ALTERNATIVE APPROACHES TO PRESENTATION OF WORM RESISTANCE BREEDING VALUES FOR AUSTRALIAN SHEEP

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SUMMARY
Faecal egg counts (FEC) are not normally distributed and require transformation prior to statistical analysis. FEC data from 13 properties across Australia were used to assess natural logarithmic and cube root transformation to normalise FEC distribution. Both transformations achieved similar outcomes in terms of normalising FEC distribution. Regardless of the transformation used, back-transformation of FEC EBVs to facilitate presentation of predicted % change in FEC resulted in an asymmetrical distribution of predicted values around the mean, due to the positive skewness of the original counts. Nevertheless, these predicted % change in FECs of offspring should be a useful tool for technology transfer in relation to breeding for parasite resistance.

Keywords: Sheep, estimated breeding values, faecal egg count, normal distribution, transformation.

INTRODUCTION
Worm burdens in sheep follow an over-dispersed distribution, whereby the majority of animals carry few worms and a small number of animals are heavily infected (Barger 1985). Faecal egg count (FEC) is the measurement used to predict the worm burden of animals (McKenna 1981) and has been found to follow the same pattern of dispersion (Eady 1995). The over-dispersed distribution of FEC introduces the need to transform counts prior to undertaking statistical analyses that assume normal distribution of the data (Woolaston & Piper 1996). In addition, heterogeneity of variance may affect the accuracy of selection unless appropriate transformation is applied, as animals will tend to be selected from the more variable year groups, especially at high selection intensity (Hill 1984). Eady (1995) found cube root (FEC^{0.33}) to be the most appropriate type of transformation for FEC data from a central test sire evaluation scheme. However, cube root transformation did not result in homogenous variances across site-year groups and an additional step of adjusting the standard deviation to a common value of 1 was required to reduce bias when ranking animals across site-year groups (Eady 1995).

This procedure produces Faecal Egg Count Estimated Breeding Values (FEC EBV) where most individuals have a FEC EBV in the range of –1 (relatively resistant) to +1 (relatively susceptible), with a mean of zero. This FEC EBV is the figure that currently appears in reports and sale catalogues for breeders in Australia. For breeders to gain some insight into the predicted effect (on FEC of offspring) of using a sire with a particular FEC EBV, an additional calculation is needed to convert the FEC EBV into a predicted FEC, and then a % change in FEC. Regardless of the transformation used, back-transformation of FEC EBVs to facilitate presentation of predicted change in FEC gives an asymmetrical distribution of predicted values around the mean, due to the positive skewness of the original counts. Given the asymmetrical distribution of FECs, EBVs of –1 and +1 do not give the same predicted absolute change in FEC, that is an EBV of –1 gives a predicted change of – 49%
while an EBV of +1 gives a predicted change of +73% in offspring. This further complicates the explanation of how to interpret FEC EBVs in the form that they are currently presented.

Expressing the estimated breeding values directly as a percentage change in FEC of offspring may be a better method of presenting information to producers, providing a prediction of how the FEC of progeny will change. This method of presentation is used for somatic cell count (SCC) in dairy cattle (Mrode et al. 1998) and for FEC in New Zealand (McEwan et al. 1997). In these instances a natural logarithmic (ln) transformation is used to convert data to a normal distribution. The use of ln transformation for SCC in dairy cattle, allows the predicted transmitting abilities (PTA) or in like terms, the estimated progeny value, to be simply expressed as a percentage reduction in SCC levels (Mrode et al. 1998). For example a bull with a PTA of −10% is expected to transmit or pass on to daughters a reduction of 10% in SCC levels (Anon. 2000). However, unlike the cube root transformation, by using logarithmic transformation proportional data is transformed to an additive scale and the antilog value of the breeding value is a ratio that can be simply converted into a percentage (Morris 1999).

The aims of this paper are to evaluate cube root and natural logarithmic transformations of FEC data from a wide range of industry sources, and to explore methods of presenting FEC EBVs in a more “user friendly” manner for ram breeders and buyers.

**MATERIALS AND METHODS**

FEC data from 13 properties (42 property-year groups) breeding for worm resistance across Australia were used to compare ln (FEC+50) (McEwan et al. 1997) and FEC\(^{0.33}\) transformations to normalise the distribution of counts. A normal distribution has skewness and kurtosis values of zero (Tabachnick & Fidell 1989). The effectiveness of each transformation in normalising data distribution was assessed on the basis of the degree of kurtosis and skewness. To assess homogeneity of variances across property-year groups the correlation between the mean and standard deviation (SD) of the transformed FEC was calculated. To simplify presentation the cube root for FEC is expressed as FEC\(^{0.33}\), but all calculations in this paper have been done on the basis of FEC\(^{0.3333}\), as less decimal places will change the result.

Estimated breeding values for ln (FEC+50) and FEC\(^{0.33}\) (with standard deviation adjusted to 1) were calculated, assuming heritability of 0.25 and no genetic links between animals.

\[
\text{FEC}^{0.33}\text{EBV} = \left(\frac{\text{FEC}^{0.33} - \text{Mean FEC}^{0.33}}{1/\text{SD FEC}^{0.33}}\right) h^2
\]

\[
\text{ln (FEC+50)EBV} = \left(\text{ln (FEC+50)} - \text{Mean ln (FEC+50)}\right) h^2
\]

Predicted change in FEC of offspring was then calculated for FEC\(^{0.33}\) EBV using the formula: Predicted FEC (epg) = ((SDFEC\(^{0.33}\) x EBV/2) + mean FEC\(^{0.33}\)) \(h^2\), where SDFEC\(^{0.33}\) = mean FEC\(^{0.33}\) x 0.4 (coefficient of variation assumed to be 40%). For example, when mean is 500epg and the sire is 200epg, the predicted FEC of offspring = ((500\(^{0.33}\)x 0.4) x (-0.17/2)) + 500\(^{0.33}\)). The % change in FEC of offspring = (449 –500)/500 x 100 = -10.1%.

