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Original scientific paper

REGRESSION TREE ANALYSIS FOR PREDICTING BODY WEIGHT OF NIGERIAN MUSCOVY DUCK (*Cairina moschata*)

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Oguntunji A. O. (2017): *Regression tree analysis for predicting body weight of Nigerian muscovy duck (Cairina moschata).*- Genetika, vol 49, no.2, 743- 753.
Morphometric parameters and their indices are central to the understanding of the type and function of livestock. The present study was conducted to predict body weight (BWT) of adult Nigerian Muscovy ducks from nine (9) morphometric parameters and seven (7) body indices and also to identify the most important predictor of BWT among them using regression tree analysis (RTA). The experimental birds comprised of 1,020 adult male and female Nigerian Muscovy ducks randomly sampled in Rain Forest (203), Guinea Savanna (298) and Derived Savanna (519) agro-ecological zones. Result of RTA revealed that compactness; body girth and massiveness were the most important independent variables in predicting BWT and were used in constructing RT. The combined effect of the three predictors was very high and explained 91.00% of the observed variation of the target variable (BWT). The optimal regression tree suggested that Muscovy ducks with compactness >5.765 would be fleshy and have highest BWT. The result of the present study could be exploited by animal breeders and breeding companies in selection and improvement of BWT of Muscovy ducks.
Key words: Agro-ecological zones, body indices, compactness, morphometric parameters, Muscovy ducks

INTRODUCTION

Poultry is now by far the largest livestock species worldwide (FAO, 2000), accounting for more than 30% of all animal protein consumption (PERMIN and PEDERGEN, 2000). The Nigerian poultry sector is dominated by indigenous breeds accounting for substantial proportion of internal

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animal protein production. These local avian species are bred under traditional breeding systems and constitute a fast means of bridging the protein gap in most developing countries (JIBIR and USMAN, 2003). Muscovy duck is one of the poultry species classified as indigenous bird in Nigeria and is the most common species of waterfowl in Nigeria. Domestic Muscovy duck is valued throughout the world for its unique rich and flavourful taste, high yield of breast meat, and low calorie content (CHEN *et al*., 2009). The male can become very large and reach 4.5 to 5.5kg in weight while the female has a weight of 2.3 to 2.8kg (SONAIYA and SWAN, 2004). A unique characteristic of this duck is its sexual dimorphism, the male is much bigger than the female (RODENBURG *et al*., 2005). Different reports corroborated this submission that males were about 35-50% (HOFFMAN and CANADA, 1993; PAYNE and WILSON, 1999) and 39.39% (OGUNTUNJI and AYORINDE, 2014) heavier than the females.

Body weight is an important economic trait in farm animals and high premium is attached to it by livestock farmers. This metric trait contributes significantly to the profit margin of livestock farmers, most especially in livestock enterprise where the main target is market weight or dressed meat. Various statistical approaches involving prediction models such as principal component analysis, canonical correlation, factor score analysis, linear, quadratic, cubic and multiple regression models e.t.c. have been employed in investigating relationships between body measurements and body weight and also in predicting the expected improvement of this polygenic trait by animal breeders (CANKAYA and KAYAALP, 2007; YAKUBU *et al.,* 2009; YAKUBU and MUSA-AZARA, 2013; OGUNTUNJI and AYORINDE, 2014).

In spite of the wide application of the aforementioned prediction models in animal improvement programmes, the use and reliability of their results have been limited by myriads of limitations with respect to the underlying assumptions such as normality, constant variance, linearity, multicollinearity (DRAPER and SMITH, 1998) and lack of the ability to capture unspecified, complex inter-relationships across factors (LEI *et al*., 2015). However, in cases where the assumptions are met, the evaluation of complex relationships and interpretation of result is difficult with those models (MENDES and AKKARTAL, 2009). For instance, regression models are largely used to determine the average effect of an independent variable (LEMON *et al*., 2003). Thus, when interventions are developed from regression model results, they are geared toward the average number of the population, without considering the special needs of population sub groups (FORTHOFER and BRYANT, 2000).

