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Using a handheld near-infrared spectroscopy (NIRS) scanner to predict meat quality

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Introduction

Consumers worldwide are willing to pay more for meat with guaranteed eating and nutritional quality, commonly measured by colour, marbling, moisture and pH, among other traits [1]. Colour and marbling are routinely graded subjectively [1], however more accurate objective measures are time-consuming, expensive and destructive [2]. The use of non-destructive technologies such as near-infrared spectroscopy (NIRS) have been extensively researched for objective and accurate measurement of these quality traits [2,3]. Recently, smaller, cheaper and portable handheld devices have been used to reduce costs and logistical issues in the abattoir [3]. The aim of this study was to test the accuracy of a handheld NIRS spectrophotometer (NIRvascan) as a predictor of meat quality compared to a conventional lab-grade NIRS spectrophotometer (LG-NIRS).

Methods

Forty-three beef and lamb retail cuts were purchased from butchers and supermarkets in Sydney, Australia to represent a range of muscle, marbling, breed, colour, freshness and price. Previously defined locations along the sample surface (6 beef, 3 lamb) were used scanned using a hand-held NIRvascan (900-1800 nm, Allied Scientific Pro, Gatineau, Canada), a lab-grade visible-NIRS (350-2500 nm, Agrispec, ASD Inc., Boulder, USA), and a CR-400 Chroma spectrophotometer for instrumental meat colour (Konica Minolta Sensing Americas Inc., New Jersey, USA). Marbling and pH were assessed as per [4], while moisture content was determined by the difference in pre- and post-freeze drying weight.

Prediction models were trained for both NIRS scanners with a 70% training set and 30% independent validation dataset using a bootstrapped decision trees algorithm in RStudio [5]. The mean predictions of 100 different models using a 99% random sample from the training set were tested. Mean predictions were used to calculate the performance against the laboratory-measured dataset. The performance indices calculated were the coefficient of determination (r^2), root mean square error (RMSE) and bias.

Results

The NIRvascan predicted pH and moisture better than the LG-NIRS (lower r^2 and higher RMSE), however NIRvascan prediction for marbling was inferior to LG-NIRS (Table 1). NIRvascan predictions were poor to average ($r^2 < 0.5$), while the only prediction above 0.5 was marbling score by LG-NIRS (Table 1). NIRvascan predictions of meat colour could not be established, although LG-NIRS showed minimal variation in predicting instrumental colour within the visible range (data not shown).

Discussion

NIRvascan predictions of beef pH were similar to those found previously for an LG-NIRS [6], though LG-NIRS predictions in the present study were lower. A general consensus is that scanning ground meat provides more accurate NIRS predictions for moisture, marbling and chemical fat than intact meat, though its destructive nature prevents industry uptake [3].The likely reason for greater predictive accuracy for colour from the LG-NIRS was its wider wavelength range compared to the NIRvascan.

Separate visible-NIRS predictions of meat redness (a*) could replace the use of a trained grader according to [3,6]. However, further research is required to establish a threshold for consumer colour preference, as well as to improve the wavelength range of handheld NIRS to include the visible spectrum for colour prediction (~380-740 nm). The prediction accuracy of NIRvascan could also be improved by collecting a larger data set, e.g. from an abattoir boning room, or by collecting more spectral data from each sample and implementing a standardised scan pattern [3]. Objective measurements of intramuscular fat and crude protein through wet chemistry would also need to be tested.

Conclusion

In this pilot study, the handheld NIRvascan was able to predict pH and moisture of retail meat samples to a modest level, and better than the LG-NIRS. Marbling and colour of samples were better predicted using the LG-NIRS. The use of a larger-scale study and further development of handheld NIRS technology to incorporate the visible spectrum can both contribute to improved 'on-the-spot' prediction of such traits in the future.

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	pH		Moisture content		Marbling	
	NIRvascan	*LG-NIRS*	*NIRvascan*	*LG-NIRS*	*NIRvascan*	*LG-NIRS*
r^2	0.485	0.287	0.481	0.070	0.261	0.539
RMSE	0.109	0.128	4.999	6.957	1.504	1.237
Bias	0.007	0.016	0.674	-0.022	0.020	0.149

Table 1. Coefficient of determination (r^2), root mean square error (RMSE) and bias of two NIRS models predicting pH, moisture content and marbling score.

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