## Validation of models to predict the intramuscular fat content of lamb loin

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**Introduction:** Intramuscular fat (IMF) content of lamb is a trait of interest for value based grading systems, given its importance to eating quality and sensory attributes (Hopkins et al. 2006). Consequently, there is much interest from the Australian industry in developing a non-destructive, non-invasive method for measuring the IMF content of lamb (Toohey, van de Ven, & Hopkins, 2018). Previous research has shown a potential for Near infrared spectroscopy (NIR) to predict the intramuscular fat content of lamb loin, however the model was not validated on independent data (Fowler et al. 2021). Consequently, a further study was completed to determine the ability of the model to predict the fat content of lamb loins which had not been included in the calibration model.

**Materials and Methods:** At 24 hr post-mortem, the left loin was collected from 246 Merino lamb carcases, in 2 sampling periods. NIR measurements were conducted using an ASD® TerraSpec4 high resolution spectrometer with integration time of 34ms and an instrument sample count of 50. A section (~30g) was then excised from the muscle, freeze dried and homogenised for analysis of IMF content using a modified AOAC (1992) method as described by Holman, Bailes, Meyer and Hopkins (2019). Prior to data analysis, spectra were converted from transmittance to absorbance and averaged by carcase and Splice correction was completed (Stevens & Ramirez-Lopez, 2014). Spectra were then corrected using the continuum removal method (Clark & Roush, 1984) and Partial Least Squares model to the predict of IMF using the pls package (Wehrens & Mevik, 2015) were conducted before model diagnostics were acquired through use of functions in the mdatools package (Kucheryavskiy, 2020) with the optimal number of components determined by assessing the lowest RMSEP and Leave One Out (LOO) cross-validation methods. PLS models were developed in the R environment (R Core Team, 2017).

**Results and Discussion:** The range of IMF measured was 2.2 – 9.0%, while the mean IMF was 4.4% (± s.d 1.3). Models to predict the IMF using calibration model described by Fowler et al. (2021) yielded a correlation between predicted and measured IMF of R2 = 0.42 and an RMSEP equal to 1.2%. Although the range of the IMF values is similar in both the calibration and validation data sets, the calibration yielded a higher correlation between the predicted and measured values (R2 = 0.60 and RMSE = 0.83) when compared to the validation model created using the independent data. Currently there is a paucity of studies to compare this finding to. While Dixit et al. (2020) and Knight et al. (2019) have considered the ability of NIR to predict the IMF content of lamb loin and found higher accuracies then the current study, transferability these models to other loins not included in the calibration model has not yet been established. Thus, further research is needed to determine if the calibration or validation can be optimised to increase accuracy and further reduce the error of prediction.

**Conclusion:** Overall, this demonstrates the potential of NIR spectra to predict the fat content of lamb is reduced when calibration models are tested on independent data.

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