IOP Conference Series:
Earth and
Environmental Science

PAPER • OPEN ACCESS

Application of Principal Component Regression in Estimating the Body Weight of SimPO and LimPO Cattle Using Body Measurements

To cite this article: Akhmad Dakhlan *et al* 2025 *IOP Conf. Ser.: Earth Environ. Sci.* **1502** 012001

IOP Conf. Series: Earth and Environmental Science **1502** (2025) 012001 doi:10.1088/1755-1315/1502/1/012001

Application of Principal Component Regression in Estimating the Body Weight of SimPO and LimPO Cattle Using Body Measurements

Akhmad Dakhlan[1]*, Ali Husni[1], Dian Kurniawati[1], Arif Qisthon[1], and Kusuma Adhianto[1]

[1] Department of Animal Husbandry, Faculty of Agriculture, Universitas Lampung, Bandar Lampung, Lampung, Indonesia

*E-mail: akhmad.dakhlan@fp.unila.ac.id

Abstract. This study aims to apply Principal Component Regression (PCR) to estimate the body weight of SimPO and LimPO cattle based on body measurements and compare its accuracy with conventional regression methods which often encounter multicollinearity issues when using multiple correlated variables. This study involves 115 SimPO and 114 LimPO cattle, aged 2.5-4.5 years, non-pregnant, and easy to handle during measurement and weighing. Data on the body measurements including body length (BL), chest girth (CG), shoulder height (SH), and chest width (CW), and body weight (BW) of SimPO and LimPO cattle were collected from the Maju Sejahtera Livestock Production Cooperative farms. Principal Component Regression (PCR) Analysis of the body measurements, and multiple linear regression analysis were conducted using the R software. The selection criteria for the best model was based on a high coefficient of determination (R^2) and Adjusted R^2, as well as low values of RSE (Residual Standard Error), AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion). Results indicate that PCR models offer comparable accuracy to conventional models while reducing redundancy and simplifying the prediction process. The body measurements of SimPO cattle were found to be more reliable predictors of body weight, as evidenced by higher R^2 and adjusted R^2 values and by lower RSE, AIC, and BIC, compared to LimPO cattle. The study concludes that PCR is an effective method for improving the accuracy and efficiency of body weight estimation in livestock, providing a valuable tool for farmers and researchers in the cattle industry.

Keywords: Prediction, Body Weight, SimPO and LimPO Cattle, Body Measurements, Principal Component Regression

1. Introduction

SimPO and LimPO cattle are the result of crossbreeding between exotic cattle (Simental and Limousin cattle) and local Indonesian cattle (Ongole Grade cattle, known as PO cattle), and they are two important types of cattle in smallholder farming as well as the livestock industry, particularly in Indonesia. These two types of cattle have different characteristics in terms of body size and weight. Measuring the body weight of cattle is crucial in farm management to ensure optimal meat production.

Accurate estimation of cattle body weight is crucial in livestock management, influencing feeding strategies, health monitoring, and overall farm productivity [1],[2]. Traditional methods of measuring body weight, such as using livestock scales, can be time-consuming, expensive, and impractical in some field conditions. As a result, alternative approaches that rely on easily measurable body dimensions have gained popularity [3].

In this context, Principal Component Regression (PCR) analysis becomes an important tool for estimating cattle body weight. PCR is a statistical method used to address multicollinearity, which occurs when independent variables are correlated in a conventional regression model [4],[5]. By using PCR, we can select the most significant principal components in predicting cattle body weight, considering the available body measurements [6],[7],[8].

Previous studies have shown that livestock body measurements, such as shoulder height, body length, and chest girth, significantly influence body weight [9],[10],[11],[12],[13],[14],[15],[16]. However, in this study, we will use the PCR approach to optimize the prediction of SimPO and LimPO cattle body weight based on a combination of these body measurements.

This paper presents a comparison between conventional regression model and the application of PCR in analyzing various body measurements of SimPO and LimPO cattle to estimate their weight more efficiently. By employing this method, we aim to improve weight prediction accuracy, reduce measurement redundancy, and offer a practical tool for farmers and researchers. Accurate estimation of cattle body weight is crucial in livestock management, influencing feeding strategies, health monitoring, and overall farm productivity. Traditional methods of measuring body weight, such as using livestock scales, can be time-consuming, expensive, and impractical in some field conditions. As a result, alternative approaches that rely on easily measurable body dimensions have gained popularity.

In this context, Principal Component Regression (PCR) analysis becomes an important tool for estimating cattle body weight. PCR is a statistical method used to address multicollinearity, which occurs when independent variables are correlated in a conventional regression model [17],[4],[5],[8]. By using PCR, we can select the most significant principal components in predicting cattle body weight, considering the available body measurements [6],[7].

Previous studies have shown that livestock body measurements, such as height, body length, and chest circumference, significantly influence body weight [9],[10],[11],[12],[13],[14],[15],[16]. However, in this study, we will use the PCR approach to optimize the prediction of SimPO and LimPO cattle body weight based on a combination of these body measurements.

This paper presents a comparison between conventional regression model and the application of PCR in analyzing various body measurements of SimPO and LimPO cattle to estimate their weight more efficiently. By employing this method, we aim to improve weight prediction accuracy, reduce measurement redundancy, and offer a practical tool for farmers and researchers.

