Research Article

A Tool for Predicting Live Weight in Huacaya Alpacas from Southern Peru

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Abstract | The aim of this study was to identify the most suitable model for predicting live weight using both original body measurements (BM) and principal component scores (PC), and to assess the relationship between body measurements (BM) and live weight (LW). LW and BM of Huacaya alpacas (n = 117) were collected from the Quimsachata Center of the National Institute of Agricultural Innovation in Peru. The following BM, including LW, withers height (WH), croup height (CH), thoracic circumference (TC), abdominal circumference (AC), cannon-bone length (CL), neck-base circumference (NBC), cannon circumference (CC), tail insertion length (TIL), rump width (RW), tail insertion circumference (TIC), body width (BDW), rump length (RL), forelimb length (FL), body length (BDL), back length (BKL), were taken. Principal component analysis (PCA) was utilized to extract and clarify the correlation between LW and their BMs. Regression equations relating LW to BM and their PCs were computed. Additionally, the root mean squared error (RMSE), Bayesian information criterion (BIC), Akaike information criterion (AIC), and coefficients of multiple determination (R^2) were used to assess the models. Four components were extracted from the PCA of BM and LW, which accounted for 67.3% of the total variance. The prediction model for LW, utilizing two PCs, showed the highest R^2 as well as the lowest BIC, AIC and RMSE values in contrast to models based on the original measurements. The findings suggest that this method is a viable alternative for predicting live weight and may be useful in breeding programs, as well as in the design of management and selection strategies for Huacaya alpacas from Peru.

Keywords | Principal component, Live weight, Stepwise Regression, Statistical criteria, Alpaca, Models

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INTRODUCTION

It is estimated that more than 5,560,313 South American camelids are found in Peru, with alpacas (*Vicugna pacos*) accounting for 77% of this total. Of these, most alpacas are found in the regions of Puno, Cusco, Arequipa and Huancavelica with 55, 12, 10, and 6 percent, respectively (MIDAGRI, 2021). The alpaca is considered the main economic source for a significant percentage of families in the high Andean region, and its breeding constitutes the main socioeconomic livelihood, especially through the production of fiber, of which 90% is destined for the foreign market (Apaza *et al*., 2022).

The commercialization of llama and alpaca meat and fiber is on the rise, signaling an increasing demand for these products. Nevertheless, inadequate infrastructure and the variability in meat and fiber quality and quantity present significant barriers to more market-driven breeding practices. This issue stems from the fact that these animals are typically managed and raised in small-scale production systems by low-income farmers, who are often marginalized within subsistence farming contexts (Quispe *et al*., 2009).

In this context, a viable alternative is to implement efficient herd management through regular assessment of production parameters, such as body weight and morphometric measurements. Among these parameters, body weight is particularly crucial as it is used to evaluate an animal's overall condition, enhance meat production through selective breeding, manage feeding practices, monitor health status, and determine the appropriate time for the fattening phase to conclude, among other purposes (Kunene *et al*., 2009; Yilmaz *et al*., 2013). However, weight scales are often unavailable to many small farms in Peru due to their high cost and limited accessibility. Consequently, there is a need to develop simpler and less biased methods for estimating body weight.

A viable approach is to use body measurements, which serve as an indirect, rapid, and cost-effective method for predicting body weight. This approach has been documented in studies involving alpacas and llamas (Ormachea *et al*., 2022; Ablondi *et al*., 2023; Buchallik-Schregel *et al*., 2024; Merlo-Maydana *et al*., 2024), as well as in various sheep breeds (Kunene *et al*., 2009; Canaza-Cayo *et al*., 2019; Markos *et al*., 2023; Derbie and Tilahun, 2023; Contreras *et al*., 2024; Silva *et al*., 2024). However, it has been observed that different models may be necessary to predict body weight under varying environmental conditions, body condition scores, and breeds (Enevoldsen and Kristensen, 1997). This requirement arises from the biological relationships among linear body measurements, which can lead to collinearity (Eyduran *et al*., 2013; Ye *et al*., 2020).

