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PREDICTION OF LIVE WEIGHT FROM MORPHOLOGICAL CHARACTERISTICS OF COMMERCIAL GOAT IN PAKISTAN USING FACTOR AND PRINCIPAL COMPONENT SCORES IN MULTIPLE LINEAR REGRESSION

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ABSTRACT

The present work was conducted on 249 local commercial goats in Southern Punjab (Pakistan), particularly Multan, with the aim to define an appropriate model for predicting live weight from linear body measurements recorded from January to June 2012. Data recorded for these goats were body length (BL), chest girth (CG), belly girth BG, rump height (RH), withers height (WH), and live weight (LW). In the statistical evaluation of the data; i) Pearson correlation coefficients between the linear body measurements were estimated, ii) multiple linear regression model was used for live weight prediction, iii) use of the scores from factor and principal component analyses as independent variables in multiple regression analysis model was employed with the purpose to predict live weight (LW). Explanatory variables were body length (BL), chest girth (CG), belly girth (BG), rump height (RH) and wither's height (WH). The factor scores (FS1, FS2 and FS3) were generated and used as predictors with LW= 0.547 FS1 + 0.313 FS2 – 0.475 FS3. FS1 increased with increasing RH, WH, and CG and indirectly BW would be expected to increase with increasing FS1. When FS2 increased with increasing BG, an increment in BW would be expected. Finally when FS3 increased with increasing BL; an increment in BW would be expected. The obtained equations for principal component analysis were written as: PC1 = –0.437 BL – 0.462WH – 0.455 RH – 0.423 BG – 0.458 CG, PC2= 0.354 BL + 0.297 WH + 0.261 RH – 0.839 BG – 0.121 CG, LW = - 0.370 PC1 + 0.262 PC2. The original variables largely effective on PC1 were BL, WH, RH, and CG, but BG had a greater effect on PC2 compared with the others. The goat having much greater BL, WH, and RH would be expected to gain greater PC1, PC2 and LW. Goat whose PC1 was negative and absolutely greater value with increasing original variables; viz. BL, WH, RH, BG, and CG would be expected to produce the greater LW. As a result, the present results confirmed that instead of multiple and stepwise regression, principal use of factor and principal component scores in multiple regression analysis might offer a good opportunity without multicollinearity problem for predicting body weight of indigenous goat. Also, if there is a genetic confirmation regarding body weight of commercial goats, their morphological characteristics could provide breeders to acquire some significant clues for further breeding studies.

Key word: Commercial goats, live weight, body measurements, factor analysis.

INTRODUCTION

In goat breeding, knowledge about the relationships among body weight and several body measurements taken at sequential periods as of birth in terms of growth-development performance gives some beneficial clues not only for determining breed traits and a good selection strategy, which is an important tool that selects animals of higher yield genetically in a flock, but also for obtaining prediction equation of body weight from these body measurements taken without weighbridges (Adeyinka and Mohammed, 2006; Khan *et al*., 2006). The prediction of body weight enables breeders to define suitable medicinal doses for remedy of an animal, its feed amount per day, and expressly for marketing (Chitra *et al*., 2012; Tadesse *et al*., 2012).

