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Variability in Linear Body Measurements and their Application in Predicting Body Weight of Afar Goats in Ethiopia

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Abstract

Goats with their broad feeding habits, adaptation to unfavorable environment, low cost, suitability for small scale production and short reproduction put them at an advantage over cattle and sheep especially for resource poor livestock keepers. Body weight is mostly used to evaluate body development and carcass characteristics in animals. Meat animals visually assessed is a subjective method of judgment. In goats, objective evaluation of body weight and linear body measurements for describing and evaluating size and conformation characteristics can overcome problems associated with subjective evaluation. Hence, the objectives were: a) to evaluate variability in linear body measurements b) to determine best fitted regression model for predicting live weight under field conditions. The study conducted in two districts of Afar National Regional State of Ethiopia used 800 random samples. The effect of district was significant ($p<0.05$) on body length, chest girth, whither height, pelvic width, and rump height, while body weight, horn length and ear length were non-significant. Sex effect was significant on body weight and other linear body measurements except pelvic width, ear length and rump height. The estimated regression model using a SAS macro, for predicting body weight, included linear effects of horn length, body length, chest girth, whither height, rump height and quadratic effect of chest girth.

Key words: quantitative morphologial traits, regression analysis, goats

Introduction

Small ruminants make a substantial contribution to the well-being of the people in Ethiopia and Sub-Saharan Africa [9, 11]. Ethiopia is endowed with varied ecological zones and possesses diverse animal genetic resources. Goats with their broad feeding habits, adaptation to unfavorable environmental conditions, low cost of maintenance, inherent suitability for small scale production and their short reproductive put them at a comparative advantage over cattle and sheep to suit the circumstances of especially resource poor livestock keepers [5, 10]. Their presence in mixed species grazing systems can lead to a more efficient use of the natural resource and add flexibility to the management of livestock [12]. In general goats are kept for the production of milk, meat and wool, particularly in arid, semitropical or mountainous countries [23]. According to CSA [7] there are about 24.06 million goats in Ethiopia. Out of these total goats, about 71.06 % are females and 28.94 % are males. Almost all of the goats in Ethiopia are indigenous breed types and account for about 99.99 % of the total [7]. Body weight is the measurement used mostly to evaluate body development and carcass characteristics in animals [8, 21]. Therefore, in livestock and poultry, particularly for meat, size and conformation are considered important characteristics. Traditionally, meat animals are visually assessed, which is a subjective method of judgment [1, 24]. In goats, objective evaluation of body weight and linear body measurements for describing and evaluating size and conformation characteristics would overcome many of the problems associated with subjective evaluation [16]. The knowledge of body weight estimation in goats is important for a number of reasons, related to the control and management of the flock during the entire rearing process, breeding (selection), nutritional rationing (i.e. feeding), health care (administering medications) and marketing of goats.

However this fundamental knowledge of obtaining direct body weight measurements at the field level has practical limitations due to the time and energy expended while determining it; and the non-availability and unaffordability of weighing scales especially in the small scale farming sector. Hence, farmers have to rely on questionable estimates of the body weight of their animals, leading to inaccuracies in decision-making, husbandry and marketing practices.

Indirect estimation of body weight to an acceptable degree of accuracy using a prediction equation based on linear body measurements is of considerable practical use. Thus, regressing body weight on linear body measurements can be a method of weighing animals without weighing scales [19, 2, 25, 26].

The accuracy of functions used to predict body weight from linear body measurements has an immense financial contribution to livestock production enterprises. When the producers and buyers of livestock are able to relate linear body measurements to body weight, an optimum production and value-based trading system will be realized from accurate predictions. This will ensure livestock farmers to be adequately rewarded rather than the middlemen and/or livestock product processors who tend to gain more profit in livestock production business, especially in the rural areas of developing countries [4]. In addition, accuracy of functions developed to predict body weight from linear body measurements could improve selection efficiency for growth by enabling the breeder to recognize early maturing and late maturing animals of different sizes.

