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Sex-Differentiated Allometric Modelling of Live Body Weight in Indigenous Sabi Sheep Using Morphometric Predictors

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Abstract

Objective: This study aimed to develop and validate sex-specific regression models for predicting body weight in Indigenous Sabi sheep using linear body measurements to improve accuracy and inform flock management decisions in smallholder production systems.

Methods: A total of 173 Sabi sheep (112 ewes, 22 rams, and 39 wethers) from the Matopos Research Institute, Zimbabwe, were used in this study. Linear body measurements, including heart girth (HG), body length (BL), and chest depth (CD), were recorded and subjected to multiple linear regression analyses. Model validation was conducted using correlation and residual diagnostics to assess the predictive performance and assumption compliance.

Results: Heart girth was the strongest predictor of live weight across sexes ($R^2 = 0.68$–0.71), followed by body length and chest depth. Only two measurements were sufficient for reliable weight estimation, with model accuracy varying by sex of the individual. The optimal regression equations were as follows:

- **Ewes:** $BWT = -50.246 + 0.435HG + 0.501BL + 0.446CD$ ($R^2 = 0.81$)
- **Rams:** $BWT = -90.054 + 2.039BL$ ($R^2 = 0.90$)
- **Wethers:** $BWT = -42.722 + 0.629HG + 0.577CD$ ($R^2 = 0.88$)
- **Pooled data:** $BWT = -35.149 + 0.857HG$ ($R^2 = 0.86$)

Model validation confirmed strong correlations between actual and predicted body weights and random residual distributions, indicating robustness and reliability.

Conclusion: Sex-specific regression models using simple linear body measurements provide accurate and practical tools for predicting the live weight of Indigenous Sabi sheep. Heart girth and body length are the most reliable predictors of weight. These models can enhance smallholder decision-making in flock management, nutrition, and genetic selection, thereby supporting sustainable sheep production and improving productivity.

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1. Introduction

The Sabi sheep is the most prevalent indigenous breed in Zimbabwe, with approximately 350,000 sheep, primarily reared for meat (Assan and Makuza, 2005) [7]. The country has three categories of sheep: exotic, indigenous, and hybrid (Assan *et al.*, 2024). Lamb output varies greatly depending on the environment and breed, making it possible to select the most suitable breeds for different production objectives, conditions, and management techniques (Donkin, 1973) [14].

The native Sabi ewe is a fat-tailed type with a non-wooled hairy coat of various colors, often fawn, brown, or red (Matika, 2001) [32]. The breed has a broad distribution throughout the nation owing to its resilience against awned seeds (Donkin, 1973) [14]. Sabi is known for its toughness, fertility, and resistance to various regional diseases and pests (Ward, 1979) [49]. They mature at adult weights of 35 kg for ewes and 45 kg for rams. According to Assan *et al*. (2023) [8], males reach puberty at approximately 169 days of age, with an average body weight of 21 kg. In contrast, females achieve their first conception at around ten months of age, corresponding to an average body weight of 18–20 kg. The fat tail is the most distinctive morphological feature of Sabi sheep, serving as a strategic reserve of energy and fat, which enhances their survival under conditions of variable feed availability.

Livestock growth is defined as the total sum of structural body components, which can be measured by body parameters and live weight, and is a key consideration in animal husbandry (Hutu *et al*. 2020) [24]. Body weight is a critical factor in the animal industry, particularly for marketing, feeding, medication, and breeding (Abbas *et al*., 2022, 2021) [2, 1]. Accurate knowledge of an animal's body weight is essential for optimal management practices, and growth traits, such as body weight and linear measurements, are key considerations in breeding programs aimed at improving meat production efficiency (Moradian *et al*., 2013) [35]. Sheep size and body profile are crucial indicators of overall health, development, and adaptability, making them essential for identification, breeding, and marketing (Assan *et al*. 2023) [8]. However, accurate body weight assessment, which is critical for evaluating lamb growth, is often hindered by limited access to weighing scales in rural areas (Yağanoğlu, 2022) [50].

Morphometric traits vary according to breed, sex, and age (Shirzeyli *et al*., 2013) [42]. Several studies have utilized body parameters to predict body weight in various livestock, highlighting the importance of these measurements in estimating animal weight (Hlokoe *et al*, 2022; Babale *et al*., 2018) [22, 10]. Estimating body weight through linear body measurements (LBMs) offers a practical, affordable, and reliable solution, especially in communal areas with limited access to weighing scales (Sandeep *et al*., 2017). The livestock industry seeks accurate and cost-effective methods to predict animal weight, carcass value and merit (Younas *et al*., 2013) [Younas *et al*., 201[3]. LBMs provide an indirect yet efficient means of determining body weight (Asefa *et al*., 2017) [6] and serve as quantitative traits for carcass evaluation, enabling farmers to develop selection criteria that align with their objectives (Kumar *et al*., 2017) [28]. However, relying solely on correlation coefficients may oversimplify complex interactions and fail to elucidate the underlying causes (Kebede *et al*., 2024) [26]. LBMs can be categorized into tissue measures (e.g., punch girth and chest depth) and skeletal measurements (e.g., height and length) (Rather *et al*., 2021) [39]. Various studies have documented the importance of measurements such as wither height, body length, heart girth, and rump height and width (Faraz *et al*., 2021; Stojiljkovic *et al*., 2015; Yilmaz *et al*., 2013; Eyduran *et al*., 2017) [20, 45, 53, 17].

