# Multivariate approach in the evaluation of performance and carcass traits of Suffolk crossbred lambs

Abordagem multivariada na avaliação de desempenho e características de carcaça de cordeiros cruzados Suffolk

Vitor Antonio Soukef Gobbi<sup>1</sup> <sup>(i)</sup>, Nathalia Ferraz<sup>2</sup> <sup>(i)</sup>, Joely Ferreira Figueiredo Bittar<sup>1</sup> <sup>(i)</sup>, Eustáquio Resende Bittar<sup>1</sup> <sup>(i)</sup>, Guilherme Costa Venturini<sup>1\*</sup> <sup>(i)</sup>

**ABSTRACT:** Evaluate associations between economically important traits is crucial as it considers the intensity of the relationship between variables and aids in excluding redundant traits, thereby facilitating the early selection of animals. The aim of this study was to evaluate the association between performance and carcass traits of crossbred lambs and to identify a trait that demonstrates higher discriminatory power, to assisting in the selection of animals. Was used 61 male lambs were used to assess trait associations via Pearson correlation, Euclidean distance, and principal components (PC). With cluster analysis, we observed the formation of two distinct groups (Euclidean distance), indicating significant dissimilarity between the groups. This dissimilarity was attributed to the group of variables RP, TD, TW, and RW, while the other group was characterized by LP, SW, HCW, and ECC. It was observed that performance with carcass traits presented linear correlations between 0.28 to 0.63. Through multivariate analysis, it was possible to 4 PCs selected that together explained 78.35% of the total variance of the data, with eigenvalues greater than 0.70. Through the first principal component, which retains the highest percentage of total variance (38.94%), redundant or non-discriminant descriptors were discarded. Within this component, four traits (SW, ECC, RW, and HCW) were considered the most important in describing the variability of the dataset studied. However, slaughter weight would be the selectable variable to represent the other carcass traits, due to greater discriminatory power. This trait can be considered easier to measure and more economical for breeders.

KEYWORDS: euclidean distance; pearson correlation; principal components; slaughter weight.

**RESUMO:** Avaliar associações entre características economicamente importantes é crucial, pois considera a intensidade da relação entre as variáveis e auxilia na exclusão de características redundantes, facilitando assim a seleção precoce dos animais. O objetivo deste estudo foi avaliar a associação entre características de desempenho e de caraça de cordeiros cruzados e identificar uma característica que demonstre maior poder discriminatório, auxiliando na seleção dos animais. Foram utilizados 61 cordeiros machos para avaliar as associações entre características através da correlação de Pearson, distância euclidiana e componentes principais (PC). Com análise de agrupamento, foi observado a formação de dois grupos distintos (Distância Euclidiana), indicando dissimilaridade significativa entre os grupos. Essa dissimilaridade foi atribuída ao grupo de variáveis RP, TD, TW e RW, enquanto o outro grupo foi caracterizado por LP, SW, HCW e ECC. Observou-se que o desempenho com as características de carcaça apresentou correlações lineares entre 0,28 e 0,63. Através da análise multivariada, foram selecionados 4 PCs que juntos explicaram 78,35% da variância total dos dados, com autovalores maiores que 0,70. Através do primeiro componente principal, que retém o maior percentual de variância total (38,94%), descritores redundantes ou não discriminatórios foram descartados. Dentro deste componente, quatro características (SW, ECC, RW e HCW) foram consideradas as mais importantes na descrição da variabilidade do conjunto de dados estudado. No entanto, o peso ao abate seria a variável selecionável para representar as demais características de carcaça, devido ao maior poder discriminatório. Essa característica pode ser considerada mais fácil de medir e mais econômica para os criadores.

PALAVRAS-CHAVE: distância euclidiana; correlação de Pearson; componentes principais; peso ao abate.