Linear body measurements have been used to predict body weight by several authors in many breeds of goats [13, 6, 14, 17, 18]. Different models might be needed to predict body weight in different environmental conditions and breeds [19, 20, 26].

Hence, the objectives of this study were twofold: a) to evaluate the variability in linear body measurements and b) to determine the best fitted regression model for prediction of live weight under field conditions.

Materials and Methods

Locations of the Study Area

The study was conducted in Afar National Regional State situated in the Northern part of Ethiopia. The region is divided into 5 zones, 29 districts, and 358 kebeles (smallest administrative unit) [3]. The survey was conducted in two of the six districts of zone 3 namely Gewane and Amibara .Gewane district consists of 9 pastoral associations (PAs). The district is generally semi-arid with a temperature level that falls between 28 and 42^0C, with an average temperature of 35^0C. The temperature is moderate in the months between September and November and also in the months of December through January. The highest temperature is in the months between March and May. It is generally low from June through August. The altitude of the research area is 560 meter above sea level. The district receives an average annual rainfall of 320mm. Most of the rain is concentrated in the months of July and August. Amibara is administratively structured into 18 PAs. Unlike the low level of urbanization in the Afar region, 51% of the population in Amibara are urban dwellers. The weather condition of the district is generally semi-arid with a temperature level between 25 and 35^0C, with an average temperature of 30^0C. The temperature is moderate between September and January and highest in February and May. Temperature is generally low in July and August. The altitude of the district ranges between 720 and 1100 masl. The district receives an average annual rainfall of 360mm

Data Collection :A random sample of 800 goats (134 males and 666 females) from the two districts formed the material for the study. To assess effect of age on the parameters measured, the goats were grouped into five age groups according to dentition: no pair of permanent incisor (0PPI), (1PPI), (2PPI), (3PPI), and (4PPI) to represent age of less than 15 months, 15.5 to 22 months, 22.5 to 27 months, 28 to 38 months and above 39 months, respectively, as per Wilson [22]. Information on age was provided by the owner which was verified using dentition.

While taking linear body measurements, the height measurement (cm) was done using a graduated measuring stick. The length and circumference measurements (cm) were effected using a tape rule while the animals were standing on a levelled surface. A spring balance (50 kg capacity) was used to take body weight measurements of goats. All measurements were taken early in the morning before the animals were fed by the same person in order to avoid individual variations.

Statistical Data Analyses

All statistical analyses were performed using the SAS software [15].

Quantitative Morphological Traits

Univariate Analysis: Quantitative morphological traits were subjected to analysis of variance using the general linear model procedure (PROC GLM) of SAS [15] with district, sex and age as fixed effects. Significant means were separated using the Duncan's New Multiple Range Test.

Prediction of Body Weight from Linear Body Measurements

Data were subjected to a multiple linear regression model using a SAS macro application REGDIAG2. First, body weight (BW) was defined as the response variable and body length (BL), chest girth (CG), ear length (EL), horn length (HL), pelvic width (PW), rump height (RH) and whither height (WH) were treated as predictors.

The multiple linear regression model adopted was:

$Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_7X_7$

where,

Y = body weight

b_0 = Y intercept

$b_1, \ldots, b_7$ = regression coefficients

$X_1, \ldots, X_7$ = predictor variables (HL, EL, BL, CG, WH, PW, and RH)

Before prediction equations were developed checks for multicollinearity, departure from homogeneity of variance, and significant heteroscedasticity of data were tested. While data on females did not violate the assumptions, the data on males did violate the assumptions due to their small number and thus, prediction equations were developed only for females.