The % change in FEC of offspring for ln (FEC+50) EBV was calculated using the formula: % change in FEC = 100 x (EXP(ln (FEC+50)EBV x 0.5)-1) (McEwan pers. comm.) For example when mean is
500 epg and the sire is 200 epg. \( \ln((FEC+50)EBV) = (5.5 - 6.3) \times 0.25 = -0.2 \) and \% change in FEC = 100 \times (\exp(-0.2/2) - 1) = -9.4\%.

**RESULTS**

The FEC distributions from all property-year groups were positively skewed and usually with a high kurtosis value. In contrast with earlier studies (Eady 1995, Woolaston and Piper 1996) the application of \( \ln(FEC+50) \) and \( FEC^{0.33} \) transformation revealed that there was no clear advantage for either transformation in normalising the distribution of counts and reducing the dependency between the mean and SD (Table 1).

**Table 1.** Average kurtosis (K) and skewness (S), mean and standard deviation (SD) values of FEC, \( \ln(FEC+50) \) and \( FEC^{0.33} \) from all property-year groups

<table>
<thead>
<tr>
<th></th>
<th>FEC</th>
<th>( \ln(FEC+50) )</th>
<th>( FEC^{0.33} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1238</td>
<td>6.5</td>
<td>8.7</td>
</tr>
<tr>
<td>SD</td>
<td>1086</td>
<td>2.3</td>
<td>3.0</td>
</tr>
<tr>
<td>K</td>
<td>11.7</td>
<td>0.9</td>
<td>1.0</td>
</tr>
<tr>
<td>S</td>
<td>2.3</td>
<td>-0.6</td>
<td>-0.4</td>
</tr>
</tbody>
</table>

Correlations between the mean and SD of FEC, \( \ln(FEC+50) \) and \( FEC^{0.33} \) across all property-year groups (\( N = 42 \)) were 0.94 (\( P < 0.001 \)), 0.25 (\( P < 0.1 \)) and 0.28 respectively (\( P < 0.1 \)). The correlation between the SD of \( \ln(FEC+50) \) and SD of \( FEC^{0.33} \) was 0.85 (\( P < 0.001 \)), indicating little difference between the distributions created by each transformation.

Predicted percentage changes in FEC of offspring (assuming rams are mated to average EBV ewes) for \( \ln(FEC+50) \) and \( FEC^{0.33} \) EBVs are shown in Table 2. These predicted changes in FEC have been estimated using the formulae presented above.

**Table 2.** Predicted \% change in FEC of offspring by back-transformation of \( \ln(FEC+50) \) EBVs and \( FEC^{0.33} \) EBVs

<table>
<thead>
<tr>
<th>EBV</th>
<th>% change in FEC (( \ln ))</th>
<th>% change in FEC (( FEC^{0.33} ))</th>
<th>EBV</th>
<th>% change in FEC (( \ln ))</th>
<th>% change in FEC (( FEC^{0.33} ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>-39</td>
<td>-49</td>
<td>1</td>
<td>65</td>
<td>73</td>
</tr>
<tr>
<td>-0.8</td>
<td>-33</td>
<td>-41</td>
<td>0.8</td>
<td>49</td>
<td>56</td>
</tr>
<tr>
<td>-0.5</td>
<td>-22</td>
<td>-27</td>
<td>0.5</td>
<td>28</td>
<td>33</td>
</tr>
<tr>
<td>-0.2</td>
<td>-10</td>
<td>-11</td>
<td>0.2</td>
<td>11</td>
<td>12</td>
</tr>
</tbody>
</table>

Back-transformation of FEC EBVs to predicted FECs of offspring resulted in an uneven distribution of values either side of zero using both \( \ln(FEC+50) \) and \( FEC^{0.33} \) (Table 2). The asymmetrical distribution is caused by the positive skewness of the original counts. Back-transformed data will show a higher predicted change in positive EBVs compared to negative EBVs. Results have shown that \( \ln(FEC+50) \) EBVs usually range no higher than 0.5 EBV, reducing the apparent skewness of log back-transformed FEC.
DISCUSSION

Cube root and logarithmic transformations appear to be equally effective in normalising FEC distributions. However, when transformed scale EBVs are back-transformed the resulting estimated percentage change in FEC of offspring are only approximates because of the over dispersion of the original FEC distributions.

An important purpose of this investigation was to address the issue of using a unit in industry that is easy to understand and helps breeders recognise the benefits of worm resistant animals. Breeders currently selecting for worm resistance in Australia have an understanding of cube root transformed units for FEC EBV and many are comfortable with using this unit. However, as more wool growers are encouraged to breed and purchase worm resistant rams, a unit that is easier to understand may accelerate adoption of this technology.

A predicted FEC of offspring or predicted % change in FEC of offspring would allow ram buyers to estimate the benefits of a resistant ram in reducing the FEC. Breeders selecting for worm resistance were sent a survey and asked whether they felt this conversion would be useful. There was encouraging feedback by most breeders with an optimistic response that this unit would demonstrate the practical value of the program and enable ram buyers to place a ‘farmer value’ on worm resistance.

Our conclusion is that a case can be made for presenting genetic merit of rams in terms of percentage change in FEC of offspring. This can be done for FEC\(^{0.33}\) and for ln (FEC+50) as both are scale independent. In NZ ln (FEC+50) EBVs are presented as percentage change in FEC and the same could be done in Australia using either transformation. We recommend that Australian service providers evaluate the merits of this proposal.

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REFERENCES