In recent years, many authors have reported data on the prediction of body weight from different body measurements with regard to animal species, which are of great significance in the sense of breeders (Khan *et al*., 2006). Concordantly, it is necessary to precisely predict body weight by means of the most suitable statistical analysis techniques. Like a Pearson correlation coefficient, simple regression equation among the most preferred approaches is a practically statistical tool to define the linear relationship between body weight and a body measurement (Eyduran *et al.,* 2009). To get information regarding the relationship between body weight and several body measurements, a multiple linear regression is frequently preferred in an attempt to explain variability in the body weight, which is of great importance in both animal breeding and human nourishment (Moaeen-ud-Din *et al*., 2006; Olatunji-Akioye and Adeyemo, 2009). However, correlation coefficients found to be strong between pairs of body measurements may lead to a difficult case, like multicollinearity problem in multiple linear regressions and, thus the biased regression coefficient found for each of body measurements may induce inadvisable results and interpretation in the prediction of body weight (Eyduran *et al*., 2009). To avoid these undesirable results in the body weight prediction operations, the most effectively operable statistical techniques; namely, i) ridge regression, ii) using principal component analysis in multiple linear regression and iii) using factor analysis for multiple linear regression in an effort to define the explained variation of the body weight biologically and statistically from linear body measurements must be applied with the purpose of making comments reliable with a higher accuracy in goat breeding. Recently, many authors have reported that these statistical techniques which were utilized for eliminating biased estimation obtained earlier in animal science have produced much better results than multiple linear regression analysis, the traditional approach to analyze relationships between body weight (dependent variable) and body measurements (independent variables), adversely affected from multicollinearity problem. Of these three statistical techniques mentioned above, using factor analysis and principal component scores in multiple regression analysis offer a respectable opportunity of not only obtaining meaningful-uncorrelated new-latent independent variables, also known as factor scores from original interrelated independent variables, but also removing multicollinearity problem for bias correction of regression coefficients (Keskin *et al*., 2007a; Keskin *et al*., 2007b). For predicting live weight of goats, multiple linear regression analysis is often applied to data regarding live weight-morphological linear traits (Adeyinka and Mohammed, 2006; Alade *et al*., 2009; Chitra *et al*., 2012). Reports on the prediction of body weight from various morphological characteristics in goat are scarce in terms of using a factor analysis-regression analysis modeling and especially principal component scores in multiple linear regression. In the view of such information, the aim of this research was to obtain a good prediction equation of body weight without multicollinearity problem by using factor and principal component scores in multiple regression analyses principal from morphological linear measurements not only taken easily from goat but also used as indirect selection criteria in the selection of superior animals with the aim of genetically progressing body weight. The weight prediction equation that possesses a great accuracy permits researchers to find out morphological measurements that can provide a great contribution to explaining a big amount of variability of body weight.

MATERIALS AND METHODS

Commercial goat flocks are commonly found in Southern Punjab (Pakistan), particularly Multan. Therefore, body measurements and body weight data from 249 local commercial goats (178 females & 71 males) with different ages among 1 – 4 years were recorded from January to June 2012. These goats were crossbreds having different genotypic constitution (product of crossbreeding between Nachi, DDP, Beetal and Teddy). Different body measurements taken from these goats were body length (BL), chest girth (CG), belly girth (BG), rump height (RH) and withers height (WH), recorded in inches and live weight (LW) in kilograms. Ages of goats were determined by dentition. These measurements were used to predict body weight. For this purpose, usage of factor analysis (with VARIMAX rotation) in multiple regression models was employed (Sakar *et al*., 2011; Yilmaz *et al*., 2011). Multicolinearity was taken into consideration in selecting predictor variables. In addition, using principal Principal component scores in multiple linear regressions was also fitted to live weight-morphological variables. Predictors with VIF >10 were not included in the prediction to avoid multicolinearity problems. All the analyses were fulfilled using Minitab (Released version) computer software (www.minitab.com).

RESULTS AND DISCUSSION

Table 1 presents Pearson's correlations between morphological characteristics and body weight, quantifiable, obtained from 249 goats at different ages, in Pakistan. Because of the nature of growth-development biologically, all these strongly positive correlations ranged from 0.617 (LW-BG) to 0.957 (RH-WH) at the significance level of 0.01 (Table 1). Khan *et al.* (2006) noted some correlations for LW-BL (0.485), LW-WH (0.746), LW-HG (0.623), for 19-24 months respectively, and for goat equal and older than 25 months; LW-BL (0.779), LW-WH (0.722), LW-HG (0.708), respectively. In another study conducted on investigating the relationship between LW and linear biometrical traits, Bello and Adama (2012) reported several Pearson correlations in concern with LW-BL (0.289 and – 0.063), LW-WH (0.169 and 0.508) and LW-CG (0.502 and 0.677) in castrate and non-castrate Savannah Brown Goats, respectively. Due to the fact that LW prediction equations have been numerously developed for various ages from different goat breeds, it is therefore an unreasonable approach to discuss the present results with earlier reports in goat breeding.

Descriptive statistics (Mean ± SE) for quantitative characteristics, which are of great significance economically, are in Table 2. Averages (range values) for BL, WH, RH, BG, CG, and LW were 25.264 inch, 27.197 inch, 28.389 inch, 30.392 inch, 27.586 inch, and 29.444 kg, respectively, which were very close values to their own median values, as perceived in Table 2.