Step i) Model Selection in Multiple Linear Regression

Modelling multiple linear regressions containing many predictors presents big challenges especially to select the best model. It is thus customary to use an automated procedure that employs information on data to select a suitable subset of variables. In this study, Maximum R^2 Improvement (MAXR^2) selection method was implemented within the SAS macro REGDIAG2. The MAXR^2 selection method does not settle for a single model. Instead, it compares all possible combinations and tries to find the best variable subsets for one variable models, two-variable models, and so on. In addition model selection criteria, i.e., R^2, R^2 (adjusted), root-mean square error (RMSE), Mallows C(p) statistics, Akakike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are generated for each model tested in the model selection methods. These model selection criteria are used to find the optimum model among all possible models.

R^2 is defined as the proportion of variance of the response variable that is predictable from the predictors. The R^2 estimate is an indicator of how well the model fits the data. However, R^2 is not recommended for selecting the best model in multiple linear regressions since it does not account for the presence of redundant predictors. Instead, R^2 (adjusted) is recommended because the sample size and number of predictors are used in adjusting the R^2 estimate. RMSE is the measure of the error standard deviation of multiple linear regression model. The Mallows C(p) statistic measures the total squared error for a subset that equals total error variance plus the bias introduced by not including the important variables in the subset. AIC and BIC are the error variance statistic of multiple linear regression model adjusted for the sample size and number of parameters. A model with minimum RMSE, C(p), AIC and BIC, and maximum R^2 and R^2 (adjusted), is considered as optimum model among others.

Step ii) Model Specification Error

When important predictors or significant higher-order model terms (quadratic and interaction) are not included in the regression model, the residual error term no longer has the random error property. While the augmented partial residual plot is very efficient in detecting the need for a quadratic term, the need for an interaction term between any two predictors could be evaluated in the interaction test plot.

Step iii) Fitting the Regression Model

Step iii is nothing but re-running of the model with the significant linear effects identified under step i plus the significant quadratic and interaction effects identified in step ii.

Results and Discussion

Univariate Analysis: ANOVA was used to test for the differences between means of live weight and linear body measurements between district, sex, age and sex by age interaction. Significant means comparison was made using Fisher's protected LSD test.The table 1 shows the ANOVA results of PROC GLM.

District effect: District was found to affect body length, chest girth, whither height, pelvic width, and rump height, while body weight, horn length and ear length of the animal were not affected by district of the goat. Thus, in both the districts goats were of similar body weight in horn and ear length.

Sex effect: Sexual dimorphism can be phenotypically expressed as differences in skeletal size and/or body mass**.** Sex of the goats exerted significant ($p<0.05$) effects on body weight and other linear body measurements except pelvic width, ear length and rump height. The influence of sex on the body weight and some morphometric traits indicate the usual difference between sexes due to hormonal actions leading to differential growth rates.

Age effect: Age in the present study, is seen to have effect on morphometric traits in the Afar goat breed type. The traits body weight, body length, chest girth, wither height, pelvic width, horn length, ear length, and rump height increased progressively and significantly ($P<0.05$) as goat increased in age. Growth rate from 0PPI to 1PPI was slower compared to that from 1PPI to ≥ 2PPI except for ear length. Generally, there was wide variability for these body measurements as the age of the animals increased. This could be because of genetic as well as environmental reasons and also may be indicative of differential expression of genes for the traits concerned in different animals.

Sex by age interaction: The interaction between sex and age significantly ($p<0.05$) affected body weight, chest girth, wither height and horn length while body length, pelvic width, ear length and rump height were not affected significantly. However, even if the analysis did not show significant difference ($P>0.05$) for body length, pelvic width and ear length numerically males were heavier than females. Sex by age interaction for body weight, chest girth, wither height and horn length is indicative of the fact that male and female behave differently with respect to these traits as age increases. This is because of the differential sex hormones, their levels and expression in males and females.

Prediction of Body Weight from Linear Boy Measurements

Step i) Model selection in Multiple Linear Regression

Table 2 gives the results of the overall regression model fit. The statistical significance of the overall regression fit is determined by an F-test by comparing the regression model variance to the error variance.

The ANOVA table for the overall regression model fit is significant ($P < 0.0001$) indicating on the one hand that at least one of the regression coefficient slopes was not equal to zero and on the other hand the reliance one has on the possibility of prediction of body weight from the linear body measurements.