In this context, a multivariate technique like principal component analysis (PCA) can be highly effective when dealing with multicollinear morphological traits (Mavule *et al*., 2013; Eyduran *et al*., 2013). PCA employs an orthogonal transformation to convert observations of potentially correlated variables into values of linearly uncorrelated variables, known as principal components (Winn, 2023). Consequently, the application of PCA for body measurements has been utilized as a tool for the description and characterization of different sheep breeds (Cerqueira *et al*., 2011; Derbie and Tilahun, 2023; Silva *et al*., 2013), predicting fiber coloration in alpacas (Cruz *et al*., 2021), and predicting body weight (Mavule *et al*., 2013; Canaza-Cayo *et al*., 2019; Kebede and Asaminew, 2023; Ormachea *et al*., 2023).

To date, there have been no studies predicting body weight using principal component scores in Huacaya alpacas raised in extensive systems in Peru through linear regression equations. Therefore, this study aimed to estimate the correlation among body measurements and body weight, and to determine the most effective model for predicting body weight, whether using original body measurements or principal component scores.

MATERALS AND METHODS

Location and animals

The data for this study were gathered during routine operations at the Quimsachata Experimental Center, part of the National Institute of Agrarian Innovation, located in the Santa Lucía district of the Puno department, Peru. The Quimsachata Station, situated at an altitude of 4,300 meters above sea level (15º 41'39" S, 70º 36'24" W), experiences temperatures ranging from 3.87 °C in July to 8.11 °C in November, with an average annual rainfall of 688.33 mm. The herd was primarily grazed on natural pastures under extensive systems, with supplementary feeding of oat hay during periods of pasture shortage. The data were provided for modeling purposes to explore alternative methods for predicting body weight, given that the exploitation of this species is typically characterized by limited use of technology.

Live weights (LW) and body measurements were recorded in 117 male Huacaya alpacas aged 12–18 months. To ensure accuracy and minimize errors due to digestive contents, both measurements were taken after an eight-hour food restriction. Live weights were measured using a digital scale, while body measurements were obtained by three technicians using a tape measure and calipers. The 15 recorded body measurements included withers height (WH), croup height (CH), thoracic circumference (TC), abdominal circumference (AC), cannon-bone length (CL), neck-base circumference (NBC), cannon circumference (CC), tail insertion length (TIL), tail insertion circumference (TIC), rump width (RW), body width (BDW), rump length (RL), forelimb length (FL), body length (BDL), and back length (BKL).

Statistical analysis

Data were organized and analyzed using several statistical packages of the R software (R Core Team, 2024). Pearson correlation coefficients were computed among live weights and body measurements and tested for significance using the ggstatsplot package of R. Stepwise regression analysis was performed using the PROC REG procedure of SAS, while principal component analysis (PCA) was performed on body trait measurements using the PROC FACTOR procedure of SAS software (SAS, 2003). PCA was applied to determine if body traits could be reduced into uncorrelated dimensions, that is, linear combinations of the original variables, referred to as principal components (PC). Before doing PCA, the Kaiser-Guttman rule was applied to decide the number of factors to be removed, that is, factors with eigenvalues greater than 1 (Kaiser, 1960). To assess the adequate level of collinearity (p < 0.05) between variables, Bartlett's test of sphericity was performed. Additionally, to validate the use of PCA, the Kaiser-Meyer-Olkin sampling adequacy measure of the correlation matrix and communality were also calculated, ensuring sampling adequacy > 0.5. Subsequently, the varimax rotation method was used to enhance the interpretability of the principal components. For the interpretation of the PCA, weights (i.e., the estimated values for each body measurement in each principal component) greater than or equal to 0.50 were considered.

To estimate live weights based on the original body measurements, the model $Y_i=\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+......+\beta_p x_{ip}+\varepsilon_i$ was used, while for those based on principal component scores, the model $Y_i=\beta_0+\beta_1 PC_{i1}+\beta_2 PC_{i2}+.....+\beta_p PC_{ip}+\varepsilon_i$ was applied. For both models, a multiple regression analysis was conducted using the stepwise selection method in SAS with the PROC REG procedure. Where Y_i is the i-th live weight; β_0 is the intercept; $\beta_1, \ldots.\beta_p$ are the p-th coefficients of partial regression; $x_{i1}+x_{i2}, \ldots, x_{ip}$ and $PC_{i1}, PC_{i2}, \ldots. PC_{ip}$ are respectively, the p-th original body traits and principal component scores, for the i-th live weight; ε_i is the residual error, assumed as $\varepsilon i \sim i.i.d.N(0, \sigma^2)$.