<sup>1</sup>Universidade de Uberaba -UNIUBE, Brasil <sup>2</sup>Universidad de la Republica Uruguay, UDELAR, Uruguai

\*Corresponding author: guilherme.venturini@uniube.br

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### INTRODUCTION

The continuous effort to enhance the quality of lamb meat is directly linked to the demands of the consumer market, which is becoming increasingly discerning. In this context, animal protein production systems aim to select animals that reach slaughter weight at earlier ages, thus producing standardized carcasses and meats with desired traits, such as tenderness and flavor. However, it is observed that there is a need to increase the amount of animal protein year after year, as the global population is expected to reach approximately 9.8 billion by 2050 (Fao, 2011; Marzi et al., 2021). Krishnan et al. (2020) emphasized that there will be a need for a significant increase in food production, estimated at around 70% by 2050. However, it should be emphasized that the focus should not solely be on increasing animal protein production but also on improving the physicochemical traits of meat. With this, Brazil, given its expansive territory, diverse climates, and favorable environments for food production (both animal- and plant-based), stands out as a key player on the global stage (Onu, 2017).

To achieve optimal production and quality parameters in sheep farming, it is essential to attain slaughter weight earlier age, thereby enabling the slaughtering of lambs at between six to eight months. This early slaughter age not only benefits the final consumer in terms of meat quality but also ensures greater profitability for the breeder. Several authors have noted the existence of phenotypic and genetic correlations among slaughter weight, carcass weight, and meat quality (Rajkumar *et al.*, 2014; Bautista-Diaz *et al.*, 2020; Landim *et al.*, 2021). It has also been reported that carcass parameters, such as weight and conformation, can be utilized to assess carcass and meat quality, enabling the prediction of consumer acceptability. This is possible because these parameters are associated with certain meat traits, such as intramuscular fat content, tenderness, and juiciness.

Numerous traits can be targeted for genetic improvement in animal husbandry, including body weight (Gizaw *et al.*, 2018; Oliveira *et al.*, 2021) and carcass traits (Landim *et al.*, 2021). However, some traits may become redundant due to their high linear and genetic associations. Therefore, the ongoing pursuit of easily measurable traits exhibiting strong associations (both phenotypically and genotypically), particularly those related to hot carcass weight and meat quality, is fundamental to increasing breeder profitability.

Additionally, for the most effective evaluation of animals and to apply selection pressure, it is essential to employ statistical methods that assess linear associations and identify redundant traits, thereby facilitating animal selection. To assess the associations between traits, various statistical tools, such as phenotypic correlation (Pearson's linear correlation) and multivariate analyses, including principal components, can be employed. These analyses can significantly enhance sheep production systems by eliminating redundant traits and subsequently reducing both the time and cost involved in data collection. In this context, studies have applied associations between age at slaughter and thoracic perimeter, body length, and rump width, as well as measurements taken directly on the carcass (Gomes *et al.*, 2021; Atac; Altincekic, 2023). The present study aimed to analyze the relationship between performance and carcass traits and to identify, through principal component analysis, the traits that represent the greatest phenotypic variability in the analyzed dataset of Suffolk crossbred lambs finished in a feedlot.

#### **MATERIAL AND METHODS**

This study was approved by the Animal Experimentation Ethics Committee 009/2020, Uniube – Uberaba University, MG. Was used 61 uncastrated male Suffolk crossbred lambs with an average slaughter weight of 35 kg. The animals were transported to a slaughterhouse, where they were kept in stalls and fasted for 16 hours. Slaughter was carried out in accordance with the standards of humane slaughter at the commercial slaughterhouse, under the State Inspection Service (SISP).

The traits analyzed in this study included Slaughter Weight (SW), Hot Carcass Weight (HCW), External Carcass Length (ECC) - measured as the distance between the base of the tail and the neck, Rump Width (RW) - defined as the maximum width between the trochanters of the femurs, Rump Perimeter (RP) - determined based on the perimeter between the femur trochanters, Thoracic Width (TW) - representing the maximum width of this anatomical region, Thoracic Depth (TD) - measured as the distance between the sternum and the back of the palette, and Leg Perimeter (LP). After data collection, the information was analyzed for consistency and descriptive statistics were generated, as presented in Table 1.