Table 1. Pearson correlation coefficients between morphological characteristics

Variable	BL	WH	RH	BG	CG
WH	0.875	-	-	-	-
RH	0.830	0.957	-	-	-
BG	0.748	0.789	0.782	-	-
CG	0.842	0.907	0.894	0.851	-
LW	0.749	0.754	0.750	0.617	0.764

All the correlations were significant (P<0.01)

Only multiple regression analysis without including factor analysis caused to occur VIF values greater than 10 as recognized in variables, WH (VIF=17) and RH (VIF=13), meaning that there was a strong indication of multicollinearity problem (data not shown). In Malabari adult female goats, Chitra *et al*. (2012), who didn't address multicollinearity problem, obtained the prediction equation of LW= - 15.2656 + 0.0897 BL + 0.0533 WH + 0.4646 HG, R^2 72.1%, MSE= 8.297. For a similar study, Gul *et al*. (2005) estimated without calculating VIF it for Damascus goat: LW= 0.138 HG+ 0.11WH+ 0.198 WTC – 0.654 with 86 R^2 (%) and LW= 0.817 HG+ 1.973HW+ 0.319HH – 78.36 with 84 R^2 (%) for Damascus kids. As it is well known, results of VIF must be estimated as an indicator of multicollinearity problem, in order to assess whether results obtained for multiple regression analysis will be trustable. For predicting unbiased regression coefficients in the multiple regression analysis, VIF values peculiar to these coefficients must be smaller than 10. There were many earlier reports that VIF values were not estimated for multiple regression model (Gul *et al*., 2005; Adeyinka and Mohammed, 2006; Alade *et al*., 2008; Chitra *et al*., 2012; Tadesse *et al*., 2012).

Table 2. Descriptive statistics for morphological characteristics

Variable	Mean	SE	SD	Min	Q1	Median	Q3	Max
BL	25264	0.409	6.,453	11.000	21.150	25.000	29.00	42.00
WH	27.197	0.337	5.,315	13.000	24.000	28.000	31.05	41.00
RH	28.389	0.322	5.,087	14.000	25.100	29.000	32.00	40.00
BG	30.392	0.407	6.,421	3.500	26.450	31.000	35.00	45.00
CG	27.586	0.337	5.,310	14.000	24.600	28.000	31.00	41.00
LW	29.444	0.840	13.,250	4.000	19.500	30.000	38.00	85.00

In the application of principal component analysis, two new principal component score variables were extracted from original independent variables with the explanation proportion of 93.6 % in the morphological data set. The standardized body weight along with these two principal component score, (derived as new independent variables) was exposed to multiple regression linear regression analysis. Thus, principal component regression revealed a determination coefficient of R^2 62.2%, R^2 adjusted 61.9%, and RMSE= 0.6170, in conjunction with VIF = 1 for both PC1 and PC2 (data not shown). The first principal component had a variance of 4.3946 (eigenvalue) with the explanation proportion of 87.9%. The explained proportion was 5.7% for the second principal component with a variance of 0.2849 (eigenvalue). This means that the first two components explained 93.6% of morphological variation. The following equations could be written in order to calculate scores regarding PC1 and PC2, respectively. It is an obvious evidence that goat whose PC1 was negative and greater absolute value with increasing original variables; viz. BL, WH, RH, BG, and CG would be expected to produce the greater LW. The strongly correlations between PC1 and morphological variables such as: BL, WH, RH, BG, and CG were found as: -0.916, -0.968, -0.954, -0.887, and -0.960, respectively (P<0.01). As examined in the equations mentioned below, the original variables largely effective on PC1 were BL, WH, RH, and CG, but BG had a greater negative effect on PC2 compared with the others. Similarly, PC2 was significantly correlated with BL (0.189; P<0.01), WH (0.159; P<0.01), RH (0.139 P<0.05), and BG (-0.448; P<0.01), respectively. The goat having much greater in BL, WH, RH, BG would be expected to gain greater PC2 and LW. However, BG was the original variable that comprised negative-effective one on PC2 and indirectly LW.

PC1 = – 0.437 BL– 0.462 WH – 0.455 RH – 0.423 BG – 0.458 CG

PC2= 0.354 BL + 0.297 WH + 0.261 RH – 0.839 BG – 0.121 CG

LW = - 0.370 PC1 + 0.262 PC2 (Multiple regression equation for Principal componentscores)

With the purpose of not only removing the multicollinearity problem occurring between other morphological characteristics (independent variables) with the exception of BW, but also deriving new-meaningful-uncorrelated latent variables from the morphological characteristics, the original independent variables were exposed to multivariate factor analysis with VARIMAX rotation. Result of Kaiser-Meyer Olkin (KMO) Measure of Sampling Adequacy (0.867) illustrated to be suitable for the data evaluated statistically for factor analysis. Also, result from Bartlett's test of Spherity with Chi-square = 1740 and 10 df confirmed the feasibility of factor analysis application on the presented data.