The results of the REGDIAG2 macro that utilized all possible regression models via the MAXR^2 selection method is given in table 3.Because 7 continuous predictors were used in the model selection, the full model had 7 predictors. Seven subsets are possible with 7 predictors. In multiple linear regression analysis the important thing to be considered is which predictors were most considered in determining the response variable.As a criterion, the value of R^2 always increased when more and more predictors were added to the regression (Table 3). The model with only one predictor (simplest model) has an R^2 value of 0.798, while the model with all the predictors (full model) has an R^2 value of 0.817. In going from the simplest to the full model, the value of R^2 increased. So, R^2 is not suitable for comparing the different model equations. Hence, instead of R^2 other model selection criteria that were not having this disadvantage viz., R^2(adj), RMSE, C(p), AIC and BIC were used. By comparing the R^2(adj), RMSE, C(p), AIC and BIC values of the full model and all subsets, one can conclude that the 5-predictor subset model (the one highlighted bold in Table 3) is superior to all other subsets and it was thus selected to be the best model in the model selection process.Taking the 5-predictors model as a reference, neither dropping any variable from this model nor going beyond this model is recommended because, the RMSE, C(p), AIC and BIC values increase except slight decrease in BIC when dropping a variable. The result also clearly indicates that R^2(adj), RMSE, C(p), AIC and BIC statistics are better indicators for model selection than R^2 and enable us to identify the most contributing variables.

Because Step i only includes the linear effects of the variables, it is recommended that this step be used as a preliminary model selection step rather than the final concluding step. The REGDIAG2 macro has also a feature for identifying predictor variables that have quadratic and interaction effects. By using the 5-predictors identified in step i as most contributing significant linear predictors, one can proceed with the second step of the analysis, i.e., model specification error, in order to examine and identify which of these 5-predictors have quadratic and/or interaction effects.

Step ii) Model Specification Error

The analysis was thus carried out using the 5-predictors identified under step i to identify the presence of quadratic and/or interaction effects. The result indicates that in addition to significant linear effects, there is a significant quadratic effect; however no significant interaction effect, according to the P-values obtained. Of the 7-predictors identified in step i, only CG has a significant quadratic effect on body weight as can be seen from Figure 2.

Step iii) Fitting the Regression Model

The overall model fit is illustrated in Figure 3 by displaying the relationship between the observed response and the predicted values. The regression parameter estimates, RMSE, and adjusted R^2 are given on the figure. The estimated regression model for predicting the mean body weight was $-27.945 + 0.0837HL + 0.1763BL + 0.688CG + 0.049WH - 0.059RH - 0.0014CG^2$.

Conclusion

- The fixed effects of district, sex, age and the interaction between sex and age were sources of variation for the most of the linear body measurements and live weight.
- Body weight of goats can be predicted from linear measurements such as horn length, body length, chest girth, whither height, and rump height using different regression models.
- The allometric model seemed to produce a better goodness of fit, followed by the quadratic and linear models respectively.
- The present findings could aid management and selection decisions on goats.

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Table 1: Least square means ±SE of body weight (kg) and linear body measurements (cm) for the effect of sex, age and sex by age interaction