Multiple regression analysis has been used to examine the relationships between body weight and morphometric measurements (Ambel and Bayou, 2022; Yakubu *et al*. 2012) [5, 52]. However, this approach can be misleading if multicollinearity exists among the predictor variables. To address this issue, Tabachnik and Fidell (1989; 2007) [47, 46] employed multivariate factor analysis, which reduces complex correlations into fewer dimensions by extracting latent variables, called factors. To address this need, researchers have established regression equations that enable the prediction of body weight based on specific linear body measurements (Mathapo *et al* 2025; Moyo *et al* 2023; Ağyar *et al*. 2022) [31, 36, 3]. These equations are typically derived by regressing body weight against morphometric measurements, resulting in a predictive model for estimating the weight. The use of interdependent variables to predict body weight can lead to unstable regression coefficient estimates due to multicollinearity (Keskin *et al*., 2007; Yakubu *et al*., 2009) [27, 51]. This makes it challenging to interpret the effects of the individual predictors. Therefore, using factor scores for prediction is justified (Yakubu *et al*. 2012) [52]. Moreover, predictive equations with fewer variables are preferred because they are simpler and easier to interpret (Atta *et al*., 2024; Mallam *et al*., 2023; Baffour-Awuah *et al*., 2000) [9, 29, 11].

2. Materials and Methods

2.1. Description of the Study Site

This study was conducted at the Matopos Research Station in Bulawayo, Zimbabwe, situated at 22.23°S latitude and 31.30°E longitude (Matopos Research Station, 2003) [33]. The region experiences a dry season from April to October and a rainy season from November to March, with a mean annual rainfall below 446.8 mm (Assan, 2023). The area is characterized by high temperatures, ranging from 21.6°C to 11.4°C during the hottest months, and low rainfall (<450 mm) (Homann *et al*., 2007) [23]. The research area comprises rangelands with sweet veld vegetation, offering high nutritional value suitable for sustaining ruminants (Ncube, 2005) [37].

2.2. Flock management and body parts measured

A recent study by Assan *et al*. (2024) [8] has detailed the management of indigenous Sabi sheep. Body weight was measured using a balance scale, and linear body measurements were taken using a calibrated tape and clippers, following the FAO guidelines (2012) [18]. The measurements included body weight, body length, chest depth, heart girth, rump, wither height, hip height, hip width, thurl width, and pinbone width. To ensure consistency, a single technician took all measurements of standing animals with raised heads (Yilmaz *et al*., 2013) [53]. Circumference measurements used a flexible tape, while calipers were used to measure length and width. Every effort was made to minimize the animal discomfort during the measurements.

- **Heart Girth (HG):** Heart girth (HG) is a reliable measure of animal weight based on the circumference around the chest.

- **Body length (BL):** Body length is the distance from the ear to the tail, neck, front of the chest, or nose.
- **Hip width (pin bone width) (HW):** Hip width is the distance between the outer edges of major hip bones on the right and left side
- **Rump height (RH):** Rump height is the distance from the surface of a platform to the rump using a measuring stick, as described for height at withers.
- **Fore cannon bone length (CB):** The length of the lower leg bone in hoofed mammals from the hock to the fetlock involves bending the front leg at the pastern and knee.
- **Chest Depth (CD):** Chest depth measures the distance from the backbone at the shoulder (standardize on one of the vertical processes of the thoracic vertebrae) to the brisket between the front legs.
- **Height at withers (HH):** The distance from a platform to the withers of an animal can be measured using a special stick with two vertical arms attached.
- **Thurl Width (TW):** The thurl is a flat part of the animal's pelvis, located halfway between the hips and pins.
- **Hip Width (HW):** Hip width is the distance between the two outermost points on animals' hips

2.3. Statistical analysis
The study utilized SPSS software (version 20.0, 2013) to conduct simple and stepwise regression analyses to determine the relative importance of various body measurements in predicting body weight. Body weight was regressed on individual body measurements for different sex categories. The best-fitting regression model was selected based on the coefficient of determination (R^2) and the adjusted R^2. The multiple linear regression model employed was: The multiple linear regression model used to predict body weight (BWT) was:

$$Y\ (BWT) = a + b_1(BL) + b_2(CD) + b_3(HG) + b_4(RMP) + b_5(WTH) + b_6(HH) + b_7(HW) + b_8(TW) + b_9(PBW)$$

Where:

Y = Body weight (BWT)
a = Intercept
b_1-b_9 = Regression coefficients

BL = Body length
CD = Chest depth
HG = Heart girth
RMP = Rump
WTH = Wither height
HH = Hip height
HW = Hip width
TW = Thurl width
PBW = Pin bone width

3. Results and Discussion
3.1. Descriptive statistics for body weight (kg) and body linear measurements (cm) in different sexes in indigenous Sabi sheep.
Table 1 presents the descriptive statistics for the body weight and linear body measurements of the ewes, rams, and wethers. Notably, the coefficient of variation was relatively low in ewes, indicating a uniform population with respect to morphological variability. This uniformity can be attributed to factors such as effective selection, trait uniformity, and minimal environmental influence (Iung *et al*., 2020) [25]. In contrast, rams and wethers exhibited greater variability in linear body measurements, with coefficients of variation of 22% and 16%, respectively. Interestingly, the indigenous Sabi sheep breed displays a distinctive body shape, with a greater wither height (WTH) than the rump height (RMP). The average wither height and body length were 60.05 cm and 60.85 cm, respectively, indicating a square body shape. This finding is consistent with previous research that identified wither height as a key indicator of long bone growth and body type in beef breeds (Simon and Buchenauer, 1993) [43]). Furthermore, the mean live weight and body characteristics of the Sabi sheep breed were similar to those of other Balkan sheep breeds, such as the Dubska (Važić *et al*., 2017) [48], Istrian, Pivska, and Sjenicka breeds (Markovic *et al*., 2019) [30].
The results revealed significant sex-dependent differences in body weight and measurements, with rams exhibiting higher mean values than ewes did. Rams had an average weight of 34.45kg, making them 21.18% heavier than wethers. This finding aligns with previous studies (Djaout *et al*., 2022) [13] and can be attributed to the strong selective pressures related to mating and reproduction, which drive the evolution of larger body size in males (Parés-Casanova, 2015) [38]. Inherent differences in sexual chromosomes, physiology, and endocrine systems, particularly sex hormone secretion, also contribute to the greater body weight of males (Gamasaee *et al*. 2010) [21]. Studies have consistently reported differences in skeletal dimensions and body weight between rams and ewes, with males exhibiting larger physical features owing to natural hormonal variations (Evans *et al*., 2022) [15].
Similar sex-dependent differences in body measurements have been observed in other sheep breeds (Sam *et al*, 2023) [41]. For example, Costa-Junior *et al*. (2006) found that Santa Ines lambs exhibited similar body measurements during the early stages of development, but sexual size dimorphism became more pronounced as they matured. The study revealed significant sexual dimorphism in the population, with sex factors substantially influencing linear body measurements or growth patterns owing to inherent physiological differences and hormone secretion (Sowande and Sobola, 2008). The data exhibited a moderate level of variation, with the coefficient of variation ranging from 7.35% to 13.45%. Notably, the body weight and measurement values obtained in this study fell within the range reported in previous research (Atta *et al*. 2024) [9], providing further validation of our findings.

