ESTIMATION OF BODY WEIGHTS OF DORPER RAMS × NON-DESCRIPT INDIGENOUS EWES' CROSSBREDS AT BIRTH AND WEANING AGE USING A MULTIVARIATE ADAPTIVE REGRESSION SPLINES ALGORITHM

MOLOSI, K. M.[1,2] – BILA, L.[3] – TYASI, T. L.[4*]

[1]*Department of Rural Development and Agrarian Reform, Amahlathi Agricultural Office, P.O. Box 166, Stutterheim 4960, South Africa*

[2]*Department of Agriculture and Animal Health, College of Agriculture and Environmental Sciences, University of South Africa, Florida 1710, South Africa*

[3]*Potchefstroom College of Agriculture, Department of Animal Production, Private Bag X1292, Potchefstroom 2520, South Africa*

[4]*School of Agricultural and Environmental Sciences, Department of Agricultural Economics and Animal Production, University of Limpopo, Private Bag X1106, Sovenga 0727, Limpopo, South Africa*

**Corresponding author*
e-mail: louis.tyasi@ul.ac.za

(Received 15th Oct 2024; accepted 4th Feb 2025)

Abstract. This study aimed to estimate the body weight (BW) of crossbred sheep at birth and weaning age using a Multivariate Adaptive Regression Splines (MARS) data mining algorithm. The BW and linear body measurements (LBM) including body length (BL), heart girth (HG), withers height (WH), sternum height (SH), body depth (BD), bicoastal diameter (BCD), head length (HL), head width (HW),ear Length (EL), ear width (EW), rump length (RL) and rump width (RW) were taken in 69 lambs at birth and weaning. The goodness of fit criteria including Pearson's correlation coefficient (r), Root mean square error (RMSE), Coefficient of determination (Rsq), and Akaike's information criterion (AIC) were used to evaluate the model performance. The results showed that MARS had higher r of 0.98 and 0.91, Rsq of 0.96 and 0.83, and lower RMSE of 0.13 and 0.24, and AIC of -191.48 and -132.66 for birth and weaning, respectively. These results suggest that MARS is the best data mining algorithm for prediction of body weight at birth and weaning of Dorper rams × Non-descript indigenous ewes crossbreds sheep.
Keywords: *Dorper sheep, non-descript sheep, crossbreed sheep, body weight, linear body measurements*

Introduction

Globally, the sheep population is estimated to be 1.263 million and about 400 million are in Africa (DAFF, 2015). In South Africa, about 21.43 million of the sheep population is owned by resource-limited farmers (DAFF, 2015). Sheep farming plays a huge part in developing cities, as it is of economic importance through job creation, poverty mitigation and holds social value in many rural areas (Sabbioni et al., 2020). Sheep are vital small-stock animals that play a fundamental role in rural areas, particularly as a source of protein (Zil and Farhat, 2019). The live body weight of sheep has been discovered as one of the desirable economic traits in livestock commodities, specifically for farm management activities, feeding procedures, growth assessment and breeding purposes (Ormachea et al., 2023; Chay-Canul et al., 2024).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

The rural genetic selection standards are fundamental selection methods that focus, on animal body features and understanding the relationship of traits of our interest and linear body measurements such as body length, heart girth, withers height, sternum height, body depth, bicoastal diameter, head length, head width, ear length, ear width, rump length and rump width (Friedman, 1991). The Multivariate Adaptive Regression Splines (MARS) is an extension of linear models that develop no assumptions about the relationship between an aimed variable and the predictor variables algorithm (Kefelegn et al., 2024); Celik, 2019). Mathapo et al. (2022) reported that MARS is a tool for managing pattern recognition difficulties in regression and classification for managing non-linear data. On the other hand, Phaladi et al. (2024) revealed that the MARS algorithm might be utilized as a strong classifier, especially when variables are more than one and might be effective in estimating the live body weight of the South African (SA) Dorper sheep breed. On the other hand, Mathapo et al. (2024) argued that data mining algorithms have the potential to overcome the multicollinearity problems in predicting the body weight of animals from linear body measurements. Hence, the data mining algorithms approach was used to predict live body weight from linear body measurement traits of dorper rams × non-descript indigenous ewes' crossbreds at birth and weaning age. Furthermore, it is in the greatest of our knowledge that there is no literature documented in South Africa on this crossbred animal. While Hasanah (2021) reported that BW is accurately estimated from linear body measurements. Numerous reports have been made by several scholars on estimating BW from linear body measurements in different animal species such as Sussex cattle, Dorper sheep, Indigenous goats and indigenous chicken (Bila et al., 2023; Phaladi et al., 2024; Mathapo et al., 2024; Assan et al., 2024). The estimation of live body weight from linear body measurements is of great fundamental, particularly for flock management, breed standardization and conservation purposes. However, based on the authors 'knowledge, there is limited information on the use of data mining algorithms specifically the MARS to estimate the live body weight of Dorper ram's × non-descript indigenous ewe's crossbreds from linear body measurement traits. Thus, the objective of this study was the estimation of the live body weight of Dorper ram's × non-descript indigenous ewe's crossbreds at birth and weaning age using the MARS data mining algorithm. This study might be helpful more so on rural sheep farmers, to use linear body measurements during the selection of breeding stock and estimation of body weight of animals for market purposes.