To determine the linear association between all traits involved in this study, we used Pearson's correlation using R software (R Development Core Team, 2020), considering associations significant at the 5% level (P < 0.05). Furthermore, multivariate analysis was used to evaluate similarities between the variables and verify which of them would present greater discriminating power. These analyses, as discussed in the studies by Reys (1997), Montoro et al. (2019), and Correddu et al. (2021), utilize a correlation matrix to transform the original variables X1, X2, ..., Xp into a new set of variables known as principal components Z1 (PC1), Z2 (PC2), ..., Zp (PCp). It is essential to note that these new sets of variables are uncorrelated. Each principal component represents a percentage of the total variance of the data and is presented in descending order, based on the amount of variation attributed to them. The primary advantage of this principal component analysis is the reduction of the number of variables under consideration.

The choice of principal components that account for the majority of the phenotypic variation in the dataset can be determined using Kaiser's criterion, which states that eigenvalues should be greater than one, and also by considering the sum of the percentage of total variance explained by the first

Trait	Mean	SD	Min	Max	CV (%)
ECC (cm)	71.62	3.47	63.00	79.00	4.85
RW (cm)	38.34	2.71	32.00	43.50	7.06
RP (cm)	32.03	1.62	28.50	38.50	5.05
TW (cm)	49.67	4.96	33.00	59.00	9.98
TD (cm)	54.74	4.98	36.50	68.00	9.09
LP (cm)	41.21	1.97	36.00	45.00	4.77
HCW (kg)	19.47	2.61	13.70	24.70	13.42
SW (kg)	44.18	5.46	32.80	54.20	12.36

Table 1. Descriptive statistics of	performance and carcass tra	its of Suffolk crossbrea	d lambs finished in feedlot.

SD – standard deviation; Min – Minimum; Max – Maximum; CV- Coefficient of variation. ECC – External Carcass Length; RW – Rump Width; RP – Rump Perimeter; TW – Thoracic Width; TD – Thorax Depth; LP – Leg Perimeter; HCW – Hot Carcass Weight; SW – Slaughter Weight.

principal components, about 70% (Kaiser, 1960; Montoro *et al.*, 2019). In this context, the results of the analysis demonstrate that the first principal component accounts for the majority of the total phenotypic variance, while the second principal component explains the second-largest portion of this total variance, and so forth, until the cumulative variance reaches 100% (Venturini *et al.*, 2013).

The calculation of a principal component j (PCj) can be obtained as follows:  $PC_j = a_{j1}X_1 + a_{j2}X_2 + \dots + a_{j2}X_z$ , where j is 1, 2, 3, ..., 8 and z is 1, 2, 3, ..., 8,  $a_{jz}$  is the z<sup>th</sup> principal component, and X<sub>z</sub> is the j<sup>th</sup> value of the original variable. The standardized coefficients are calculated as follows:  $a_{jz} = \frac{eigenvector_{jz}}{\sqrt{eigenvalue_z}}$ , where  $a^{jz}$  represents the standardized coefficient for the phenotypic values of the j<sup>th</sup> variable in the z<sup>th</sup> principal component.

The multivariate analysis, including dendrogram, estimates of the variances (eigenvalues -  $\lambda_i$ , total variance - %, accumulated variance, and PCA), was conducted using Statistica 8.0 software (Statistica 8.0, Statsoft Inc., Tulsa, OK), the discrimination criteria being based on the formation of homogeneous groups based on the similarity between observations using Euclidean distance, eigenvalues greater than 0.70, besides identification and maximization of the total variation of the data (above 70%), represented by principal components (CORREDDU *et al.*, 2021). Therefore, discriminant analysis was used to assess the discrimination capability among different groups based on specific traits and, thus, identify which variables contribute significantly to the separation between the groups. This led to a more in-depth understanding of the relationships among the studied traits.

