

PREDICTING BEEF CARCASS COMPOSITION FROM WEIGHT AND RIB FAT DEPTH

A. Williams^{1*}, C.G. Jose¹, P. McGilchrist¹, B.J. Walmsley², M.J. McPhee², P.L. Greenwood², and G.E. Gardner¹

¹School of Veterinary and life Sciences, Murdoch University, Murdoch, WA 6150, Australia;

²New South Wales Department of Primary Industries, University of New England, Armidale, NSW 2351, Australia.

*Corresponding author email: Andrew.Williams@murdoch.edu.au

Abstract – Six independent beef datasets with CT composition data were used to demonstrate how well the industry standard measurements of hot carcass weight (HCW) and rib fat depth predict carcass fat content (or percentage). Equations predicting computed tomography (CT) fat% were derived in all six datasets then transported to the other five datasets. It was shown that the accuracy and precision of prediction is highly variable when transported between datasets.

Key Words – Computed Tomography.

I. INTRODUCTION

Lean meat yield is an important profit driver for the beef industry [1]. The current industry standard for determining carcass composition is based on carcass weight and a measurement of fat depth either on the hot carcass at the P8 site located at the intersection of a line parallel to the spine from the tuber ischium and a line perpendicular to it from the spinous process of the third sacral vertebra [2], or on the cold carcass at the rib quartering site between the 5th and 13th ribs [3]. When predicting carcass yield both the 12th rib and P8 measurements have been shown to be equally accurate when used in conjunction with hot carcass weight [4].

There is concern within the Australian beef industry that these measures are prone to error due to a range of factors including, poor precision of this method for predicting lean meat yield and poor transportation of this method across differing populations of cattle, as well as operator errors made during measurement. However there is little data available to properly quantify this error. A key limitation is the method for determining carcass composition. Historically this has been reflected through carcass bone out data, yet this is problematic due to varying bone out specifications across datasets as well as large human imposed operator effects. In Australia with the introduction of CT scanning methodologies, datasets are now available to assess the efficiency of predicting carcass composition using carcass weight and a single point measurement of fat depth. This study assesses the capacity of rib fat and carcass weight to predict CT carcass fat% across multiple datasets.

II. MATERIALS AND METHODS

This study compiled six different beef datasets where carcass measurements and CT scan data were available. All animals were Bos Taurus, dataset 1 being a mix of Angus and Hereford, dataset 2, mixed breeds, and datasets 3-6 pure-bred Angus. P8 fat depths were not available across all datasets and therefore rib fat (measured as fat depth over the 12th rib) and hot carcass weight was used to predict CT fat% in the carcass. CT scanned data was captured using Picker PQ 5000 spiral CT scanners at either Murdoch University or the University of New England. In both cases the spiral abdomen protocol was selected with settings: pilot scan length of 512 mm, field of view set at 480mm, Index 20, kV 110, mA 150, revs 40, pitch 1.5 and standard algorithm. Prior to scanning the carcasses were dissected into 16 primal sections to fit the limitations of the CT aperture. The primals were scanned in 10 mm or 5mm slice widths, with each slice taken 10 mm or 15mm apart. Image analysis was done according to the method described by Anderson et al [5].

General linear models (SAS) were used to predict CT fat% from hot carcass weight and rib fat depth using leave-one-out cross-validation (GLM Select procedure in SAS). To demonstrate transportability a number of approaches were tested. Firstly equations were derived in each dataset separately and then validated in each of the remaining five datasets (models 1-6, Table 2). Secondly, to normalize for the variation in data range and number of animals an

equation was derived in 5 of the datasets and then validated in the 6th. This process of “leave-one-out” validation was repeated until validation had occurred in all 6 datasets independently (models 8-13, Table 2). Lastly an equation was derived in all of the datasets combined, and then tested within each of the 6 data subsets. For the relationship between actual versus predicted CT fat%, R-square of the prediction and root mean square error of the prediction (RMSEP) are shown as indicators of precision, and slope and bias estimates are shown to represent accuracy within each dataset. Bias represents the difference between the predicted and actual values at the median of the dataset. An example of this process of training and validation is shown in Figure 1.

