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PREDICTION OF BODY WEIGHT OF NIGERIAN NON-DESCRIPT GOATS FROM MORPHOMETRIC TRAITS USING CLASSIFICATION AND REGRESSION TREE MODEL

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ABSTRACT

This study was conducted to evaluate the relationship between body weight and eleven (11) morphometric traits (body weight, body length, height at withers, rump height, chest girth, hind leg, fore leg, head length, ear length, neck length, and tail length) of non-descript goats using classification and regression tree technique. The data were generated from 120 non-descript goats randomly selected from different herds in three LGA areas of Kaduna State, North West Nigeria. Pearson's moment correlation (r) between body weight and morphometric traits ranged from low to high values ($r = 0.21$-0.97; $P \leq 0.05$, $P \leq 0.01$). Based on the importance of the independent variables in predicting the body weight of goats, six body measurements namely; chest girth, body length, rump height, height at withers, head length and neck length were found to be more efficient. Thus, they were the variables entered to obtain the optimal regression tree. Among these six variables, chest circumference was found to be the primary splitting variable; and together with neck length accounted for about 84.20% of the variation in body weight. The regression tree analysis indicated that animals with chest circumference > 60.00cm and neck length >15cm could be expected to have higher body weights. This information could be exploited by livestock producers and researchers for determining the feed amount, drug dose, and market price of an animal, management, selection and genetic improvement of Nigerian non-descript goats.

Keywords: Body measurement, Body weight, correlation, non-descript goats, tree regression, Model

INTRODUCTION

In recent years, the application of data-driven models and machine-learning techniques has gained significant attention in various domains, including agriculture and animal science (Chakraborty and Shivakumar, 2019). These approaches have proven to be valuable tools in predicting and optimizing various aspects of livestock production (Chibonokwu and Nlebedim, 2018). The prediction of body weight is very important in assessing animal growth, productivity, and health. Accurate estimation of body weight enables informed decision-making regarding feeding strategies, breeding programmes, and overall management practices. Nigerian non-descript goats, widely reared in Nigeria, play a crucial role in the country's livestock industry (De Boor, 2001). However, the accurate prediction of their body weight remains a challenge due to various factors such as genetics, nutrition, environment, and management practices (Segun, 2022). Traditional methods, such as linear regression models, have been used in the past for body weight prediction. However, these models often fail to capture the complex nonlinear relationships that exist between the predictors and the response variable.

To overcome these limitations, regression tree analysis has emerged as a powerful technique for predicting complex relationships in datasets with both numerical and categorical variables. Regression trees can be used for interactive exploration and description and prediction of patterns and processes (Yakubu, 2012). Regression trees provide a flexible framework for partitioning the predictor space and fitting separate regression models in each partition. This approach allows for the detection of nonlinear relationships and interactions among predictors, making it suitable for analyzing complex datasets with numerous variables.

The findings of this study will have significant implications for the goat farming industry in Nigeria. Accurate prediction of body weight will enable farmers to make informed decisions regarding breeding selection, feeding strategies, and overall management practices (Montero and Vilar, 2014). Moreover, the results can contribute to the development of targeted breeding programmes aimed at improving the growth and productivity of Nigerian non-descript goats because of its contribution to economy by producing meat and milk which serve as part of human diet, moreover they play a role when performing religious and cultural ceremonies (Hassen and Tesfay, 2014). Challenges experienced in rural areas are that farmers are disadvantaged when it comes to selling, feeding, and providing medication to their goats due to lack of weighing scales, as they are expensive (Mokoena *et al*., 2023). There is limited information of prediction of BW from morphological traits and characterizes using classification and regression tree in non-descript goats in Southern Kaduna. Hence, the objective of the study was to apply regression tree analysis to predict the body weight (BW) using body length (BL), height at withers (HW), chest girth (CG), rump height (RH), hind leg (HL), fore leg (FL), head length (HDL), ear length (EL), Neck length (NL) and tail length (TL) of Nigerian non-descript indigenous goats in Southern Kaduna. The study will provide information that will help the farmer to select the best biometric traits that might be used to predict BW.