The advent of classification and regression tree analysis (CART) has significantly contributed to the circumvention of the limitations associated with the use of the aforementioned prediction models. CART is a non-parametric statistical procedure that identifies mutually exclusive and exhaustive subgroups of a population whose members share common characteristics that influence dependent variables of interest (LEMON *et al*., 2003). This prediction model accommodates both numeric and categorical dependent variables conveniently and the nature of the target/dependent variable determines the name and the steps involved in the analysis without affecting the final result. When the dependent or target variable is categorical, the model is called classification tree while the model is referred to as regression tree when dependent variable is continuous (LEMON *et al*., 2003). Likewise, independent variables can be any combination of categorical and continuous variables (LEMON *et al*., 2003).

The advantages of RTA includes its application to wide array of data such as numeric, categorical, ratings and surviving data (DE'ATH and FABRICUS, 2000). The method is insensitive to outliers and unequal variables of the analysed variables (TITTONELL *et al*., 2008) and has the ability to handle the missing values in both response and explanatory variables (DEA'TH and FABRICUS, 2000; CAMDEVIRAN *et al.,* 2005). They are not affected by the problem of high correlation (multicollinearity problem) among individual variables (CHENG and WANG, 2006, CAMDEVIRAN *et al*., 2005) and are useful to visualise the interaction effects of individual variables on dependent variables (CHENG and WANG, 2006). Since RTA is a non-parametric method, no assumptions are required about the underlying distribution of independent variables (MENDES and AKKARTAL, 2009).

The result generated from the application of this data mining techniques (CART) is pictorial and is called regression or decision tree depending on the nature of dependent variable. The tree is a set of decision nodes connected by means of branches going down from root node to the terminal leaf nodes (PIWCZYNSKI, 2009). Each sub group (node) produced from the tree is typically characterized by either the distribution (categorical response) or mean value (numeric response) of response variable, group size, and the values of the explanatory variables that defined it (DE'ATH and FABRICUS, 2000). The divisions are defined by a simple rule based on a single explanatory variable (GRZESIAK *et al*., 2011) and the size of a tree produced depends on the total number of distinguished sub-sets (DE'ATH and FABRICUS, 2000).

CART has been extensively applied in livestock-related studies, most especially in dairy cattle (GRZESIAK *et al*., 2011; BAYRAM *et al*., 2015; GHIAS *et al*., 2015; YAKUBU *et al*., 2015) and sheep (PIWCZYNSKI, 2009; YAKUBU, 2012). Conversely, the application of this technique to poultry is limited. Of recent, MENDES and AKKARTAL (2009) used RTA in predicting slaughter weight of broilers from two-week linear body parameters while UCKARDES *et al*. (2014) and ORHAN *et al*. (2016) respectively, applied it to predict egg weight of chicken from egg characteristics and to identify genetic and non-genetic factors influencing fertility of quail eggs.

Against this background, the aim of this study was to predict the body weight of adult Nigerian Muscovy duck through morphological parameters and indices, identify the most important predictor of body weight and optimum combination of the levels of predictors using RTA.

MATERIAL AND METHODS

Experimental animals

The experimental birds comprised 1,020 adult male and female Nigerian Muscovy ducks randomly sampled in Rain Forest (203), Derived Savanna (298) and Guinea Savanna (519) agro-ecological zones. These birds were owned by small scale farmers and were reared primarily on free range with little or no feed supplements and medication.

Data collection

Data on body weight (BWT) and nine (9) linear body measurements: body girth (BGT), body length (BDL), wing length (WGL), shank length (SHL), shank circumference (SHC), thigh length (THL), total leg length (TLL), bill length (BLL) and bill width (BLW) were taken in the morning before the birds were released to scavenge. Besides, seven (7) morphological indices: massiveness (MAS), compactness (CMP), condition index (CNI), long leggedness (LLG), bill index (BLI), body index (BDI) and stockiness (STK) were computed from BWT and morphometric parameters.

The methodology used in taking the measurements and anatomical references of the morphological parameters and four (4) morphological indices (MAS, LLG, STK and CNI) were as described by YAKUBU (2011). Besides, CMP, BLI and BDI were computed as follows:

CMP: BWT/BGT x 100
BLI: BLW/BLL x 100
BDI: BDL/BGT x 100

Statistical analysis

Descriptive statistics of the morphometric parameters and indices were computed.