Material and methods

Study site

The study was conducted at Glencoe Farm, which is situated in Cathcart, at Amahlathi Local Municipality of Amathole District, in the Eastern Cape Province, of South Africa (*Fig. 1*). Cathcart lies 32'18.55 South and 27'9.37 East at 792 m above sea level. The average maximum and minimum annual temperatures were 28°C and 4°C, respectively. The district receives an annual rainfall between 600 and 1000 m. The rainy season was usually between October and March [Agriculture Geo-Reference Information System, 2017]. The farm was chosen because it was the only project that received Dorper rams from the government livestock improvement scheme in Amahlathi local municipality, Eastern Cape province of South Africa. Amahlathi Local Municipality has a fragmented topography and consists of a wide-ranging. Glencoe

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

farm was 45 km from Cathcart, on the way to Mpofu training centre, the area vegetation and landscape consisted of mountains and moderately undulating slopes below peaks, often with ridges of rock or boulder outcrops.

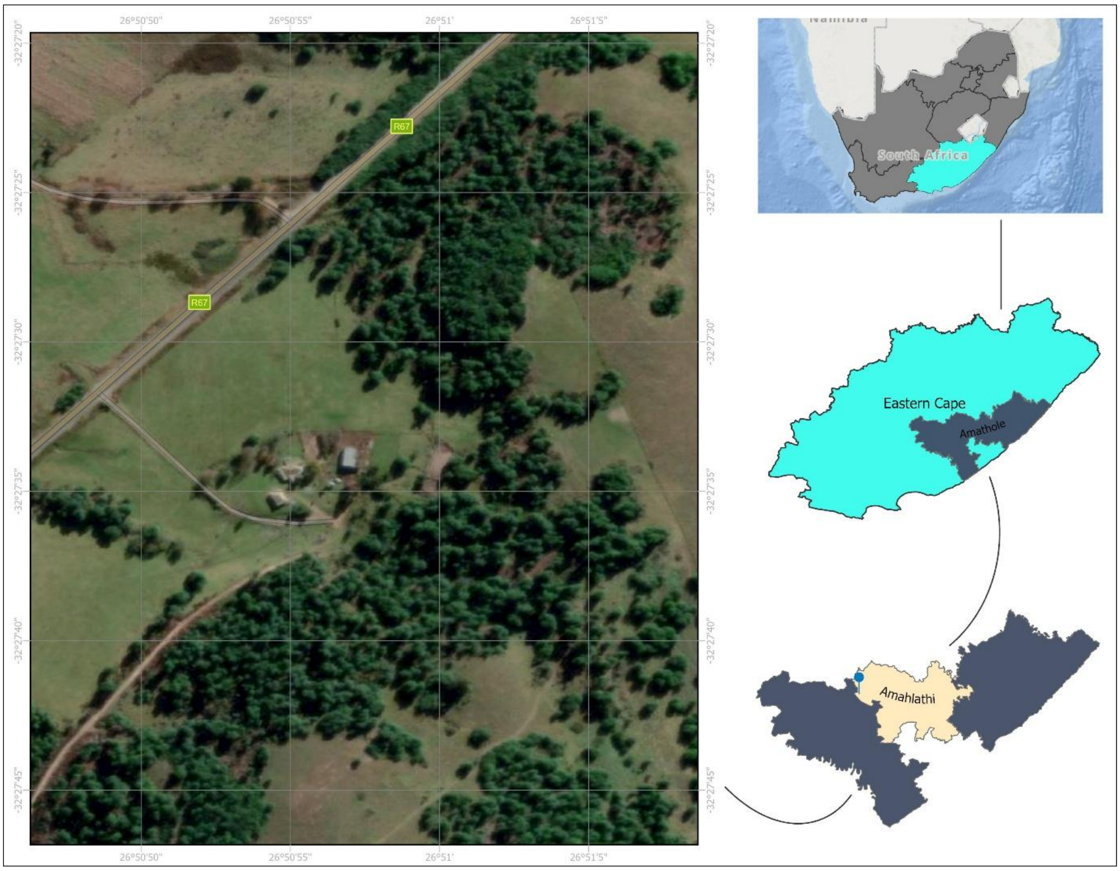

Figure 1. *The geographic map indicating the study area.*

Animal management

All the animals used in the study were kept under an extensive farming system, which allowed animals to freely graze in the camps during the day and afternoon. Fresh clean water was always made available in the camps for animals to drink. The animals received a routine inspection and dipping for herd health management purposes. Linear body measurements were measured while the animal was in a standing position with its head elevated up and weighted on all four feet. A satisfactory-built functional handling facility with a crowding pen, operational crush and head gate was used for handling the animals to lessen movement during the measuring process.

Data collection

Linear body measurements and live body weight at birth and weaning were taken in 69 (males = 41 and females = 28) lambs. The animals used in the study at birth age were measured following a 12-h fasting period and weaning was between 6 months old. The live body weight (BW) at birth and weaning was measured using a tal-tec weighing scale while the linear body measurement traits were measured using measuring tape standardized in centimeters (cm). The body weight at birth, weaning and linear body

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

measurement traits such as Body length (BL), Heart girth (HG), Withers height (WH), Sternum height (SH), Body depth (BD), Bicoastal diameter (BCD), Head length (HL), Head width (HW), Ear length (EL), Ear width (EW), Rump length (RL) and Rump width (RW) were measured by the same individual to avoid variations on the measurements. The measured traits were taken following the guidelines defined by Rashijane et al. (2023) and Phaladi et al. (2024) (*Table 1*).