MATERIALS AND METHODS

Research animals, design, and management

The experiment made use of a random sample of 120 Nigerian non-descript indigenous goats of not less than 8 months comprising both male and female goats. A cross-sectional design was used with one replicate per goat. The animals which were reared through the extensive management system originated from different herds sampled in three LGA areas (Jaba, Jema'a and Kaura) of Kaduna State, North West Nigeria.

Data collection and measurements

Eleven (11) morphometric traits were measured on each animal. The body parameters were the body weight (BW), body length (BL), height at withers (HW), chest girth (CG), rump height (RH), hind leg (HL), fore leg (FL), head length (HDL), ear length (EL), Neck length (NL) and tail length (TL). All measurements were taken according to the suggestion of Norris *et al.* (2015). Body weight (kg) was taken using a spring balance. The height measurement (cm) was done using a graduated measuring stick. To achieve this, animals were placed on a flat ground and held by two field assistants. The length and circumference measurements (cm) were effected using a tape rule while the width measurements were taken using a calibrated wooden calliper. Briefly, HW: distance from the highest point of the shoulder (wither) to the ground surface in relation to level of the fore legs, CG: This refers to the body circumference and was measured just behind the fore-legs using a measuring tape (cm), BL: distance between anterior shoulder point to the posterior extremity of the pin bone, RH: distance from the top of the pelvic girdle to the ground surface in relation to the level of hind legs. HL**:** This is the distance from the base of the hind leg to the tip or feet of the hind leg (cm), EL**:** Measured from the ear base to the zygomatic arch of the ear (cm)**.** All measurements were carried out by the same person in order to avoid between individual variations or errors.

Descriptive statistics of the body weight and biometric traits of non-descript goats were computed. Pearson's moment correlation coefficients were calculated to determine the dependence between the goats' body weight and body dimensions. To gain a comprehensive understanding of the influence of the different independent variables on body weight, their importance scores were determined. To calculate a variable importance score, emphasis was laid on the improvement measure attributable to each variable in its role as a surrogate to the primary split. The values of these improvements are summed over each node and summed, and are scaled relative to the best-performing. The variable with the highest sum of improvements is scored 100, and all other variables will have lower scores ranging downward to zero (Banerjee *et al.*, 2008). The tree building process starts by partitioning a sample or the root node into binary nodes based upon a very simple question of the form: is $X \leq d$? where X is a variable in the data set, and d is a real number. Initially, all observations are placed at the root node. This node is impure or heterogeneous. The goal is to devise a rule that will initially break up these observations and create groups or binary nodes that are internally more homogenous than the root node (Yohannes and Hoddinott, 2006). In choosing the best splitter, the programme seeks to maximize the average "purity" of the two child nodes. As the response variable in the present study (body weight) is continuous, the Least Squared Deviation method was used as a measure of the homogeneity of nodes (Bevilacqua *et al.*, 2003). The tree building process continued until it became impossible. The maximum tree value was obtained after the tree reached a maximum dimension. 10-fold cross-validation was used as an error estimation method; this was to provide estimates of the future prediction error for each sub-tree (Camdeviren *et al.*, 2005). The statistical package employed in the analysis was Statistical Package for Social Sciences (SPSS, 2016)

Classification and regression tree (CART) algorithm

Classification and regression tree (CART) algorithm CART algorithm is a tree decision technique that was developed by Breiman *et al.* (1984) and it is mostly used in the animal industry because it is very simple, easy, and applied to visualize. CART was performed as described by Zaborski *et al*. (2019) and Tyasi *et al.* (2021).

Briefly, CART was applied to estimate BW as the dependent variable from ten biometric traits viz. BL, HW, CG, RH, HL, FL, HDL, EL, NL and TL.