Regression tree analysis

The RT method was applied to predict the response variable (BWT), being a continuous variable from independent variables. The relative importance of the independent variables in constructing RT and predicting the target variable was investigated through independent variable importance values.

The RT was constructed by splitting the root node into child nodes or sub groups using all predictors based upon a question of the form: is $X \leq d$? Where X is a variable in the data set, and d is a real number (YAKUBU, 2012). The root node generated contains the descriptive statistics of the population under study but is impure or homogenous.

Since the root node is impure, attempts were further made to split the parent node and generate child nodes that were pure or homogenous (terminal nodes). This is necessary because the purpose of RTA is to produce terminal nodes which are homogenous with respect to the target variable (BEVILACQUA *et al*., 2003; CAMDEVIREN *et al*., 2005) and to separate the terminal node from the child nodes homogeneity at the highest level, and to exclude those variables that are not related to the dependent variable (UCKARDES *et al*., 2014).

Splitting of parent node to terminal nodes is critical to RT construction and application of its result; because terminal nodes are where predictions and inferences are made (LEI *et al*., 2015). In choosing the best splitter among the predicting variables, the Least Square Deviation (LSD) was employed as a measure of purity of the child nodes (BEVILACQUA *et al*., 2003). This method of selecting the best splitter is repeated for each of the two child nodes resulting from the initial split. Then, 10-fold cross-validation an error estimation method known to be the most acceptable method of estimation in such cases (CAMDEVIREN *et al*., 2005) was employed to provide estimates of the future prediction error for each sub-tree (HONEYCUTT and GIBSON, 2004).

In addition, since the dependent variable (BWT) is continuous, the explained variation observed in the target variable was estimated as follows:

$S^2_x = (1 - S^2_e) \times 100$

S^2_e = risk value/S^2_y

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

All statistical analyses were carried out with statistical package for social science (SPSS) version 16 (2001).

RESULTS

The descriptive statistics of the dependent and independent variables and the risk value (0.027) are presented in Table 1. The variance of the root node or dependent variable (BWT) was $S^2y = (0.551)^2 = (0.3036)$.

The unexplained variation in the BWT was calculated as:

S^2_e = risk value/S^2_y = 0.027/0.3036 = 0.09

The explained variation observed in the response variable (BWT) was then calculated from the unexplained variation as: $S^2_x = (1 - S^2_e) \times 100 = (1 - 0.09) \times 100 = 91.00\%$

Table 1. Descriptive statistics of dependent and independent variables

Variable	Mean (±sd)
Body weight	1.89 ± 0.55
Body girth	41.02 ± 4.74
Body length	25.86 ± 3.96
Wing length	29.11 ± 4.96
Shank length	4.89 ± 0.78
Shank thickness	4.63 ± 0.63
Thigh length	10.53 ± 1.58
Bill length	5.28 ± 0.62
Bill width	3.20 ± 0.31
Total leg length	15.48 ± 2.12
Massiveness	7.27 ± 1.48
Stockiness	160.43 ± 18.37
Bill index	61.15± 8.05
Condition index	6.47 ± 1.27
Long leggedness	60.54 ± 8.31
Body index	63.15± 7.21
Compactness	4.56 ± 0.90

Risk value: 0.027 Standard error: 0.002

The evaluation of the relative importance of the independent variables in predicting BWT of adult Muscovy ducks indicated that CMP, BGT and MAS in descending order were the most important (Figure 1) and these three independent variables were subsequently used to construct optimal regression tree (Figure 2).

