Feasibility of the direct application of near-infrared reflectance spectroscopy on intact chicken breasts to predict meat color and physical traits

M. De Marchi, M. Penasa,[1] M. Battagin, E. Zanetti, C. Pulici, and M. Cassandro

Department of Animal Science, University of Padova, Viale dell'Università 16, 35020 Legnaro, Italy

ABSTRACT Physical and color characteristics of chicken meat were investigated on 193 animals by directly applying a fiberoptic probe to the breast muscle and using the visible–near-infrared (NIR) spectral range from 350 to 1,800 nm. Data on pH was recorded 48 h postmortem (pH); lightness (L*), redness (a*), and yellowness (b*) 48 h postmortem; thawing and cooking losses and shear force after freezing. Partial least squares regressions were performed using untreated data, raw absorbance data (log(1/R)), and multiplicative scatter correction plus first or second derivative spectra. Models were validated using full cross-validation, and their predictive ability was determined by root mean square error of cross-validation ($RMSE_{CV}$) and correlation coefficient of cross-validation (r_{cv}). Means (±SD) of pH, L*, a*, b*, thawing loss, cooking loss, and shear force were 5.83 ± 0.13, 44.54 ± 2.42, −1.90 ± 0.62, 3.21 ± 3.28, 4.84 ± 2.44%, 19.39 ± 2.95%, and 16.08 ± 3.83 N, respectively. The best prediction models were developed using log(1/R) spectra for b* (r_{cv} = 0.93; $RMSE_{CV}$ = 1.16) and a* (r_{cv} = 0.88; $RMSE_{CV}$ = 0.29), while a medium predictive ability of NIR was obtained for pH, L*, and thawing and cooking losses (r_{cv} from 0.69 to 0.76; $RMSE_{CV}$ from 0.01 to 1.73). Finally, predicted model for shear force (r_{cv} = 0.41; $RMSE_{CV}$ = 3.18) was unsatisfactory. Results suggest that NIR is a feasible technique for the assessment of several quality traits of intact breast muscle.

Key words: chemometrics, chicken, meat quality, near-infrared reflectance spectroscopy

2011 Poultry Science 90:1594–1599
doi:10.3382/ps.2010-01239

INTRODUCTION

The consumption of chicken meat is growing worldwide (FAO, 2010), mainly because it is inexpensive and its attributes (e.g., high polyunsaturated fatty acids content and low cholesterol content) are suitable for human health. Also, consumers are increasingly interested in the qualitative aspects of poultry meat such as tenderness, color, and cooking losses; these aspects are important because they can provide reliable information about meat quality (Lyon and Lyon, 1991).

Analytical techniques for the assessment of physical characteristics as well as chemical composition of meat are destructive and costly in terms of personnel and time. Therefore, the development of fast, nondestructive, and accurate methodologies might help to increase processing efficiency. Near-infrared (**NIR**) spectroscopy is one of the most promising techniques for this purpose and has found considerable interest in safety and quality controls of poultry meat. Several applications of NIR demonstrated its ability to predict chemical composition of meat (Venel et al., 2001; Alomar et al., 2003; Liu et al., 2004; Prieto et al., 2006; De Marchi et al., 2007) and to provide information on different molecular bonds and tissue ultrastructure (Downey and Hildrum, 2004). Applications also include the quantitative evaluation of physical characteristics of heat-treated chicken patties (Chen and Marks, 1998), the prediction of chemical components in chicken muscles (Cozzolino et al., 1996), the distinction between slow-growing and industrial chickens (Fumiere et al., 2000), and the identification of fresh and frozen chicken meat (Lyon et al., 2001).

Current efforts focus on the development of portable NIR instruments for the on-line monitoring of meat quality in the industry. Therefore, the objective of this study was to test the ability of NIR technology to estimate physical and color characteristics of chicken meat by directly applying a fiberoptic probe to the breast muscle.

