

Body weight prediction using digital image analysis for slaughtering beef cattle

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ABSTRACT

In this study, it was aimed to predict body weight of slaughtering beef cattle by using both traditional methods and digital image analysis system. Some digital images and body measurements such as body weight, body area, wither height, body length, chest depth, hip width and hip height of beef cattle; One hundred and forty (140) animals were used and prediction models were developed. There were significant differences ($P < 0.05$) between the body measurements obtained by traditional methods and digital image analysis system. The R^2 values of prediction equations were 52.1, 63.6, 53.2, 47.1, 43.1 and 49.8% for body area, body length, wither height, hip height, hip width and chest depth respectively. The regression equations which included only body area, body length or wither height showed that the prediction ability of digital image analysis system was better than the rest of the equations contained other body traits.

The results showed that the prediction ability of digital image analysis system was very promising to predict body weight. However, there is a need for further studies in order to develop better techniques to use for prediction.

INTRODUCTION

Prediction of liveweight and meat yield has been the major focus of many studies in the developed countries. Therefore, an evaluation procedure for predicting weights and yields of carcasses and beef retail cuts becomes of great importance for the beef industry (Cross and Belk, 1994).

Several technologies have been evaluated to determine the accuracy and precision for predicting body weight and carcass meat weights, but more recently, video image analysis have drawn attention to be used as an evaluation tool in the development of cattle marketing systems (Gardner et al. 1997; McClure et al. 2003).

Digital image analysis has been considered to be one of the most promising methods for prediction of body weight. It has also been utilised for determination of colour and fat thickness, marbling scores and water retention capacity in beef (Teira et al. 2003). No information on the use of such systems for the determination of preslaughter body weight of live animal is available. Therefore, in this study it was aimed to predict body weight of slaughtering beef cattle by using both traditional methods and digital image analysis system.

MATERIALS AND METHODS***Animals***

For this study, one hundred and forty (140) animals in total were selected from commercial slaughterhouses in Isparta and Burdur provinces in the Mediterranean part of Turkey. All animals were weighed by a digital weighing scale prior to slaughter (Marmara 0580 MEB).

Body Measurements

Some digital images and body measurements of live animal were taken using a video camera (Canon MV850i) and measuring stick and tape (Hauptner, Germany) respectively.

Body measurements such as body weight, body area, wither height, body length, chest depth, hip width and hip height were taken while animals were standing in a crush. All body traits were measured by measuring stick and tape.

The camera was set on a standard quality (640×512 pixel resolution). Location of camera and camera settings were tried to be constant while taking images. Whole body images were taken by placing the reference card over each live animal (Figure 1) and obtaining two sequential but separate images without moving the camera head unit in a fixed position.

Digital images were downloaded from the camera to a computer file and processed using Image Pro Plus.5 software to obtain body measurements from the images in cm.



Figure 1. Typical digital body measurements in Image Pro plus software

Statistical Procedure

Body Measurements

The differences between actual and predicted body measurements were examined by pair T-test using statistical program (Minitab v.13). The actual and predicted body measurements were also compared using MSPE (Mean Square Prediction Error).

$$MSPE = \frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2$$

Where n is the number of pairs of actual and predicted values being compared.

$i = (1, 2, 3, \dots, n)$

O_i is the observed (or actual) measurements with i th variable.

P_i is the predicted measurements with i th variable.

The MSPE can be considered as the sum of three components described by Rook et al. (1990).

$$MSPE = (\bar{O} - \bar{P})^2 + S_p^2(1 - b)^2 + (1 - r^2)S_o^2$$

Where, S_o^2 and S_p^2 are the variances of the actual and predicted measurements respectively. $\bar{O}$ and $\bar{P}$ are the means of the observed (actual) and predicted measurements, b is the slope of the regression of actual values on predicted and r is the correlation coefficient between O and P .

Apart from common regression analysis, MSPE has been used to determine the prediction ability of regression models and sources of error components in many studies by Smoler et al. (1998), Bozkurt and Ap Dewi, (2001), Yan et al. (2003), Bozkurt, (2006).

Body Weight

The best prediction equations for body weight (BW) from other body traits, including body area (BA), wither height (WH), body length (BL), chest depth (CD), hip width (HW) and hip height (HH), were determined.

Regression of body weight on BA, WH, BL, CD, HW and HH utilizing individual observations were performed. The body measurements obtained by image analysis system included body area (BA) as a different parameter for prediction of body weight. Pearson's correlation coefficients were calculated between actual and predicted values obtained by image analysis. Linear, quadratic and cubic effects of the independent variables were also considered and included in the following model:

$$Y_i = b_0 + b_1x_i + b_2x_i^2 + b_3x_i^3 + e_i$$

Where

Y_i = BW observation of an i th animal

b_0 = intercept

b_1, b_2, b_3 = corresponding linear, quadratic and cubic regression coefficients i

x_i = body measurements (BA, WH, BL, CD, HW and HH)

e_i = residual error term

RESULTS AND DISCUSSION

The differences between actual and predicted values (mean bias) together with mean square prediction error and proportions of MSPE (%) with its components are shown in Table 1. Mean biases were found to be statistically significant ($P > 0.05$) for all body traits.