III. RESULTS AND DISCUSSION

Descriptive statistics of datasets 1 to 6 are shown in Table 1. The model fitted within all datasets combined demonstrated an RMSE for predicting CT fat% of 3.15 and described 80.6% of the variation within the data. However within subsets of its own training data the performance of this model (model 7, Table 2) showed considerable variation in precision, with RMSE varying from 4.04 to 2.03 CT fat% units, and described between 12% and 85% of the variation within these populations. When models were trained within individual datasets (models 1-6 in Table 2), the RMSE for predicting CT fat% varied markedly from 4.05 CT fat% units, to 1.84 CT fat% units, and described between 13% and 88% of the variation within these populations.

Table 1. Descriptive statistics including mean±STDEV (minimum, maximum) for CT fat %, rib fat depth and hot carcass weight.

Dataset	1	2	3	4	5	6
N	102	51	37	40	50	127
CT Fat%	23.8 ± 8.71 (11.7, 42.3)	21.1 ± 8.55 (6.98, 47.0)	24.3 ± 2.84 (17.5, 29.8)	17.2 ± 2.63 (12.5, 22.8)	26.7 ± 4.30 (15.1, 36.9)	17.6 ± 4.45 (11.2, 29.4)
Rib Fat (mm)	9.21 ± 5.95 (1, 30)	9.20 ± 8.16 (1, 36)	9.89 ± 2.49 (6, 15)	4.90 ± 1.72 (1, 9)	13.9 ± 3.38 (7, 24)	4.47 ± 3.48 (1, 13)
Hot Carcase Weight (kg)	330.5 ± 118.5 (152.0, 581.8)	307.8 ± 70.1 (156.0, 467.0)	363.2 ± 31.1 (312.0, 438.0)	258.3 ± 19.9 (222.0, 312.0)	241.4 ± 25.7 (192.8, 302.8)	229.6 ± 73.4 (118.0, 404.0)