Effects and levels	BW	BL	CG	WH	PW	HL	EL	RH
	LSM±SE	LSM±SE	LSM±SE	LSM±SE	LSM±SE	LSM±SE	LSM±SE	LSM±SE
Overall	22.09±0.02	60.69±0.02	64.90±0.02	60.95±0.03	12.11±0.03	13.90±0.03	13.06±0.03	61.10±0.03
CV%	17.38	7.68	6.97	6.15	11.10	31.90	22.47	6.65
R^2	52.56	51.83	57.61	49.20	43.81	35.99	5.04	40.72
District	**NS**	*	*	*	*	**NS**	**NS**	*
Gewane	18.15±0.27	55.44±0.32	59.17±0.31	56.39±0.26	11.06±0.09	11.19±0.31	12.80±0.20	58.92±0.28
Amibara	18.38±0.27	56.67±0.33	60.03±0.32	58.96±0.26	10.66±0.09	11.06±0.31	12.57±0.20	57.03±0.28
Sex	*	*	*	*	NS	*	NS	NS
Male	18.93±0.38	56.85±0.46	59.99±0.45	58.15±0.37	10.92±0.13	12.13±0.44	12.99±0.29	58.35±0.41
Female	17.60±0.25	55.26±0.30	59.21±0.30	57.20±0.24	10.81±0.09	10.12±0.29	12.38±0.19	57.59±0.27
Age	*	*	*	*	*	*	*	*
0 PPI	12.15±0.46	48.91±0.56	51.79±0.54	52.22±0.45	9.43±0.16	6.69±0.53	11.35±0.35	52.88±0.49
1 PPI	17.75±0.46	55.60±0.60	58.77±0.54	57.55±0.45	10.40±0.16	9.78±0.53	13.45±0.35	57.97±0.48
≥ 2 PPI	24.90±0.23	63.65±0.28	68.24±0.27	63.25±0.22	12.77±0.07	16.92±0.28	13.28±0.17	63.06±0.24
Sex by age	*	NS	*	*	NS	*	NS	NS
Male, 0 PPI	11.90±0.78	48.95±0.95	51.09±0.92	51.85±0.77	9.47±0.27	6.76±0.90	11.38±0.60	52.87±0.83
Male, 1 PPI	18.78±0.73	57.03±0.88	59.56±0.86	58.42±0.71	10.42±0.25	10.70±0.84	14.33±0.56	58.51±0.77
Male,≥ 2 PPI	26.12±0.42	64.57±0.52	69.33±0.50	64.18±0.41	12.88±0.15	18.93±0.49	13.27±0.32	63.67±0.45
Female, 0 PPI	12.40±0.48	48.88±0.58	52.49±0.57	52.61±0.47	9.38±0.17	6.61±0.55	11.31±0.37	52.90±0.51
Female, 1 PPI	16.72±0.56	54.17±0.67	57.98±0.66	56.68±0.54	10.38±0.19	8.86±0.64	12.56±0.42	57.42±0.59
Female,≥2 PPI	23.68±0.16	62.73±0.20	67.15±0.19	62.33±0.16	12.67±0.06	14.90±0.19	13.28±0.12	62.46±0.17

Means with different superscripts within the same column and class are statistically different. NS = Non significant;* = significant at 0.05.

Table 2 Testing the overall regression model fit by ANOVA

Source	DF	SS	MS	F-value	P-value
Model	13	12616.00	970.49	115.46	<0.0001
Error	465	3908.59	8.41		
Corrected Total	478	16525.00			

Table 3 Best two subsets in all possible MAXR^2 selection method

Nr.	R^2	R^2 (adj.)	RMSE	C(p)	AIC	BIC	Variables in Model
1	0.798	0.798	2.465	78.11	1443.78	1453.15	CG
1	0.693	0.693	3.038	531.38	1777.88	1787.25	BL
2	0.812	0.812	2.378	18.61	1387.42	1401.47	BL CG
2	0.803	0.802	2.437	59.13	1426.35	1440.40	HL CG
3	0.815	0.815	2.360	7.40	1376.31	1395.04	HL BL CG
3	0.813	0.812	2.375	17.69	1386.53	1405.27	BL CG RH
4	0.816	0.815	2.357	6.10	1374.99	1398.42	HL BL CG RW
4	0.816	0.815	2.360	8.02	1376.92	1400.34	HL BL CG WH
5	**0.817**	**0.816**	**2.352**	**5.13**	**1374.01**	**1402.11**	**HL BL CG WH RH**
5	0.816	0.815	2.357	7.14	1376.04	1404.14	HL EL BL CG RH
6	0.817	0.815	2.354	6.47	1375.34	1408.12	HL EL BL CG WH RH
6	0.817	0.815	2.355	6.59	1375.46	1408.25	HL BL CG WH PW RH
7	0.817	0.815	2.355	8.00	1376.87	1414.34	HL EL BL CG WH PW RH