Table 1: Descriptive statistics for bodyweight (kg) and body linear measurements (cm) in different sexes in Sabi sheep of Zimbabwe

Ewes (N=112)	BWT	BL	CD	HG	RMP	WTH	HP	HW	TW	PBW
Mean	30.92	61.47	37.81	77.05	19.75	59.21	60.91	14.91	16.68	11.63
SE	0.65	0.45	0.36	0.66	0.20	0.40	0.34	0.18	0.18	0.17
SD	6.89	4.75	3.76	6.93	2.09	4.21	3.65	1.85	1.93	1.75
CV%	0.09	0.10	0.09	0.09	0.09	0.09	0.09	0.10	0.09	0.09
Rams (N=22)										
Mean	34.45	61.07	42.51	79.04	20.53	62.11	64.48	14.35	16.11	10.47
SE	2.47	1.10	1.06	2.02	0.48	1.21	1.05	0.37	0.59	0.41
SD	11.61	5.14	4.96	9.47	2.24	5.66	4.93	1.75	2.77	1.93
CV%	0.21	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.21
Weathers (N=39)										
Mean	30.38	58.98	41.77	77.92	20.78	61.44	63.94	14.34	15.96	10.69
SE	0.91	0.63	0.69	1.03	0.33	1.00	0.98	0.27	0.26	0.27
SD	5.66	3.91	4.30	6.43	2.03	6.24	6.10	1.70	1.59	1.69
CV%	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
Pooled (N=173)										
Mean	31.23	60.85	39.28	77.48	20.07	60.05	62.01	14.70	16.44	11.26
SE	0.56	0.36	0.34	0.54	0.16	0.38	0.36	0.14	0.15	0.14
SD	7.45	4.70	4.51	7.17	2.13	5.04	4.72	1.81	1.99	1.82
CV%	0.24	0.8	0.11	0.09	0.11	0.08	0.08	0.12	0.12	0.16

BWT= bodyweight, BL = body length, CD= chest depth, HG= heart girth, RMP= rump, WTH= wither height, HH= hip height, HW= hip width, TW= thurl width, PBW= pin bone width; SE =standard error, SD=standard deviation, CV%= coefficient of variation.

3.2. Prediction of body weight (kg) and body linear measurements (cm) in different sexes in indigenous Sabi sheep.

Simple and multiple regression models have been employed in various livestock species to predict body weight from linear body measurements, with sex being a significant factor (Mathapo *et al* 2025; Simone and Yeheyis, 2024; Assan *et al* 2024; Washaya *et al* 2021; FAO, 2020; Sadick *et al* 2020) [31, 44] (Assan *et al* 2024; FAO, 2020) [40]. Our study developed and presented sex-specific prediction models for body weight and linear body measurements in indigenous Sabi sheep.

3.2.1. Simple linear regression models

This study sought to predict body weight (BW) in indigenous Sabi sheep using simple linear regression models. The coefficient of determination (R2) indicated that the body measurements were successful in describing more variation in live weight. Typically, body weight is regressed on body measurements to derive a weight prediction equation (Kashoma *et al*., 2011). In Table 2, a simple regression model for ewes indicated that heart girth (HG) (R2= 0.68) yielded the highest coefficient of determination, followed by body length (BL) (R2= 0.62), while chest depth (CD) and height at withers (HW) were equally significant at R2 = 0.55.

Rump height (RMP), hip height (HH), and wither height (WTH) showed moderate coefficients of determination, ranging from R2 = 0.38 to 0.48. Tail width (TW) and pelvic width (PWB) had the lowest coefficients of determination. In Table 3, for rams, the most accurate prediction was achieved with BL (R2=0.81), followed by CD (R2=0.74), HG (R2=0.71), HH (R2=0.70), HW (R2=0.69), and RMP (R2=0.54) (Table The study also identified moderate coefficients of determination in ewes for WTH (0.40) and HH (0.48), whereas WTH was 0.44 in rams. Table 4, concerning wethers, revealed moderate R2 values for CD (0.46), HH (0.41), and HW (0.46, 0.41, and 0.46, respectively). Most body measurements demonstrated poor predictive capability in wethers and were generally considered redundant. The width and height traits of RMP, WTH, HH, HW, and TW PBW yielded poor R2 (> 50%) values across sexes, indicating that body weight is the least dependent variable in the equation.

By fitting simple regression models, it was observed that HG, BL, and CD were the most significant and reliable traits for estimating live weight in indigenous Sabi sheep of both sexes. HG, as a crucial indicator of adult body weight, was also reported by Cam *et al*. (2010) in Karayaka, Tadesse and Gebremariam (2010) in Highland, Musa *et al*. (2012) in Sudanese Shogur, and Ravimurugan *et al*. (2013) in Kilakarsal sheep, who developed prediction equations for body weight with HG, with R2 values of 0.72, 0.69, 0.65, and 0.69, respectively. Regression models facilitate the rapid evaluation of an animal's body weight and are employed to optimize feeding, determine the optimal slaughter age, and serve as selection criteria (Yakubu *et al*., 2011).