The estimate of the future error of prediction for each node and explained the variation observed in the dependent variable was predicted as follows:

$S^2_x = (1 – S^2_e) \times 100$

S^2_e = risk value/S^2_y
Where in detail:
S^2_x = explained variation,
S^2_e = unexplained variation
S^2_y = variance of the root node (standard deviation of the root node)^2.

Data analysis

The data were analysed using Statistical Package for Social Sciences (IBM SPSS, 2016) software. A probability of 5% for significance was used and a probability of 1% for highly significant between traits was also used. Descriptive statistics such as mean, standard error, standard deviation, minimum, maximum, and coefficient of variation were calculated. Pearson's correlation coefficient was used to estimate the relationships between all the measured traits while the classification and regression tree (CART) was computed to develop a model.

RESULTS AND DISCUSSION

Descriptive statistics for body weight (kg) and body measurements (cm) of non-descript goas is presented in Table 1. The average mean±SE body weight is 25.18±0.77 and the maximum weight of goats sampled is 66.80 while the minimum is 2.70. The coefficient of variation is 57.70 %.

The least square means of live weight and the body measurements obtained in this study were within the range reported by Sowande *et al*. (2010) who worked on West African dwarf goats of similar to with the goats used in this study. Similarly, the average body weight, body length, chest girth were within the ranges reported by Tyasi *et al*. (2021) who reported 25.66±1.49kg body weight of South African non-descript goats of less than or equal to 1 year old of age. Meanwhile, the average value obtained for body weight (25.18±0.77kg) in this study was higher than the value obtained by Yakubu and Mohammed (2012) whole reported body weight of 22.32kg for Red Sokoto goats. The variations could be due to differences in breeds, age and environmental factors like nutrition.

Table 1: Descriptive statistics for body weight (kg) and body measurements (cm) of non-descript goats

Traits	Mean±SE	SD	CV (%)	Maximum	Minimum
BW (kg)	25.18±0.77	14.53	57.70	66.80	2.70
BL (cm)	42.03±0.47	8.95	21.29	65.00	20.00
HW (cm)	42.94±0.39	7.48	17.42	61.00	22.00
RH (cm)	47.13±0.43	8.08	18.69	63.00	25.00
CG (cm)	51.58±0.56	10.65	20.65	74.00	26.00
HL (cm)	40.55±0.31	5.89	16.81	54.00	24.00
FL (cm)	35.03±0.31	5.91	16.87	47.00	7.00
HDL (cm)	19.20±0.15	2.85	14.84	25.00	12.00
EL (cm)	10.84±0.11	2.17	20.02	28.00	7.00
NL (cm)	18.06±0.18	3.44	19.05	28.00	8.00
TL (cm)	14.84±0.18	3.40	22.91	22.00	7.00

SE: Standard Error, CV: Coefficient of Variation, SD: Standard Deviation, BW: Body Weight, BL: Body length, HW: Height at Withers, CG: Chest Girth, RH: Rump Height, BL: Body Length, HL: hind leg, FL: fore leg, HDL: head length, EL: ear length, NL: Neck length, TL: Tail length.

Phenotypic correlations of body weight and body measurements of non-descript goats is presented in Table 2. The phenotypic correlations between body weight and body measurements ranged from low to high values (0.21-0.97; $P \leq 0.05$, $P \leq 0.01$). There is no significant difference between foreleg and ear length. The highest correlation coefficient ($r = 0.97$) was found between HW and RH and the lowest correlation coefficient (r = 0.21) was obtained between FL and EL. The results indicated that BW had a positive correlation with all the body measurements although some are low. However, the use of correlation coefficients is not enough to show the relationship between body weight and body measurements.