The summary results; namely, sorted rotated factor loadings, communalities, and factor score coefficients relating to factor analysis are depicted in Table 3. In order to supply reliable results statistically from original characteristics, three new latent variables were extracted, and were able to be accepted as independent variables for multiple linear regression analysis, as also defined by many authors (Keskin *et al*., 2007a; Keskin *et al*., 2007b; Eyduran *et al*., 2009; Eyduran *et al*., 2010; Moses, 2010). Highly communalities (known to be the explained variation of original characteristics by factors, 1, 2, and 3, respectively whose eigenvalues are greater than one, and extracted from five characteristics) found for original characteristics had a narrow range of 0.928 to 0.999, all of which were most desired values for factor analysis. A great variation observed in the assessed data was 97.4 %, accounted for by three factors through 40.9%, 30.6% and 25.9 %, respectively from original five morphological characteristics measured under the investigation. All the factor loadings, also defined as Pearson correlation, expressing the direction-degree of a linear relationship between original and factor score variables, were very significant (P<0.01) as observed in Table 3. RH (0.824), WH (0.772) and CG (0.645) determined to have a great contribution to the formation of factor 1 as compared with other original characteristics studied in the current investigation (P<0.01). BG (0.864) was associated with the structuring of factor 2, and BL (-0.810) was also connected with the occurrence of factor 3 (P<0.01). Despite the fact that BL was negatively correlated with factor 3 (P<0.01), there were positive meaningful correlations between pairs of factor scores (FS1 and FS2) and original characteristics (P<0.01) (data not shown). In addition, Pearson correlations between factor score variables; FS1, FS2, and FS3 were zero (r = 0.000) as statistically expected.

With the aim of determining the relationship of body weight with morphological characteristics, multiple regression analysis was applied after obtaining three new-uncorrelated (factor score) variables extracted on the basis of eigenvalues. The obtained results by using factor and multiple linear regression analyses jointly are summarized in Table 4. ANOVA result reflected understandably that multiple linear regression modeling with three uncorrelated variables after factor analysis was very significant (P<0.01). Prediction equation of LW with zero intercept was LW= 0.547 FS1 + 0.313 FS2 – 0.475 FS3 with 62.3 % R^2, 61.9% R^2 adjusted and 0.617355 RMSE (Root of Mean Square Error), respectively. Factor score variables, FS1, FS2 and FS3 are very significant (P<0.01), respectively. With increasing one unit of FS1 and FS2, LW would be expected to increase averagely 0.547 and 0.313, respectively. In response to increasing FS3, LW would be expected to decrease 0.47545 averagely but an increment in BL, providing significant contribution in the formation of Factor 3, would be expected to increase LW In agreement with those reported by earlier authors, VIF values as indicators of multicollinearity problem were found as unity for each factor score, meaning that multicollinearity was removed definitely in multiple linear regression in consequence of factor scores in multiple regression analysis, as well as regression coefficients estimated were able to be reliable (Keskin *et al*., 2007a; Keskin *et al*., 2007b; Eyduran *et al*., 2009 ; Eyduran *et al*., 2010).

Table 3. Results of factor analysis applied for independent variables (Sorted Rotated Factor Loadings and Communalities).

Variable	Factor1	Factor2	Factor3	Communality
RH	**0.824**	0.397	-0.373	0.977
WH	**0.772**	0.395	-0.471	0.974
CG	**0.645**	0.579	-0.421	0.928
BG	0.378	**0.864**	-0.316	0.990
BL	0.456	0.367	**-0.810**	0.999
Variance	2.0430	1.5299	1.2947	4.8676
% Var	0.409	0.306	0.259	0.974