The stepwise procedure was employed to derive the optimal prediction equations for body weight, excluding variables with P > 0.05, as recommended by Diaz *et al.* (2004) and Marshall *et al.* (2005). The accuracy of these prediction equations was evaluated using the coefficients of multiple determination (R2) and the root mean square error (RMSE). Additionally, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used to assess model quality in terms of fit and complexity. The model that best fits should exhibit the lowest AIC (Akaike, 1974) and BIC (Schwarz, 1978) values, along with the highest R2 and the lowest RMSE.

To find a middle ground between the mathematical optimum and the applicable one, considering the profile of the farmers, an additional analysis was carried out using the decision tree methodology. To build and visualize the decision tree, the rpart package in the R software was used (R Core Team, 2024). Initially, the model was trained to predict the variable of interest (live weight) using the "anova" method for regression analysis. After creating the model, the visualization was improved using the rpart.plot package.

RESULTS AND DISCUSSION

Descriptive analysis of live weight and body measurements

Descriptive statistics of body measurements and live weight are showed in Table 1, Notably, greater phenotypic variability was observed among animals for live weight (LW), tail insertion circumference (TIC), rump length (RL), and neck-base circumference (NBC), with coefficients of variation (CV) ranging from 17.22% to 9.02%. In contrast, the other characteristics showed less variability (CV < 9%).

Table 1: Descriptive statistics of live weight (kg) and body measurements (cm) of Huacaya alpacas.

Measure-ments	Average	SD	Min.	Max.	CV (%)
LW	40.47	6.97	28	65	17.22
WH	84.38	4.14	77	96	4.91
CH	85.17	4.25	77	96	4.99
TC	87.06	6.77	67	110	7.77
AC	89.99	7.31	75	115	8.12
CL	26.11	1.94	20	31	7.42
CC	11.39	1.02	9	14	8.92
NBC	31.70	2.86	26	42	9.02
TIL	20.39	1.80	15	26	8.84
TIC	9.28	0.93	7	12	9.99
RW	22.68	1.75	18	29	7.69
BDW	20.28	1.53	16	25	7.55
RL	21.36	2.06	15	25	9.63
FL	55.37	2.34	50	61	4.22
BDL	82.74	6.11	69	102	7.38
BKL	63.09	5.07	53	83	8.04

SD: standard deviation; CV: coefficient of variation, LW: live weight, WH: withers height, CH: croup height, TC: thoracic circumference, AC: abdominal circumference, CL: cannon-bone length, CC: cannon circumference, NBC: neck-base circumference, TIL: tail insertion length, TIC: tail insertion circumference, RW: rump width, BDW: body width, RL: rump length, FL: forelimb length, BDL: body length, BKL: back length.

The average live weight (LW) was 40.47 ± 6.97 kg. The wither height (WH) averaged 84.38 cm, and the croup height (CH) was 85.17 cm. The average thoracic circumference (TC) was 87.06 cm, and the abdominal circumference (AC) was 89.99 cm. The cannon region measurements were 26.11 cm in length and 11.39 cm in circumference. The average body length (BDL) was 82.74 cm. Access to such data is crucial for achieving optimal production efficiency and enhancing the value of products derived from these animals.

Pearson's correlation coefficients

Pearson's correlation coefficients (r) obtained between live weight and body measurements, as well as between body measurements, are presented in Figure 1. In this one, one can observe that the body measurements TC, BDL, AC, BKL, NBC, CH, and WH showed high positive and significant correlations with LW (r = 0.63 to 0.81; P < 0.05), while the measurements BDW, RW, TIC, and TIL showed positive correlations, but with moderate magnitudes (r= 0.32 to 0.58; P < 0.05). However, the correlations between LW and the measurements RL, FL, CL and CC were not significant (r = 0.16 to -0.05; P > 0.05). Already, among body measurements, the strongest correlations were observed between croup height (CH) and withers height (WH) (r = 0.87; P < 0.05), and between body width (BDW) and rump width (RW) (r = 0.77; P < 0.05). Thus, the presents results corroborate with those reported by Ccora *et al.* (2019), Buchallik-Schregel *et al.* (2024), Merlo-Maydana (2024), in vicuñas (*Vicugna vicugna*), alpacas and llamas, respectively.