Table 1. *Linear body measurement traits*

Traits	Description
Body length	Measured horizontally from the anterior shoulder point to the posterior extremity of the pin bone
Heart girth	Measured as the circumference of the chest just behind the scapula
Withers height	Measured vertically from the highest point of the shoulder (wither) to the ground surface in relation to the level of forelegs
Sternum height	Measured as the vertical position from the lower tip of the sternum to the ground as the animal standing
Body depth	Measured as the height between the end sheep front legs and its back
Bicoastal diameter	Measured from dorsal into two arcus costa
Head length	Measured from the temple of the head to the tip of the horn
Head width	Measured as the space between the edges of the head
Ear length	Measured as the space from the position of attachment to the tip of the ear
Ear width	Measured as the distance between the middle of the top and bottom edge of the ear
Rump length	Measured as the distance from the hip bone to edge of the pin bone
Rump width	Measured as the position between two tuber coxae

Statistical analysis

The Statistical Package for Social Sciences (SPSS, 2019) version 28.0 with a probability for significance was used to analyze the data for analysis of the descriptive statistics and Pearson's correlation matrix of measured traits amongst the different age and sex of the linear body measurement traits. Decision tree algorithms were used to design the model to estimate BW from linear body measurements traits of crossbred lambs at birth and weaning using the study of Rashijane et al. (2023). The cross-validation was kept at 10, as recommended by Celik and Yilmaz (2018). The goodness of fit criteria was used to run the estimation of BW from linear body measurements of crossbred lambs of MARS as suggested by Aytekin et al. (2018).

Multivariate adaptive regression spline algorithm

The multivariate adaptive regression spline algorithm is an extension of linear models that develops no assumptions about the relationship between aimed variable and the predictor variables algorithm introduced by Friedman (1991) for managing pattern recognition difficulties in regression and classification for managing non-linear data. For this motive, the MARS model is ideal for users who prefer outcomes in the form of similar regression while capturing essential non-linear and interactions that fit a sequence of straight-line regression functions for estimating the figures of the resume

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

dependent variable Rashijane et al. (2023). A multivariate adaptive regression spline algorithm was accomplished as reported by Bila et al. (2023).

MARS data mining algorithm can be defined as:

$$f(x) = \beta_0 + \sum_{M=1}^{M} \beta_m \prod_{k=1}^{k_m} h_m(X_{v(k,m)}) \quad \text{(Eq.1)}$$

where: f(x) is the estimated value of the dependent variable, β_0 and β_m are intercept, $h_m(X_{v(km)})$ is the basis function, where $v(k, m)$ is an index of the predictor for the m_{th} component of the k_{th} product, K is the parameter regulating the order of interaction. After building the most suitable MARS model, the basic functions that did not contribute much to the model fitting performance were removed in the pruning process based on the following generalized cross-validation error (GCV) Zarboski et al. (2019).

$$GCV(\lambda) = \frac{\sum_{i=1}^{n}(y_i - y_{ip})^2}{\left(1 - \frac{M(\lambda)}{n}\right)^2} \quad \text{(Eq.2)}$$

where: n is the number of training cases, y_i is the observed value of a response variable, y_{ip} is the estimated value of a response variable, and $M(\lambda)$ is a penalty function for the complexity of the model with λ terms.

MARS predictive performance

The goodness of fit criteria was used to estimate the performance of MARS on prediction of body weight Rashijane et al. (2023). The following goodness of fit were adopted in the study:

Pearson's correlation coefficient (r)

$$\mathrm{r} = \frac{\mathrm{cov}(y_i, y_{ip})}{S_{yi}\, S_{Yip}} \quad \text{(Eq.3)}$$

Relative root means square error (RRME)

$$\mathrm{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y) \times 2}}{\bar{y}} \quad \text{(Eq.4)}$$

Mean error (ME)

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_{ip}) \quad \text{(Eq.5)}$$

Performance index (PI)

$$\mathrm{PI} = \frac{\mathrm{rRMSE}}{1 + \mathrm{r}} \quad \text{(Eq.6)}$$

Coefficient of determination (Rsq)

$$\mathrm{Rsq} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{(Eq.7)}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

Adjusted coefficient of determination (ARsq)

$$\mathrm{ARsq} = 1 - \frac{\frac{1}{n-k-1}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\frac{1}{n-1}\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{Eq.8}$$

Root-mean-square error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \tag{Eq.9}$$

Standard deviation ratio (SDR)

$$\mathrm{SDR} = \sqrt{\frac{\frac{1}{n-1}\sum_{i=1}^{n}(\varepsilon_i-\bar{\varepsilon})^2}{\frac{1}{n-1}\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{Eq.10}$$

Akaike information criteria (AIC)

$$\mathrm{AIC} = \mathrm{N}\,\mathrm{Ln}\left(\frac{\mathrm{SSE}}{\mathrm{N}}\right) + 2\mathrm{p} \tag{Eq.11}$$

Mean absolute percentage error (MAPE)

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Yi-\hat{Y}i}{Yi}\right| \times 100 \tag{Eq.12}$$

Mean absolute deviation (MAD)

$$\mathrm{MAD} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Yi-\hat{Y}i}{Yi}\right| \tag{Eq.13}$$

