On-line prediction of yield grade, longissimus muscle area, preliminary yield grade, adjusted preliminary yield grade, and marbling score using the MARC beef carcass image analysis system[1]

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ABSTRACT: The present experiment was conducted to evaluate the ability of the U.S. Meat Animal Research Center's beef carcass image analysis system to predict calculated yield grade, longissimus muscle area, preliminary yield grade, adjusted preliminary yield grade, and marbling score under commercial beef processing conditions. In two commercial beef-processing facilities, image analysis was conducted on 800 carcasses on the beef-grading chain immediately after the conventional USDA beef quality and yield grades were applied. Carcasses were blocked by plant and observed calculated yield grade. The carcasses were then separated, with 400 carcasses assigned to a calibration data set that was used to develop regression equations, and the remaining 400 carcasses assigned to a prediction data set used to validate the regression equations. Prediction equations, which included image analysis variables and hot carcass weight, accounted for 90, 88, 90, 88, and 76% of the variation in calculated yield grade, longissimus muscle area, preliminary yield grade, adjusted preliminary yield grade, and marbling score, respectively, in the prediction data set. In comparison, the official USDA yield grade as applied by online graders accounted for 73% of the variation in calculated yield grade. The technology described herein could be used by the beef industry to more accurately determine beef yield grades; however, this system does not provide an accurate enough prediction of marbling score to be used without USDA grader interaction for USDA quality grading.

Key Words: Beef, Carcasses, Instrumentation, Processing

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Introduction

At present, beef carcass value is primarily a function of USDA quality (a subjective estimate of meat palatability) and USDA yield grades (a subjective estimate of carcass composition). Although expert calculated USDA yield grade is a relatively accurate predictor of carcass composition (Abraham et al., 1980), the development of an objective system to predict beef carcass cutability has been an industry priority. In 1997, Shackelford et al. (1998) developed a system to predict beef carcass cutability based on image analysis of the 12th-rib cross section that was removed from carcasses for tenderness classification. The ARS entered into a cooperative research and development agreement with IBP, Inc. to adopt this technology for application directly to beef carcasses. The resulting beef carcass image analysis system was designed to predict beef carcass value-determining characteristics based on an image of the 12th-rib cross section that is used for quality and yield grading. The system was designed to be functional under industrial conditions without modification of conventional slaughter, dressing, trimming, and ribbing procedures. This experiment was conducted to evaluate the ability of this system to predict calculated yield grade, longissimus muscle area, preliminary yield grade, adjusted preliminary yield grade, and marbling score under commercial beef processing conditions.

[1]Names are necessary to report factually on available data; however, the USDA neither guarantees nor warrants the standard of the product, and the use of the name by USDA implies no approval of the product to the exclusion of other products that may also be suitable. The authors are grateful to J. W. Wise, S. Cave, W. G. Goad, and C. R. Rains for providing the expert estimates of yield and quality grade factors. The authors are grateful to P. Bambrick, P. Beska, K. Brockmoller, T. Burch, D. Danilson, H. Eger, P. Grueber, P. Haagensen, A. Hinz, I. Hwang, J. Johnson, L. Kershner, C. Koritzky, B. McFarlane, L. Nemec, R. Rothe, and S. Roggenbauer for their assistance in the execution of this agreement, and to M. Bierman and C. Grummert for their secretarial assistance. The authors are grateful to M. E. Dikeman, K. A. Leymaster, J. W. Savell, J. W. Wise, and J. Wray for their review of this manuscript.