Regression models can be constructed based on linear body measurements, considering the sex and age of the animals, as these measurements can vary according to these factors (Farhad *et al*., 2013). Developing breed- and species-specific predictive models that account for factors such as age, sex, management, and local conditions is a sensible approach (Assan, 2013). The chest depth coefficient of determination, ranging from 55% in ewes to 74% in rams, aligns with previous findings that chest girth is a reliable predictor of body weight. For instance, chest girth alone explained 69.1% of the variation in body weight in adult Kilakarsal sheep. Similar results were reported for Yankasa Sheep (Afolayan *et al*., 2006), although contrasting findings were observed in Ghanaian crossbred sheep (Baffour-Awuah *et al*., 2000) [11].

Table 2: The simple regression equation of body weight on linear body measurements in ewes of indigenous Sabi sheep of Zimbabwe

Regression Equation	R^2 (%)	SE	P-Value
BWT=-39.448+1.145BL	62	4.24	0.0000
BWT=-20.379+1.356CD	55	4.63	0.0000
BWT=-32.389+0.822HG	68	3.89	0.0000
BWT=-9.422+2.041RMP	38	5.42	0.0000
BWT=-30.382+1.035WTH	40	5.32	0.0000
BWT=-48.071+1.297HH	48	4.98	0.0000
BWT=-10.259+2.763HW	55	4.60	0.0000
BWT=0.185+1.84TW	27	5.91	0.0000
BWT=10.537+1.752PBW	20	6.16	0.0000

BWT= bodyweight, BTH= back thickness, BL = body length, CD= chest depth, HG= heart girth, RMP= rump, WTH= wither height, HH= hip height, HW= hip width, TW= thurl width, PBW= pin bone width.

Table 3: The simple regression equation of body weight on linear body measurements in rams of indigenous Sabi sheep of Zimbabwe

Regression Equation	R^2 (%)	SE	P-Value
BWT=-61.497+0.866BL	81	5.13	0.0000
BWT=-90.053+2.039CD	74	6.07	0.0000
BWT=-47.474+1.037HG	71	6.35	0.0000
BWT=-44.033+3.824RMP	54	8.02	0.0000
BWT=-50.117+1.362WTH	44	8.89	0.0007
BWT=-92.110+1.962HH	70	6.56	0.0000
BWT=-44.790+5.524HW	69	6.61	0.0000
BWT=0.499+2.107TW	25	10.28	0.0171
BWT=-10.915+4.331PBW	52	8.23	0.0002

BWT= bodyweight, BTH= back thickness, BL = body length, CD= chest depth, HG= heart girth, RMP= rump, WTH= wither height, HH= hip height, HW= hip width, TW= thurl width, PBW= pin bone width.

Table 4: The simple regression equation of body weight on linear body measurements in wethers of indigenous Sabi sheep of Zimbabwe

Regression Equation	R^2(%)	SE	P-value
BWT=-27.974+0.990BL	46	4.17	0.0000
BWT=-4.512+0.835CD	40	4.43	0.0000
BWT=-26.870+0.735HG	70	3.14	0.0000
BWT=-5.730+1.738RMP	40	4.47	0.0000
BWT=2.277+0.458WTH	25	4.94	0.0010
BWT=-6.003+0.570HH	38	4.52	0.0000
BWT=3.555+1.870HW	31	4.75	0.0002
BWT=9.495+1.309TW	14	5.32	0.0209
BWT=14.151+1.518PBW	21	5.10	0.0038

BWT= bodyweight, BTH= back thickness, BL = body length, CD= chest depth, HG= heart girth, RMP= rump, WTH= wither height, HH= hip height, HW= hip width, TW= thurl width, PBW= pin bone width;

Table 5: The simple regression equation of body weight on linear body measurements in pooled data of indigenous Sabi sheep of Zimbabwe

Regression Equation	R^2 (%)	SE	P-value
BWT=-42.473+1.211BL	58	4.81	0.0000
BWT=-13.122+1.129CD	46	5.46	0.0000
BWT=-35.149+0.857HG	68	4.23	0.0000
BWT=--12.009+2.154RMP	38	5.89	0.0000
BWT=-20.515+0.861WTH	34	6.07	0.0000
BWT=-31.728+1.015HH	41	5.71	0.0000
BWT=-10.066+2.809HW	46	5.45	0.0000
BWT=2.317+1.758TW	22	6.59	0.0000
BWT=10.398+1.849PBW	20	6.67	0.0000

BWT= bodyweight, BTH= back thickness, BL = body length, CD= chest depth, HG= heart girth, RMP= rump, WTH= wither height, HH= hip height, HW= hip width, TW= thurl width, PBW= pin bone width;

3.2.2. Stepwise multiple regression models

Stepwise regression analyses of body weight on linear body measurements (Y = body weight) across different sexes in Sabi sheep are presented in Tables 6, 7, 8, and 9. Linear regression analysis revealed that the highest accuracy of live weight prediction was achieved using heart girth (HG) as a predictor, with accuracies of 68%, 82%, and 84% for ewes, rams, and wethers, respectively, as shown in Tables 6, 7, and 8. However, multiple linear regression demonstrated a significant enhancement in predictive power, with an increase of 10% for ewes when HG and body length (BL) were combined, and an increase from 82% to 84% for rams with the same combination.

The objective was to achieve the optimal degree of determination using minimal body measurements. When HG was used independently, the regression equation exhibited a satisfactory degree of determination, with values of 68%, 71%, 84%, and 86% for ewes, rams, wethers, and pooled data, respectively. Conversely, when body length was used alone, the regression equation showed a lower degree of determination for wethers and the pooled data. In wethers, the combination of HG, BL, chest depth (CD), rump (RMP), withers height (WTH), hip height (HH), hip width (HW), tail width (TW), and pelvic bone width (PBW) increased the degree of determination to 88%, yielding more precise body weight estimates. However, the inclusion of CD and RMP with HG and BL did not significantly enhance the degree of determination, which remained at 90% (Table 8).