#### RESULTS

The phenotypic correlation between performance and carcass traits of Suffolk crossbred lambs finished in the feedlot ranged from -0.15 (RW vs. LP) to 0.63 (HCW vs. SW) (Table 2). Among these, traits that showed significant correlations (P < 0.05) with the two traditional selection traits (SW and HCW) included SW with ECC (0.61), RW (0.35), RP (0.50), TW (0.53), TD (0.28), LP (0.40), HCW (0.63), and HCW with ECC (0.37), TW (0.29), and LP (0.30). Other significant correlations (P < 0.05) were observed between ECC and TW (0.30), ECC and LP (0.44), RW and TW (0.28), RP and TW (0.32), RW and TD (0.35), and TW and TD (0.47).

The multivariate analysis using cluster analysis (Figure 1) revealed two significantly dissimilar groups when Ward's method with Euclidean distance was employed, with a linkage distance set at 10. The first group comprised ECC, HCW, SW, and LP, while the second group included RW, TW, TD, and RP. However, the retention of only two groups did not account for the major portion of the variation observed in the formation of principal components. Consequently, the results obtained from the principal component analysis indicated that four principal components should be selected: PC1, PC2, PC3, and PC4 (Table 3).

The results of the PC analysis demonstrated that from 8 initial dimensions (ECC, RW, RP, TW, TD, LP, HCW, and SW), only 4 principal components collectively captured 78.40% of the phenotypic value variance, with PC1 contributing 38.93%, PC2 18.79%, PC3 10.76%, and PC4 9.86% (Table 3). Each of these components exhibited eigenvalues exceeding 0.70. The variables projected in the coordinate plane (Figure 2) and the weighting coefficients (eigenvectors) (Table 3), it was observed that in Factor 1 (PC1), the performance and carcass traits had negative eigenvectors ranging from -0.44 (LP) to -0.91 (SW). In Factor 2 (PC2), this variation ranged from -0.68 (LP) to 0.64 (TD), while in Factor 3 (PC3), it ranged from -0.60 (RP) to 0.55 (RW), and in Factor 4 (PC4), it ranged from -0.46 (RP) to 0.41 (TD).

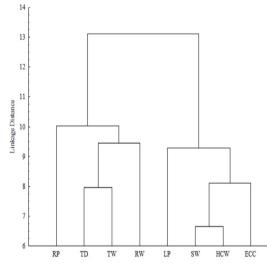
The trait that retained the most phenotypic variation in Factor 1 (PC1) was SW (-0.91), followed by ECC and RW (-0.69), and HCW (-0.64) (Table 3 and Figure 2 A). In PC2, it was observed that the TD and LP traits had the highest eigenvectors (-0.68 and 0.64, respectively) (Table 3 and Figure 2 A). Moreover, in PC3 and PC4, the RP trait stood out as it retained the most phenotypic variation, with an eigenvector of -0.60 and -0.48, respectively (Table 3 and Figure 2 B, C). Additionally, in PC1, which accounted for 38.93% of the total variance, a dissimilarity (or lack of association) was observed between SW, HCW, ECC, and LP with RP, TW, RW, and TD.

#### DISCUSSION

The SW trait presented a medium to high magnitude of linear correlation with ECC, RW, RP, TT, TD, LP, and PCC. Similar results were found in a study that evaluated multivariate techniques in the analysis of carcass characteristics of Morada Nova sheep, in which a significant association was found between SW and HCW, TP, LP, RW, and RP (Guedes; Ribeiro; Carvalho, 2018). Ribeiro *et al.* (2018) used principal components to assess the in vivo and carcass conformations of crossbred Anglo-Nubian goats and observed high correlation coefficients between SW and ECC (0.91) and SW with RP (0.71), and moderate correlations between SW and TD (0.46) and SW with PR (0.31). With that, one can consider the slaughter weight of small ruminants as a selection goal, as this trait may bring substantial gains in carcass traits.