MATERIALS AND METHODS

Birds and Meat Samples

The project was approved by the Ethical Committee for the Care and Use of Experimental Animals of the University of Padova (Italy). The trial was conducted at the experimental farm of the Department of Ani-

Received November 16, 2010.
Accepted March 19, 2011.
[1]Corresponding author: mauro.penasa@unipd.it

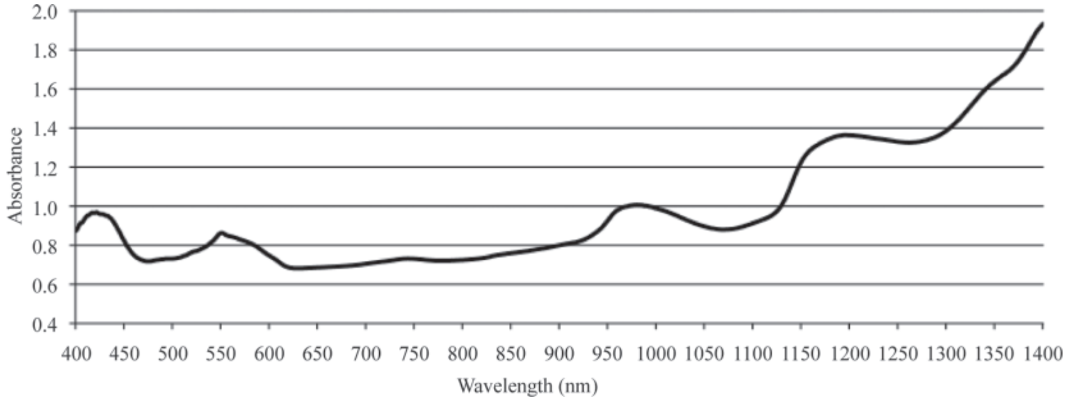

Figure 1. Example of algorithm-pretreated [log(1/R)] near-infrared reflectance spectrum.

mal Science (Legnaro, Italy) and involved 193 chickens (104 males and 99 females) of 3 genotypes: the Padovana local breed (n = 109); a commercial, slow-growing Berlanda-Gaina line (n = 42); and their cross (n = 42). All birds were born on the same day, fed ad libitum with the same diet, and slaughtered at 131 (n = 104) and 180 (n = 89) days of age. Feed was withdrawn 18 h before slaughter and animals were weighed before being transported to the abattoir. Birds were electronically stunned, plucked, and eviscerated. Carcasses were cooled in a tunnel and refrigerated at 4°C for 24 h. After 48 h postmortem, the breast muscles (pectoralis superficialis) were removed and frozen. Near-infrared spectra were collected and analyzed according to the procedures described below.

Spectra Collection

Visible-NIR measurements were recorded through a LabSpec2500 (Qualityspec Pro, ASD Inc., Boulder, CO) by placing the scanning head over the surface of the exposed pectoralis superficialis muscle without skin. The spectrophotometer used a detection wavebands range from 350 to 1,800 nm and interpolated the data to produce measurements in 1-nm increments; this resulted in a diffuse reflectance spectrum of 1,451 data points. The instrument was operated by the proprietary software package Indico Pro (Qualityspec Pro, ASD Inc.). Four measurements of NIR spectra were collected for each sample and absorbance data were stored as log (1/R), R being the reflectance.