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Materials and Methods

Experiment 1. Predictive Accuracy

Carcasses. Image analysis was conducted on the beef-grading chain immediately after the conventional USDA beef quality and yield grades were applied at IBP's Lexington, NE, and Amarillo, TX, beef processing facilities. These two beef processing plants were chosen for this experiment in order to include any possible differences among plants in chilling regimen, ribbing method, grading chain speed, and cattle type. At each facility, 400 carcasses were selected for inclusion in this experiment in 10 groups of 40 consecutive carcasses on the bloom chain prior to grading and image analysis. Carcasses were selected in groups of consecutive carcasses so that image analysis was conducted under the same conditions as would be applied in those facilities (i.e., grading rates of 350 to 425 carcasses per hour). The number of carcasses selected in each group was limited to 40 because that was the number of carcasses that could be off-railed onto a single regrade rail for expert evaluation of quality and yield grade factors. By sampling 20 groups of carcasses, the sample included carcasses from 57 different livestock producer lots and included extreme variation in all carcass grade traits. The number of cattle sampled per lot ranged from 1 to 40.

A single technician conducted the image analysis for the entire experiment. The technician's duties included: 1) determining which side of the carcass should be imaged in order to provide the most accurate prediction of yield grade (i.e., which side had the least severity of s.c. fat removed or which side was most correctly or completely ribbed); 2) preparing the longissimus muscle cross section for image analysis (i.e., removal of bone dust, pieces of fat, exudate, water, and tags from the longissimus muscle); 3) properly positioning the camera unit on the 12th-rib cross section; 4) triggering the computer to initialize the image acquisition and analysis process; and 5) observing the analyzed image to see that the process was completed correctly. Another technician recorded which side of the carcass was imaged.

Carcass Grade Data. After the image analysis process was completed, carcasses were transferred to stationary rails in regrade bays with ample lighting and space for expert evaluation of quality and yield grade factors. Hot carcass weight (**HCW**) and official USDA quality and yield grades were recorded.

For the imaged side of each carcass, three meat scientists independently traced the outline of the 12th-rib longissimus muscle cross section onto acetate paper. Subsequently, each acetate tracing was digitized using a flatbed scanner, and the longissimus muscle area was measured in triplicate using image analysis (Image-Pro Plus, version 4.1, Media Cybernetics, Silver Springs, MD). The overall mean longissimus muscle area, which was calculated as the simple mean of all nine observations (triplicate tracing × triplicate measurement), was used for subsequent calculation of yield grade and other analyses.

A team of three supervisory level personnel from the Standardization and Meat Grading branches of the Livestock and Seed Program of USDA Animal Meat Science determined preliminary yield grade (measured on the side that was imaged), adjusted preliminary yield grade, kidney, pelvic, and heart fat percentage, and marbling score. As with conventional quality grading, marbling score was recorded for the side of the carcass with the highest degree of marbling.

Statistical Analysis. For each plant, the carcasses were ranked by observed calculated yield grade, and alternating carcasses were assigned to either a calibration data set, which was used to develop regression equations, or a prediction data set, which was used to validate the regression equations (Neter et al., 1989). The calibration and prediction data sets each contained a total of 400 carcasses (200 from each plant). This method of assignment ensured that the calibration and prediction data sets had similar simple statistics for carcass traits (Table 1).

Regression equations were developed using two sets of independent variables. The first set included image analysis traits and HCW. The second set only included image analysis traits.

Because there were 63 independent variables, the RSQUARE procedure (SAS Inst., Inc., Cary, NC) would not solve for high-order equations. Therefore, backward stepwise regression was used to narrow the pool of predictors to 40 for each dependent variable. For each dependent variable, the RSQUARE procedure of SAS was used to select the best 1- to 10-variable equation from the appropriate unique set of 40 independent variables. For each dependent variable, the highest-order equation in which the partial significance of each component was less than 0.001 was selected as the regression for that trait and was tested against the prediction data set. Mallow's (1973) C_P statistic was calculated for each equation. However, because the C_P statistic exceeded the number of variables for each equation, it was not used in the equation selection process.