Global relative approximation error (RAE)

$$\mathrm{RAE} = \sqrt{\frac{\sum_{i=1}^{n}(Yi-\hat{Y}i)2}{\sum_{i=1}^{n}Y_{i}^{2}}} \tag{Eq.14}$$

Coefficient of variance (CV)

$$\mathrm{CV} = \sqrt{\frac{\frac{1}{n-1}\sum_{i=1}^{n}(\varepsilon_i-\bar{\varepsilon})^2}{\bar{Y}}} \times 100 \tag{Eq.15}$$

Results

Descriptive statistics at birth

Descriptive statistics of live body weight and linear body measurements for male and female lambs at birth age are presented in *Table 2*. The descriptive statistics of body

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

weight and linear body measurements for male and female lambs discovered a significant difference ($P < 0.05$) in all the measured traits. Moreover, the male lambs had higher mean numeric values as compared to female lambs at birth.

***Table 2.** Descriptive statistics of body weight and linear body measurements in crossbred's lambs at birth*

Traits	Males (n = 41) mean ± SE	Females (n = 28) mean ± SE	P-value
BW (kg)	$4.98^{a} \pm 0.24$	$3.90^{b} \pm 0.78$	0.000
BL (cm)	$31.46^{a} \pm 0.35$	$28.50^{b} \pm 0.87$	0.001
HG (cm)	$33.93^{a} \pm 0.37$	$30.54^{b} \pm 0.82$	0.000
WH (cm)	$29.83^{a} \pm 0.38$	$27.32^{b} \pm 0.67$	0.001
SH (cm)	$12.98^{a} \pm 0.16$	$12.18^{b} \pm 0.29$	0.012
BD (cm)	$14.41^{a} \pm 0.19$	$13.46^{b} \pm 0.32$	0.008
BCD (cm)	$5.41^{a} \pm 0.09$	$4.39^{b} \pm 0.10$	0.000
HL (cm)	$12.27^{a} \pm 0.12$	$10.61^{b} \pm 0.23$	0.000
HW (cm)	$10.29^{a} \pm 0.19$	$8.71^{b} \pm 0.28$	0.000
EL (cm)	$6.17^{a} \pm 0.22$	$5.00^{b} \pm 0.15$	0.000
EW (cm)	$4.44^{a} \pm 0.89$	$3.86^{b} \pm 0.09$	0.000
RL (cm)	$10.90^{a} \pm 0.10$	$9.89^{b} \pm 0.18$	0.000
RW (cm)	$9.61^{a} \pm 0.12$	$8.96^{b} \pm 0.21$	0.005

^{ab}Means in the same row with different superscripts are significantly different. BW: body weight, BL: body length, HG: heart girth, WH: wither height, SH: sternum height, BD: body depth, BCD: bicoastal diameter, HL: head length, HW: head width, EL: ear length, EW: ear width, RL: rump length, RW: rump width, SE: standard error, KG: kilogram, CM: centimeter

Descriptive statistics at weaning

Descriptive statistics of body weight and linear body measurements for male and female lambs at weaning age are presented in *Table 3*. The descriptive statistics of body weight and linear body measurements for male and female lambs discovered a significant difference ($P < 0.05$) in all the measured traits. Moreover, the male lamb had higher mean numeric values in all the measured traits.

Correlation matrix at birth

Table 4 shows Pearson's correlation coefficients for the relationship between live body weight and linear body measurements of male and female lambs at birth. In male lambs, the BW was positively highly correlated with HL, BCD, HW and EL ($P < 0.01$) while no significant correlation with BL, HG, WH, SH, BD, RL and RW. In female lambs, BW was positively highly correlated with WH ($P < 0.01$) while insignificant correlated with EL. The BW was found significant ($P < 0.05$) correlated with HG, (BD, BCD, HL and HW.

Correlation matrix at weaning

Table 5 shows Pearson's correlation coefficients for the relationship between body weight at weaning (WW) and linear body measurement traits. In male lambs, WW was

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

highly correlated with BL (P < 0.01) while negatively no significant correlation with RL. In female lambs, WW was highly correlated with BL, BCD, and RL (P < 0.01) while insignificant correlated with EW.

Table 3. *Descriptive statistics of body weight and linear body measurements in crossbred's lambs at weaning*

Traits	Male (n = 41) mean ± SE	Female (n = 28) mean ± SE	P-value
BW (kg)	41.95^{a} ± 0.23	35.75^{b} ± 0.34	0.000
BL (cm)	66.88^{a} ± 0.36	59.93^{b} ± 0.86	0.000
HG (cm)	73.88^{a} ± 1.21	57.93^{b} ± 0.78	0.000
WH (cm)	70.66^{a} ± 0.68	60.64^{b} ± 0.86	0.000
SH (cm)	36.61^{a} ± 0.23	34.36^{b} ± 0.42	0.000
BD (cm)	41.78^{a} ± 0.37	36.68^{b} ± 0.50	0.000
BCD (cm)	17.73^{a} ± 0.25	16.82^{b} ± 0.18	0.08
HL (cm)	20.15^{a} ± 0.12	19.57^{b} ± 0.17	0.007
HW (cm)	12.54^{a} ± 0.99	12.11^{b} ± 0.79	0.003
EL (cm)	10.32^{a} ± 0.74	9.89^{b} ± 0.06	0.000
EW (cm)	8.12^{a} ± 0.16	7.18^{b} ± 0.27	0.002
RL (cm)	19.15^{a} ± 0.14	16.79^{b} ± 0.25	0.000
RW (cm)	17.68^{a} ± 0.16	15.25^{b} ± 0.20	0.000