Table 1. Mean square prediction error and proportions of MSPE (%)

					Proportion of MSPE (%)			
N=140		Mean	SE	Mean Bias*	MSPE	Bias	Line	Random
BL	Actual	141.9	0.80					
	Predicted	145.4	0.87	3.5±0.575	24.3	0.50	0.063	0.44
WH	Actual	128.8	0.66					
	Predicted	130.9	0.67	2.14±0.422	11.6	0.37	0.019	0.61
HH	Actual	133.5	0.66					
	Predicted	135.6	0.68	2.1±0.581	16.9	0.26	0.065	0.677
HW	Actual	44.4	0.39					
	Predicted	46.2	0.38	1.8±0.594	15.6	0.21	0.110	0.682
CD	Actual	66.4	0.48					
	Predicted	69.6	0.53	3.2±0.530	20.7	0.51	0.082	0.412

* statistically significant ($P < 0.05$).

Body measurements were overpredicted for all traits and in terms of contribution of components to MSPE; the values of bias, line and random error were 24.3%, 11.6%, 16.9%, 15.6% and 20.7% respectively (Table 1). The model had a greater proportion of error derived from both bias and random than line component. A small proportion of line as a component of MSPE showed that the error derived from line was substantially low and there was a statistically significant variation between predicted and actual measurements.

Results of regressions of body weight on the linear, quadratic and cubic effects of each body measurement are presented in Table 2. Multiple regressions of animal body weight on various body measurements using individual observations are shown in Table 3.

Table 2. Linear, quadratic and cubic effects of the independent variables

Measurements	Constant	Linear	Quadratic	Cubic	R ² %
BA	—32.5	0.033	-	-	52.1
	—111.7	0.043	—0.000 ^{ns}	-	52.1
	2031.8	—0.364	0.000 ^{ns}	—0.000 ^{ns}	52.6
BL	—752.6	8.459	-	-	63.6
	—622.8	6.685	0.006 ^{ns}	-	63.6
	10020.8	—210.77	1.481 ^{ns}	—0.003 ^{ns}	63.9
WH	—841.9	10.07	-	-	53.2
	—531.8	5.33	0.018 ^{ns}	-	53.2
	44208.8	—1022.41	7.865 ^{ns}	—0.019	55.2
HH	—776.7	9.253	-	-	47.1
	—2348.4	32.42	—0.085 ^{ns}	-	47.4
	45634.3	—1027.95	7.705 ^{ns}	—0.019 ^{ns}	48.7
HW	—252.2	15.79	-	-	43.1
	—864.4	42.13	—0.281 ^{ns}	-	43.8
	8530.8	—554.47	12.20 ^{ns}	—0.086	49.2
CD	—376.1	12.26	-	-	49.8
	486.3	—12.26	0.173 ^{ns}	-	50.5
	—4728.5	212.96	—3.046 ^{ns}	0.015 ^{ns}	50.9

ns: statistically non-significant ($P > 0.05$).

Table 3. Multiple linear regression equations to predict bodyweight using body measurements.