2. Materials and methods

This research was conducted at the Maju Sejahtera Livestock Production Cooperative, in Wawasan Village, Tanjung Sari District, South Lampung Regency, during June – July 2024. The tools and materials used in this research include a measuring tape, a digital cattle scale (capacity of 2,000 kg with an accuracy of 0.05 kg), a mobile phone camera, writing instruments, and paper. The

IOP Conf. Series: Earth and Environmental Science **1502** (2025) 012001 doi:10.1088/1755-1315/1502/1/012001

primary subjects of this research were 115 SimPO and 114 LimPO cattle, aged 2.5-4.5 years, non-pregnant, and easy to handle during measurement and weighing. Data on the body measurements and body weight of SimPO and LimPO cattle were collected from several representative farms. The body measurements taken include height, body length, and chest girth.

The research method used was a survey, with sample selection done through purposive sampling based on the criteria mentioned above. Body weight (BW) is obtained by weighing the cattle using a digital scale, measured in kilograms. Chest girth (CG) is measured by wrapping the measuring tape around the chest, just behind the shoulders, in centimeters. Body length (BL) is measured as the distance between the shoulder joint and the rear edge of the pelvic bone, using a measuring tape in centimeters. Height or shoulder height (SH) is the distance from the ground to the highest point of the shoulder, right behind the scapula, measured using a measuring stick in centimeters. Chest width (CW) is the distance between the midpoints of the left and right sternum, measured using calipers [9],[11],[12],[13].

The collected body measurement data were tabulated using Excel and then analyzed using Principal Component Analysis (PCA) to identify the main components that most influence the variability in cattle body weight. Based on the PCA results, a model for estimating cattle body weight will be developed using the most significant principal components. The model will be constructed using a suitable regression technique, Principal Component Regression (PCR), as per the following model:

$$BW = b_0 + b_1PC_1 + b_2PC_2 + b_3PC_3 + b_4PC_4$$

where b_0 is the intercept, and $b_{1\text{-}4}$ are the partial regression coefficients for the scores of PC_1, PC_2, PC_3, and PC_4.

To test the goodness of fit of the PCR-generated regression model, it will be compared with a conventional regression model, i.e., multiple linear regression, formulated as follows:

$$BW = b_0 + b_1CC + b_2BL + b_3SH + b_4CW$$

where b_0 is the intercept, and $b_{1\text{-}4}$ are the partial regression coefficients for CG, BL, SH, and CW, respectively.

Principal Component Regression (PCR) Analysis of the body measurements, and multiple linear regression analysis were conducted using the R software [18],[19]. The selection criteria for the best model were based on a high coefficient of determination (R^2) and Adjusted R^2, as well as low values of RSE (Residual Standard Error), AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion) [9],[11],[12],[13].

3. Results and discussion

3.1 Statistic overview of body weight and body measurements of SimPO and LimPO cattle

The research results on body weight and body measurements of SimPO and LimPO cattle can be seen in the boxplot visualizations in Figure 1 and Figure 2, respectively. The results indicate that the body weight and body measurements of both SimPO and LimPO cattle are normally distributed.

IOP Conf. Series: Earth and Environmental Science **1502** (2025) 012001 doi:10.1088/1755-1315/1502/1/012001