Table 3a. Factor Score Coefficients

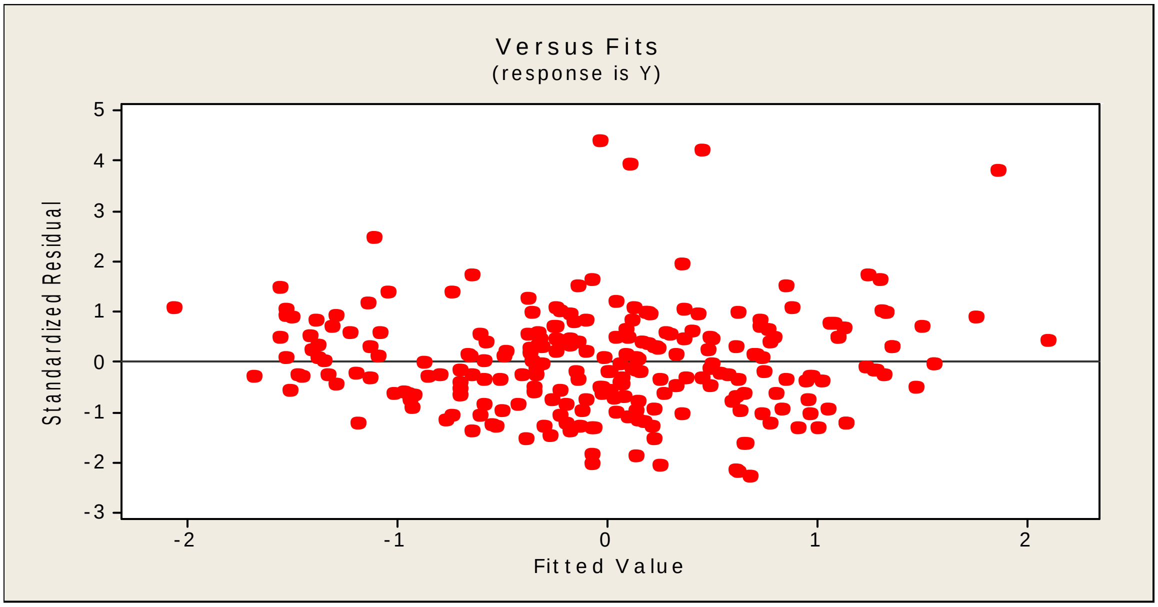
Variable	Factor1	Factor2	Factor3
BL	-0.793	-0.332	-1.798
WH	0.735	-0.375	0.116
RH	1.073	-0.353	0.586
BG	-0.655	1.435	0.304
CG	0.244	0.292	0.205

Considering the results in Tables 3 and 4 together in order to make better interpretation, a) FS1 increased with increasing RH, WH, and CG and indirectly LW would be expected to increase with increasing FS1 in the prediction equation of LW= 0.547 FS1 + 0.313 FS2 – 0.475 FS3.

b) Similarly, when FS2 increased with increasing BG in the prediction equation of LW= 0.547 FS1 + 0.313 FS2 – 0.475 FS3, an increment in BW would be expected.

c) In the similar way, FS3 (negative sign) increased with increasing BL (negative sign) in the prediction equation of LW= 0.547 FS1 + 0.313 FS2 – 0.475 FS3; an increment in LW would be expected.

Graph of standardized residuals versus fitted values is depicted in Figure 1. Most of the residuals were in an interval of -2 to +2, illustrating that there was a clear verification for validity of normality assumption in respect of the residuals. In addition, Table 7 gives results of regression diagnostics (residual, and studentized residual) with the intention of determining unusual observations, undesirably influencing sum of error squares in multiple linear regression analysis. Diagnostics results of Table 7 demonstrated that, for example; observations with 14, 31, 220 numbers were the observations negatively affecting error term or sum of error squares of the regression model. As summarized in Table 7, R denotes an observation with a large standardized residual. X denotes an observation whose X value gives it large influence. However, bold marked observations in the last two columns of Table 7 due to having absolutely values greater than 2 were determined to be outliers and potential (influence) observations.



The regression equation is LW = 0.0000 + 0.547 FS1 + 0.313 FS2 – 0.475 FS3

Table 4. Result of multiple regression analysis determining the relationship of live weight and factor scores

Predictor	Coef	SE Coef	T	P	VIF
FS1	0.5474	0.0392	13,96	0.000	1.0
FS2	0.3127	0.0392	7,98	0.000	1.0
FS3	-0.47545	0.0392	-12,13	0.000	1.0

S = 0.617355 R^2 = 62.3% R^2(adj) = 61.9%

Table 5. Analysis of Variance

SOV	df	SS	MS	F	P
Regression	3	154.624	51.541	135.23	0.0000
Residual error	245	93.376	0.381		
Total	248	248.000			

Table 6. Analysis of variance for FS at single degree of freedom

SOV	df	Seq SS
FS1	1	74.314
FS2	1	24.250
FS3	1	56.060

In the present study, summary results of multiple linear regression, use of factor score in multiple regression analysis, and principal component regression for male and female goat are given in Table 8.