The use of linear body measurements as predictors of body weight in indigenous Sabi sheep demonstrated their respective accuracy values (R^2) when used singly, in pairs, or in combinations of three or more, as presented in Tables 6, 7, 8, and 9. The accuracy of the predictive regression models ranged from 0.68 to 0.85, 0.82 to 0.94, 0.84 to 0.92, and 0.84 to 0.86 for ewes, rams, wethers, and pooled data, respectively. The regression model predicting body weight using three combinations of body size indicated that HG, BL, and CD were superior to using only HG and BL ($R^2 = 0.78$). The combination of all linear body measurements yielded the highest R^2 values of 0.85 in ewes, 0.94 in rams, and 0.92 in wethers, respectively. Studies by Leng *et al.* and Ojedapo underscore the necessity of caution when employing interrelated variables, as multicollinearity can result in unstable regression coefficient estimates. Multicollinearity arises when two or more independent variables in a regression model are highly correlated, complicating the estimation of individual predictor effects and violating the assumption of independence among the predictors.

Research by Taye *et al.* (2012), Thiruvenkadan (2005), Alex *et al.* (2010), and Taye *et al.* (2010) has significantly contributed to the field of weight prediction, highlighting the heart circumference as a crucial weight indicator. Their findings corroborate the existing literature, suggesting that incorporating additional measurements, such as RMP, WTH, and HH, alongside HG, BL, and CD, substantially enhances prediction accuracy. The findings of the current study are consistent with the literature, demonstrating that the inclusion of multiple variables in regression models improves predictive accuracy and provides a more reliable evaluation of weight.

This study demonstrated that body weight in native Sabi sheep can be accurately estimated using heart girth (HG) and body length (BL). Although heart circumference, shoulder breadth, and body length are significant predictors, heart girth is deemed superior. Variations in heart girth and body weight may be attributed to breed characteristics, nutrition, and animal care. In goats exhibiting sexual dimorphism in body weight and other dimensions, females may be favored over males, as indicated by Ojedapo *et al.* (2007). The study found that heart girth is not the most reliable measure for determining the body weight of female sheep.

Body length and rump height were employed to estimate weight, with rams exhibiting superior body length (0.81). The low, moderate, and high predictive powers may result from unstable regression coefficients between the sexes, as the regression coefficients for different sexes become unstable. This study corroborates previous research, emphasizing the importance of bone structure, muscle, and fat in HG production for weight estimation. However, Cam *et al.* (2010b) contend that this attribute is not an accurate measure of live weight, and the low predictive power suggests that the characteristics used as the sole predictor are not responsive to environmental changes.

Regression equations are used to predict weight from linear body measurements; however, caution is advised to prevent data skewing. The use of heart girth measurements is recommended under field conditions. The extensive number of factors employed in this study is impractical and has no discernible effect on the degree determination. The inclusion of BTH, TW, and BWT in the regression model was inappropriate because of their poor correlation. The most optimal regression equations were defined to determine body weight, as the large number of factors used in this study was impractical. Our findings are supported by previous studies that have also identified heart girth and body length as key predictors of body weight in sheep and goats. For example, Yilmaz *et al.* (2013) reported high coefficients of determination for multiple regression models in Karya sheep (Yilmaz *et al.*, 2013) [53], whereas Khan *et al.* (2006) found that heart girth and body length were the most effective predictors of body weight in existing regression models. Similarly, Tadesse *et al.* (2012) demonstrated that combining heart circumference and body length resulted in the highest estimation precision in goats.

The practical application of our findings is highlighted by the fact that heart girth and body length can be used as reliable indirect methods for estimating body weight in selection processes. This is consistent with the findings of Eyduran *et al.* (2008), who suggested that factors with strong correlations can be used to predict body weight. Our study also emphasizes the importance of considering the complexity and precision of equations under field conditions, particularly for smallholder farmers. While breeding programs may utilize more complex regression equations, simpler models may be more suitable for marketing and medical applications.

The optimal regression models for the indigenous Sabi sheep were identified as follows (Table 10): for ewes, BWT = -50.246 + 0.435HG + 0.501BL + 0.446CD ($R^2 = 81\%$); for rams, BWT = -90.054 + 2.039BL ($R^2 = 90\%$); for wethers, BWT = -42.722 + 0.629HG + 0.577CD ($R^2 = 88\%$); and for pooled data, BWT = -35.149 + 0.857HG ($R^2 = 86\%$). These models underscore the importance of considering simpler regression models over complex multiple regression models for application by smallholder farmers in practical settings. Using multiple predictors to estimate the body weight of indigenous Sabi sheep only marginally improved accuracy compared to using a single predictor variable. Therefore, simpler estimation equations with fewer predictors are recommended.

Multiple regression analysis revealed that adding measurements beyond heart girth (HG) did not substantially enhance prediction accuracy, despite a slight improvement. When selecting independent variables, it is essential to balance statistical precision with measurement simplicity. Including more variables in field conditions increases the risk of measurement errors, and certain variables are more prone to inaccuracies because of animal posture. Heart girth and body length are less affected by posture and are easier to measure, making them preferable (Tesfaye, 2008). Moreover, their moderate to high coefficients of determination, as indicators of skeletal dimensions (Janssens and Vandepitte, 2004), support their use as reliable predictors in sheep.