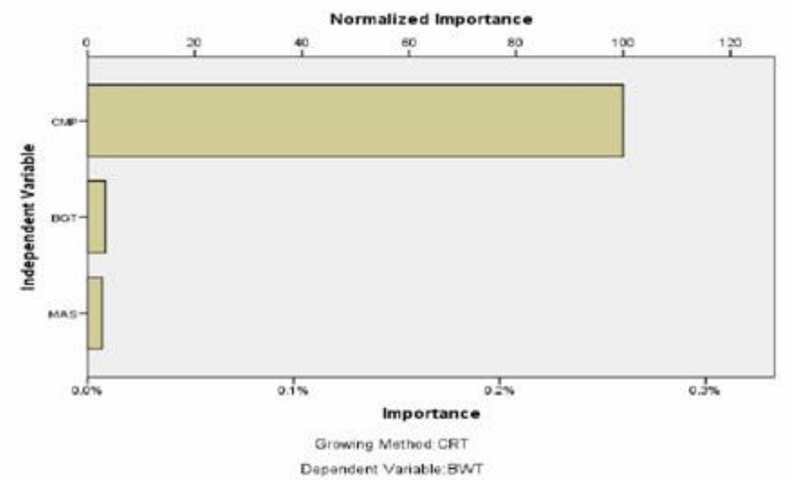

Figure 1. Independent variable importance

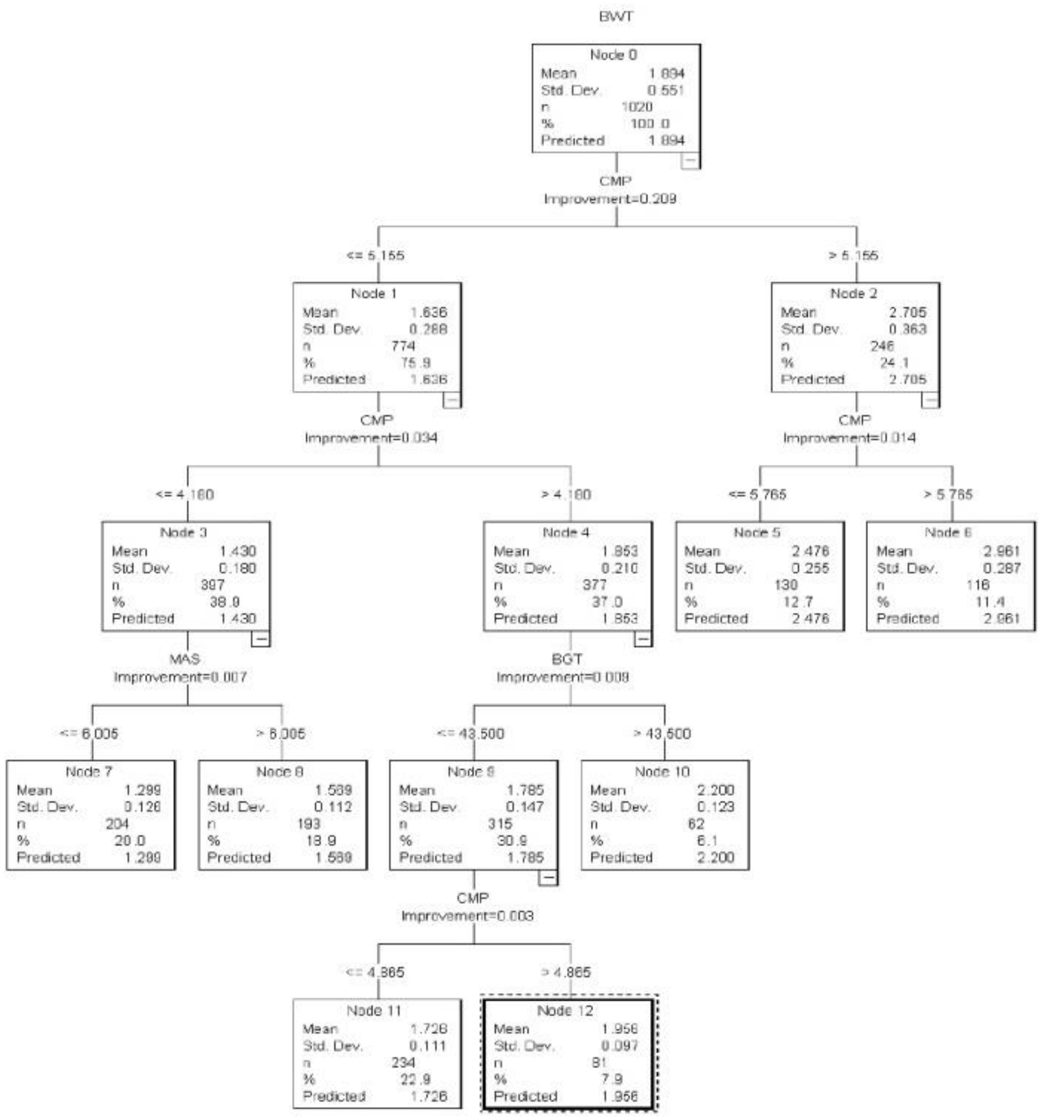

Figure 2. The optimum regression tree structure

Further investigation to the impact of contribution of the three most important independent variables to predict BWT revealed CMP as the best predictor. In addition, using the three most important variables in constructing RT and estimating BWT of adult Muscovy ducks resulted in regression optimal tree with 13 nodes and 7 terminal nodes (5, 6, 7, 8, 10, 11 and 12) (Figure 2).

The two child nodes (1 and 2) branching out of the parent node (node 0) was based on CMP. Ducks captured in node 1 had lower CMP (<5.155) and lower predicted BWT (1.636kg) compared to those in node 2 with higher CMP (>5.155) and predicted BWT (2.705kg).

Furthermore, on the basis of CMP, node 1 split into two sub-groups; nodes 3 (<4.180) and 4 (>4.180). Birds classified in node 4 were fewer compared to those in node 3 but had superior estimated BWT. Similarly, on the basis of CMP, node 2 divided into 2 sub-groups (5 and 6) and ducks with CMP >2.961 (node 6) had higher estimated BWT than those with CMP >5.765 (node 5). The predicted BWTs of ducks in nodes 5 and 6 were higher than that observed in the root node. Besides, these two nodes were terminal nodes.

The splitting variable of node 3 into sub-groups 7 and 8 was MAS. Birds in node 8 had higher MAS (>6.005) and were predicted to have higher BWT (1.569kg) compared to birds in node 7 with lower MAS (< 6.005) and BWT (1.299kg). These two child nodes were homogenous and terminal. Node 4 divided on the basis of BGT to two sub groups; nodes 9 (<43.500) and 10 (>43.500); however, node 10 was homogenous and was also a terminal child node. The relative importance of CMP in predicting BWT of the population under study resurfaced again, being the splitting variable for node 9 into child nodes11 (<4.865) and 12 (>4.865). In addition, child nodes 11 and 12 were terminal nodes since they could not be split further.