A positive relationship was observed between body weight and all the body measurements investigated. Correlation findings indicated that BW had a positive highly significant correlation with body length, height at withers, rump height, chest girth, hind leg, fore leg, head length, neck length, and tail length. The positively high correlations amongst the biometric traits might cause an increase in BW and lead to genetic improvement. The current findings agree with the report of Yakubu and Mohammed (2012), where there is a positive highly significant correlation between body weight and body length, body weight and heart girth in Red Sokoto goats. Yakubu (2009), observations are in harmony with the current study where there is a positive highly significant correlation between BW and withers height, rump height, body length and , heart girth in West African dwarf goats. Norris *et al.* (2015), had a positive highly significant correlation between BW and heart girth. Contrary to the current study, Tyasi *et al*. (2020b) reported that BW showed the lowest correlation with heart girth, and no correlation with rump height in South African non-descript indigenous female goats. Study differences might be due to age group of goats used in the study.

Table 2: Phenotypic correlations of body weight and body measurements of non- descript goats

Traits	BW	BL	HW	RH	CG	HL	FL	HDL	EL	NL	TL
BW		0.94^{**}	0.85^{**}	0.85^{**}	0.93^{**}	0.78^{**}	0.76^{**}	0.86^{**}	0.45^{*}	0.78^{**}	0.76^{**}
BL			0.90^{**}	0.89^{**}	0.95^{**}	0.82^{**}	0.80^{**}	0.91^{**}	0.48^{*}	0.80^{**}	0.80^{**}
HW				0.97^{**}	0.92^{**}	0.91^{**}	0.85^{**}	0.91^{**}	0.49^{*}	0.80^{**}	0.83^{**}
RH					0.93^{**}	0.92^{**}	0.87^{**}	0.91^{**}	0.50^{*}	0.82^{**}	0.83^{**}
CG						0.86^{**}	0.84^{**}	0.93^{**}	0.46^{*}	0.83^{**}	0.83^{**}
HL							0.89^{**}	0.89^{**}	0.46^{*}	0.75^{**}	0.76
FL								0.84^{**}	0.21^{NS}	0.74^{**}	0.74^{**}
HDL									0.47^{*}	0.81^{**}	0.83^{**}
EL										0.39^{*}	0.37^{*}
NL											0.76^{**}
TL											

*P<0.05; **P<0.01; ns: No Significant, BW: Body Weight, BL: Body length, HW: Height at Withers, CG: Chest Girth, RH: Rump Height, BL: Body Length, HL: hind leg, FL: fore leg, HDL: head length, EL: ear length, NL: Neck length, TL: Tail length

Table 3: The importance of each independent (predictor) variable in predicting the body weight of non-descript goats. Chest girth was found as the most important variable (100%), chronologically followed by body length (96.3%), rump height (91.7%), height at withers (91.0%), head length (89.8%), neck length (86.2%), hind leg (72.5%), fore leg (67.6%), tail length (67.1%) and ear length (59.1%). Among the above variables, chest girth, body length, rump height, height at withers, head length and neck length were included in the regression model to predict body weight.

Table 3: Independent variables importance in predicting the body weight of non-descript goats

Independent Variable	Importance	Normalized Importance
CG (cm)	159.593	100.0%
BL (cm)	153.651	96.3%

RH (cm)	146.351	91.7%
HW (cm)	145.163	91.0%
HDL (cm)	143.282	89.8%
NL (cm)	137.510	86.2%
HL (cm)	115.699	72.5%
FL (cm)	107.941	67.6%
TL (cm)	107.074	67.1%
EL (cm)	94.260	59.1%

BL: Body length, HW: Height at Withers, CG: Chest Girth, RH: Rump Height, BL: Body Length, HL: hind leg, FL: fore leg, HDL: head length, EL: ear length, NL: Neck length, TL: Tail length