In the present study, prediction equation obtained in the multiple regression analysis for male goats was LW = - 31.0 + 1.10BL+0.29WH- 0.10RH + 0.002BG + 1.08CG, which produced a very severe multicollinearity problem with VIF values greater than 10 and biased estimation. The prediction equation of stepwise regression analysis for male goats was LW= -30.9 + 1.20CG + 1.16BL for giving more better results due to the VIF values of 3.5 compared to the equation of multiple regression analysis, but goodness of fit criteria for these regression analyses had virtually results. No multicollinearity problem for using factor and principal component scores together with multiple regression analysis with much lower RMSE values was detected in comparison with stepwise and multiple regressions, with higher RMSE values. For using factor score in multiple regression, the obtained prediction equation was estimated as: LW = 0.502 FS1 – 0.538 FS2 – 0.365 FS3 ($P<0.01$ for FS1, FS2, FS3) without multicollinearity problem (VIF=1). Original variables BG and CG significantly contributed to FS1 more than others due to the fact that highly correlations at a significance level of ($P<0.01$) were FS1-BG (0.795) and FS1-CG (0.771). BL which contributed greatly in the construction of FS2 significantly was correlated with FS2 (- 0.820). The greatest contributions of RH and WH for FS3 were similarly detected. Because of the fact that the signs of FS1, FS2, and FS3 in LW prediction equation and the estimated correlations were equal, original variables caused to an increment in FS1, FS2, and FS3, and indirectly an increment in LW would be expected. Derived from principal component regression, three prediction equations with the purpose to remove multicollinearity problem were predicted as follows:

LW = – 0.378 PC1 + 0.195 PC2 (P<0.01 for only PC1)

PC1= – 0.430 BL – 0.456WH – 0.455RH – 0.446BG – 0.449 CG

Table 7. Unusual Observations

Obs	FS1	LW	Fit	SE Fit	Residual	St Resid
14	-0.49	0.4193	-1.1097	0. 0762	1.5291	2.,50R
31	-1.00	1.1741	1.2450	0.1455	-0.0709	-0.,12X
37	4.74	2.3062	2.0985	0.3956	0.2076	0.44X
39	-1.07	0.4193	1.1495	0.1418	-0.7301	-1.22X
69	0.36	-0.7127	0.6198	0.0517	-1.3326	-2.17R
122	0.17	2.6835	-0.0369	0.0469	**2.7204**	**4.42R**
149	-0.34	3.0609	0.4502	0.0603	**2.6107**	**4.25R**
173	-0.11	-1.3165	-0.0716	0.0397	-1.2450	-2.02R
179	0.50	-0.7127	0.6115	0.0513	-1.3242	-2.15R
188	1.31	-0.7127	0.6827	0.0665	-1.3955	-2.27R
200	0.71	-1.0146	0.2449	0.0491	-1.2595	-2.05R
202	0.52	2.5326	0.0936	0.0665	**2.4389**	**3.97R**
209	2.11	4.1930	1.9089	0.1057	**2.2841**	**3.76R**
220	-0.85	1.1741	1.2539	0.1387	-00798	-0.13X
227	-1.15	0.,4193	1.1666	0.1485	-07473	-1.25X

Almost close contributions of original variables to PC1 were observed, together with highly negative correlations between PC1 and original variables as illustrated in Table 8. The signs of the estimated correlations and contribution values to PC1 were same-negative, meaning that original variables would provide an increment in PC1, and then an increment in LW would be expected with increasing PC1.