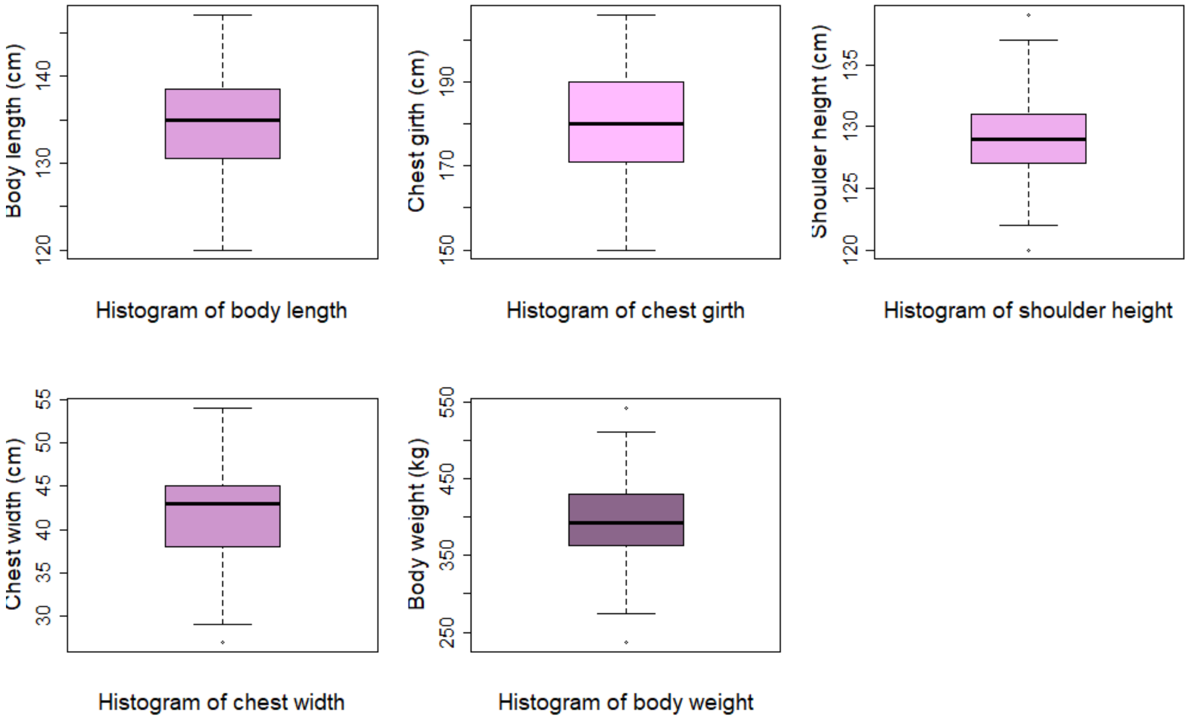

Figure 1. Boxplot of body measurements and body weight of SimPO cattle

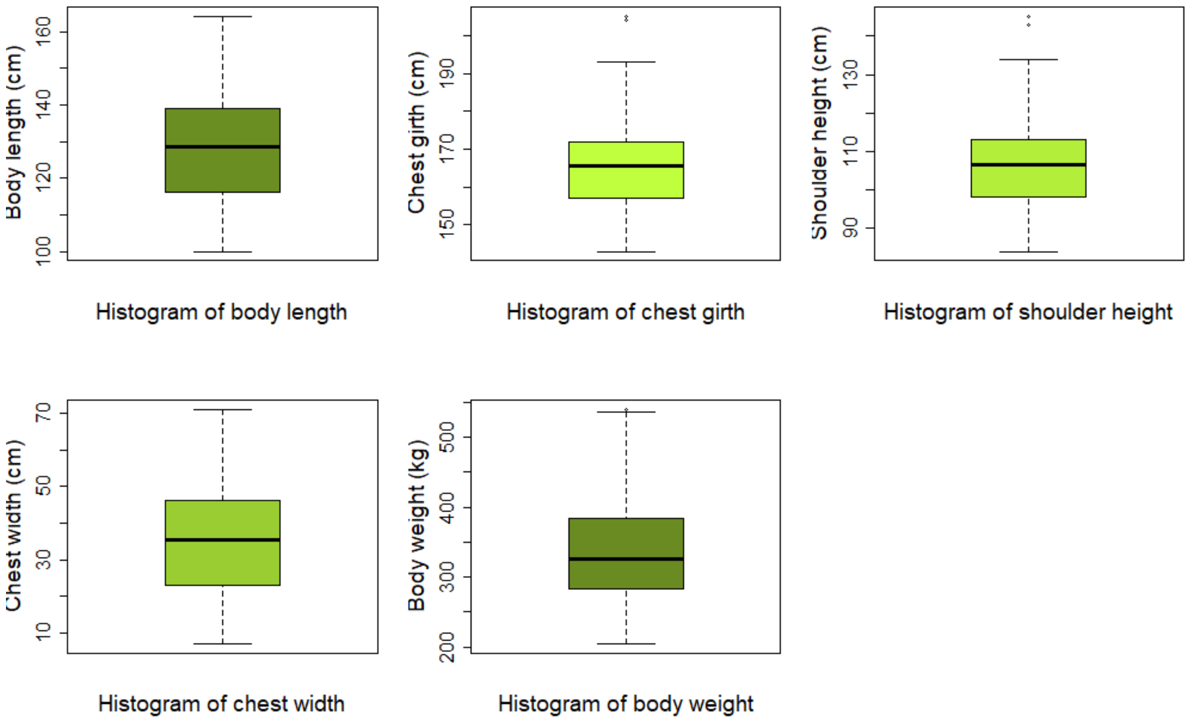

Figure 2. Boxplot of body measurements and body weight of LimPO cattle

In examining the body weight and body measurements of SimPO and LimPO cattle, the research results presented in Figure 1 (SimPO cattle) and Figure 2 (LimPO cattle) suggest that both populations follow a normal distribution meaning that most individuals have body weight and body measurements clustered around the mean, with fewer individuals at the extremes. This finding has several implications. First, the normal distribution of these traits in both cattle types suggests a consistent genetic and environmental influence on growth and development. The bell-shaped distribution indicates that most cattle fall within an average range for weight and measurements, with fewer individuals at the extremes (either very large or very small).

Additionally, this normal distribution is useful for breeders aiming to select animals for specific traits. Because the traits are normally distributed, selection for desired traits (such as increased body weight) will likely result in a predictable improvement over time, following the rules of quantitative genetics.

In terms of management, these results could help inform decisions about feed and care. Knowing that most cattle fall within a certain range allows for more precise resource allocation, helping to optimize growth and development in line with expected averages for both SimPO and LimPO breeds.

Lastly, this distribution highlights the lack of extreme variability, suggesting that the current breeding and rearing conditions are relatively stable and standardized across both populations, ensuring that the majority of animals grow within a typical range.

3.2 Correlation among variables (body weight and body measurements) of SimPO and LimPO cattle

The correlation among variables (body weight and body measurements) of SimPO cattle and LimPO cattle are shown in Figure 3 and Figure 4, respectively. The research on the correlation among variables (body weight and body measurements) for SimPO and LimPO cattle, as shown in Figure 3 and Figure 4, reveals important insights into the relationships between these traits in both cattle populations.