Experiment 2. Repeatability

As before, image analysis was conducted on the beef-grading chain at IBP's Lexington, NE, beef-processing facility. Images were captured in triplicate on each of 200 carcasses at chain speed by repeating the process of camera unit placement on the cross section, image acquisition, and camera unit removal. Because of the time required to repeat the process of positioning the camera on the longissimus muscle cross section three times, it was not possible to sample consecutive carcasses for this experiment. Instead, alternating carcasses were tested. For each trait, repeatability was calculated as $\sigma^2_{carcass}/(\sigma^2_{carcass} + \sigma^2_{error})$.

Table 1. Simple statistics of carcass traits for calibration (n = 400) and prediction (n = 400) data sets

Data Set	Trait	Mean	SD	Minimum	Maximum
Calibration	Hot carcass weight, kg	351	41	227	460
Prediction	Hot carcass weight, kg	350	38	220	460
Calibration	Marbling score[a]	505	106	250	1090
Prediction	Marbling score	507	105	240	1020
Calibration	Preliminary yield grade	3.07	0.58	2.1	5.5
Prediction	Preliminary yield grade	3.07	0.57	2.1	5.4
Calibration	Adjusted preliminary yield grade	3.29	0.62	2.0	5.6
Prediction	Adjusted preliminary yield grade	3.31	0.61	2.0	5.6
Calibration	Adjustment of preliminary yield grade	0.22	0.22	−0.3	1.1
Prediction	Adjustment of preliminary yield grade	0.24	0.24	−0.6	1.4
Calibration	Kidney, pelvic, and heart fat, %	2.08	0.69	0.0	4.5
Prediction	Kidney, pelvic, and heart fat, %	2.11	0.71	0.5	5.0
Calibration	Longissimus area, cm^2	90.2	11.3	53.5	135.5
Prediction	Longissimus area, cm^2	90.5	11.0	65.8	135.5
Calibration	Yield grade	2.65	1.06	−0.5	6.3
Prediction	Yield grade	2.65	1.04	0.0	5.4

[a]200 = Practically Devoid^0; 300 = Traces^0; 400 = Slight^0; 500 = Small^0; 600 = Modest^0; 700 = Moderate^0; 800 = Slightly Abundant^0; 900 = Moderately Abundant^0; 1000 = Abundant^0.

Results and Discussion

Approximately two-thirds of the carcasses in the calibration (68%) and prediction data (65%) sets were steers, and approximately one-third of the carcasses were heifers. Simple statistics of the calibration and prediction data sets are presented in Table 1. The SD of yield grade was greater for the present data sets (1.06 and 1.04) than for the 1990, 1995, and 2000 National Beef Quality Audits (SD = 0.9, 0.8, and 0.87, respectively; Lorenzen et al., 1993; Boleman et al., 1998; McKenna et al., 2001). In comparison to the National Beef Quality Audit-2000 (McKenna et al., 2001), our data sets contained a substantially higher percentage of yield grade 1 carcasses (26 vs 12%) and a lower percentage of yield grade 3 carcasses (25 vs 39%).

Prediction of Marbling Score. When HCW was included in the independent variable set, it was not one of the variables in the “best” equation. However, inclusion of HCW altered the process of variable selection slightly and resulted in different equations being selected as the best equation when HCW was included and excluded from the independent variable set. In each case, a nine-variable regression equation accounted for 79% of the variation in marbling score in the calibration data set and 76 or 75% of the variation in marbling score in the prediction data set (Table 2). Steiner et al. (2000) reported that 66 or 49% of the variation in expert marbling scores was accounted for by the CVS Computer Vision System or VIAscan (both of which are marketed by Research Management Systems, Inc., Calgary, Alberta, Canada), respectively. Although the proportion of variation in expert marbling scores accounted for by this system is greater than that accounted for by CVS or VIAscan, this system is not accurate enough to be used for USDA quality grading. For the prediction data set, the mean absolute error was 39% of one degree of marbling and the error of prediction was greater than one marbling degree for 4.8% of the carcasses.