In the present study, prediction equation of multiple regression analysis for female goats was LW = -19.1 + 0.731BL- 0.355WH+ 0.833RH - 0.312BG + 0.861CG with a severe multicollinearity problem owing to its VIF values greater than 10. This case may lead to biased parameter estimation and untrusted comments, biologically. The prediction equation is LW= - 19.2 + 0.659 BL + 0.645 RH- 0.310 BG+0.822 CG for stepwise regression analysis giving more accurate results by reason of VIF values smaller than 10 in comparison with multiple regression analysis, whereas goodness of fit criteria for both analysis methods yielded nearly results. No multicollinearity problem for using factor and principal component scores together with multiple regression analysis with much lower RMSE values was detected because of the fact that all VIF values were equal to one, meaning that the most reliable results were taken without multicollinearity problem by comparison with stepwise and multiple regressions, with higher RMSE values. With the help of using factor score in multiple regression, the following prediction equation was estimated as: LW = 0.559 FS1 + 0.273 FS2 – 0.491 FS3. Original variables RH, WH, and CG contributed to

Table 8. The summary results of prediction equations from different analysis techniques

Male Goat	**The summary results of prediction equations**
Multiple linear regression	LW = - 31.0 + 1.10BL+0,29WH- 0.10RH + 0.002BG + 1.08CG VIF (BL)= 4.9, VIF (WH)= 24.2, VIF (RH)= 24.0, VIF(BG)= 11.2 VIF (CG)=12.1 RMSE = 9.34015 R^2 = 67,9% R^2 (adj) = 65,4%
Stepwise Regression	LW = - 30,9 + 1,20 CG + 1,16 BL VIF (CG)=3.5 VIF (BL)= 3.5, RMSE = 9.14091, R^2= 67.8%, R^2 (adj)= 66,9%
Use of factor scores in multiple regression	LW = 0.502 FS1 – 0.538 FS2 – 0.365 FS3 (P<0.01 for FS1, FS2, FS3) VIF (FS1)=VIF(FS2)=VIF(FS3)=1

	RMSE = 0.582562 R^2= 67,5% R^2 (adj)= 66,1% The original variables significantly contributing to FS1= BG and CG FS1-BG correlation: 0.795 (P<0.01), FS1-CG correlation: 0.771 (P<0.01) The original variable significantly contributing to FS2: BL FS2-BL correlation: – 0.820 (P<0.01) The original variables significantly contributing to FS3: RH and WH FS3-RH correlation: – 0.692, FS3-WH correlation: – 0.681
Use of principal component scores in multiple regression	LW = – 0.378 PC1 + 0,195 PC2 (P<0.01 for only PC1) RMSE = 0.586303 R^2 = 66,6% R^2 (adj) = 65,6% VIF (PC1)=VIF(PC2)=1 PC1= – 0.430 BL – 0.456WH – 0.455RH – 0.446BG – 0.449 CG PC2= 0.800 BL+0.046WH + 0.014RH – 0.494BG – 0.338 CG PC1- BL correlation: –0.923(P<0.01), PC1-WH correlation: –0.977(P<0.01) PC1-RH correlation: –0.976(P<0.01), PC1-BG correlation: –0.956(P<0.01) PC1-CG correlation: –0.963 (P<0.01)
Female Goat Multiple linear regression Use of factor scores in multiple regression Use of principal component scores in multiple regression	
Female Goat	**The summary results of prediction equations for female goat**
Multiple linear regression	LW = - 19.1 + 0.731BL- 0,355WH+ 0.833RH - 0.312BG + 0.861CG VIF (BL)= 4.7, VIF (WH)= 15.8, VIF (RH)= 11.9, VIF(BG)= 3.1 VIF (CG)=7.9 RMSE = 7.31972 R2 = 64.3% R2 (adj) = 63.3%
Stepwise Regression	LW= - 19,2 + 0,659 BL + 0,645 RH- 0,310 BG+0,822 CG VIF (BL)= 3.7, VIF (RH)= 5.1, VIF(BG)= 3.1, VIF (CG)=7.7 RMSE = 7.31372, R2= 64.1%, R2 (adj)= 63.3%
Use of factor score in multiple regression	LW = 0.559 FS1 + 0.273 FS2 – 0.491 FS3 (P<0.01 for FS1, FS2, FS3) VIF (FS1)=VIF(FS2)=VIF(FS3)=1 RMSE = 0.614663 R2= 62.9% R2 (adj)= 62.2% The original variables significantly contributing to FS1= RH, WH, CG FS1-RH correlation: 0.849 (P<0.01), FS1-WH correlation: 0.783 (P<0.01) FS1-CG correlation: 0.656 (P<0.01). The original variable significantly contributing to FS2: BG FS2-BG correlation: 0.882 (P<0.01) The original variables significantly contributing to FS3: BL FS3-BL correlation: – 0.813
Principal component regression	LW = – 0.372 PC1 + 0.282 PC2 (P<0.01 for PC1 and PC2) RMSE = 0.615761 R2 = 62.5% R2 (adj) = 62.1% VIF (PC1)=VIF(PC2)=1 PC1= – 0.440 BL – 0.464WH – 0.456RH – 0.414BG – 0.461 CG PC2= 0.256 BL+0.317WH + 0.291RH – 0.862BG – 0.076 CG PC1- BL correlation: –0.914, PC1-WH correlation: –0.964, PC1-RH correlation: –0.947, PC1-BG correlation: –0.861 PC1-CG correlation: –0.959 PC2- BL correlation: 0.149 (P<0.05), PC2-WH correlation: 0.184(P<0.05), PC2-RH correlation: 0.169(P<0.05), PC2-BG correlation: –0.500 (P<0.01), PC2-CG correlation: –0.044(NS) LW = – 0.372 PC1 + 0.282 PC2 (P<0.01 for PC1 and PC2) PC1= – 0.440 BL – 0.464WH – 0.456RH – 0.414BG – 0.461 CG PC2= 0.256 BL+0.317WH + 0.291RH – 0.862BG – 0.076 CG