Figure 1 shows the classification and regression tree model (CART). The model reflected factors that can affect the body weight of Nigerian non-descript goats from three local government areas of Southern Kaduna, Kaduna. Node 0 (25.175 ± 14.33kg; n = 360) was divided according to chest girth into four subgroups as node 1 ≤ 46.0 cm (11.545± 4.458kg; n = 117), node 2 = 46.0cm (20.403 ± 2.269kg; n = 102), node 3 ≤ 53.0cm (32.117 ±4.309kg; n=69), node 4 < 60.0cm (47.432±11.058kg; n=72). Successively, node 2 was further divided into node 5 and node 6. Node 5= 15.0cm (9.285±4.074kg; n=66), node 6> 15.0cm (14.47± 3.009 kg; n = 51). Here, five terminal nodes (nodes 2, 3, 4, 5, and 6) were formed. Node 0, which is called the root node, contains descriptive statistics related to the body weight of non-descript goats.

The mean body weights of animals in nodes 1, 2, 3, 4, 5, and 6 were 11.545, 20.403, 32.117, 47.432, 9.285, and 14.471, respectively. Although the mean body weight of animals in node 4 is higher than other nodes, this information was not enough to base a decision on. Since nodes 2, 3, 4, 5, and 6 were not divided into subgroups, they could be said to be homogenous (terminal nodes). Node 4 offers a better prediction weight (47.432±11.058kg) with a second variance higher $(11.058)^2 = 122.279$.

The variance of the root node or the dependent variable in the current study was:
$S^2_y = (14.533)^2 = 211.209$
The unexplained variation in the body weight was found to be:
S^2_e = risk value (estimated) $\div S^2_y = 33.320 \div 211.209 = 0.158$.
The variation in the dependent variable (body weight) explained by the regression model was:
$S^2_y = 1 - S^2_e = 1 - 0.158 = 0.842 = 84.20\%$.

The classification and regression tree model (CART) algorithm was used in the current study to develop a model to predict the body weight (BW) from chest girth (CG), body length (BL), rump height (RH), height at withers (HW), head length (HDL) and neck length (NL) of Nigerian non-descript goats. The current findings indicated that chest girth (CG), body length (BL), rump height (RH), height at withers (HW), head length (HDL), and neck length (NL) explained 84.2% of the variation in body weight of Nigerian non-descript goats. The model developed from the current study suggests that CG had the highest remarkable role in body weight followed by BL, RH, HW, HDL, and NL, respectively as indicated in Table. The risk value shows the variance within the nodes, and this can be used as a model fitness criterion. The optimal tree obtained in this study explained about 84.2% of the variation in body weight of non-descript goats. This is an indication that the prediction of body weight from body measurements is reliable (Yakubu, 2012). The resulting model is easy to understand and assimilate by humans. The current study is in agreement with the report of Afolayan *et al.* (2006) who reported in Yankasa sheep that chest circumference or chest girth is a good indicator of the live body weight of animals. Similarly, Fourie *et al.* (2002) reported that heart girth or chest girth had the largest influence on the body weight of Dorper rams; and was also the most important contributor to selection index. To maintain good animal husbandry, the measurement of live body weight is essential for breeding, nutrition, and health management. A related study in broiler chickens by Mendes and Akkartal (2009) successfully used regression tree methodology to predict the slaughter weight of broilers. Regression tree analysis has many advantages compared to traditional methods such as multiple regression, logistic regression, discriminant, and cluster analyses.

The current study is slightly varied from the report of Tyasi *et al.* (2021) who reported that body length (BL) had the highest remarkable role in body weight followed by heart girth. Results of the authors disagreed with the current study, where 68.90% of the variability of the BW was explained with withers height, rump height, and abdominal width and chest depth, while withers height played the highest role and chest depth played the lowest role on BW.

Tyasi *et al*. (2020a) performed a study on Potchefstroom Koekkoek laying hens and discovered that wing length played a higher role in body weight than other traits using, followed by beak length, and the traits found on CART explained 57% of the variation in body weight. The reason for variation may be due to species differences.