Principal componente analysis (PCA)

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was high for Huacaya alpacas (0.84), supporting the suitability of the correlation matrix for PCA. This indicates the presence of distinct principal component (PC) factors (Yakubu *et al.*, 2011). Additionally, Bartlett's test of sphericity yielded a highly significant chi-square (χ^2 = 1115.726, P < 0.001), further endorsing the use of PCA.

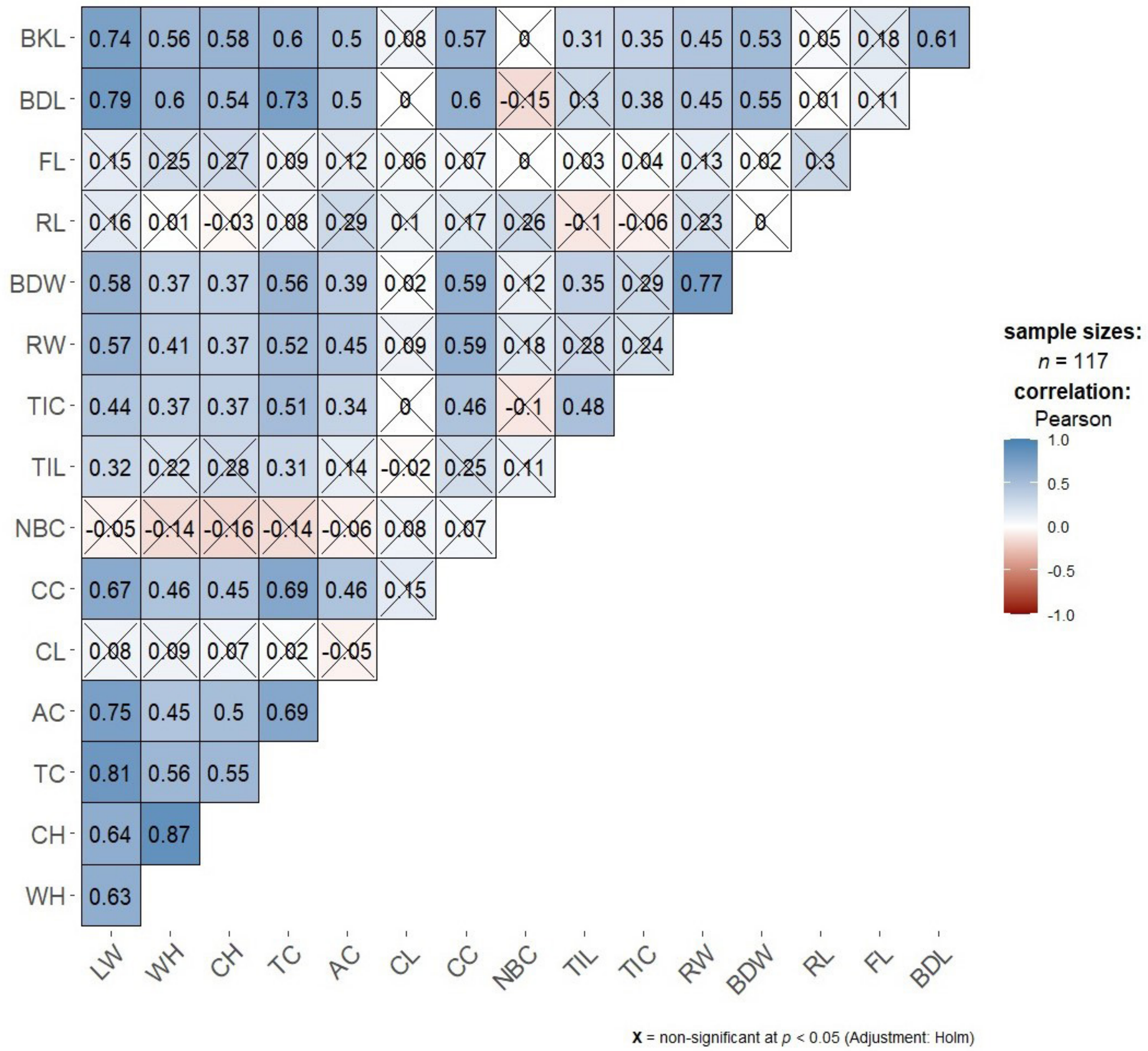

Figure 1: Pearson's correlation coefficients between liveweight and body measurements in Huacaya alpacas.