^{ab}Means in the same row with different superscripts are significantly different. BW: body weight, BL: body length, HG: heart girth, WH: wither height, SH: sternum height, BD: body depth, BCD: bicoastal diameter, HL: head length, HW: head width, EL: ear length, EW: ear width, RL: rump length, RW: rump width, SE: standard error, KG: kilogram, CM: centimeter

Table 4. *Correlation matrix of measured traits at birth, male below diagonal and female above diagonal*

Traits	BW	BL	HG	WH	SH	BD	BCD	HL	HW	EL	EW	RL	RW
BW		0.36^{ns}	0.43*	0.56**	0.32^{ns}	0.39*	0.43*	0.84*	0.58*	0.21^{ns}	0.43^{ns}	0.29^{ns}	0.23^{ns}
BL	0.20^{ns}		0.98**	0.32^{ns}	0.56**	0.48*	0.27^{ns}	-0.30^{ns}	0.20^{ns}	0.17^{ns}	0.20^{ns}	0.22^{ns}	0.47*
HG	0.04^{ns}	0.83**		0.36^{ns}	0.59**	0.49**	0.31^{ns}	-0.22^{ns}	0.32^{ns}	0.19^{ns}	0.19^{ns}	0.22^{ns}	0.44*
WH	0.21^{ns}	-0.38*	-0.36*		0.77**	0.83**	-0.01^{ns}	0.36^{ns}	0.17^{ns}	-0.26^{ns}	-0.42*	-0.28^{ns}	-0.07^{ns}
SH	0.07^{ns}	0.23^{ns}	0.04^{ns}	-0.27^{ns}		0.95**	0.00^{ns}	0.16^{ns}	0.12^{ns}	-0.22^{ns}	-0.34^{ns}	-0.14^{ns}	0.16^{ns}
BD	0.15^{ns}	0.07^{ns}	-0.15^{ns}	-0.20^{ns}	0.79**		0.04^{ns}	0.24^{ns}	0.12^{ns}	-0.26^{ns}	-0.35^{ns}	-0.19^{ns}	0.07^{ns}
BCD	0.42**	-0.10^{ns}	-0.07^{ns}	0.22^{ns}	-0.07^{ns}	-0.04^{ns}		0.02^{ns}	0.52**	0.19^{ns}	0.09^{ns}	0.17^{ns}	0.16^{ns}
HL	0.50**	-0.32*	-0.29^{ns}	0.23^{ns}	-0.32*	-0.09^{ns}	0.34*		0.53**	0.08^{ns}	-0.12^{ns}	0.09^{ns}	0.05^{ns}
HW	0.39**	0.15^{ns}	0.33*	0.04^{ns}	-0.29^{ns}	-0.24^{ns}	0.18^{ns}	0.34*		0.39*	0.27^{ns}	0.38*	0.31^{ns}
EL	0.44**	0.15^{ns}	0.15^{ns}	0.22^{ns}	-0.08^{ns}	-0.19^{ns}	0.19^{ns}	0.27^{ns}	0.32*		0.64**	0.30^{ns}	0.22^{ns}
EW	0.37*	0.16^{ns}	0.64^{ns}	0.11^{ns}	-0.07^{ns}	-0.02^{ns}	0.13^{ns}	0.26^{ns}	0.38*	0.51**		0.39*	0.29^{ns}
RL	0.06^{ns}	0.19^{ns}	0.27^{ns}	-0.09^{ns}	0.11^{ns}	0.05^{ns}	-0.09^{ns}	0.06^{ns}	0.35*	0.19*	0.13^{ns}		0.80**
RW	0.04^{ns}	0.16^{ns}	0.14^{ns}	-0.08^{ns}	0.09^{ns}	0.05^{ns}	-0.21^{ns}	0.06^{ns}	0.34*	0.16^{ns}	0.19^{ns}	0.78**	

BW: body weight, BL: body length, HG: heart girth, WH: wither height, SH: sternum height, BD: body depth, BCD: bicoastal diameter, HL: head length, HW: head width, EL: ear length, EW: ear width, RL: rump length, RW: rump width, ns: not significant, * significant (p > 0.05), ** significant (p < 0.01)

MARS model at birth and weaning

MARS model findings are presented in *Table 6*. The first term of the model had an intercept that had a coefficient of 5.03. While the second term, WH, with a negative

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

coefficient of 0.34. The third term, EW, had a negative coefficient of 0.30. The fourth term, RL, had a negative coefficient of 0.30. The fifth term, RL, had a negative coefficient of 0.35. The sixth term was WH and HW with a positive coefficient of 0.03. Lastly, sex (female) at birth age SH and EL, with a negative coefficient of 0.01. The basic functions that reduce the performance of the model obtained after the forward and backward pass stages were eliminated due to the GCV in MARS modeling. At weaning the first term of the model had an intercept that had a coefficient of 4.99. The second term, sex (female) at weaning age, had a negative coefficient of 0.88. The third term, WH, had a negative coefficient of 0.09. The basic functions that reduce the performance of the model obtained after the forward and backward pass stages were eliminated due to the GCV in MARS modeling.