Laboratory Analyses on Breast Muscle

The pH values were collected on breasts 48 h postmortem using a Crison Basic 20 electrode (Crison, Barcelona, Spain); 3 measurements were taken for each sample and averaged before statistical analysis. Color determination was carried out 48 h postmortem on breast cores without skin using a Minolta colorimeter (CM_508c, D65 illuminant and 10° observer, Konica-Minolta Sensing Inc., Ramsey, NJ); 3 consecutive readings were taken at random locations of breast sample and averaged before data analysis. Color was expressed in terms of CIE (1978) values for lightness (***L****), redness (***a****), and yellowness (***b****). Thawing and cooking losses were measured on breast muscles after 12 d postmortem according to ASPA (1996) procedures. Frozen samples were left at room temperature for 15 h, extracted from the bag, blotted dry, and weighed. Thawing losses were calculated as the difference between weight of sample before and after freezing. To determine cooking losses, samples were weighed, held in plastic bags, and immersed in a water bath monitored with a thermocouple until the internal temperature reached 75°C for 60 min. Then, bags were cooled in water for 20 min and samples were blotted dry with paper towels and weighed. Cooking losses were the difference of weight before and after cooking. Shear force was assessed according to ASPA (1996) procedures on 3 cylindrical cores (1.13 cm diameter) of each cooked sample using a TA-HDi Texture Analyzer (Stable Macro System, London, UK) with a Warner-Bratzler shear attachment (10 N load cell, 2 mm/s crosshead speed). Results were interpreted by means of texture expert software (Joseph, 1979).

Chemometric Models for Data Analysis

Partial least squares (**PLS**) regressions (Unscrambler software, version 9.6; Camo A/S, Oslo, Norway) were used to establish calibration models (Hubert and Vanden Branden, 2003). The analysis was carried out on untreated NIR spectra, raw absorbance data [log (1/R)], and multiplicative scatter correction with first or second derivative spectra. Spectral data subjected to PLS produced a new and smaller set of variables called loadings ($\mathbf{L_N}$). Prediction models were developed using PLS regressions and confirmed using full cross-validation. All prediction residuals were combined to compute the root mean square error of cross-validation ($\mathbf{RMSE_{CV}}$; Hubert and Vanden Branden, 2003). To determine and compare the proficiency of predictive models, $RMSE_{CV}$, the correlation coefficient of cross-validation ($\mathbf{r_{CV}}$), and L_N were used (Hubert and Vanden Branden, 2003). If 2 or more models provided the same results for a given parameter, the preferred model

Table 1. Statistical summary of weights and quality traits of breast meat[1]

Trait[2]	Mean	SD	Minimum	Maximum
Live weight (g)	2,406	718	1,280	4,740
Carcass weight (g)	1,816	590	982	3,644
Breast weight (g)	340	107	150	738
pH	5.83	0.13	5.51	6.15
L^*	44.54	2.42	38.14	49.99
a^*	−1.90	0.62	−3.29	0.04
b^*	3.21	3.28	−4.86	16.33
Thawing loss (%)	4.84	2.24	1.16	12.42
Cooking loss (%)	19.39	2.95	13.36	29.18
Shear force (N)	16.08	3.83	8.14	29.06

[1]n = 193.

[2]L^* = lightness; a^* = redness; b^* = yellowness.

was the one with the lowest $RMSE_{CV}$ and the largest r_{CV}. Also, if more than 1 model satisfied these criteria, then the preferred model was the one incorporating the lowest L_N (Dal Zotto et al., 2008; De Marchi et al., 2009).

The ratio performance deviation (**RPD**), obtained by dividing the SD and the $RMSE_{CV}$ of a given trait (Edney et al., 1994), and the range error ratio (**RER**), calculated as the ratio between the range and the $RMSE_{CV}$ of the trait, were used to assess the practical utility of the prediction models. In particular, models with RER values lower than 3 have little practical utility, RER values between 3 and 10 indicate limited to good practical utility, and RER values greater than 10 indicate high utility of the model (Williams, 1987).