Reinforcing this association, Rajkumar *et al.* (2014) evaluated a linear association between slaughter weight with carcass traits and the meat quality of lambs. The authors observed that animals with higher slaughter weight had significantly (p < 0.05) higher lean fat content in their carcasses and better organoleptic qualities in their meat compared to animals with lighter weights at slaughter. Bautista-Díaz *et al.* (2020) studied the carcass traits of sheep using body measurements and indicated that these measurements can serve as an accurate and reliable tool for predicting carcass traits in these lambs. With this, it is possible to say that selection through performance traits can lead to increased productivity due to this relationship with carcass traits that are considered more expensive to evaluate. However, for greater reliability, the utilization of principal components becomes crucial. Those analyses not only evaluate and reduce the dimensionality of the original set of variables but also identify whether a trait possesses the most effective discriminatory power.

The results of the principal components analysis demonstrated its importance in reducing the number of variables, considering there were 8 original variables. According to Kaiser (1960), the eigenvalues for the selection of principal components must be greater than 1, and in this context, only the two main components, PC1 and PC2, responded to this criterion (Table 3). This result is important, as it reduces the original



ECC – External Carcass Length; RW – Rump Width; RP – Rump Perimeter; TW – Thoracic Width; TD – Thorax Depth; LP – Leg Perimeter; HCW – Hot Carcass Weight; SW – Slaughter Weight.

**Figure 1.** Dendrogram of the eight variables related with performance and carcass traits of crossbred lambs.

Trait	ECC	RW	RP	тw	TD	LP	HCW	SW
ECC	-	0,23 (0,07)	0,20 (0,12)	0,30* (0,02)	0,12 (0,37)	0,44** (0,0003)	0,37** (0,003)	0,61** (<0,0001)
RW		-	0,16 (0,24)	0,28* (0,03)	0,35** (0,006)	-0,15 (0,24)	0,14 (0,27)	0,35** (0,005)
RP			-	0,32** (0,01)	0,23 (0,07)	0,11 (0,39)	0,21 (0,11)	0,50** (<0,0001)
TW				-	0,47** (0,0001)	0,16 (0,22)	0,29* (0,02)	0,53** (<0,0001)
TD					-	-0,06 (0,63)	0,06 (0,67)	0,28* (0,03)
LP						-	0,30* (0,02)	0,40** (0,003)
HCW							-	0,63** (<0,0001)
SW								-

Table 2. Pearson correlations coefficient and p-values (in parentheses) for performance and carcass traits of Suffolk crossbred lambs in feedlot.

ECC – External Carcass Length; RW – Rump Width; RP – Rump Perimeter; TW – Thoracic Width; TD – Thorax Depth; LP – Leg Perimeter; HCW – Hot Carcass Weight; SW – Slaughter Weight.

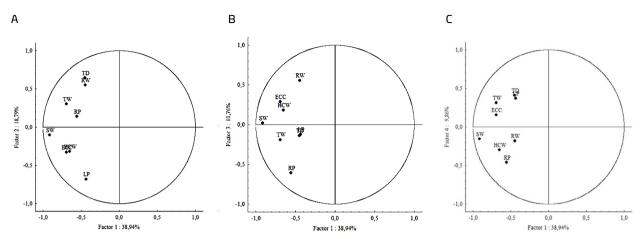


Figure 2. Principal component analysis with the phenotypic values of the performance and carcass traits of crossbred lambs. 2a) Factor1 vs. Factor2; 2b) Factor1 vs. Factor2 and 2c) Factor1 vs. Factor4.

**Table 3.** Estimates of the variances (Eigenvalues  $\lambda_i$ ), total variance (%) and accumulated variance (%) of the eight principal components (PC) and weighting coefficients of the principal components maintained, considering the traits in order of major importance related with performance and carcass traits of Suffolk crossbred lambs.