Prediction Equations	Constant	BA(cm ²)	BL	WH	HH	HW	CD	R ² %
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—778	0.00194 ^{ns}	5.94	2.67 ^{ns}	-1.63 ^{ns}	4.98	0.04 ^{ns}	66.7
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅	—779	0.00194 ^{ns}	5.96	2.67 ^{ns}	-1.63 ^{ns}	4.98	-	66.7
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄ +b ₆ X ₆	—790	0.00241 ^{ns}	6.75	2.81 ^{ns}	-1.00 ^{ns}	-	0.25 ^{ns}	64.5
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₅ X ₅ +b ₆ X ₆	—825	0.00035 ^{ns}	5.69	1.83 ^{ns}	-	4.76	0.14 ^{ns}	66.5
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—737	0.00199 ^{ns}	6.64	-	-0.24 ^{ns}	5.06	0.25 ^{ns}	66.1
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—710	0.00594 ^{ns}	-	4.46	-0.61 ^{ns}	6.16	4.44	62.9
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—805	-	6.09	2.68 ^{ns}	-1.38 ^{ns}	5.01	0.04 ^{ns}	66.7
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄	—792	0.00241 ^{ns}	6.88	2.82 ^{ns}	-1.01 ^{ns}	-	-	64.5
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₅ X ₅	—826	0.00035 ^{ns}	5.76	1.83 ^{ns}	-	4.77	-	66.5
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃ +b ₆ X ₆	—819	0.00140 ^{ns}	6.57	2.28 ^{ns}	-	-	0.30 ^{ns}	64.4
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₄ X ₄ +b ₅ X ₅	—739	0.00198 ^{ns}	6.78	-	-0.25 ^{ns}	5.07	-	66.1
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₄ X ₄ +b ₆ X ₆	—746	0.00246 ^{ns}	7.50	-	0.46 ^{ns}	-	0.47 ^{ns}	63.8
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₅ X ₅ +b ₆ X ₆	—749	0.00166 ^{ns}	6.55	-	-	5.01	0.26 ^{ns}	66.0
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅	—730	0.00836 ^{ns}	-	6.03	-0.31 ^{ns}	7.14	-	60.5
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₄ X ₄ +b ₆ X ₆	—712	0.00723 ^{ns}	-	4.95	0.36 ^{ns}	-	5.46	59.4
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₅ X ₅ +b ₆ X ₆	—729	0.00526 ^{ns}	-	4.11	-	6.05	4.41	62.9
Y=a+b ₁ X ₁ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—620	0.00688 ^{ns}	-	-	2.12 ^{ns}	6.55	5.76	60.9
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅	—805	-	6.11	2.68 ^{ns}	-1.38 ^{ns}	5.01	-	66.7
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄ +b ₆ X ₆	—822	-	6.94	2.81 ^{ns}	-0.69 ^{ns}	-	0.24 ^{ns}	64.5
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₅ X ₅ +b ₆ X ₆	—829	-	5.73	1.86 ^{ns}	-	4.78	0.14 ^{ns}	66.5
Y=a+b ₂ X ₂ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—764	-	6.79	-	0.01 ^{ns}	5.08	0.25 ^{ns}	66.0
Y=a+b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—789	-	-	4.62	0.26 ^{ns}	6.33	4.78	62.5
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₃ X ₃	—822	0.00138 ^{ns}	6.73	2.29 ^{ns}	-	-	-	64.4
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₄ X ₄	—750	0.00246 ^{ns}	7.75	-	0.46 ^{ns}	-	-	63.8
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₅ X ₅	—752	0.00165 ^{ns}	6.68	-	-	5.02	-	66.0
Y=a+b ₁ X ₁ +b ₂ X ₂ +b ₆ X ₆	—723	0.00311 ^{ns}	7.70	-	-	-	0.46 ^{ns}	63.8
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₄ X ₄	—739	0.0106 ^{ns}	-	7.06	0.94 ^{ns}	-	-	55.6
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₅ X ₅	—740	0.00801 ^{ns}	-	5.85	-	7.09	-	60.5
Y=a+b ₁ X ₁ +b ₃ X ₃ +b ₆ X ₆	—701	0.00766 ^{ns}	-	5.17	-	-	5.49	59.4
Y=a+b ₁ X ₁ +b ₅ X ₅ +b ₆ X ₆	—480	0.0109	-	-	-	7.27	6.50	60.2
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₄ X ₄	—824	-	7.06	2.83	-0.70 ^{ns}	-	-	64.5
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₅ X ₅	—830	-	5.80	1.86 ^{ns}	-	4.78	-	66.5
Y=a+b ₂ X ₂ +b ₃ X ₃ +b ₆ X ₆	—834	-	6.73	2.39 ^{ns}	-	-	0.29 ^{ns}	64.4
Y=a+b ₂ X ₂ +b ₄ X ₄ +b ₅ X ₅	—766	-	6.93	-	0.01 ^{ns}	5.09	-	66.0
Y=a+b ₂ X ₂ +b ₄ X ₄ +b ₆ X ₆	—780	-	7.70	-	0.78 ^{ns}	-	0.46 ^{ns}	63.7
Y=a+b ₃ X ₃ +b ₄ X ₄ +b ₅ X ₅	—847	-	-	6.44	0.99 ^{ns}	7.51	-	59.6
Y=a+b ₃ X ₃ +b ₄ X ₄ +b ₆ X ₆	—809	-	-	5.16	1.47 ^{ns}	-	5.92	58.8
Y=a+b ₃ X ₃ +b ₅ X ₅ +b ₆ X ₆	—784	-	-	4.81	-	6.40	4.82	62.5
Y=a+b ₄ X ₄ +b ₅ X ₅ +b ₆ X ₆	—708	-	-	-	3.25	6.77	6.21	60.3
Y=a+b ₁ X ₁ +b ₂ X ₂	—727	0.00310 ^{ns}	7.95	-	-	-	-	63.7
Y=a+b ₁ X ₁ +b ₃ X ₃	—709	0.0118	-	7.66	-	-	-	55.6
Y=a+b ₁ X ₁ +b ₄ X ₄	—589	0.0140	-	-	6.26	-	-	49.8
Y=a+b ₁ X ₁ +b ₅ X ₅	—306	0.0203	-	-	-	10.1	-	53.7
Y=a+b ₁ X ₁ +b ₆ X ₆	—363	0.0158	-	-	-	-	8.55	55.0
Y=a+b ₂ X ₂ +b ₃ X ₃	—837	-	6.88	2.40 ^{ns}	-	-	-	64.4
Y=a+b ₂ X ₂ +b ₄ X ₄	—783	-	7.95	-	0.78 ^{ns}	-	-	63.7
Y=a+b ₂ X ₂ +b ₅ X ₅	—766	-	6.93	-	-	5.10	-	66.0
Y=a+b ₂ X ₂ +b ₆ X ₆	—749	-	8.22	-	-	-	0.45 ^{ns}	63.6
Y=a+b ₃ X ₃ +b ₄ X ₄	—890	-	-	7.64	2.70 ^{ns}	-	-	54.1
Y=a+b ₃ X ₃ +b ₅ X ₅	—829	-	-	7.23	-	7.79	-	59.4
Y=a+b ₃ X ₃ +b ₆ X ₆	—780	-	-	6.31	-	-	6.20	58.8
Y=a+b ₄ X ₄ +b ₅ X ₅	—748	-	-	-	6.05	8.76	-	54.7
Y=a+b ₄ X ₄ +b ₆ X ₆	—720	-	-	-	4.92	-	7.62	56.0
Y=a+b ₅ X ₅ +b ₆ X ₆	—511	-	-	-	-	8.66	8.45	58.0
Y=a+b ₁ X ₁	—32.5	0.0328	-	-	-	-	-	52.1
Y=a+b ₂ X ₂	—753	-	8.46	-	-	-	-	63.6
Y=a+b ₃ X ₃	—841	-	-	10.1	-	-	-	53.2
Y=a+b ₄ X ₄	—777	-	-	-	9.25	-	-	47.1
Y=a+b ₅ X ₅	—252	-	-	-	-	15.8	-	43.1
Y=a+b ₆ X ₆	—376	-	-	-	-	-	12.3	49.8