RESULTS AND DISCUSSION

Reference Values of Color and Physical Traits of Breast Muscle

Table 1 shows descriptive statistics of the studied traits. Means were calculated on the whole data set and not within genotype, sex, and age at slaughter; this choice allowed us to increase the variability of traits and fit more accurate prediction models. As expected, pH values decreased from slaughter to 48 h postmortem (5.98 vs. 5.83) and showed low variability. Thawing and cooking losses were 4.84 and 19.39%, respectively, with high variability. The high value of pH at 48 h postmortem might be related to the presence in the trial of the Padovana native breed, characterized by higher aggressive and alert behavior than commercial lines. The Padovana is particularly sensitive to stressful conditions before slaughter and this can lead to poor glycogen content in muscle at the time of death (Jaturasitha et al., 2008; Zanetti et al., 2010). Thawing losses in our study were slightly lower than those reported by Rizzi et al. (2007) for similar breeds reared in an organic production system.

Prediction of Color and Physical Traits by NIR

Figure 1 depicts an example of NIR spectrum; the predictability of meat traits is related to specific absorbance of O-H bonds at 1,450 nm, N-H bonds between 1,460 and 1,570 nm, and C-H bonds between 1,100 and 1,400 nm (Murray, 1986; Murray and Williams, 1987; Shenk et al., 1992). Prediction models were developed

Table 2. Partial least squares predictions results for meat quality traits using untreated and pretreated near-infrared spectra[1]

	Untreated data			Log(1/R)[3]			MSC + first derivative[4]			MSC + second derivative[5]				
Trait[2]	$RMSE_{CV}$	r_{CV}	L_N	$RMSE_{CV}$	r_{CV}	L_N	$RMSE_{CV}$	r_{CV}	L_N	$RMSE_{CV}$	r_{CV}	L_N	RER[6]	RPD[7]
pH	0.10	0.66	11	0.09	0.71	10	0.09	0.66	6	0.12	0.24	2	7.23	1.42
L^*	1.94	0.60	9	1.73	0.69	11	1.90	0.62	5	2.35	0.24	2	6.84	1.40
a^*	0.33	0.82	5	0.29	0.88	6	0.30	0.56	5	0.58	0.45	6	11.36	2.14
b^*	1.54	0.88	4	1.16	0.93	5	1.37	0.91	4	2.18	0.75	8	18.27	2.82
Thawing loss (%)	1.67	0.59	5	1.00	0.70	8	1.74	0.58	3	1.69	0.33	4	11.26	2.14
Cooking loss (%)	2.00	0.70	7	1.88	0.76	10	2.15	0.64	3	2.21	0.05	1	8.41	1.57
Shear force (N)	3.73	0.27	6	3.18	0.41	10	3.37	0.35	5	3.61	0.16	2	6.58	1.20

[1]RMSECV = root mean square error of cross-validation; r_{CV} = coefficient of correlation of cross-validation; L_N = number of partial least squares loadings.

[2]L^* = lightness; a^* = redness; b^* = yellowness.

[3]Raw absorbance data; preferred model.

[4]Multiplicative scatter correction and first derivative (Savitzky-Golay; 3 data points either side).

[5]Multiplicative scatter correction and second derivative (Savitzky-Golay; 3 data points either side).

[6]RER = range error ratio of preferred model.

[7]RPD = ratio performance deviation of preferred model.