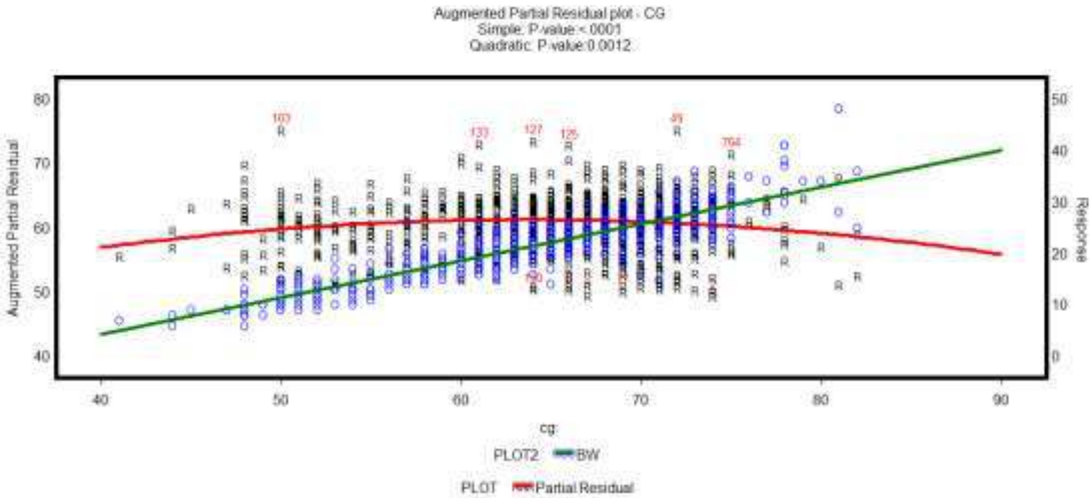

Figure 2 Overlay plot simple linear regression and augmented partial residual plot

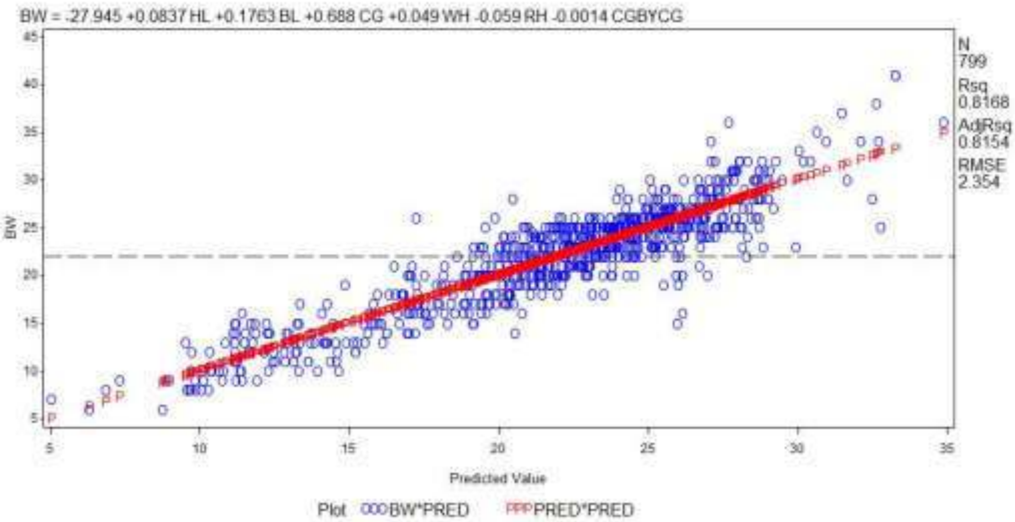

Figure 3: Overall model fit plot