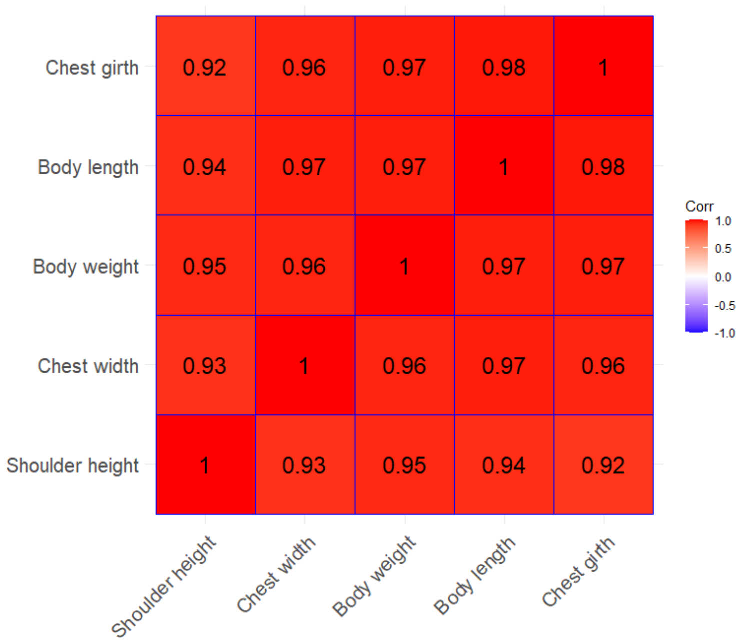

Figure 3. Correlation among variables of SimPO cattle

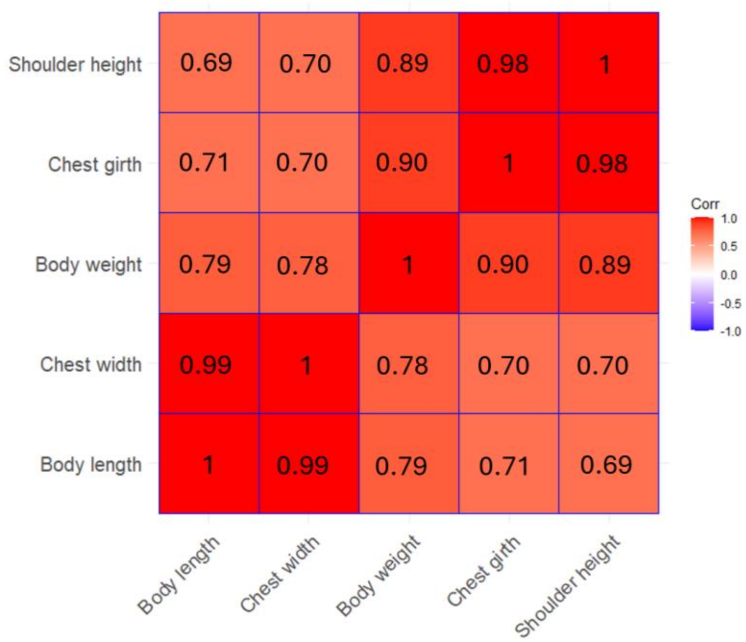

Figure 4. Correlation among variables of LimPO cattle

For both SimPO and LimPO cattle, the correlation analysis helps to identify how body measurements (such as height, length, and girth) are associated with body weight. Strong positive correlations suggest that as certain body measurements increase, body weight also tends to increase, reflecting how structural dimensions contribute to the overall mass of the animal.

For example, in many cattle breeds, traits like chest girth and body length often have a strong correlation with body weight, as these measurements are indicative of the overall body volume and musculature. If similar correlations are observed in both SimPO and LimPO cattle, it suggests that selection for improved body measurements could directly impact body weight, which is a valuable trait for breeders focused on meat production.

On the other hand, weak or negative correlations between certain measurements and body weight would indicate that some dimensions of the animal's body are not necessarily predictive of its overall mass. Understanding these nuances allows breeders to make more informed decisions when selecting cattle for breeding, focusing on the traits most closely tied to productivity.

The analysis of Figures 3 and 4 reveals significant correlations between body measurements (such as height, length, and girth) and body weight in both SimPO and LimPO cattle, with correlation values ranging from 0.69 to 0.98. This strong correlation suggests that increases in body measurements are closely associated with increases in body weight, making these traits reliable indicators for estimating the overall mass of the cattle. However, the presence of such high correlations also indicates the potential for multicollinearity, particularly when multiple body measurements are used together in predictive models. Multicollinearity can complicate statistical analyses, as it implies that some measurements are highly interrelated, which may affect the stability and interpretation of regression models when predicting body weight.

Additionally, a notable difference is observed between the two cattle breeds. The correlation between body measurements and body weight is higher in SimPO cattle compared to LimPO cattle. This suggests that the body structure of SimPO cattle is more uniform and consistent, with less variation in how body dimensions relate to weight. This regularity in SimPO cattle could be advantageous for breeders aiming to use body measurements as proxies for body weight in selection programs, as the consistency provides more reliable data for making breeding decisions. In contrast, the lower correlation in LimPO cattle indicates more variability, which might suggest less predictability or a need for a more breed-specific approach when using body measurements to estimate weight.

The findings underline the importance of considering both breed-specific differences and the potential for multicollinearity when utilizing body measurements for practical applications in breeding and cattle management. In particular, the stronger and more consistent correlations in SimPO cattle could make them more suitable for breeding programs that emphasize body weight and structural traits, while LimPO cattle may require more nuanced selection strategies to account for greater variability.

Differences in correlation strength between SimPO and LimPO cattle could also suggest genetic or environmental variations between the two breeds. These insights might help in designing breed-specific strategies for improving overall cattle performance.