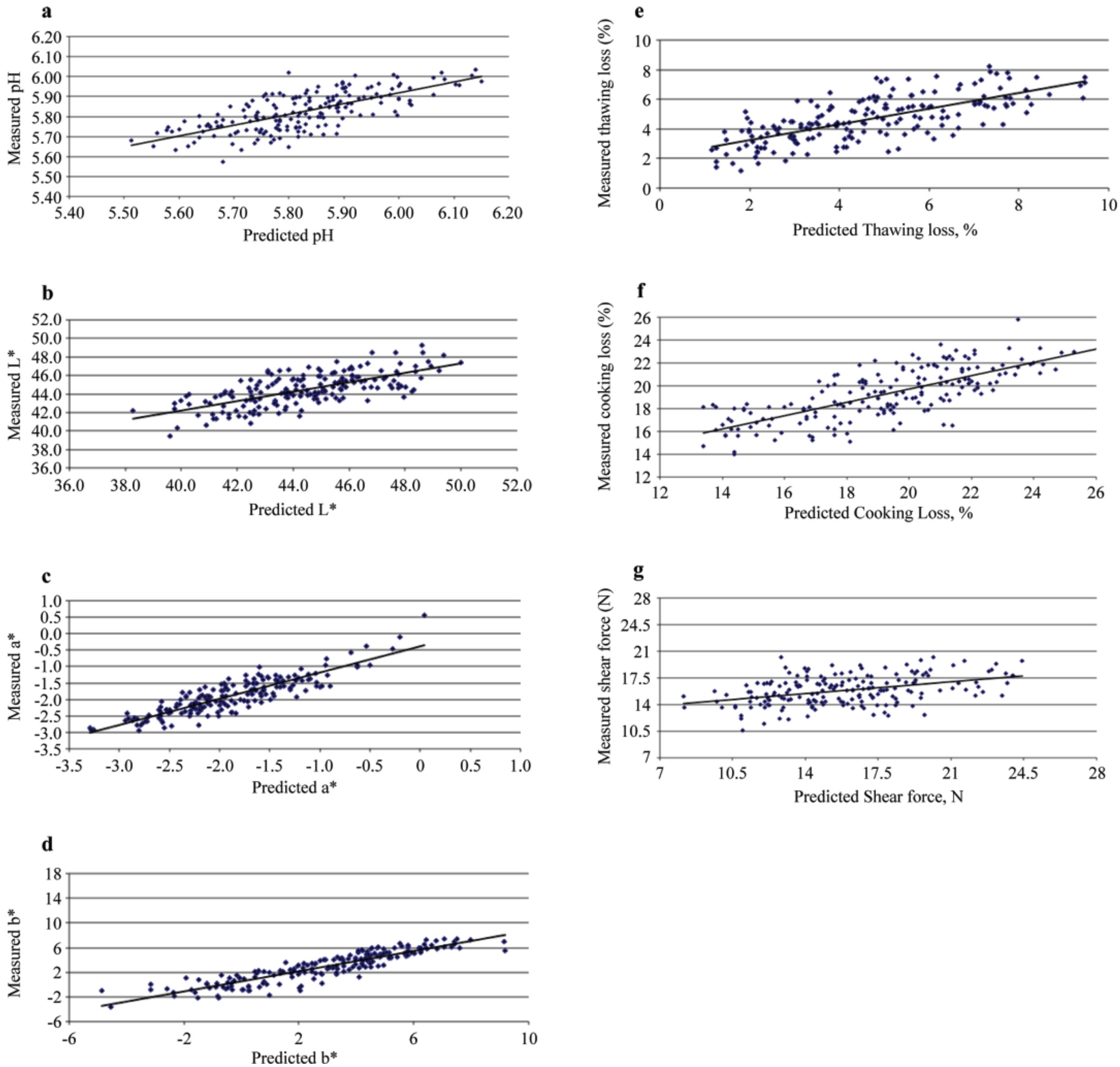

Figure 2. Linear regression plots of measured versus predicted a) pH, b) L^*, c) a^*, d) b^*, e) thawing loss, f) cooking loss, and g) shear force using the best prediction models. L^* = lightness; a^* = redness; b^* = yellowness. Color version available in online PDF.

using spectra in several forms: untreated data, raw absorbance data [log(1/R)], and multiplicative scatter correction with first or second derivative spectra, giving 4 models for each predicted parameter. The absorbance spectra showed the best prediction models (Table 2). The best prediction models were obtained for b^* and a^* with r_{CV} and $RMSE_{CV}$ of 0.93 and 1.16 and 0.88 and 0.29, respectively. Thawing and cooking losses showed good prediction results with r_{CV} and $RMSE_{CV}$ of 0.70 and 1.00 and 0.76 and 1.88, respectively. No satisfactory results were obtained for shear force (r_{CV} and $RMSE_{CV}$ of 0.41 and 3.18 N, respectively). The medium to low predictive ability of pH in our study was consistent with that reported by Liu et al. (2004), Berzaghi et al. (2005), and Prieto et al. (2009); these authors argued that the low predictive ability of models for pH might be related to the low variation of measures of this trait.

