions from a linear model, and were regressed on their sire's EBV. The expectation of the regression coefficient is 0.50. A lower value indicates an over-dispersion of sire EBVs relative to the variance observed in the progeny performance data, while a higher value reflects under-dispersion.

RESULTS AND DISCUSSION

Genetic parameters. Variance components estimated from the current data are presented for eye muscle depth and fat depth in Table 1. Heritability estimated for post-weaning eye muscle depth and fat depth were 0.25 and 0.18 respectively, averaged over breeds. These heritability values were smaller than previous estimates of 0.32 and 0.26 for post-weaning EMD and FD respectively (Brown *et al.* 2016). The difference might be due to that previous study not including a sire by flock-year interactions in the model, this study having more recent records and heritability estimates in this paper are breed specific while the latter are across-breeds estimates.

Table 1. Variance components used to estimate BLUP solutions

Traits(Breed)	V_a	V_m	V_{mp}	V_{sfy}	V_e	h^2
EMD (WS)	1.17	0.050	0.03	0.028	3.24	0.25
EMD (PD)	1.10	0.064	0.08	0.073	3.37	0.23
FD (WS)	0.08	0.005	0.01	0.009	0.35	0.18
FD (PD)	0.09	0.005	0.01	0.009	0.35	0.19

EMD: Eye Muscle Depth, FD: Fat Depth, WS: White Suffolk, PD: Poll Dorset

$V_{a,}$ additive genetic variance, V_m, maternal genetic variance, V_{mp}, permanent environment effect of the dam, V_{sfy}, sire by flock year variance, $h_{2,}$ direct heritability

Comparison between pre-adjustment factors. The average linear regression of eye muscle depth on body weight is higher (0.38; Table 2) than the OVIS assumption (0.31) indicating that the eye muscle depth of animals, relative to the body weight, has increased over the years. On the other hand, the average linear component for fat depth (0.08) was lower than the current OVIS factor (0.09) (Brown and Reverter 2002), indicating that fat depth of the animals relative to the body weight has decreased over the years.

Table 2. Adjustment factors currently used in OVIS and updated estimates

Fixed effect	Level	OVIS EMD	Updated EMD		OVIS FD	Updated FD	
			WS	PD		WS	PD
weight	Intercept	27.44	28.48	29.01	3.03	3.39	2.88
	Linear	0.31	0.38	0.38	0.09	0.07	0.08
	Quadratic	-0.001	-0.003	-0.003	-0.004	-0.0001	-0.0004

EMD: Eye Muscle Depth, FD: Fat Depth, WS: White Suffolk, PD: Poll Dorset

Comparison between the linear model and pre-adjustment of data. Updated pre-adjustment factors produced a slightly better regression slope (0.62) than pre-adjustment factors that are currently used in OVIS (0.64) for fat depth but identical prediction for eye muscle depth (Table 3). The complete linear model produced significantly better regression slopes of progeny performance on sire EBV (0.60 and 0.50) than with the EBVs based on pre-adjustment (0.67 and 0.62), comparing values averaged across breeds for eye muscle depth and fat depth, respectively. The regression slope for eye muscle depth was higher than 0.50, indicating under-dispersion of EBVs. Regression slopes for fat depth were close to 0.50, indicating that sire EBVs were able to predict progeny performance reliably. Further, regression slopes are closer to expectation in White Suffolk than in the Poll Dorset breed. Moreover, the regression slopes obtained from models with interactions did not give significantly different estimates of slope. Models with extra interaction effects, use significantly more computation time, and require more degrees of freedom. Based on these results, including interaction effects in routine evaluation may not be necessary.

Table 3. Regression slopes of progeny performance on sire EBVs for ultrasound scan traits

Models	Eye muscle depth		Fat depth	
	White Suffolk	Poll Dorset	White Suffolk	Poll Dorset
Pre- adjustment (OVIS)	0.63±0.01	0.70±0.01	0.61±0.02	0.67±0.02
Pre-adjustment (updated)	0.63±0.01	0.71±0.01	0.58±0.02	0.66±0.02
Linear models				
1 = (CG + Wt + Wt^2)	0.57±0.01	0.64±0.01	0.49±0.02	0.50±0.02
1 + sex*Wt + sex*Wt^2	0.56±0.01	0.64±0.01	0.49±0.02	0.50±0.02
1 + YOB*Wt + YOB*Wt^2	0.56±0.01	0.64±0.01	0.49±0.02	0.50±0.02
1 + flock*Wt + flock*Wt^2	0.58±0.01	0.64±0.01	0.50±0.02	0.52±0.02
1 + flock*sex*Wt + F*S*Wt^2	0.58±0.01	0.63±0.01	0.49±0.02	0.52±0.02

CG: Contemporary Group, Wt: Weight, S: Sex, YOB: Year of Birth, F: Flock,

CONCLUSIONS

The predictive ability of a model can be improved marginally by using updated pre-adjustment factors for ultrasound scanned carcass traits, and is not recommended. A complete linear model brings more improvement in the capability of EBVs to predict future progeny performance and is recommended for use in future OVIS evaluations if it is computationally feasible. Interaction effects between body weights with other fixed effects did not significantly increase the predictive capability of a model and can be ignored to simplify computation.

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