The results of this study are consistent with previous research showing that body measurements are highly correlated with livestock body weight, and chest girth is the body measurement most strongly correlated with body weight [20],[21],[9],[12],[13],[14],[22]. However, few previous studies have reported that body length [15] has the highest correlation with body weight in Sakub sheep or that shoulder height has the highest correlation with body weight in Hanwoo cattle [16].

The findings from Figures 3 and 4 offer valuable guidance for future breeding programs, management practices, and even nutritional plans, as they help establish which traits are most indicative of healthy growth and productivity in these cattle populations.

3.3 Regression models between body weight and body measurements of SimPO and LimPO cattle

This study aims to apply regression analysis with and without Principal Component Analysis (PCA) to estimate the body weight of SimPO and LimPO cattle based on body measurements. The variables used include body length (BL), chest girth (CG), shoulder height (SH), and chest width (CW). The analysis was conducted on both types of cattle to understand the relationship patterns between body weight and body measurements, as well as to evaluate the accuracy of the prediction models.

The conventional regression equations obtained from the analysis are presented in Table 1 (SimPO cattle) and Table 3 (LimPO cattle). Meanwhile, the regression equations based on the PCA analysis results are presented in Table 2 (SimPO cattle) and Table 4 (LimPO cattle). In general, both the regression equations from conventional regression analysis and those from PCA analysis can be used to estimate the body weight of SimPO and LimPO cattle, with a high coefficient of determination (R^2) and adjusted R^2.

The model with one predictor variable (Table 1) shows that body length (BL) has the highest R^2 (0.945) among the other simple models. This indicates that body length is a strong predictor of body weight in SimPO cattle. The multiple regression models, which use more than one predictor variable, generally provide a higher R^2 than the simple models. For example, the model combining BL, CG, SH, and CW has an R^2 of 0.965, indicating improved prediction accuracy. The model with three predictor variables (CG, SH, CW) has the highest R^2 (0.965) and the lowest residual standard error (RSE) of 9.59, as well as lower AIC and BIC values, indicating that this model is better at predicting body weight than the simple models.

IOP Conf. Series: Earth and Environmental Science **1502** (2025) 012001 doi:10.1088/1755-1315/1502/1/012001

Table 1. Conventional regression models between body weight and body measurements of SimPO cattle

No	Regression models	R^2	Adj.R^2	RSE	AIC	BIC
1	BW = -769.52 +8.63BL	0.945	0.945	11.90	900.03	908.26
2	BW = -370.20 + 4.21CG	0.932	0.931	13.30	925.49	933.73
3	BW = -1688.50 + 16.12SH	0.903	0.902	15.86	966.00	974.24
4	BW = 42.30 + 8.39CW	0.931	0.930	13.34	926.21	934.44
5	BW = -652.99 + 5.98BL + 1.33CG	0.949	0.948	11.57	894.43	905.41
6	BW = -1083.03 + 6.16BL + 5.01SH	0.955	0.954	10.88	880.37	891.35
7	BW = -470.90 + 5.40BL + 3.26CW	0.954	0.953	10.98	882.31	893.29
8	BW = -973.60 + 2.57CG + 6.98SH	0.959	0.958	10.33	868.46	879.44
9	BW = -177.48 + 2.16CG + 4.26CW	0.952	0.951	11.17	886.45	897.43
10	BW = -687.84 + 6.68 SH + 5.21CW	0.953	0.952	11.10	884.92	895.90
11	BW = -973.03 + 2.26BL + 1.77CG + 5.73SH	0.961	0.960	10.18	865.97	879.69
12	BW = -394.93 + 3.44BL + 1.09CG + 3.05CW	0.956	0.955	10.75	878.41	892.14
13	BW = -716.48 + 1.72CG + 5.35SH + 2.58CW	0.965	0.964	9.59	852.21	865.93
14	BW = -786.58 + 3.70BL + 4.37SH + 2.80CW	0.961	0.960	10.16	865.47	879.19
15	BW = -731.08 + 0.66BL + 1.53CG + 5.08SH + 2.43CW	0.965	0.964	9.62	853.83	870.30

Note: R^2 = Coefficient of determination, Adj.R^2 = adjusted R^2, RSE = residual standard error, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, BW = body weight, BL = body length, CG = chest girth, SH = shoulder height, CW = chest width

Table 2. Regression models between body weight and principal component

No	Regression equation	R^2	Adj.R^2	RSE	AIC	BIC
1	BW = 394.57 + 25.21PC_1 - 1.11PC_2 - 0.37PC_3 - 10.69PC_4	0.965	0.964	9.62	853.83	870.30
2	BW = 394.57 + 25.21PC_1 - 1.11PC_2 - 0.37PC_3	0.964	0.963	9.66	853.93	867.66
3	BW = 394.57 + 25.21PC_1 - 1.11PC_2	0.964	0.964	9.62	851.94	862.92
4	BW = 394.57 + 25.21PC_1	0.964	0.964	9.58	850.09	858.32

Note: R^2 = Coefficient of determination, Adj.R^2 = adjusted R^2, RSE = residual standard error, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, PC_{1-4} = component 1-4

Table 3. Conventional regression models between body weight and body measurements of LimPO cattle