Few studies reported predictions of L^*, a^*, and b^* using NIR. Results from our study were consistent with those of Liu et al. (2004) and Cecchinato et al. (2011). As reported by Prieto et al. (2008) the CIE indexes prediction is related to the absorption at wavelengths between 1,230 and 1,400 nm. Moreover, the prediction of a^* is related to the water content of meat and the concentration of myoglobin, which are easily predicted using visible together with NIR regions (Cozzolino et al., 2003; Liu et al., 2003). Concerning the use of NIR for the prediction of thawing and cooking losses, no applications were found in the literature on poultry meat whereas Prieto et al. (2009) reported limited to moderate capacity to estimate drip loss and cooking loss in beef.

The predictions for shear force were consistent with those reported by Liu et al. (2004) and Meullenet et al. (2004). The wavelengths most related to the prediction of tenderness are 1,400 nm (water absorption) and 1,300 to 1,400 nm (C-H molecular bonds) as reported by Barlocco et al. (2006) and Prieto et al. (2008). The poor accuracy of shear force prediction could be attributed to the small scanning area; Geesink et al. (2003) reported that scanning the meat sample over a larger area could improve the prediction of this trait.

Figure 2 shows the plots of the best prediction equations for the physical and color characteristics and their practical utility assessed using RER and RPD. These indexes suggest a high practical utility of prediction models developed for a^*, b^*, and thawing losses, with RER and RPD values of 11.36 and 2.14, 18.27 and 2.82, and 11.26 and 2.14, respectively. For the prediction models the number of L_N ranged from 5 to 11. The number of L_N for a^*, b^*, and thawing losses found in our study were consistent with those reported by Prieto et al. (2009) using the same software to predict chemicophysical and sensory characteristics of beef quality.

The poultry industry is characterized by high throughput and productivity, and birds are usually packaged and marketed within a few hours of slaughter. Therefore, the assessment of meat quality traits in the abattoir relies heavily on new technologies able to rapidly collect information on the carcasses. Our study demonstrated the feasibility of the direct application of NIR on intact breast muscles to determine pH, color, and thawing and cooking losses. Spectral data were collected 48 h postmortem, which in some cases may not be feasible for the poultry industry. However, these promising results show that NIR can potentially be implemented on-line for the assessment of meat quality.

ACKNOWLEDGMENTS

Financial support by Bando Progetti di Ricerca di Ateneo (University of Padova, Italy; 2008 codice: CPDA087448/08 “Application of proteomics to the characterization of poultry meat”) is gratefully acknowledged.

REFERENCES

Alomar, D., C. Gallo, M. Castañeda, and R. Fuchslocher. 2003. Chemical and discriminant analysis of bovine meat by near infrared reflectance spectroscopy (NIRS). Meat Sci. 63:441–450.

ASPA (Animal Science and Production Association). 1996. Metodiche per la Determinazione delle Caratteristiche Qualitative della Carne (Procedures for Meat Quality Evaluation). University of Perugia, Perugia, Italy.

Barlocco, N., A. Vadell, F. Ballesteros, G. Galietta, and D. Cozzolino. 2006. Predicting intramuscular fat, moisture and Warner-Bratzler shear force in pork muscle using near infrared reflectance spectroscopy. Anim. Sci. 82:111–116.

Berzaghi, P., A. Dalla Zotte, L. M. Jansson, and I. Andrighetto. 2005. Near-infrared reflectance spectroscopy as a method to predict chemical composition of breast meat and discriminate between different n-3 feeding sources. Poult. Sci. 84:128–136.