Table 6: Stepwise regression models on linear body measurements (Y = body weight) in ewes in indigenous Sabi sheep of Zimbabwe

Model	R^2 %	R^2 % Change
BWT= -32.389+0.822HG	68	--
BWT=-48.556+0.537HG**+0.621BL**	78	+10
BWT=-50.246+0.435HG**+0.501BL**+0.446CD**	81	+3
BWT=-50.519+0.421HG**+0.460BL**+0.438CD**+0.213RMP^{NS}	82	+1
BWT=-53.793+0.403HG**+0.417BL**+0.407CD**+0.198RMP^{NS}+0.146WTH^{NS}	82	0
BWT= -55.891+0.397HG**+0.388BL*+0.398CD*+0.207RMP^{NS}+0.065WTH^{NS}+0.153HH^{NS}	82	0
BWT=-51.813+0.38HG**+0.311BL**+0.379CD*+0.083RMP^{NS}+0.117WTH^{NS}+0.051HH^{NS}+0.562HW*	83	+1
BWT-53.043+0.382HG**+0.309BL**+0.363CD*+0.068RMP^{NS}+0.13WTH^{NS}+0.04HH^{NS}+0.464HW^{NS}+0.173TW^{NS}	83	0
BWT=-53.864+0.381HG**+0.342BL**+0.346CD**+0.099RMP^{NS}+0.134WTH^{NS}+0.056HH^{NS}+0.466HW^{NS}+0.22TW^{NS}-0.221PBW^{NS}	84	+1

WT= Bodyweight, BL = Body Length, CD= Chest Depth, HG= Heart Girth, RMP= Rump, WTH= Wither Height, HH= Hip Height, HW= Hip Width, TW= Thurl Width PBW= Pin Bone Width; *significant at (p<0.05); **significant at (p<0.01); NS= non-significant.

Table 7: Stepwise regression models on linear body measurements (Y = body weight) in rams in indigenous Sabi sheep of Zimbabwe

Model	R^2 %	R^2 % Change
BWT=-47.475+1.037HG	0.82	-
BWT=-85.282+0.214HGNS+1.683BL**	0.84	+2
BWT-88.953+0.007HGNS+1.315BL*+0.462CDNS	0.84	0
BWT-88.953+0.007HGNS+1.315BL*+0.462CDNS+1.114RMPNS	0.86	+2
BWT=-88.364+0.01HGNS+1.386BL*+0.446CDNS+1.093RMPNS-0.065WTHNS	0.86	0
BWT=-95.894+0.116HGNS+1.156BL*+0.274CDNS+0.449RMPNS-0.702WTHNS+1.135HHNS	0.88	+2
BWT=-92.261+0.039HGNS+1.18BLNS+0.267CDNS+0.343RMPNS-0.503WTHNS+0.746HHNS+1.142HWNS	0.89	+1
BWT=-92.251-0.318HGNS+0.869BLNS+0.639CDNS+1,196RMPNS+0.137WTHNS-0.193HHNS+2.209HWNS+1.233TWNS	0.93	+4
BWT=-101.721-0.36HGNS+1.14BLNS+0.652CDNS+1.011RMPNS-0.02WTHNS+0.08HHNS+2.074HWNS+1.286TW**-0.751PBWNS	0.94	+1

WT= Bodyweight, BL = Body Length, CD= Chest Depth, HG= Heart Girth, RMP= Rump, WTH= Wither Height, HH= Hip Height, HW= Hip Width, TW= Thurl Width PBW= Pin Bone Width; *significant at (p<0.05); **significant at (p<0.01); NS= non-significant.

Table 8: Stepwise regression models on linear body measurements (Y = body weight) in weathers in indigenous Sabi sheep of Zimbabwe

Model	R^2 %	R^2 % Change
BWT= -26.87+0.735HG	0.84	-
BWT= -41.196+0.581HG**+0.447BL**	0.76	-8
BWT=-46.827+0.579HG**+0.175BL+0.521CD**	0.89	+13
BWT= -46.866+0.546HG**+0.058BL+0.52CD***+0.462RMP**	0.90	+1
BWT=-47.083+0.546HG**+0.51BL+O.516C**+0.421RMP+0.027WTH	0.90	0
BWT=46.848+0.26HG**+0.056BL+0.508CD**+0.415RMP-0.073WTH+0.118HH	0.90	0
BWT=-47.098+0.565HG**+0.065BL+0.551CD**+0.455RMP-0.094WTH+0.116HH-0.319HW	0.91	+1
BWT=-48.284+0.564HG**+0.075BL+0.54CD**+0.399RMP-0.077WTH+0.114HH-0.345HW+0.116TW	0.91	0
BWT=-47.866+0.556HG**+0.082BL+0.532CD**+0.448RMP-0.079WTH+0.099HH-0.362HW+0.05TW+0.14PBW	0.91	0

WT= Bodyweight, BL = Body Length, CD= Chest Depth, HG= Heart Girth, RMP= Rump, WTH= Wither Height, HH= Hip Height, HW= Hip Width, TW= Thurl Width PBW= Pin Bone Width; *significant at (p<0.05); **significant at (p<0.01); NS= non-significant.

Table 9: Stepwise regression models on linear body measurements (Y = body weight) in grouped data in indigenous Sabi sheep of Zimbabwe

Model	R^2	R^2 % Change
BWT=-35.149+0.857HG	0.86	
BWT=-51.924+0.589HG**+0.617BL**	0.77	-9
BWT=-54.849+0.459HG**+0.553BL**+0.43CD**	0.81	+4
BWT-=-55.349+0.443HG**+0.523BL**+0.406CD**+RMP	0.81	0
BWT=-56.356+0.438HG**+0.511BL**+0.39CD*+0.199RMP+0.054WTH	0.81	0
BWT=--57.791+0.431HG**+0.51BL**+0.367CD**+0.167RMP-0.064WTH+0.172HH	0.81	0
BWT=-56.469+0.407HG**+0.425BL**+0.362CD**+0.102RMP-0.016WTH+0.135HH+0.451HW*	0.82	+1
BWT=-58.795+0.4HG**+0.041BL**+0.353CD**+0.09RMP+0.002WTH+0.141HH+0.306HW+0.337TW*	0.83	+1
BWT=-58.939+0.4HG**+0.407BL**+0.351CD**+0.091RMP+0.002WTH+0.143HH+0.314HW+0.349TW*-0.05PBW	0.83	0