Prediction of Longissimus Muscle Area. A 10-variable regression equation that included HCW and image analysis variables accounted for 91 and 88% of the variation in longissimus muscle area in the calibration and prediction data sets, respectively (Table 2). A 10-variable regression equation that included only image analysis variables accounted for 90 and 87% of the variation in longissimus muscle area in the calibration and prediction data sets, respectively. Cannell et al. (1999) reported that the VIAscan system predicted 88% of the variation in longissimus muscle area. Steiner et al. (2000) reported that the CVS and VIAscan systems predicted 81 and 69% of the variation in longissimus muscle area, respectively.

Prediction of Preliminary Yield Grade. A three-variable regression equation that included HCW and image analysis variables accounted for 91 and 90% of the variation in preliminary yield grade in the calibration and prediction data sets, respectively (Table 2). A five-variable regression equation that included only image analysis variables accounted for 91 and 90% of the variation in preliminary yield grade in the calibration and prediction data sets, respectively. Cannell et al. (1999) reported that the VIAscan system predicted 71% of the variation in preliminary yield grade.

Prediction of Adjusted Preliminary Yield Grade. A six-variable regression equation that included HCW and image analysis variables accounted for 88% of the variation in adjusted preliminary yield grade in the calibration and prediction data sets (Table 2). A five-variable regression equation that included only image analysis variables accounted for 88% of the variation in adjusted preliminary yield grade in the calibration and predic-

Table 2. Prediction equations for estimating yield grade, longissimus area, preliminary yield grade (PYG), adjusted PYG, and marbling score using image analysis variables in combination with hot carcass weight or alone

			Calibration data set			Prediction data set				
Trait	HCW[a]	No. of variables	R^2	RSD	Mean absolute error[b]	R^2	RSD	Mean absolute error[b]	Intercept β_0	Slope β_1
Yield grade	Yes	6	0.91	0.32	0.25	0.90	0.32	0.25	−0.04[x]	1.01[y]
Yield grade	No	4	0.86	0.42	0.32	0.84	0.39	0.31	−0.05[x]	1.02[y]
Longissimus area	Yes	10	0.91	3.5	2.8	0.88	3.8	3.0	0.83[x]	0.99[y]
Longissimus area	No	10	0.90	3.6	2.8	0.87	3.9	3.1	0.61[x]	0.99[y]
PYG	Yes	3	0.91	0.18	0.13	0.90	0.18	0.13	−0.01[x]	1.00[y]
PYG	No	5	0.91	0.17	0.13	0.90	0.18	0.13	0.02[x]	0.99[y]
Adjusted PYG	Yes	6	0.88	0.21	0.17	0.88	0.21	0.16	0.02[x]	0.99[y]
Adjusted PYG	No	5	0.88	0.22	0.17	0.88	0.21	0.16	0.03[x]	0.99[y]
Marbling score	Yes	9[c]	0.79	49	36	0.76	52	40	3[x]	1.00[y]
Marbling score	No	9[c]	0.79	49	36	0.75	52	39	0[x]	1.00[y]

[a]HCW = hot carcass weight. "Yes" indicates that image analysis variables and HCW were included in the independent variable set and "No" indicates that only image analysis variables were included in the independent variable set.
[b]Mean absolute error is the mean of the absolute values of the individual prediction errors (unit of measure for longissimus area is cm^2 and the unit of measure for marbling score is percentage of a degree of marbling).
[c]When HCW was included in the independent variable set, it was not one of the variables in the "best" equation. However, inclusion of HCW altered the process of variable selection slightly and resulted in different equations being selected as the best equation when HCW was included and excluded from the independent variable set.
[x]Intercept does not differ from 0 ($P > 0.05$).
[y]Slope does not differ from 1 ($P > 0.05$).

tion data sets. Cannell et al. (1999) reported that the VIAscan system predicted 72% of the variation in adjusted preliminary yield grade. Steiner et al. (2000) reported that the CVS and VIAscan systems predicted 44 and 76% of the variation in adjusted preliminary yield grade, respectively.