Table 2: Eigenvalues and factor loadings (PCs) after varimax rotation and commonality of live weight and body measurements of Huacaya alpacas.

Body measurements	PC1	PC2	PC3	PC4	Commonality
LW	0.92	-0.02	0.05	0.12	0.86
WH	0.67	-0.29	0.17	0.46	0.76
CH	0.66	-0.32	0.20	0.45	0.78
TC	0.88	-0.07	0.10	-0.02	0.79
AC	0.80	-0.06	-0.26	-0.03	0.72
CL	-0.07	0.26	0.15	0.60	0.46
CC	-0.09	0.79	-0.02	0.08	0.65
NBC	0.76	0.24	0.14	0.08	0.66
TIL	0.29	0.22	0.68	0.08	0.60
TIC	0.48	-0.06	0.49	0.05	0.48
RW	0.69	0.46	0.04	0.03	0.70
BDW	0.70	0.38	0.25	-0.11	0.71
RL	0.20	0.41	-0.67	0.26	0.72
FL	0.14	-0.04	-0.28	0.68	0.57
BDL	0.81	-0.13	0.15	0.04	0.70
BKL	0.74	0.01	0.17	0.22	0.62
Eigenvalues	6.66	1.62	1.41	1.08	
% of total variation	41.60	10.14	8.79	6.74	
Cumulative variance (%)	41.60	51.74	60.53	67.27	

LW: live weight, WH: withers height, CH: croup height, TC: thoracic circumference, AC: abdominal circumference, CL: cannon-bone length, CC: cannon circumference, NBC: neck-base circumference, TIL: tail insertion length, TIC: tail insertion circumference, RW: rump width, BDW: body width, RL: rump length, FL: forelimb length, BDL: body length, BKL: back length.

The estimated factor loadings extracted by PCA, the eigenvalues, and the variation explained by each factor are presented in Table 2. After applying a varimax rotation to the component matrix, four principal components (PCs) with eigenvalues equal to or greater than one were extracted. This indicates that each principal component captures more variance than an original variable. The extraction of these four PCs improved the understanding of complex correlations between body measurements and facilitated the use of more parsimonious models. These models require lower computational demands and are less prone to numerical errors (Legarra *et al*., 2004; Mota *et al*., 2016). Essentially, a reduced number of PCs often captures a significant proportion of the overall variability (Boligon *et al*., 2013).

The four principal components (PCs) accounted for 67.27% of the total variation among all body measurements. Specifically, 41.60% of this total variation was attributed to the first component (PC1), which had high positive loadings for live weight (LW), withers height (WH), croup height (CH), thoracic circumference (TC), abdominal circumference (AC), neck-base circumference (NBC), rump width (RW), body width (BDW), body length (BDL), and back length (BKL). The second component (PC2) explained 10.14% of the total variation and was characterized by high positive loadings for cannon circumference (CC) and rump width (RW). The third component (PC3), associated with tail insertion length (TIL), tail insertion circumference (TIC), and rump length (RL), accounted for 8.79% of the total variation. Lastly, the fourth component (PC4) had high positive loadings for withers height (WH), cannon-bone length (CL), and forelimb length (FL), contributing 6.74% of the total variation.

Furthermore, the communalities, representing the proportion of the variance in the original variables explained by the PCs, were generally high for almost all body measurements, ranging from 0.46 (CL) to 0.86 (LW) in Huacaya alpacas (Table 2). Therefore, the use of four PCs is crucial in the classification of animals, providing an opportunity to better select animals using groups of body measurements rather than relying on a single measurement (Yakubu *et al*., 2011; Pinto *et al*., 2006).