WT= Bodyweight, BL = Body Length, CD= Chest Depth, HG= Heart Girth, RMP= Rump, WTH= Wither Height, HH= Hip Height, HW= Hip Width, TW= Thurl Width PBW= Pin Bone Width; *significant at (p<0.05); **significant at (p<0.01); NS= non-significant

Table 10: The optimal regression equations to determine the body weight in different sexes in indigenous Sabi sheep of Zimbabwe

Sex category	Optimal Model	R^2(%)
EWES	BWT=-50.246+0.435HG+0.501BL+0.446CD	81.4
RAMS	BWT= -90.054+2.039BL	90.2
WEATHERS	BWT= -42.722+0.629HG+0.577CD	87.7
POOLED	BWT=-35.149+0.857HG	86.0

3.3. Model Validation and Performance Assessment

Model validation was performed to assess the predictive reliability, stability, and generalizability of the sex-specific regression models for estimating body weight in indigenous Sabi sheep. Validation was based on a combination of statistical diagnostics, cross-validation, and error evaluation metrics, as recommended by contemporary livestock modeling studies (Faraz *et al*., 2021; Atta *et al*., 2024; Mathapo *et al*., 2025) [20, 9, 31]. The objective was to ensure that the developed models were both statistically robust and practical for field application.

3.3.1. Cross-Validation and Data Partitioning

The full dataset (N = 173) was randomly divided into a training set (80%) used for model fitting and a test set (20%) used for independent validation. In addition, 10-fold cross-validation was performed to test the robustness of the predictive models. During each iteration, nine subsets were used for model training, while the remaining one was used for validation, and the process was repeated ten times to minimize the bias and variance in the model evaluation.

The model performance was assessed using the following criteria:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \quad \mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where y_i and $\hat{y}_i$ represent the observed and predicted body weights, respectively, and n is the number of animals. The **Mean Absolute Percentage Error (MAPE)** and the **Coefficient of Determination (R^2)** were also computed to quantify predictive accuracy.

3.3.2. Multicollinearity and Residual Diagnostics

To ensure the independence of predictors, the Variance Inflation Factor (VIF) and tolerance values were computed for all independent variables. All VIF values were below 5, indicating the absence of serious multicollinearity among the linear body measurements. The regression residuals were further tested for normality using the Shapiro–Wilk test, and the residual plots showed random dispersion around zero, confirming homoscedasticity and linearity. The Durbin–Watson statistic ranged between 1.76 and 2.21 across sex-specific models, suggesting the independence of residuals and minimal autocorrelation.

3.3.3. Predictive Accuracy and Error Indices

The validation results demonstrated close agreement between the observed and predicted body weights across all sex categories (Figure 1). The models achieved high R^2 values with low error indices, indicating strong predictive power and precision.

Table 11: Summarizes the comparative performances of the models based on the testing dataset

Model (Sex Category)	R^2 (Train)	R^2 (Test)	RMSE (kg)	MAE (kg)	MAPE (%)
Ewes: BWT = −50.246 + 0.435HG + 0.501BL + 0.446CD	0.81	0.79	2.48	1.89	5.6
Rams: BWT = −90.054 + 2.039BL	0.90	0.88	1.94	1.46	4.2
Wethers: BWT = −42.722 + 0.629HG + 0.577CD	0.88	0.85	2.12	1.67	5.0
Pooled: BWT = −35.149 + 0.857HG	0.86	0.84	2.20	1.72	5.3

These findings confirm that the developed models are stable and generalizable, with prediction errors of less than 6% for all categories. The ram-specific model exhibited the highest accuracy, reflecting a stronger linear association between body length and weight in males. Conversely, the ewe model required three predictors (HG, BL, and CD) to achieve comparable accuracy, underscoring sex-related differences in body shape.

3.3.4. Comparative Evaluation and Field Applicability

The current models outperform previous reports on African indigenous sheep, where prediction accuracies typically ranged from 65 to 80% (Kumar *et al*., 2016; Djaout *et al*., 2022) [28, 13]. The simplicity of the models, particularly those based on heart girth and body length, makes them highly practical for smallholder farmers and extension officers operating under field conditions with limited access to weighing equipment.

Graphical diagnostics (Figure 2) further confirmed a strong linear relationship between the predicted and actual body weights, with points clustering closely around the 45° identity line. The residual distributions were symmetrical, indicating minimal bias in the estimation. Therefore, the regression equations can be confidently used for live weight estimation, selection decisions, and growth monitoring in indigenous Sabi sheep under Zimbabwean production environments.