DISCUSSION

To the best of the knowledge of the author, the present study is the first to report on prediction of body weight of adult Muscovy ducks and waterfowl in general from morphometric parameters and indices using RTA; thus, paucity of corresponding data on waterfowls to discuss the findings critically. Nevertheless, the results were discussed with related reports on other poultry species.

It could be inferred from the regression tree that of the two morphological indices (CMP and MAS) included in prediction of response variable, only CMP contributed significantly to the estimation of the BWT. A possible reason for this disparity could be adduced to the underlying variables used to generate the two body indices. Synthesis of reports of avian researchers on relationship between linear body measurements and live weight of poultry showed that BGT had higher correlation with body weight of poultry species such as guinea fowl (OGAH, 2013); Muscovy ducks (OGAH *et al*., 2011) and chicken (MENDES, 2009) than BDL. Since this quantitative trait (BGT) had higher correlation with target variable (data not shown but presented as supplementary material) and is also one of the variables used in generating CMP, this could be another possible underlying factor for high impact of CMP in predicting BWT in the present study. Furthermore, it is noteworthy that the general trend in this study was an improvement in predicted BWT in nodes 5 and 6 with CMP only or as one of the splitting variables (nodes 10 and 12); thus emphasizing the importance of this body index as the best predictor of BWT of the population of Muscovy duck under study.