There are few studies applying principal component analysis to alpacas. However, it is possible to draw associations with studies carried out on other small ruminants, such as in the case of sheep, which have larger quantities of scientific production. Silva *et al*. (2015), using a classification method in performance tests in the Morada Nova sheep population, reported that the first three PCs best explained most of the variability of all body measurements evaluated. Already, in a population of Bordaleira sheep in Portugal, Cerqueira *et al*. (2011) observed that two PCs were sufficient to explain 70.5% of the total variation, with PC1 explaining 61.4% by itself. These authors reported that the body measurements of withers height, back height, dorsal length, head length, cannon circumference, and live weight contributed positively to most of the variation. In the Mavule *et al*. (2013) study, two populations of Zulu sheep (young and adult) were evaluated, reporting that two PCs for the young population and four PCs for the adult population were sufficient to explain most of the variability. In another study, but conducted in Peru with Corriedale sheep, Canaza-Cayo *et al*. (2019) found that the first four PCs retained 68.7% of the total variation. It is clear that the variability of body measurements may differ between breeds and species, but some body measurements influence sheep populations regardless of breed and this may possibly be found in other small ruminants. This indicates that these body measurements could integrate a selection index in breeding programs for different species and/or breeds of small ruminants, or even generate information at the phenotypic prediction level for decision-making within the production routine, for example, adjusting stocking rate according to forage supply.

Figure 2 shows the graph with the first two principal components PCs for body measurements. In this graph it is evident that the body measurements were grouped into the following four groups: 1- by CH, WH, TIC, BDL, AC, BKL, TC, and LW; 2- by CC, BDW and RW; 3- by TIL, RL and NBC; 4- by FL and CL.

Live weight predictions of Huacaya alpacas

Table 3 presents the regression equations predicting the live weight (LW) of male Huacaya alpacas aged between one and one and a half years, based on original body measurements and their principal component (PC) scores. The stepwise multiple regression analysis revealed thatthoracic circumference (TC) alone explained 65% of the variation in LW. When back length (BKL) was added, this proportion increased to 75%. Further inclusion of abdominal circumference (AC), body length (BDL), and rump width (RW) improved the model accuracy to 76%. This model, with the highest R^2 and the lowest AIC, BIC, and RMSE values, confirmed its superior fit compared to models using original body measurements alone.

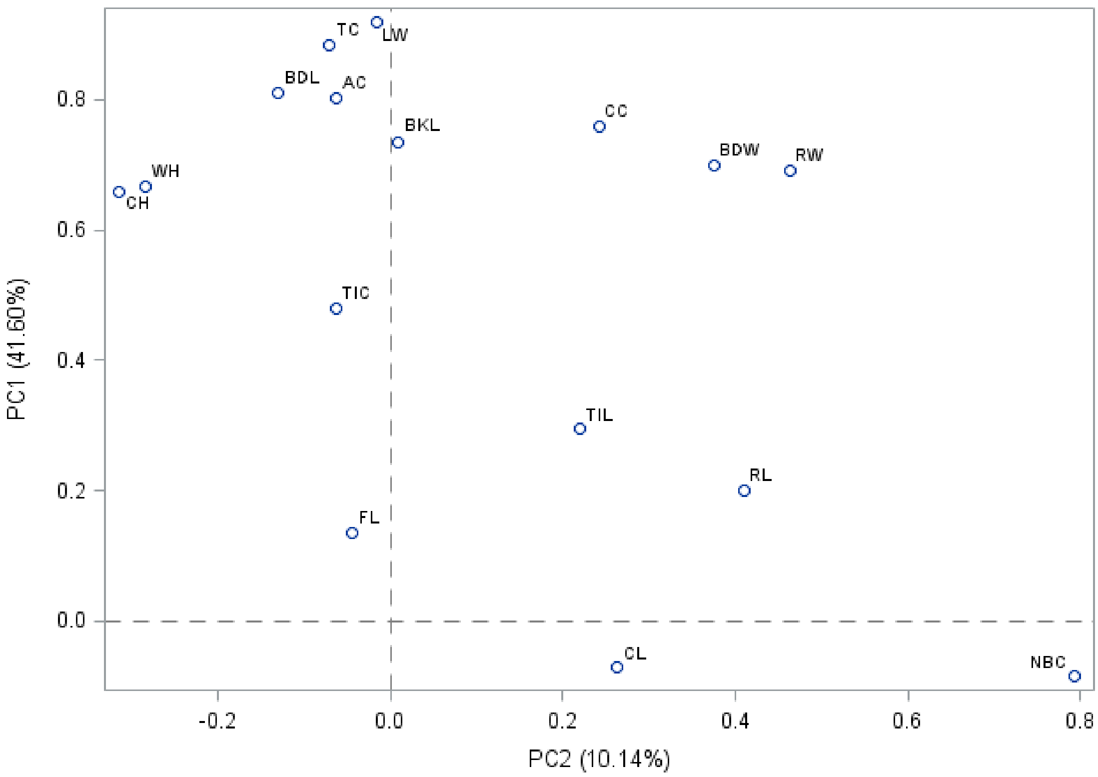

Figure 2: Score plot of the first two principal components of body measurements of Huacaya alpacas.