Prediction of Yield Grade. A four-variable regression equation that included HCW and image analysis variables accounted for 91 and 90% of the variation in expert yield grade in the calibration and prediction data sets, respectively (Table 2). A seven-variable regression equation that included only image analysis variables accounted for 86 and 84% of the variation in expert yield grade in the calibration and prediction data sets, respectively. Belk et al. (1997) proposed a system where an instrument would be used to measure longissimus muscle area, online USDA graders would assess carcass fatness, and yield grade would be calculated using a computer. Steiner et al. (2000) reported that such a system could account for 81 or 74% of the variation in expert yield grade if longissimus muscle area was measured by CVS or VIAscan, respectively. Thus, it appears that yield grade can be predicted more accurately by our system than by augmented yield grading. In our experiment, the official USDA yield grade as applied by online graders accounted for 73% of the variation in calculated yield grade.

The percentage of carcasses in the prediction data set assigned to each yield grade by "official" USDA graders, expert yield grades, and image analysis predicted yield grades is presented in Table 3. The percentage of carcasses assigned to yield grade 1 was lower ($P < 0.01$) for "official" USDA grades than expert yield grades. In contrast, image analysis assigned the appropriate percentage of carcasses to yield grade 1. Image analysis assigned more carcasses to yield grade 1 than did the USDA graders during "official" online grading. This suggests that if this technology were implemented, the percentage of carcasses that would be assigned yield grade 1 payment premiums would increase.

There are numerous ways in which predicted yield grade could be used in a formula or grid to determine carcass value. A regression equation could be used to linearly relate yield grade to value. However, that probably is not appropriate because value is likely not linearly related to yield grade. For example, although the average yield difference between yield grade 4.2 carcasses and yield grade 3.8 carcasses is small, the value difference is often quite large because specifications for many product lines exclude yield grade 4 or higher carcasses. Therefore, if predicted yield grade from this technology is used in a value-determining formula, it is likely that value would be assigned using a grid, even though that is not the most accurate method of using image analysis-predicted yield grade. The structure of such a grid will affect the amount of information that will be retained from predicted yield grade. For example, as a continuous variable, image analysis-predicted yield grade accounted for 90.5% of the variation in observed yield grade in the prediction data set. When those carcasses were assigned to a grid that was structured the same as the current yield grades (i.e., five classes divided at 2.0, 3.0, 4.0, and 5.0), predicted yield grade only accounted for 80.8% of the variation in observed yield grade. That is, 56% ([90.5 − 80.8]/[90.5 − 73.3]) of the gain in predictive accuracy that could be

Table 3. Percentage of carcasses in the prediction data set assigned to each yield grade by "official" USDA graders, expert yield grades, and image analysis-predicted yield grades

Yield grade	Official (online)	Expert (offline)	Image analysis (online)
1	18.6	26.5[a]	26.8[a]
2	41.8	39.0	38.8
3	32.9	24.7[a]	26.5
4	5.9	8.2	6.6
5	0.8	1.5	1.3

[a]Percentage assigned to that yield grade differs from percentage assigned to that yield grade by "official" online grader ($P < 0.05$).

obtained by using image analysis-predicted yield grade vs the official USDA yield grade would be lost by assigning the carcasses to a grid in that manner. Because 6% of carcasses had yield grades below 1.0, a portion of the loss in information that occurred in this scenario arose from the broad grouping of all carcasses with a predicted yield grade less than 2.0 into the same class. By classifying carcasses with predicted yield grades less than 1.00 separately from those with predicted yield grades between 1.00 and 2.00, a greater proportion of the variation in observed yield grade was accounted for by the yield grade classification (Table 4). As the width of the yield-grade classes was decreased from 1.0 to 0.2 units, there was an increase in the proportion of the variation in observed yield grade accounted for by the yield grade classification. For the prediction data set, essentially all of the predictive accuracy was retained when carcass were classified into 30 yield-grade classes in 0.2 increments as <0.2, 0.2 to 0.4, 0.4 to 0.6, …, 5.4 to 5.6, 5.6 to 5.8, ≥5.8 (Table 4). However, practical application of predicted yield grade in a grid structure might require the use of fewer classes. Cannell et al. (1999) reported that expert yield grades assigned to the nearest tenth accounted for more (74 vs 66%) of the variation in closely trimmed subprimal cut yields than expert yield grades assigned to the whole grade. In their analysis, Cannell et al. (1999) included all carcasses with yield grades less than 2.0 in the same yield grade.