Cecchinato, A., M. De Marchi, M. Penasa, A. Albera, and G. Bittante. 2011. The relevance of near-infrared reflectance spectroscopy predictions as indicator traits in breeding programs for enhanced beef quality. J. Anim. Sci. doi:10.2527/jas.2010-3740.

Chen, H., and B. P. Marks. 1998. Visible/near infrared spectroscopy for physical characteristics of cooked chicken patties. J. Food Sci. 63:279–282.

CIE. 1978. International Commission on Illumination Recommendations on Uniform Color Spaces, Color-Difference Equations, Psychometric Color Terms. Commission Internationale de l’Eclairage, Paris, France.

Cozzolino, D., N. Barlocco, A. Vadell, A. Ballesteros, and G. Gallieta. 2003. The use of visible and near infrared reflectance spectroscopy to predict color on both intact and homogenized pork muscle. Leben.-Wiss. Technol. 36:195–202.

Cozzolino, D., I. Murray, and R. Paterson. 1996. Visible and near infrared reflectance spectroscopy for the determination of moisture, fat, and protein in chicken breast and thigh muscle. J. Near Infrared Spectrosc. 4:213–223.

Dal Zotto, R., M. De Marchi, A. Cecchinato, M. Penasa, M. Cassandro, P. Carnier, L. Gallo, and G. Bittante. 2008. Reproducibility and repeatability of measures of milk coagulation properties and predictive ability of mid-infrared reflectance spectroscopy. J. Dairy Sci. 91:4103–4112.

De Marchi, M., P. Berzaghi, A. Boukha, and M. Merisola., and LGallo, . 2007. Use of near infrared spectroscopy for assessment of meat quality traits. Ital. J. Anim. Sci. 6(Suppl. 1):421–423.

De Marchi, M., C. C. Fagan, C. P. O’Donnell, A. Cecchinato, R. Dal Zotto, M. Cassandro, M. Penasa, and G. Bittante. 2009. Prediction of coagulation properties, titratable acidity, and pH of bovine milk using mid-infrared spectroscopy. J. Dairy Sci. 92:423–432.

Downey, G., and K. I. Hildrum. 2004. Analysis of meat. Pages 599–632 in Near-Infrared Spectroscopy in Agriculture. L. Al-Almoodi, R. Craig, J. Workman III, and J. Reeves III, ed. American Society of Agronomy Inc., Crop Science Society of America Inc., and Soil Science Society of America Inc., Madison, WI.

Edney, M. J., J. E. Morgan, P. C. Williams, and L. D. Campbell. 1994. Analysis of feed barley by near infrared reflectance technology. J. Near Infrared Spectrosc. 2:33–41.

FAO. 2010. Accessed September 30, 2010. http://faostat.fao.org/site/603/default.aspx#ancor.

Fumiere, O., G. Sinnaeve, and P. Dardenne. 2000. Attempted authentication of cut pieces of chicken meat from certified production using near-infrared spectroscopy. J. Near Infrared Spectrosc. 8:27–34.

Geesink, G. H., F. H. Schreutelkamp, R. Frankhuizen, H. W. Vedder, N. M. Faber, R. W. Kranen, and M. A. Gerritzena. 2003. Prediction of pork quality attributes from near infrared reflectance spectra. Meat Sci. 65:661–668.

Hubert, M., and K. Vanden Branden. 2003. Robust methods for partial least squares regression. J. Chemometr. 17:537–549.

Jaturasitha, S., T. Srikanchai, M. Kreuzer, and M. Wicke. 2008. Differences in carcass and meat characteristics between chicken indigenous to northern Thailand (Black-boned and Thai native) and imported extensive breeds (Bresse and Rhode Island Red). Poult. Sci. 87:160–169.

Joseph, R. L. 1979. Recommended method for assessment of tenderness. Pages 596–606 in The Future of Beef Production in the European Community. J. C. Bowman and P. Susmel, ed. Martinus Nijhoff, The Hague, the Netherlands.