Table 5. *Correlation matrix of measured traits at weaning, male below diagonal and female above diagonal*

Traits	BW	BL	HG	WH	SH	BD	BCD	HL	HW	EL	EW	RL	RW
BW		0.89**	0.13^{ns}	0.11^{ns}	0.31^{ns}	0.32^{ns}	0.69**	0.45*	-0.11^{ns}	0.34^{ns}	-0.25^{ns}	0.82**	0.32^{ns}
BL	0.62**		-0.09^{ns}	-0.12^{ns}	0.25^{ns}	0.19^{ns}	0.73**	0.57**	0.16^{ns}	0.38*	-0.46*	0.79**	0.77**
HG	0.29^{ns}	0.51**		0.94**	0.38*	0.57**	-0.12^{ns}	-0.38*	-0.32^{ns}	-0.04^{ns}	0.38*	0.14^{ns}	0.18^{ns}
WH	0.08^{ns}	-0.05^{ns}	0.09^{ns}		0.43*	0.61**	-0.09^{ns}	-0.34^{ns}	-0.41*	-0.05^{ns}	0.42*	0.15^{ns}	0.21^{ns}
SH	0.16^{ns}	0.19^{ns}	-0.29^{ns}	0.35*		0.85**	0.35^{ns}	0.24^{ns}	-0.08^{ns}	0.06^{ns}	0.46*	0.15^{ns}	0.27^{ns}
BD	0.13^{ns}	0.39*	0.49**	0.31*	0.19		0.34^{ns}	0.14^{ns}	-0.24^{ns}	-0.04^{ns}	0.44*	0.29^{ns}	0.35^{ns}
BCD	-0.21^{ns}	0.01^{ns}	0.50**	0.00^{ns}	-0.42**	0.45**		0.68**	0.39^{ns}	0.31^{ns}	-0.30^{ns}	0.61**	0.59**
HL	0.03^{ns}	0.23^{ns}	0.53**	-0.14^{ns}	-0.47**	0.38*	0.71**		0.32^{ns}	0.35^{ns}	-0.16^{ns}	0.49**	0.45*
HW	0.03^{ns}	0.22^{ns}	0.09^{ns}	0.09^{ns}	0.12^{ns}	0.18^{ns}	0.12^{ns}	0.44**		0.09^{ns}	-0.47*	-0.09^{ns}	-0.06^{ns}
EL	0.24^{ns}	0.38*	0.21^{ns}	0.08^{ns}	0.18^{ns}	0.39*	0.18^{ns}	0.27^{ns}	0.42**		-0.20^{ns}	0.38*	0.41*
EW	0.02^{ns}	0.33*	0.19^{ns}	0.49**	0.30^{ns}	0.39**	0.08^{ns}	-0.02^{ns}	0.17^{ns}	0.39*		-0.31	-0.22^{ns}
RL	-0.25^{ns}	0.17*	0.08^{ns}	0.31^{ns}	0.12^{ns}	0.35*	0.14^{ns}	0.04^{ns}	0.30^{ns}	0.07^{ns}	0.52**		0.94**
RW	-0.15^{ns}	0.26^{ns}	0.11^{ns}	0.23^{ns}	0.22^{ns}	0.43**	0.10^{ns}	-0.07^{ns}	0.31*	0.11^{ns}	0.48**	0.84**	

BW: body weight, BL: body length, HG: heart girth, WH: wither height, SH: sternum height, BD: body depth, BCD: bicoastal diameter, HL: head length, HW: head width, EL: ear length, EW: ear width, RL: rump length, RW: rump width, ns: not significant, * significant ($p > 0.05$), ** significant ($p < 0.01$)

Table 6. *MARS model*

Variables	Coefficients
Birth	
Intercept	5.03
h(31-WH)	-0.34
h(4-EW)	-0.30
h(10-RL)	-0.35
h(31-WH) * HW	0.03
Sex 2 * SH * EL	-0.01
Weaning	
Intercept	4.99
Sex (female)	-0.88
h (28-WH)	-0.09

WH: wither height, EW: ear width, RL: rump length, HW: head width, SH: sternum height, EL: ear length

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

Performance of MARS model

The presentation for the MARS model results for training and test datasets built on goodness of fit is given in *Table 7*. The results indicated that the best estimative model was realized from the training dataset for the proportion 70% (Training) and 30% (Test). The training set had the lowest RMSE, RRMSE, SDR, MAPE, CV, MAD, AIC, CAIC, and ME than the test dataset but equal to RAE with an expected value was zero. While at weaning age, the results indicated that the best estimative model was realized from the training dataset for the proportion 70% (Training) and 30% (Test). The training set had the lowest RMSE, RRMSE, MAPE, CV, AIC, and CAIC, than the test dataset but equal with MRAE, MAD and RAE with expected values was zero.