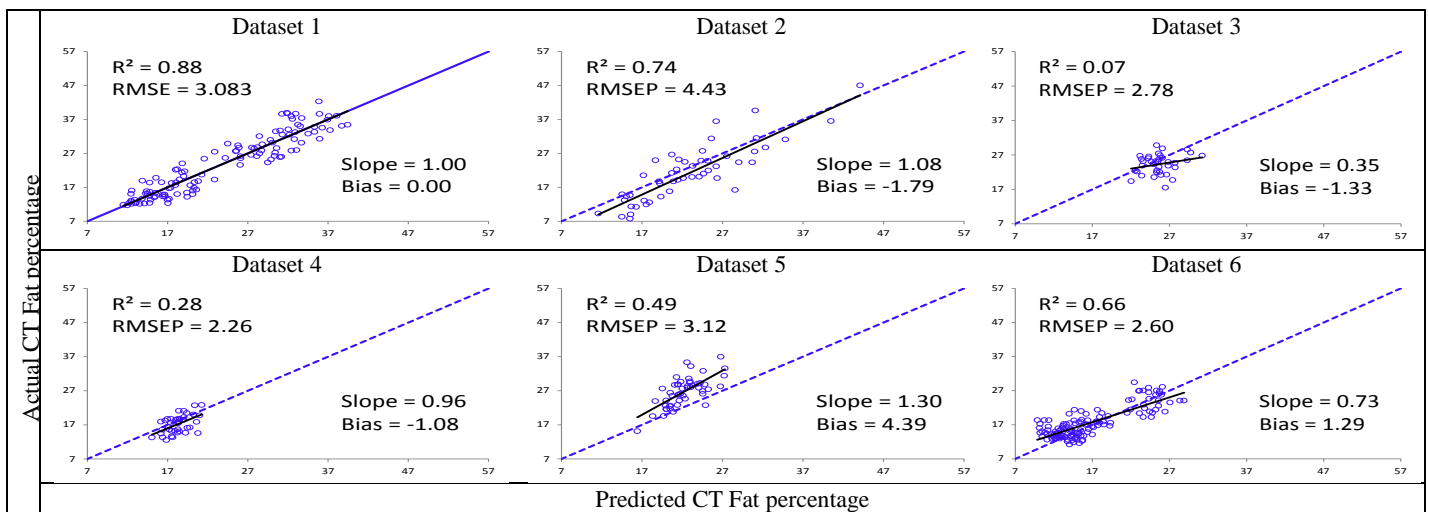


Figure 1. Relationship between actual CT fat % and predicted CT fat % from a model containing hot carcass weight (kg) and rib fat depth (mm). This represents an example of the training and validating procedure, in this case with the prediction derived in dataset 1 and transported to datasets 2, 3, 4, 5, and 6. Dashed lines represent a perfect prediction; solid lines show the performance of the transported equation.

Transporting models across datasets showed marked variation in precision compared to the training data, which is evident when comparing precision estimates within columns in Table 2. Across all validation tests for Models 1-6 in Table 2 the RMSEP varied from 1.85 to 4.88 and bias estimates varied from -6.47 to 4.39 CT fat% units. Furthermore, the slope of these relationships also deviated markedly from 1, ranging from 0.28 to 3.15, implying that the bias would change a great deal if it were estimated at a value higher or lower than the median CT fat%. In part this marked variation is due to a limited range within the training data (ie datasets 3, 4, and 5), and the resultant extrapolation beyond this range when validated. Thus it is not surprising that the populations with smaller range and therefore

smaller standard deviations demonstrate better precision, but these still show marked prediction bias from their actual values. In practice within industry any predictive model will be exposed to the weakness of extrapolation, however within the current study dataset 1 is the least exposed to this limitation, given its range. Yet in spite of this the model trained in this dataset still demonstrated considerable variation in performance across validation datasets (see Figure 1 and Table 2). For example the RMSEP within dataset 1 varied from 3.08 to as high as 4.88, slope ranged between 0.78 and 3.15, and bias estimates ranged between -4.44 and 2.23 fat percentage units at the median for dataset 1.

This effect of data range can be further normalized by training models using 5 datasets and then testing in the 6th, as shown for models 8 – 13. In this case there was still considerable variation in performance across the validation datasets, with RMSEP varying from 2.035 to as high as 4.049, slopes ranging between 0.81 and 1.25, and bias estimates ranging between -2.11 and 2.29 fat percentage units at the median for each validation dataset.

Table 2. Precision and accuracy estimates for the relationship between actual CT fat % and predicted CT fat % from models containing hot carcass weight (kg) and rib fat depth (mm). Precision estimates include R-square and root mean square error of the prediction, and accuracy estimates include slope of the relationship and bias at the median.