Table 3: Stepwise multiple regression models from original body measurements and their principal component (PC) scores of Huacaya alpacas.

Model	Predictors	Models	R^2	RMSE	AIC	BIC
Original body measurements as predictors						
1	TC	LW = -32.02 + 0.83TC	0.65	4.12	333.14	332.37
2	TC, BKL	LW = -45.12 + 0.59TC + 0.55BKL	0.75	3.48	294.84	294.95
3	TC, BKL, AC	LW = -50.99 + 0.40TC + 0.49BKL + 0.29AC	0.80	3.14	271.70	272.00
4	TC, BKL, AC, BDL	LW = -57.88 + 0.19TC + 0.36BKL + 0.31AC + 0.38BDL	0.85	2.77	243.51	245.84
5	TC, BKL, AC, BDL, RW	LW = -60.74 + 0.17TC + 0.34BKL + 0.30AC + 0.37BDL + 0.35RW	0.85	2.74	241.32	244.16
Principal Components as predictors						
1	PC1	LW = 40.47 + 6.41PC1	0.85	2.76	239.12	240.86
2	PC1, PC2	LW = 40.47 + 6.41PC1 + 0.81PC2	0.86	2.64	230.44	232.60

LW: live weight, TC thoracic circumference, AC: abdominal circumference, RW: rump width, BDL: body length, BKL: back length. R^2: coefficients of determination, RMSE: root mean square error, AIC: Akaike information criterion, BIC: Bayesian information criterion.

Kunene *et al.* (2009) found that linear regression coefficients of chest circumference and withers height could estimate the body weight of Zulu sheep, with R^2 values ranging from 0.66 to 0.49, respectively. Similarly, Yilmaz *et al.* (2013) reported that a model incorporating all body measurements (rump height, withers height, back height, chest depth, chest width, and body length) yielded the best $R^2 = 0.76$ for estimating the mature live weight of Karya breed sheep in the Anatolian Peninsula.

Better results were obtained using the principal components (PC) methodology compared to the original body measurements (Table 3). As previously mentioned, four PCs contributed 67.27% of the total variation among the recorded body measurements. Performing a stepwise multiple regression analysis using the four PCs, the model fit improved significantly with the inclusion of only two PCs. Although more parsimonious models are generally preferred, the model that included two PCs exhibited the lowest BIC, AIC and RMSE values, as well as the highest R^2 (Table 3). This model was more parsimonious and provided the best fit among those using original measurements.

Similar research with Madgyal breed sheep populations, Yadav *et al.* (2016) found that the model of live weight prediction with PC1 and PC2 had better R^2 (0.94) and lower RMSE (1.86) compared to the model that used only PC1 (R^2 = 0.80 and RMSE = 3.84). In Corriedale breed sheep, Canaza-Cayo *et al.* (2019) identified the best model using four PCs, with R^2, AIC, BIC, and RMSE values of 0.83, 137.78, 140.30, and 1.94, respectively. These results suggest that the PCs from this study can be used as variables in a selection index, with only two weighted coefficients, reducing computational demands (Pinto *et al.*, 2006; Mota *et al.*, 2016).

Based on these results, it can be suggested that predicting the live weight of male Huacaya alpacas aged between one and one and a half years using body measurements is feasible. This approach is advantageous for farmers who cannot afford to purchase weight scales. Moreover, predicting live weight using two principal components (PCs) derived from body measurements is a superior alternative to using original measurements. The four PCs reported here have a strong association with most of the body measurements evaluated, demonstrating their effectiveness.

Practical recommendations for Huacaya alpaca farmers based on a decision tree model

Even though the best model for predicting the live weight of male Huacaya alpacas between one and one and a half years of age is the one that used two PCs (Table 3), in practice, breeders may find it difficult to process the data and apply the model to obtain live weights, which is a challenge in the application of the technology. However, the best model that used only body measurements obtained an R^2 of 0.85, which, when compared to the models using PCs with R^2 of 0.85 and 0.86 (Table 3), is very close mathematically. Therefore, considering the profile of the farmers, focusing on applicability, the model using the five body measurements appears to be more feasible from a practical point of view. Thus, aiming at an extension of this article's findings, a decision tree was created to have values that, immediately after the measurement, provide information that can be instantly useful.