No	Regression equation	R^2	Adj.R^2	RSE	AIC	BIC
1	BW = -173.78 + 3.95BL	0.618	0.614	46.81	1204.4	1212.6
2	BW = -658.76 + 6.01CG	0.817	0.816	12.35	1120.2	1128.4
3	BW = -310.55 + 6.07SH	0.822	0.820	31.96	1117.4	1125.6
4	BW = 193.92 + 3.94CW	0.616	0.612	46.92	1204.9	1213.1
5	BW = -619.62 + 1.45BL + 4.64CG	0.858	0.856	28.63	1093.3	1104.3
6	BW = -349.72 + 1.42BL + 4.72SH	0.861	0.858	28.36	1091.1	1102.1
7	BW = -2698.27 + 31.08BL – 27.10CW	0.623	0.616	46.67	1204.7	1215.6
8	BW = 2112.35 - 41.58CG + 47.95SH	0.836	0.833	30.80	1110.0	1120.9
9	BW = -486.22 + 4.65CG + 1.44CW	0.858	0.855	28.68	1093.7	1104.6
10	BW = -218.24 + 4.73 SH + 1.41CW	0.860	0.858	28.41	1091.5	1102.4
11	BW = 1618.22 + 1.34BL - 33.74CG + 38.77SH	0.870	0.867	27.53	1085.4	1099.0
12	BW = -2468.86 + 21.36BL + 4.62CG - 19.87CW	0.861	0.857	28.45	1092.9	1106.5
13	BW = 1744.45 - 33.78CG + 38.82SH + 1.33CW	0.870	0.866	27.58	1085.7	1099.4
14	BW = -2198.70 + 21.31BL + 4.70SH - 19.86CW	0.864	0.860	28.18	1090.6	1104.3
15	BW = -242.69+21.43BL-33.85CG+38.86SH-20.06CW	0.873	0.869	27.33	1084.6	1101.0

Note: R^2 = Coefficient of determination, Adj.R^2 = adjusted R^2, RSE = residual standard error, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, BW = body weight, BL = body length, CG = chest girth, SH = shoulder height, CW = chest width

Table 4. Regression models between body weight and principal component

No	Regression equation	R^2	Adj.R^2	RSE	AIC	BIC
1	$BW= 334.50+37.02PC_1-15.69PC_2-575.48PC_3+441.82PC_4$	0.873	0.869	27.33	1084.6	1101.0
2	$BW = 334.50 + 37.02PC_1 - 15.69PC_2 - 575.48PC_3$	0.870	0.866	27.56	1085.6	1099.3
3	$BW = 334.50 + 37.02PC_1 - 15.69PC_2$	0.859	0.857	28.52	1092.4	1103.3
4	$BW = 334.50 + 37.02PC_1$	0.834	0.833	30.82	1109.1	1117.3

Note: R^2 = Coefficient of determination, Adj.R^2 = adjusted R^2, RSE = residual standard error, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, PC_{1-4} = component 1-4

Table 2 shows the regression models using principal components (PCA) as predictor variables. This model aims to reduce multicollinearity between body measurements and simplify the model by using components that represent the largest variation in the data. The model using all principal components (PC_{1-4}) gives an R^2 of 0.965, equivalent to the best model without PCA. This shows that PCA does not reduce the model's accuracy. Reducing the number of components from four PC to one PC does not significantly affect the model's accuracy, as the model using only PC_1 still has an R^2 of 0.964 and a low RSE (9.58). It can be seen from the scree plot of body weight and body measurements of SimPO cattle (Figure 5) that PC_1 explain 96.17% variability of the data. Addition of PC_2, PC_3, and PC_4 may not be important enough to include. By using PCA, the model becomes simpler while maintaining high accuracy, demonstrating the effectiveness of PCA in handling data dimensions without sacrificing predictive accuracy.

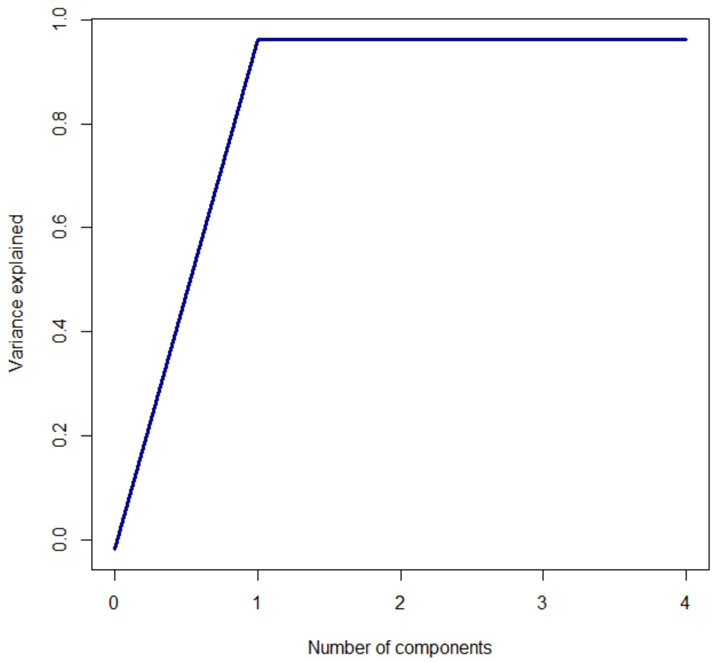

Figure 5. Scree plot of body weight and body measurements of SimPO cattle

In Table 3, regression models for LimPO cattle are presented, with results differing from those for SimPO cattle. In general, the R^2 values for LimPO cattle are lower, indicating that body measurements for LimPO cattle are not as strong in predicting body weight as for SimPO cattle. The model using chest girth (CG) as a predictor variable gives an R^2 of 0.817, higher than models using other single variables like body length (BL) or chest width (CW). The multiple regression model combining BL, CG, and SH produces an R^2 of 0.873 with an RSE of 27.33, indicating that the model with three variables provides better predictions than the simple models. AIC and BIC values also show that models with more variables tend to perform better in predicting the body weight of LimPO cattle.