Model No. (ID of training data)		Validation dataset					
		Data 1	Data 2	Data 3	Data 4	Data 5	Data 6
Model 1* (Data 1)	R ²	<i>0.88</i>	<i>0.74</i>	<i>0.07</i>	<i>0.28</i>	<i>0.49</i>	<i>0.66</i>
	RMSEP	<i>3.083</i>	<i>4.426</i>	<i>2.783</i>	<i>2.26</i>	<i>3.115</i>	<i>2.6</i>
	Slope	<i>1</i>	<i>1.08</i>	<i>0.35</i>	<i>0.96</i>	<i>1.3</i>	<i>0.73</i>
	Bias	<i>0</i>	<i>-1.79</i>	<i>-1.33</i>	<i>-1.08</i>	<i>4.39</i>	<i>1.29</i>
Model 2* (Data 2)	R ²	<i>0.84</i>	<i>0.78</i>	<i>0.12</i>	<i>0.43</i>	<i>0.43</i>	<i>0.77</i>
	RMSEP	<i>3.515</i>	<i>4.046</i>	<i>2.699</i>	<i>2.015</i>	<i>3.275</i>	<i>2.14</i>
	Slope	<i>1.19</i>	<i>1</i>	<i>0.45</i>	<i>1.11</i>	<i>0.98</i>	<i>0.97</i>
	Bias	<i>2.23</i>	<i>0</i>	<i>1.84</i>	<i>0.51</i>	<i>2.97</i>	<i>1.8</i>
Model 3* (Data 3)	R ²	<i>0.72</i>	<i>0.76</i>	<i>0.13</i>	<i>0.46</i>	<i>0.36</i>	<i>0.83</i>
	RMSEP	<i>4.612</i>	<i>4.202</i>	<i>2.681</i>	<i>1.963</i>	<i>3.464</i>	<i>1.851</i>
	Slope	<i>3.15</i>	<i>2.23</i>	<i>1</i>	<i>2.5</i>	<i>1.85</i>	<i>2.95</i>
	Bias	<i>-0.88</i>	<i>-3.6</i>	<i>0</i>	<i>-5.09</i>	<i>0.3</i>	<i>-5.67</i>
Model 4* (Data4)	R ²	<i>0.72</i>	<i>0.76</i>	<i>0.13</i>	<i>0.46</i>	<i>0.37</i>	<i>0.83</i>
	RMSEP	<i>4.591</i>	<i>4.198</i>	<i>2.681</i>	<i>1.963</i>	<i>3.461</i>	<i>1.853</i>
	Slope	<i>1.26</i>	<i>0.89</i>	<i>0.4</i>	<i>1</i>	<i>0.74</i>	<i>1.18</i>
	Bias	<i>2.17</i>	<i>-0.29</i>	<i>2.15</i>	<i>0</i>	<i>0.28</i>	<i>0.5</i>
Model 5* (Data 5)	R ²	<i>0.88</i>	<i>0.74</i>	<i>0.07</i>	<i>0.29</i>	<i>0.49</i>	<i>0.67</i>
	RMSEP	<i>3.084</i>	<i>4.389</i>	<i>2.778</i>	<i>2.245</i>	<i>3.114</i>	<i>2.58</i>
	Slope	<i>0.78</i>	<i>0.84</i>	<i>0.28</i>	<i>0.76</i>	<i>1</i>	<i>0.57</i>
	Bias	<i>-4.44</i>	<i>-5.89</i>	<i>-6.47</i>	<i>-4.25</i>	<i>0</i>	<i>-1.01</i>
Model 6* (Data 6)	R ²	<i>0.69</i>	<i>0.76</i>	<i>0.13</i>	<i>0.46</i>	<i>0.35</i>	<i>0.83</i>
	RMSEP	<i>4.883</i>	<i>4.256</i>	<i>2.682</i>	<i>1.964</i>	<i>3.495</i>	<i>1.84</i>
	Slope	<i>1.03</i>	<i>0.72</i>	<i>0.32</i>	<i>0.8</i>	<i>0.58</i>	<i>1</i>
	Bias	<i>0.88</i>	<i>-1.56</i>	<i>0.66</i>	<i>-0.71</i>	<i>-2.85</i>	<i>0</i>
Model 7# (All Data)	R ²	<i>0.85</i>	<i>0.78</i>	<i>0.12</i>	<i>0.42</i>	<i>0.44</i>	<i>0.76</i>
	RMSEP	<i>3.424</i>	<i>4.049</i>	<i>2.705</i>	<i>2.031</i>	<i>3.250</i>	<i>2.190</i>
	Slope	<i>1.09</i>	<i>0.94</i>	<i>0.42</i>	<i>1.03</i>	<i>0.94</i>	<i>0.88</i>
	Bias	<i>0.30</i>	<i>-1.83</i>	<i>-0.30</i>	<i>-1.01</i>	<i>1.27</i>	<i>0.59</i>
Model 8-13^ (Leave one out)	R ²	<i>0.80</i>	<i>0.78</i>	<i>0.42</i>	<i>0.42</i>	<i>0.46</i>	<i>0.75</i>
	RMSEP	<i>3.947</i>	<i>4.049</i>	<i>2.035</i>	<i>2.035</i>	<i>3.201</i>	<i>2.255</i>
	Slope	<i>1.25</i>	<i>0.92</i>	<i>1.04</i>	<i>1.04</i>	<i>1.05</i>	<i>0.81</i>
	Bias	<i>1.15</i>	<i>-2.11</i>	<i>-1.15</i>	<i>-0.88</i>	<i>2.29</i>	<i>1.26</i>

*Within rows estimates in the training data are listed in italics and validated across the remaining datasets.