Figure 3 shows nine paths within the decision tree that lead to an average weight. However, the statistics of this method are inferior to the Stepwise multiple regression models, with R^2 and RMSE of 0.83 and 2.88, respectively, but these results are more applicable at the field level and can be considered.

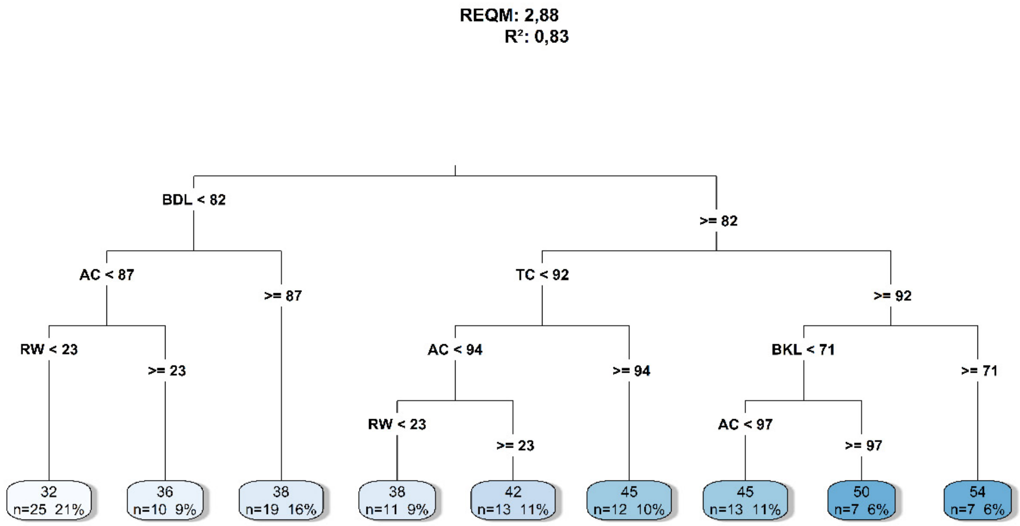

Figure 3: Decision tree for predicting live weight using body measurements of Huacaya alpacas.

Based on Figure 3, after taking the five measurements of body length (BDL), abdominal circumference (AC), thoracic circumference (TC), back length (BKL), and rump width (RW), it is possible to get an idea of the average weight of the animals. For example, if an animal has a BDL of 83 cm, TC of 91 cm, AC of 92 cm and RW of 22 cm, its weight is expected to be 38 kg. In this way, the producer can make the best decision immediately after knowing the measurements.

CONCLUSIONS

The present results suggest that principal component analysis (PCA) is an appropriate method for assessing live weight and body measurements in the Huacaya alpaca population of Peru. This approach enables the prediction of live weight through regression equations using the scores of the principal components. From a practical standpoint, a decision tree can be used as a guide. Although less accurate, it represents a more viable alternative for farmers who cannot afford weighing scales and need to make decisions at the time of measurements.

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NOVELTY STATEMENT

This study introduces a multivariate approach for predicting live weight in Huacaya alpacas using principal component scores derived from body measurements. The results demonstrate that principal component-based models improve prediction accuracy compared with conventional models based on original measurements, providing a useful tool for alpaca breeding and management programs.

AUTHOR'S CONTRIBUTION

RCH: Conceptualization, Formal analysis, Writing – original draft. AWCC: Methodology, Data curation, Formal analysis, Writing – review & editing. FAS: Formal analysis, Writing – review & editing. FHRH: Investigation, Writing – review & editing. FMB: Resources, Writing – review & editing. RTFF: Supervision, Investigation. HJNP: Resources, Investigation. All authors read and approved the final version of the manuscript.

GENERATIVE AI AND AI ASSISTED TECHNOLOGY STATEMENT

The authors declare that no generative AI and AI assisted technology was used in the creation of this manuscript.

CONFLICT OF INTEREST

The authors have declared no conflict of interest.

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