PC	Eigenvalue ( $\lambda_i$ )	Total Variance (%)	Cumulative Eigenvalue	Cumulative Variance (%)
1	3.11	38.93	3.11	38.93
2	1.50	18.79	4.62	57.72
З	0.86	10.76	5.48	68.49
4	0.78	9.86	6.27	78.40
5	0.66	8.29	6.93	86.65
6	0.46	5.73	7.40	92.38
7	0.42	5.29	7.81	97.68
8	0.18	2.32	8.00	100.00
TRAITS	PC1	PC2	PC3	PC4
ECC	-0,69	-0,32	0,28	0,16
RW	-0,45	0,55	0,55	-0,18
RP	-0,55	0,14	-0,60	-0,46
TW	-0,69	0,30	-0,19	0,31
TD	-0,45	0,64	-0,14	0,41
LP	-0,44	-0,68	-0,12	0,37
HCW	-0,64	-0,32	0,18	-0,30
SW	-0,91	-0,10	0,02	-0,16

ECC – External Carcass Length; RW – Rump Width; RP – Rump Perimeter; TW – Thoracic Width; TD – Thorax Depth; LP – Leg Perimeter; HCW – Hot Carcass Weight; SW – Slaughter Weight.

variables to less than half. However, the percentage of cumulative variance with only these components (PC1 and PC2) did not exceed 70% (57.72%), as observed by other authors (Dominguez; Goodall; Todd, 2015; Correddu *et al.*, 2021). In their evaluation of principal component analysis in laying hen production traits, Paiva *et al.* (2010) emphasized the selection of principal components exceeding 70% or eigenvalues greater than 0.70. This observation is also echoed in the literature, with criteria above 70% considered satisfactory for selecting the number of principal components (Dominguez; Goodall; Todd, 2015; Correddu *et al.*, 2021). Consequently, it was necessary to consider four principal components (PC1, PC2, PC3, and PC4) to ensure a cumulative percentage of variance equal to 78.40% (Table 3).

In a study of New Zealand lambs, Ngo *et al.* (2015) similarly did not achieve cumulative variance above 70% until the fifth principal component. Similar behavior was observed in the studies of Guedes; Ribeiro; Carvalho (2018), which focused on the Morada Nova breed of sheep. They observed cumulative variance above 70% (74.98%) with 4 PCs, which differed from Ribeiro *et al.* (2018). They evaluated Anglo-Nubian crossbred goats and, with 3 PCs, achieved 72.81% of cumulative variance. Based on these results, it can be confirmed that principal components provide suitable adjustments for evaluating the often-complex correlations between several traits of economic interest. The dimensionality reduction achieved through principal component analysis is due to the moderate to high correlations among the various variables. This observation was also underscored by Ribeiro *et al.* (2018) and Leal *et al.* (2022).

It was observed that SW in Factor 1 (PC1) exhibited a stronger association with ECC and HCW, and a weaker phenotypic association with LP (Figure 2A). However, in the PC2 dimension, there was less discrimination among the associations for SW with the other traits, as the SW projection in PC2 was close to the intersection of the axes (near 0). The variables that showed stronger phenotypic associations were TD with RW; a weaker phenotypic association was observed between LP and ECC, and HCW (Figure 2A). Furthermore, in the case of PC4, it was noted that the RP trait displayed a stronger association with HCW and RW, as observed in PC4 (Figure 2C). These results, found in the present study and in the literature, not only provide important understanding about the relationships between the evaluated traits, but also offer valuable information for improving selection strategies based on performance traits that seek to optimize carcass and meat traits in small ruminants.

## CONCLUSION

In conclusion, the variable slaughter weight was identified as the representative of other carcass traits due to its higher discriminatory power. Moreover, this trait can be deemed more convenient to measure and cost-effective for breeders.

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