#Estimates represent performance within subsets of the training data.

^Estimates of models 8-13 represent performance in the validation dataset only.

These results highlight inaccuracies and loss of precision when using carcass weight and a single point measure of fatness to reflect carcass fat percentage. This work aligns well with previous studies where carcass weight and individual point measures of fatness [1] or even multiple carcass measures [6] produced highly variable results.

The fact that these models still vary in their performance across groups, even after normalizing for range, is likely due to a number of factors. Firstly the successful prediction of carcass fat percentage from carcass weight and a single measure of fat depth relies upon accurate and consistent fat depth measurement. Although these are experimental datasets in which great care has been taken during the collection of rib fat measurements, there are still likely to be processing and operator effects which would show up most strongly between datasets. Under commercial conditions these rib fat measurements would show even greater variation, hence the prediction of carcass fatness would be even more variable than that already demonstrated in this study. Secondly the prediction of carcass fat composition from fat depth relies upon a highly robust correlation between fat depth measured in one region with fat composition elsewhere in the carcass. There is evidence in sheep that suggests that genetics can strongly influence this correlation, redistributing bone, muscle and fat tissue within the carcass [5, 7]. It is quite possible that this effect also exists in beef, and therefore the genetic differences present across datasets may offer an additional source of error that contributes to the bias and variable precision evident in this study. Based on the genotypic variation present in herds across the Australian beef industry, and the likely increase in measurement error under commercial conditions, we conclude that the variation in bias and precision demonstrated in this study could well be understating that present in commercial reality.

IV. CONCLUSION

These results demonstrate the variability in estimating carcass fat composition from carcass weight and a single point of measurement of fat depth. Factors influencing this prediction include restricted range of training data, measurement and processing error, and genetic differences between groups. This illustrates why the Australian beef industry has little confidence in these measurements to reflect carcass composition and highlights the need for a whole carcass composition measurement that is independent of breed, processing and operator error.

ACKNOWLEDGEMENTS

Beef CRC, Meat and Livestock Australia, NSW Department of Primary Industries, University of New England and Murdoch University are thanked for their contribution of data to this analysis.

REFERENCES

1. McIntyre, BL and Frapple, PG (1988) Estimation of the yield of beef carcasses from measurements of fat thickness over the rib and rump. *Proceedings of the Australian Society of Animal Production*. 17:242-245.
2. Johnston, DJ, Reverter, A, Burrow, HM, Oddy, VH, Robinson, DL (2003) Genetic and phenotypic characterisation of animal, carcass, and meat quality traits from temperate and tropically adapted beef breeds. 1. Animal measures. *Australian Journal of Agricultural Research* 54, 107-118.
3. Watson, R, Polkinghorne, R, Thompson, JM (2008) Development of the Meat Standards Australia (MSA) prediction model for beef palatability. *Australian Journal of Experimental Agriculture* 48, 1368-1379.
4. Johnson, ER (1987) Comparison of 12th Rib and Rump Fat Thickness Measurements for Predicting Commercial Beef Yield in Local Market Carcasses. *Australian Journal of Experimental Agriculture* 27, 613-617.
5. Anderson, F, Williams, A, Pannier, L, Pethick, DW, Gardner, GE (2015) Sire carcass breeding values affect body composition in lambs-1. Effects on lean weight and its distribution within the carcass as measured by computed tomography. *Meat Science* 108, 145-154.
6. Meat and Livestock Australia (2017) Addressing key issues affecting compliance rates of pasture-fed cattle in southern Australia, Final report B.SBP.0110
7. Anderson, F, Williams, A, Pannier, L, Pethick, DW, Gardner, GE (2016) Sire carcass breeding values affect body composition in lambs-2. Effects on fat and bone weight and their distribution within the carcass as measured by computed tomography. *Meat Science* 116, 243-252.