Table 7. *Goodness of fit criteria for MARS at birth age and weaning age*

Criteria	Birth		Weaning		Decision
	Training	Test	Training	Test	
r	0.98	0.93	0.91	0.93	Greater is better
RMSE	0.13	0.28	0.24	0.25	Greater is better
SDR	0.21	0.39	0.41	0.39	Smaller is better
CV	2.78	5.43	5.40	5.58	Greater is better
PI	1.39	3.17	2.79	2.92	Greater is better
ME	0.00	0.14	0.00	-0.06	Smaller is better
RRMSE	2.75	6.12	5.34	5.62	Greater is better
RAE	0.00	0.00	0.00	0.00	The expected value is zero
MRAE	0.00	0.01	0.01	0.01	The expected equal value is one
MAPE	2.10	4.51	3.68	4.00	Greater is better
MAD	0.09	0.19	0.15	0.15	The expected equal value is one
Rsq	0.96	0.79	0.83	0.84	Greater is better
ARsq	0.95	0.69	0.82	0.81	Smaller is better
AIC	-191.48	-39.47	-132.66	-48.74	Greater is better
CAIC	-189.48	-33.01	-132.13	-47.24	Greater is better

Pearson's correlation coefficient (r), Root mean square error (RMSE), Standard deviation ratio (SDR), Coefficient of variation (CV), Performance index (PI), Mean error (ME), Relative root mean square error (RRMSE), Relative approximation error (RAE), Mean relative approximation error (MRAE), Mean absolute percentage error (MAPE), Mean absolute deviation (MAD), Coefficient of determination (Rsq), Adjusted coefficient of determination (ARsq), Akaike's information criterion (AIC), Corrected Akaike's information (CAIC)

Discussion

The linear body measurement traits have a positive relationship in estimating the live body weight of an animal (Abbas et al., 2021; Rashijane et al., 2023). The current study first, evaluated the descriptive statistics of the body weight and linear body measurement traits of lambs at birth. The descriptive statistics showed that the minimum birth weight was 4 kg and 5 kg as the maximum weight in male lambs, while a minimum weight of 3 kg and 5 kg as the maximum weight was observed in female lambs. The findings of the current study were consistent with those of Aytekin et al. (2018), who reported that body weight had a highly significant correlation with rump height, heart girth, rump length and body length in Dorper sheep of villages in

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

Limpopo. Further, reported that heart girth and withers heights are effectual estimators of body weight in males. The second descriptive statistics showed the minimum weight of 39 kg and 45 kg as the maximum weight in male lambs at weaning age, while a minimum weight of 34 kg and 40 kg as the maximum weight was observed in female lambs at weaning age. These findings are similar to those of Mathapo et al. (2024) who reported 22 kg as the minimum weight while 48 kg was the maximum weight found in non-descript indigenous goats in Limpopo villages. The results on descriptive statistics of body weight and linear measurements for male and female lambs at birth and weaning age were observed with significant differences in all the measured linear traits. The findings of the study are similar to the report made by Bila et al. (2023) who reported that HG, HL, WH, HH, BL, RL and RW had a significant correlation on influencing body weight of Sussex cows at weaning age. The correlation results showed that the male lambs at birth were highly correlated with head length**,** while insignificant correlated with heart girth 0.04 and rump width 0.04. In female lambs, the body weight at birth age was highly correlated with wither height, while insignificant correlated with ear length. The findings of the study were consistent with the report made by Rashijane et al. (2023), who reported that males were positively correlated with body length, heart girth, rump height and withers height, while females were positively correlated with heart girth, withers height, body length and rump height in Savanna goats in Polokwane farms. The body weight at weaning age in male lambs was highly correlated with body length while negatively insignificant correlated with rump length. In female lambs, the body weight at weaning age was highly correlated with body length, while negatively insignificant correlated with ear width. The observations of the current study are similar to the reports reported by Kefelegn et al. (2024) on indigenous sheep that there is an association between body weight and linear body measurements such as heart girth, body length, rump height and further emphasize that heart girth as the most important estimator followed by Body length and rump height. Hence, data mining algorithms have been used to estimate body weight from linear body measurements of the crossbred lambs at birth and weaning age. The current study used MARS as an algorithm in the estimation of the body weight of Dorper rams crossed with non-descript indigenous ewes, crossbred at birth and weaning age. The findings of the study revealed that MARS is an accurate estimator in the algorithm. The results of the study indicate that the MARS algorithm can be used to estimate the body weight at birth and weaning age in crossbred lambs. Pearson's correlation value for the training data set was higher than that of the test data set. MARS data mining algorithm had been recommended for the estimation of body weight in Dorper sheep by Phaladi et al. (2024). Additionally, MARS has been reported as outperforming algorithms as an effective and accurate estimator in goats Celik (2019). Lastly, Assan et al. (2024) recommended that MARS as an algorithm that truly influences the body from linear measurements in chickens.

Conclusion

The research findings revealed a positive association between body weight and some linear body measurements of crossbred lambs at birth and weaning age. MARS showed that head length, bi-coastal diameter, head width and ear length were effective estimators in male lambs at birth. While in female lamb's withers, height was also found effective. The heart girth, body depth, bicoastal diameter, head length and head

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641

width were found to be effective in estimating body weight in female lambs at birth. The body length in both male and female lambs was found to be a more effective estimator, followed by bi-coastal diameter, rump length and head length at weaning age. More investigation studies need to be conducted on MARS algorithms for estimating the body weight of sheep breeds. It is recommended that sheep keepers consider applying the MARS algorithm for the estimation of live body weight using linear body measurement traits (WH, EW, RL, HW, SH and sex).

Acknowledgements. The authors are thankful to the Glencoe farm owner (Msiwa Mzimkhulu) for allowing us to collect the data from the animals as well as the farm workers who assisted during the data collection process.

Funding. Financially, this study is self-supported.

Conflict of interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability. Data is available on request to the corresponding author.