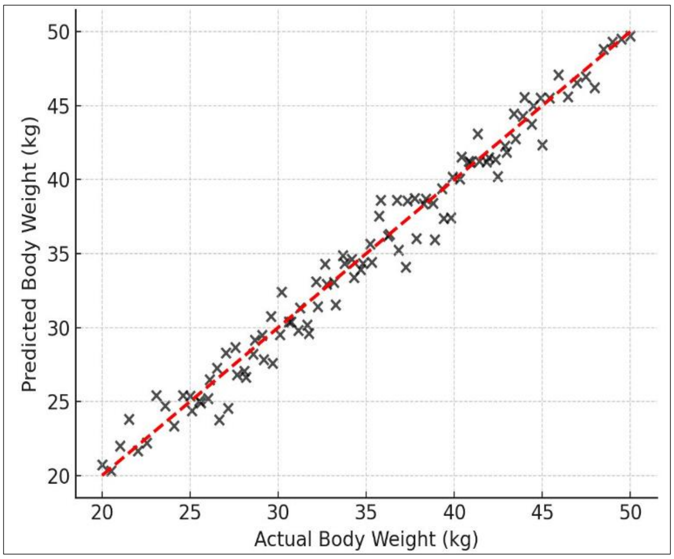

Fig 1: Relationship Between Actual and Predicted Body Weights in Sabi Sheep

The scatter plot illustrates the close correspondence between the observed and predicted body weights across the sex-specific regression models. The data points were clustered tightly along the 45° line, indicating high model precision and predictive accuracy for ewes, rams, and wethers. The strong alignment demonstrates the robustness of the regression models developed for field-based live weight estimation. This scatter plot shows a strong linear association between the observed and predicted weights across the sex-specific models. The close clustering of points along the 45° line demonstrates the high model accuracy and predictive reliability. In figure 2, the residuals are evenly scattered around the zero line, confirming the assumptions of homoscedasticity and linearity in the models. The absence of visible trends or heteroscedastic patterns validates the suitability of the selected regression equations and confirms that the prediction errors are random and unbiased.

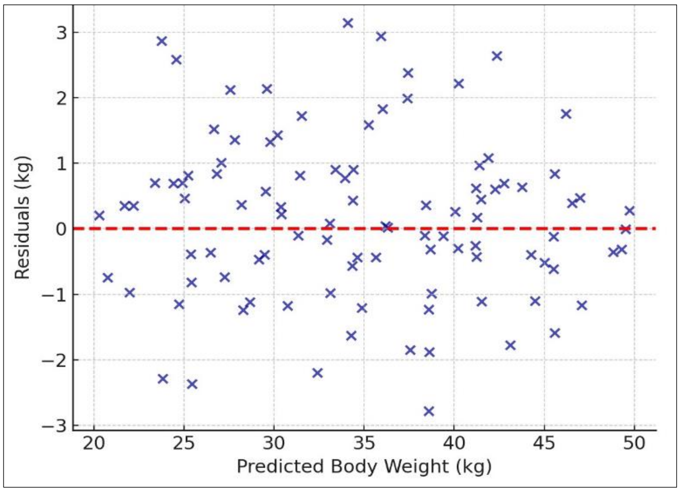

Fig 2: Residual Distribution of the Regreesion Models

The validation results further confirmed the robustness and practical reliability of the sex-specific regression models developed in this study. The strong correlation between the actual and predicted body weights (Figure 1) demonstrates that the models accurately captured the biological relationship between linear body measurements and live weight across sex categories. The residual analysis (Figure 2) showed a random and symmetrical distribution around zero, confirming that the model assumptions of linearity, independence, and homoscedasticity were satisfied (Keskin *et al*., 2007; Hlokoe *et al*., 2022) [27, 22]. These results, together with low prediction errors (RMSE < 2.5 kg and MAPE < 6%), highlight the high predictive performance and generalizability of the models in field conditions.

Compared with earlier studies on African indigenous sheep, the current models achieved higher R^2 values while maintaining simplicity and field applicability (Faraz *et al*., 2021; Atta *et al*., 2024; Mathapo *et al*., 2025) [20, 9, 31]. These findings imply that heart girth, body length, and chest depth are not only statistically significant predictors of body weight but also practical measurement traits for smallholder farmers and extension workers who lack access to weighing scales (Ağyar *et al*., 2022; Djaout *et al*., 2022) [3, 13]. Therefore, the developed equations provide a scientifically validated, low-cost, and scalable tool for live weight estimation, selection, and flock management in indigenous Sabi sheep production systems (Assan *et al*., 2023; Mallam *et al*., 2023) [8, 29].

4. Conclusions

In conclusion, we successfully developed and validated sex-specific regression models for predicting the live body weight of indigenous Sabi sheep using linear body measurements. The validation process, which included cross-validation, residual diagnostics, and error analysis, confirmed that the models were statistically sound, accurate, and generalizable across sex categories. The strong correlation between actual and predicted weights ($R^2 = 0.79–0.90$) and low prediction errors (RMSE < 2.5 kg; MAPE < 6%) indicate high predictive performance and model stability.

Heart girth, body length, and chest depth emerged as the most influential and reliable predictors of body weight, whereas sex significantly affected the choice and precision of the model. Rams exhibited the highest prediction accuracy due to the stronger linear association between body length and body weight, whereas ewes required a combination of three measurements for optimal precision. Importantly, residual analysis confirmed that the regression assumptions of normality, linearity, and homoscedasticity were met, ensuring the reliability of the parameter estimates.

Beyond their statistical robustness, these models hold practical significance for field applications. The identified measurements are easy to obtain with simple equipment, such as a measuring tape, allowing smallholder farmers and livestock extension workers to estimate live weight without the need for weighing scales. This offers a cost-effective, gender-inclusive, and sustainable approach to flock management, particularly in resource-limited and rural settings.

This study provides a validated framework for integrating simple morphometric tools into on-farm decision-making, supporting improved feeding, selection, and marketing practices for indigenous sheep in Zimbabwe and other semi-arid regions of sub-Saharan Africa. Future research should explore the integration of these models with digital livestock monitoring systems and nonlinear or machine learning approaches to enhance their precision and scalability across diverse agro ecological zones.

Highlights

- Developed sex-specific regression models for predicting the body weight of indigenous Sabi sheep of Zimbabwe.
- Model validation confirmed high accuracy ($R^2 = 0.79–0.90$; RMSE < 2.5 kg).
- Heart girth, body length, and chest depth were the key predictors of weight.
- Residual and cross-validation analyses confirmed the robustness of the model.
- It provides a low-cost, field-applicable tool for smallholder flock management.

Author contributions

Both authors (AD and NA) contributed to the conceptualization, methodology, formal analysis, original draft preparation, and manuscript review and editing. NA supervised the study. Both authors have read and approved the final manuscript.

Conflict of interest

The authors declare no conflicts of interest.

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Statement of animal rights

The study was approved by the Matopos Research and Academic Research Committee for Experimental Animals, Zimbabwe.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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