Table 4 shows the application of PCA in the regression of LimPO cattle. The results are similar to those for SimPO cattle, where using PCA does not reduce prediction accuracy. The model with four principal components (PC_{1-4}) has an R^2 of 0.873, comparable to the best model without PCA. Reducing the number of components down to just PC_1 still gives a good result, with an R^2 of 0.834, although there is a slight decrease in accuracy. The scree plot in Figure 6 indicated that the use only PC1 already explained 86.65% variability of the data of LimPO cattle.

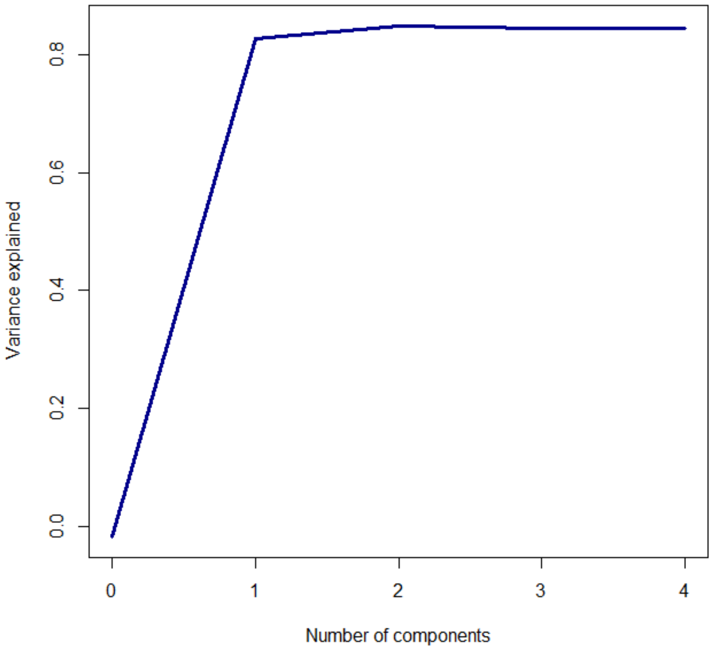

Figure 6. Scree plot of body weight and body measurements of LimPO cattle

The result of this study confirmed to the result reported by Dakhlan et al. [8] that both conventional linear regression and PCA-derived regression equations produce similar accuracy with similar selection criteria, but using PCR did not have potential multicollinearity. From the regression results above, it can be explained that the body measurements of SimPO cattle are more reliable for predicting body weight compared to LimPO cattle, as indicated by the higher R^2 values for SimPO cattle. Meanwhile, PCA proves useful in simplifying the model without reducing accuracy for both SimPO and LimPO cattle.

4. Conclusion

The application of Principal Component Regression (PCR) is effective in predicting the body weight of SimPO and LimPO cattle while maintaining prediction accuracy. SimPO cattle have a stronger relationship between body measurements and body weight compared to LimPO cattle. Additionally, multiple regression models provide more accurate results than simple regression models for both types of cattle.

Acknowledgement

The author is very grateful to Hassem Muhamad Indonant, Galang Ramadhan, and Fatkhurrohman for their assistance in data collection. The author also thanks the Maju Sejahtera Livestock Production Cooperative for facilitating this research. Gratitude is also extended to the Dean of the Faculty of Agriculture, University of Lampung, for funding this research through the DIPA project of the Faculty of Agriculture, Unila, in 2024.

References

[1] Wang Z, Shadpour S, Chan E, Rotondo V, Wood K M and Tulpan D 2021 ASAS-NANP SYMPOSIUM: Applications of machine learning for livestock body weight prediction from digital images *J. Anim. Sci.* **99**(2), 1-15. Oxford University Press. https://doi.org/10.1093/jas/skab022

[2] Xiong Y, Condotta I C F S, Musgrave J A, Brown-Brandl T M and Mulliniks J T 2023 Estimating body weight and body condition score of mature beef cows using depth images *Translational Anim. Sci.* **7**(1), 1-14. https://doi.org/10.1093/tas/txad085

[3] Ma W, Qi X, Sun Y, Gao R, Ding L, Wang R, Peng C, Zhang J, Wu J, Xu Z, Li M, Zhao H, Huang S and Li Q 2024 Computer Vision-Based Measurement Techniques for Livestock Body Dimension and Weight: A Review *Agric. (Switzerland)* **14**(2), 306. https://doi.org/10.3390/agriculture14020306

[4] Negash F 2021 Application of principal component analysis for predicting body weight of Ethiopian indigenous chicken populations *Trop. Anim. Health Prod.* **53**(104), 1-15. https://doi.org/10.1007/s11250-020-02526-w

[5] Canaza-Cayo A W, Mota R R, Amarilho-Silveira F, Duarte A S and Cobuci J A 2021 Principal Component Analysis for Body Weight Prediction of Corriedale Ewes from Southern Peru *J. Anim. Health Prod.* **9**(4), 417–424. https://doi.org/10.17582/journal.jahp/2021/9.4.417.424

[6] Putra W P B, Said S and Arifin J 2020 Principal component analysis (PCA) of body measurements and body indices in the Pasundan cows *Black Sea J. Agric.* **3**(1), 49–55.