Liu, Y., B. G. Lyon, W. R. Windham, C. E. Lyon, and E. M. Savage. 2004. Prediction of physical, colour, and sensory characteristics of broiler breasts by visible/near infrared reflectance spectroscopy. Poult. Sci. 83:1467–1474.

Liu, Y., B. G. Lyon, W. R. Windham, C. E. Realini, T. D. D. Pringle, and S. Dickett. 2003. Prediction of colour, texture, and characteristics of beef steaks by visible and near infrared reflectance spectroscopy. A feasibility study. Meat Sci. 65:1107–1115.

Lyon, B. G., and C. E. Lyon. 1991. Shear value ranges by Instron Warner-Bratzler and single-blade Allo-Kramer devices that correspond to sensory tenderness. Poult. Sci. 70:188–191.

Lyon, B. G., W. R. Windham, C. E. Lyon, and F. E. Barton. 2001. Sensory characteristics and near-infrared spectroscopy of broiler breast meat from various chill-storage regimes. J. Food Qual. 24:435–452.

Meullenet, J. F., E. Jonville, D. Grezes, and C. M. Owens. 2004. Prediction of the texture of cooked poultry pectoralis major muscles by near-infrared reflectance analysis of raw meat. J. Texture Stud. 35:573–585.

Murray, I. 1986. The NIR spectra of homologous series of organic compounds. Pages 13–28 in Proc. Int. NIR/NIT Conf., Budapest, Hungary. J. Hollo, K. J. Kaffka, and J. L. Gonczy, ed. Akademiai Kiado, Budapest, Hungary.

Murray, I., and P. C. Williams. 1987. Chemical principles of near-infrared technology. Pages 17–34 in Near Infrared Technology in the Agricultural and Food Industries. P. C. Williams and K. Norris, ed. American Association of Cereal Chemists, St. Paul, MN.

Prieto, N., S. Andrés, F. J. Giráldez, A. R. Mantecón, and P. Lavín. 2006. Potential use of near infrared reflectance spectroscopy (NIRS) for the estimation of chemical composition of oxen meat samples. Meat Sci. 74:487–496.

Prieto, N., S. Andrés, F. J. Giráldez, A. R. Mantecón, and P. Lavín. 2008. Ability of near infrared reflectance spectroscopy (NIRS) to estimate physical parameters of adult steers (oxen) and young cattle meat samples. Meat Sci. 79:692–699.

Prieto, N., R. Roehe, P. Lavín, G. Batten, and S. Andrés. 2009. Application of near infrared reflectance spectroscopy to predict meat and meat products quality: A review. Meat Sci. 83:175–186.

Rizzi, C., A. Marangon, and G. M. Chiericato. 2007. Effect of genotype on slaughtering performance and meat physical and sensory characteristics of organic laying hens. Poult. Sci. 86:128–135.

Shenk, J. S., M. O. Westerhaus, and J. J. Workman. 1992. Application of NIR spectroscopy to agricultural products. Pages 383–431 in Handbook of Near Infrared Analysis, Practical Spectroscopy Series. D. A. Burns and E. W. Ciurczak, ed. Marcel Dekker, New York, NY.

Venel, C., A. M. Mullen, G. Downey, and D. J. Troy. 2001. Prediction of tenderness and other quality attributes of beef by near infrared reflectance spectroscopy between 750 and 1100 nm; further studies. J. Near Infrared Spectrosc. 9:185–198.

Williams, P. C. 1987. Implementation of near-infrared technology. Pages 143–167 in Near-Infrared Technology in the Agricultural and Food Industries. 2nd ed. P. C. Williams and K. Norris, ed. American Association of Cereal Chemists, St. Paul, MN.

Zanetti, E., M. De Marchi, C. Dalvit, C. Molette, H. Remignon, and M. Cassandro. 2010. Carcass characteristics and qualitative meat traits of three Italian local chicken breeds. Br. Poult. Sci. 6:629–634.