Ethics. The experimental procedures were conducted following the University of South Africa (UNISA) Ethics code for the use of live animals in research, ethics reference number: 2024/CAES-AREC/2568).

REFERENCES

[1] Abbas, A., Ullah, M. M., Waheed, A. (2021): Body weight prediction using different data mining algorithms in Thalli sheep: a comparative study. – Veterinary World 14(9): 2332.

[2] Assan, N., Mpofu, M., Musasira, M., Mokoena, K., Tyasi, T. T., Mwareya, N. (2024): Predicting body weight of three chicken genotypes from linear body measurements using MARS and CART data mining algorithms. – Applied Ecology and Environmental Research 22(3).

[3] Aytekin, I., Eyduran, E., Koksal, K., Akşahan, R., Keskin, I. (2018): Prediction of fattening final live weight from somebody measurements and fattening period in young bulls of crossbred and exotic breeds using MARS data mining algorithm. – Pakistan Journal Zoology 50: 189-195.

[4] Bila, L., Malatji, D. D., Tyasi, T. L. (2023): Predicting body weight of South African Sussex cattle at weaning using multivariate adaptive regression splines and classification and regression tree data mining algorithms. – Journal of Applied Animal Research 51(1):608-615.

[5] Celik, S. (2019): Comparing predictive performances of tree based data mining algorithms and MARS algorithm in the prediction of live body weight from body traits in Pakistan goats. – Pakistan Journal of Zoology 51(4): 1447-1456.

[6] Celik, S., Yilmaz, O. (2018): Prediction of body weight of Turkish Tazi dogs using data mining techniques: classification and regression tree (CART) and multivariate adaptive regression splines (MARS). – Pakistan Journal of Zoology 50(2): 575-583.

[7] Chay-Canul, A. A., Camacho-Pérez, E., Casanova-Lugo, F., Rodríguez-Abreo, O., Cruz-Fernandez, Rodríguez-Reséndiz, J. (2024): Neural network-based body weight prediction in Pelibuey Sheep through biometric measurements. – Technologies 12: 59.

[8] Department Agriculture Forestry and Fisheries–South Africa (DAFF) (2015): A Profile of the South African Wool Market Value Chain. – DAFF, Pretoria.

[9] Friedman, J. (1991): Multivariate adaptive regression splines. – Annals of Statistics 9: 1-67.

[10] Hasanah, S. H. (2021): Multivariate adaptive regression splines for modelling. – The Student Status at Universitas Terbuka 7: 51-58.

[11] IBM SPSS (2019): SPSS Release 26.0 Statistical Packet Program, SPSS for Windows. – SPSS Inc., Chicago, IL.
[12] Kefelegn, K., Mesfin, A., Ashenafi, G. M. (2024): Predicting the body weight of indigenous sheep from linear body measurement traits using classification and regression tree data mining algorithm. – Biomed Journal of Science & Technologies Res 56(4)-2024.
[13] Mathapo, M. C., Tyasi, T. L., Mokoena, K., Hlokoe, R. V., Molabe, M. K. (2024): Comparison of MARS, CART, and Linear Regression Models for Prediction of Body Weight of Non-descript Indigenous Goats in Lepelle-Nkumbi Local Municipality, South Africa. – In: Yadav, J. (ed.) Recent Advances in Association Rule Mining and Data Mining. IntechOpen, London, pp. 1-12.
[14] Mathapo, M. M., Mugwabana, T. T., Tyasi, T. L. (2022): Prediction of body weight from morphological traits of South African non-descript indigenous goats of Lepelle Nkumbi Local Municipality using different data mining algorithm. – Tropical Animal Health Production 54: 102.
[15] Mucina, L., Rutherforf, M. M., Powrie, L. (2006): Vegetation Map of South Africa, Lesotho and Swaziland. – SANBI, Pretoria.
[16] Ormachea, V. V., Calsin, B. B., Aguilar, E. E., Ormachea, B. B., Gonzales, H. H., Masias, Y. M. G. (2023): Principal component analysis of morphological characteristics in creole sheep (Ovis aries). – Advance Animal Veterinary Science 11(6): 903-909.
[17] Phaladi, A. A., Tyasi, T. T., Tada, T., Mogashoa, S. (2024): Use of data mining algorithms to predict body weight of Dorper sheep Breed in two selected villages of Lepelle-Nkumpi local municipality in Limpopo province, South Africa. – Smart Agricultural Technology 8: 100479.
[18] Rashijane, L. L., Mokoena, K., Tyasi, T. L. (2023): Using multivariate adaptive regression splines to estimate the body weight of savanna goats. – Animals 13: 1146.
[19] Sabbioni, A., Beretti, V., Superchi, P., Ablondi, M. (2020): Body weight estimation from body measures in Cornigliese sheep breed. – Italian Journal of Animal Science 19(1): 25-30.
[20] Zaborski, D., Ali, M., Eyduran, E., Grzesiak, W., Tariq, M. M., Abbas, F., Waheed, A., Tirink, C. (2019): Prediction of selected reproductive traits of indigenous Harnai sheep under the farm management system via various data mining algorithms. – Pakistan Journal Zoology 51(2) 421.
[21] Zil, H., Farhat, I. (2019): Predicting the body weight of Balochi sheep using a machine learning approach. – Turkish Journal of Veterinary and Animal Sciences 43.4(10): 500-506.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_66296641