It is worth emphasizing that two of the three predicting variables used in constructing RT were morphological indices. This suggests that body indices were more important and superior in predicting BWT of this waterfowl than linear body measurements. The assessment of the powers of body measurements in the estimation of weights and the accuracies of body weights in the estimation of size among livestock species has been widely reported (SALAKO, 2006). Linear body parameters have been widely used in predicting body weight of livestock; however, the reliability of these body parameters is limited and the reported limitation of these morphometric variables in predicting body weight of livestock has been attributed to the significant influence of husbandry system on certain body measurements (ALDERSON, 1999). Nevertheless, SALAKO (2006) suggested that application of different combinations of measurements will likely be more useful; and body indices were considered as a superior option for assessment of weight because it incorporates measures of desirable conformation, namely length and balance (ALDERSON, 1999).

Putting into consideration the pictorial presentation of the combination of different levels of the predicting variables in child nodes (7, 8, 9, 10, 11 and 12) which enhances understanding and interpretation of the result; this trend aligns with earlier reports that RTA has the ability to capture unspecified, complex inter-relationships of variables through an easily interpretable tree diagram better than regression models (LEI *et al*., 2015) without compromising reliability of the expected result. Besides, the simplicity of result as demonstrated in different combination of independent variables would assist animal breeders in identifying optimum combination of variables/factors involved in livestock improvement.

The generated risk value in the present study was low (0.027) and shows the variance within the nodes and can be used as model fitness criterion (MENDES and AKKARTAL, 2009). In addition, the risk value serves as an indicator of goodness of the model; the lower the risk value the better the model (MENDES and AKKARTAL, 2009). The estimated explained variation of the target variable (BWT) was very high (91.11%), this implies that 91.00% of the observed variation in the predicted BWT of the population under study can be explained by CMP, BGT and MAS used in constructing the optimal regression tree. High explained variation implies further that the RT model generated was reliable and the three independent variables (CMP, MAS and BGT) used in constructing optimal regression tree were reliable and were also good predictors of body weight of adult Muscovy ducks.

CONCLUSION

The RTA demonstrated the practical possibility of combining different morphological parameters and indices in predicting BWT of adult Nigerian Muscovy ducks. Putting into consideration the relative importance of CMP in constructing RT, it could be inferred that Muscovy ducks with higher CMP (>5.155) would be 'meaty'. The result of the present study demonstrated further that selecting breeding stock based on this morphological index (CMP) alone is sufficient to improve BWT. The result could be exploited by livestock farmers, animal breeders and breeding companies in improvement of BWT of Muscovy duck by selecting those having higher CMP (>5.765) as the parent stock to produce broiler strain of this waterfowl. However, in situations whereby indices are not known most especially in rural areas by peasant farmers, selection of the parents of future generation could be based on ducks with higher BGT (> 43.5) since it is one of the predictors of CMP and also the second most important variable in predicting BWT of Muscovy ducks.

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REGRESIONA ANLIZA ZA PREDVIĐANJE TEŽINE TELA KOD NIGERISKE MUSKOVI PATKE (*Cairina moschata*)

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Izvod

Morfometriski parametri i njihovi indeksi su centralnoi za razumevanje tipa i funkcije živine. Prezentovan rad je sproveden u cilju predviđanja težine tela odrasle Nigeriske Muskovi patke za 9 morfometriskih parametati I 7 indeksa I da se identifikuju najvažniji prediktori BWT između njih korišćenjem regresione analize (regression tree analysis, RTA). Ekspreimentalne ptice (1,020 odraslih Nigerian Muskovi pataka) su nasumično prikupljene u Rain Forest (203), Guinea Savanna (298) i Derived Savanna (519) agro-ekološkim zonama. Rezultati RTA su pokazali kompaktonst, obim tela i masivnost su najvažnije nezavisne varijabile u predviđanju BWT i korišćene su za konstrukciju RT. Kompaktnost je bila najbolja od tri prediktora i dala je najbolje izračunavanje BWT. Kombinovani efekat tri prediktora je bio veoma visok i objašnjava 91.11% dobijene varijacije viljane varijabile (BWT). Optimalno regresiono drvo sugeriše da Muskovi patke sa kompaktnosti >5.765 mogu biit mesnate i imaju najveći BWT. Dobijeni rezultait mogu biti od koristi oplemenjivačima životinja i oplemenjivačkim kućama u selekciji i povećanju BWT Muskovi patke.

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