[7] Gomez-Vazquez A, Tırınk C, Cruz-Tamayo A A, Cruz-Hernandez A, Camacho-Pérez E, Okuyucu İ C, Şahin H A, Dzib-Cauich D A, Gülboy Ö, Garcia-Herrera R A and Chay-Canul A J 2024 Prediction of Body Weight by Using PCA-Supported Gradient Boosting and Random Forest Algorithms in Water Buffaloes (Bubalus bubalis) Reared in South-Eastern Mexico *Anim.* **14**(2), 293. https://doi.org/10.3390/ani14020293

[8] Dakhlan A, Adhianto K, Qisthon A and Husni A 2024 Optimizing Ongole Grade Cattle weight prediction through Principal Component Analysis *IOP Conference Series: Earth and Environmental Science* **1360**(1). https://doi.org/10.1088/1755-1315/1360/1/012027

[9] Dakhlan A, Saputra A, Hamdani M D I and Sulastri 2020 Regression Models and Correlation Analysis for Predicting Body Weight of Female Ettawa Grade Goat using its Body Measurements. *Adv. in Anim. Vet. Sci.* **8**(11), 1142–1146. https://doi.org/10.17582/journal.aavs/2020/8.11.1142.1146

[10 Sabbioni A, Beretti V, Superchi P and Ablondi M 2020 Body weight estimation from body measures in Cornigliese sheep breed *Italian J. Anim. Sci.* **19**(1), 25–30. https://doi.org/10.1080/1828051X.2019.1689189

[11] Shoimah U S, Dakhlan A, Sulastri and Hamdani M D I 2021 Use of body measurements to predict live body weight of Simmental bull in Lembang Artificial Insemination Center, West Java *IOP Conference Series: Earth and Environmental Science* **888**(1), 012030. https://doi.org/10.1088/1755-1315/888/1/012030

[12] Dakhlan A, Hamdani M D I, Putri D R, Sulastri and Qisthon A 2021 Short communication: Prediction of body weight based on body measurements in female saburai goat *Biodiversitas* **22**(3), 1391–1396. https://doi.org/10.13057/biodiv/d220341

[13] Dakhlan A, Qisthon A and Hamdani M D I 2021 Predicting Body Weight Based on Body Measurements at Different Ages and Sex in Saburai Goat *Adv. in Anim. Vet. Sci.* **9**(11), 1791–1799. https://doi.org/10.17582/journal.aavs/2021/9.11.1791.1799

[14] Ibrahim A, Artama W T, Budisatria I G S, Yuniawan R, Atmoko B A and Widayanti R 2021 Regression model analysis for prediction of body weight from body measurements in female batur sheep of Banjarnegara district, Indonesia *Biodiversitas* **22**(7), 2723–2730. https://doi.org/10.13057/biodiv/d220721

[15] Jannah Z N, Atmoko B A, Ibrahim A, Harahap M A and Panjono 2023 Body weight prediction model analysis based on the body size of female Sakub sheep in Brebes District, Indonesia *Biodiversitas* **24**(7), 3657–3664. https://doi.org/10.13057/biodiv/d240702

[16] Firdaus F, Atmoko B A, Baliarti E, Widi T S M, Maharani D and Panjono P 2023 The meta-analysis of beef cattle body weight prediction using body measurement approach with breed, sex, and age categories *J. Adv. Vet. Anim. Res.* **10**(4), 630–638. https://doi.org/10.5455/javar.2023.j718

[17] Shrestha N 2020 Detecting Multicollinearity in Regression Analysis *American J. Appl. Math. Stat.* **8**(2), 39–42. https://doi.org/10.12691/ajams-8-2-1

[18] R Core Team 2023 *R: A Language and Environment for Statistical Computing, Vienna, Austria*. https://www.r-project.org/

[19] Dakhlan A 2019 *Experimental Design and Data Analysis Using R* (1st ed.) (Yogyakarta: Graha Ilmu (Matematika)). https://grahailmu.id/product/experimental-design-and-data-analysis-using-r/

[20] Paputungan U, Hakim L, Ciptadi G and Lapian H F N 2013 The estimation accuracy of live weight from metric body measurements in Ongole grade cows. *J. the Indonesian Tropical Anim. Agric.* **38**(3), 149–155. https://doi.org/10.14710/jitaa.38.3.149-155

[21] de Moraes Weber V A, de Lima Weber F, da Costa Gomes R, da Silva Oliveira A, Menezes G V, de Abreu U G P, de Souza Belete N A and Pistori H 2020 Prediction of Girolando cattle weight by means of body measurements extracted from images *Revista Brasileira de Zootecnia* **49,** e20190110. https://doi.org/10.37496/RBZ4920190110

[22] Dakhlan A, Aziz R, Kurniawati D, Adhianto K and Qisthon A 2024 Body weight prediction of ongole grade cattle using body volume and body measurements *The 4Th International Conf. on Applied Sciences, Mathematics, and Informatics: Icasmi2022* **2970**, 030033. https://doi.org/10.1063/5.0208162