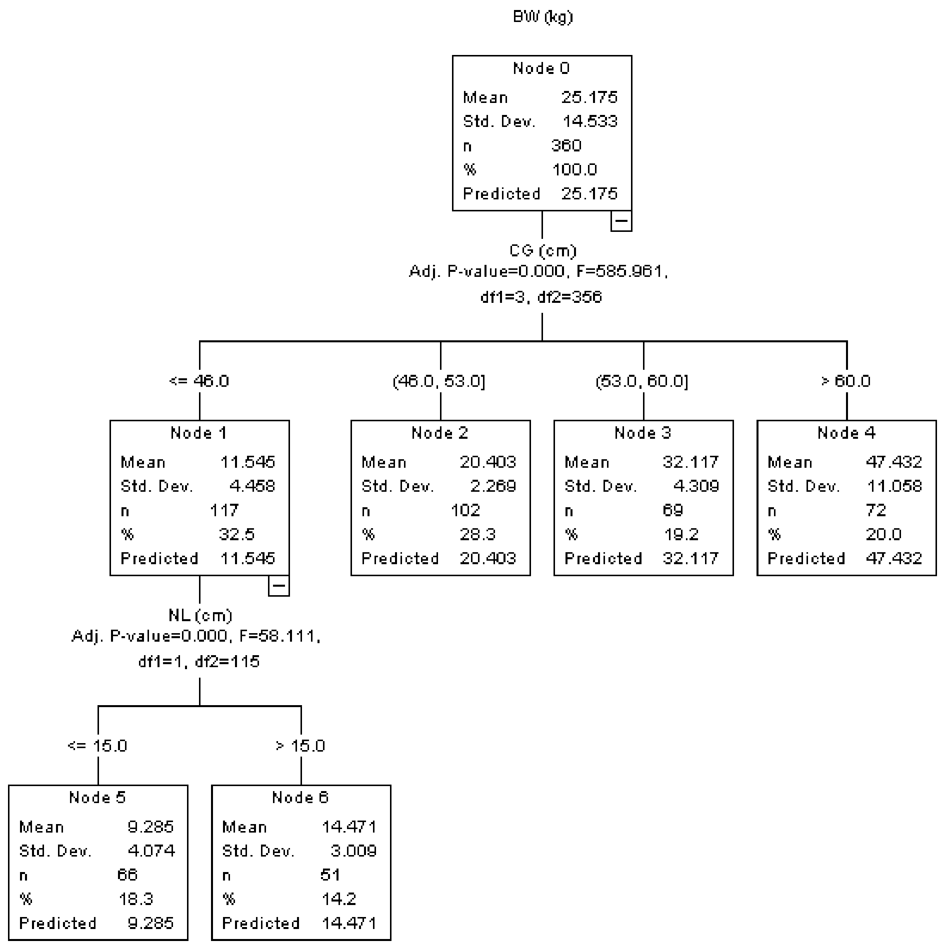

Figure 1. Classification and regression tree model (CART)

CONCLUSION AND RECOMMENDATIONS

It can be concluded that there is a positive highly significant relationship between body weight and biometric traits (body length, height at withers, rump height, chest girth, hind leg, fore leg, head length, neck length, and tail length) of Nigerian non-descript goats in three local government areas of Southern Kaduna, Kaduna State, Nigeria.

The study suggests that the aforementioned biometric traits can be used as a selection criterion to improve the body weight of Nigerian non-descript goats.

The CART model can be used to predict the body weight of Nigerian non-descript goats precisely due to its high coefficient of determination. The model suggests that chest girth alone can be used to predict the body weight of Nigerian non-descript goats.

The results obtained in this study may be used by livestock producers and researchers for determining the feed amount, drug dose, and market price of an animal, in improving the profitability of animal farms, selection, and management purposes, since weight is the pivot on which animal production thrives.

It is recommended that prediction of body weight using biometric traits, especially in rural areas might save farmers' expenses for scales, and help in decision-making for breeding purposes for economically important traits such as body weight. However, further studies need to be performed on the prediction of body weight using the CART algorithm in different goat breeds with more sample sizes.

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