the formation of FS1 more than others due to the fact that strongly significant correlations at (P<0.01) were estimated for FS1-RH (0.849), FS1-WH (0.783), and FS1-CG (0.656). BG which had the greatest contribution in the formation of FS2 was highly correlated with FS2 (0.882). The greatest contribution of BL on FS3 was noted due to the correlation (– 0.813) between themselves. Owing to the fact that the signs of FS1, FS2, and FS3 in LW prediction and the correlations mentioned above were identical, original variables led to an increment in FS1, FS2, and FS3 and an increment in LW would be expected. In context of principal component regression, three equations with the intention of removing multicollinearity problem were predicted as follows.

LW = – 0.372 PC1 + 0.282 PC2 (P<0.01 for PC1 and PC2)

PC1= – 0.440 BL – 0.464WH – 0.456RH – 0.414BG – 0.461 CG

PC2= 0.256 BL+0.317WH + 0.291RH – 0.862BG – 0.076 CG

Almost close contributions of original variables to PC1 were observed with highly negative correlations between PC1 and original variables as illustrated in Table 8. The signs of the estimated correlations and contribution values to PC1 were same-negative, meaning that original variables would provide an increment in PC1, and then an increment in LW would be expected with increasing PC1. Similarly, if the signs of correlation of PC2-each original variable with contribution values for PC2 were identical mathematically, LW would also increase. The greatest contribution was provided by BG (-0.862) in PC2. In immature West African goat, Moses (2010) with use of factor scores in multiple regression analysis estimated 86.6% and 75.2% for male and female goats, which were greater than corresponding estimations in the current research work.

There have been many studies reported on the prediction of live weight from different morphological traits through multiple regression analysis, but use of factor scores in multiple regression analysis for various aims may be gained importance with the purpose to eliminate multicollinearity problem as in the current study (Keskin *et al*, 2007a; Keskin *et al*, 2007b; Eyduran *et al*, 2009; Eyduran *et al*, 2010; Moses, 2010). Differences between present results and earlier published results, which were nonissuable with one another, may be ascribed to use of different goat breeds, various traits, and statistical analysis techniques. This report is the first study to estimate live weight from various body measurements by using comparatively multiple regression, stepwise regression, factor analysis plus multiple regression, and principal component regression. The obtained results might offer some valuable clues without multicollinearity problem in the improvement of live weight in further breeding studies.

Conclusion: In the literature, multiple linear regression analysis has been widely preferred by many authors with the goal to predict live weight from various body measurements of different goat breeds. However, use of factor analysis scores of principal component scores in multiple regression in order to remove multicollinearity problem is very limited. Hence, the present results confirmed that multicollinearity problem were removed in these two approaches with very smaller RMSE due to VIF=1 for each of new-uncorrelated-variables. However, in order to generalize the present results, further studies must be carried out on various goat breeds and much larger populations. As a result, by contrast with multicollinearity problem in multiple regression, the prediction equations obtained for using factor scores in and principal component scores could be employed reliably in multiple linear regression with the aim to remove multicollinearity problem and indirect effects between original variables and especially to derive useful new-uncorrelated variables

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