Repeatability of Image Analysis (Exp. 2). Repeatability estimates for predicted calculated yield grade, longissimus muscle area, preliminary yield grade, adjusted preliminary yield grade, and marbling score were 0.99, 0.98, 0.99, 0.99, and 0.97, respectively. That is, the process of collecting and analyzing the images was highly repeatable.

Implications

The technology described herein could be used by the beef industry to more accurately determine beef yield

Table 4. Effect of the structure of the yield-grade classes to which image analysis-predicted yield grade is applied on the proportion of variation in calculated yield grade that is accounted for by the yield grade classification

Number of classes	Yield grade class structure	R^2
5[a]	Official online USDA yield grade	0.733
Infinite	Continuous variable	0.905
60[b]	<0.10, 0.10 to 0.20, 0.20 to 0.30, …, 5.70 to 5.80, 5.80 to 5.90, ≥5.90	0.905
30[b]	<0.20, 0.20 to 0.40, 0.40 to 0.60, …, 5.40 to 5.60, 5.60 to 5.80, ≥5.80	0.905
24[b]	<0.25, 0.25 to 0.50, 0.50 to 0.75, …, 5.25 to 5.50, 5.50 to 5.75, ≥5.75	0.900
18[b]	<0.33, 0.33 to 0.67, 0.67 to 1.00, …, 5.00 to 5.33, 5.33 to 5.67, ≥5.67	0.894
12[b]	<0.50, 0.50 to 1.00, 1.00 to 1.50, …, 4.50 to 5.00, 5.00 to 5.50, ≥5.50	0.887
6[b]	<1.00, 1.00 to 2.00, 2.00 to 3.00, 3.00 to 4.00, 4.00 to 5.00, ≥5.00	0.838
50[c]	<1.10, 1.10 to 1.20, 1.20 to 1.30, …, 5.70 to 5.80, 5.80 to 5.90, ≥5.90	0.898
25[c]	<1.20, 1.20 to 1.40, 1.40 to 1.60, …, 5.40 to 5.60, 5.60 to 5.80, ≥5.80	0.896
20[c]	<1.25, 1.25 to 1.50, 1.50 to 1.75, …, 5.25 to 5.50, 5.50 to 5.75, ≥5.75	0.891
15[c]	<1.33, 1.33 to 1.67, 1.67 to 2.00, …, 5.00 to 5.33, 5.33 to 5.67, ≥5.67	0.883
10[c]	<1.50, 1.50 to 2.00, 2.00 to 2.50, …, 4.50 to 5.00, 5.00 to 5.50, ≥5.50	0.871
5[c]	<2.00, 2.00 to 3.00, 3.00 to 4.00, 4.00 to 5.00, ≥5.00	0.808

[a]Official online USDA yield grade is shown for comparison to image analysis-predicted yield grade.
[b]Scenarios in which carcasses with predicted yield grades below 1.00 were classified separately from carcasses in the lowest yield grade 1 category.
[c]Scenarios in which carcasses with predicted yield grades below 1.00 were classified together with carcasses in the lowest yield grade 1 category.

grades and, thus, should help facilitate value-based beef marketing systems. This technology may improve the ability of packers to identify which carcasses should be fabricated into closely trimmed cuts. Given the complexity of beef marketing, where changes in yield grade are often antagonistic toward quality grade, it is difficult to predict the impact of this technology. Producers may use information from an objective grading instrument in selection strategies to improve the leanness of beef.

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