ns: statistically non-significant (P>0.05).

The highest R² value was obtained from the equation contained all body traits (R²=66.7%). It was observed that inclusion of BL in the equations increased R² greatly (Table 3). Results also showed that a 1 cm² change in BA resulted in approximately 0.033 kg change in weight. Similarly, a 1 cm change in BL, WH, HH, HW, and CD resulted in 8.46, 10.07, 9.25, 15.8 and 12.3 kg change in weight respectively (Table 2). It was evident that a 1 cm² change in BA resulted in lesser weight change compared to the rest of body traits. The R² values of prediction equations were 52.1, 63.6, 53.2, 47.1, 43.1 and 49.8% for BA, BL, WH, HH, HW and CD

respectively. The regression equations which included only BL, BA or WH showed that the prediction ability of digital image analysis system was better than the rest of the equations contained other body traits.

In this study, while all linear terms of all body traits were significant ($P < 0.05$), quadratic and cubic terms of all body traits were not significant ($P > 0.05$) except the cubic terms of WH and HW. The R^2 values from the regressions indicate that BL, BA and WH height to be the most highly related to body weight considering all linear, quadratic and cubic coefficient terms. For all body traits, addition of the cubic term increased the R^2 values slightly.

Correlation coefficients of the traits are shown in Table 4.

Table 4. Correlation coefficients between body weight and body measurements

Variables	BW	BA	BL	WH	HH	HW
BA	0.65					
BL	0.80	0.78				
WH	0.73	0.75	0.86			
HH	0.69	0.80	0.84	0.88		
HW	0.66	0.59	0.68	0.64	0.65	
CD	0.71	0.69	0.88	0.76	0.73	0.61

All correlation values obtained for all body traits were statistically significant ($P < 0.05$). Considering the correlation between BW and other body traits, amongst all the body measurements, the highest correlation was found between BL and BW ($r=0.80$). The second highest correlation was between WH and BW ($r=0.73$). In addition, the correlation value between heart girth and wither height ($r=0.84$) was higher than the correlation between the rest of the traits

CONCLUSION

It can be concluded that body area (BA) and body length (BL) obtained by digital image analysis can provide a considerably reliable prediction of body weight. It is unavoidable that some images may not be clear enough for processing or improper position of live animal and of reference cards placed on live animal can make it difficult to measure correctly on digital images. Prediction ability of the equations may also be affected by the variation of the animal's breed type and size.

Therefore, the prediction ability of digital image analysis system was very promising to predict BW. However, there is still a need for further investigations for different breeds of cattle, taking in to account of their size as well under better controlled experimental conditions.

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