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Prediction of body mass in dairy cows using LiDAR technology

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Abstract. Precision livestock farming has driven the search for technological solutions that enable remote and non-invasive monitoring of animal health and zootechnical performance. This study aimed to investigate the use of computer vision for predicting body mass (BM) in a herd of Holstein Friesian dairy cows using three-dimensional images acquired via LiDAR (Light Detection and Ranging). From these images, the individual body volume (BV) of each animal was digitally estimated. Subsequently, the correlation between LiDAR-derived BV and body mass measured using the conventional weighing method was evaluated. Based on this relationship, statistical regression models were fitted to predict BM from BV. The results showed that BV measured using LiDAR achieved a coefficient of determination (R^2) of 0.7861 and a mean absolute percentage error (MAPE) of 4.43%. These findings demonstrate the feasibility of LiDAR technology as an effective, non-invasive alternative tool for estimating bovine body mass. The use of LiDAR enabled detailed recording of morphological characteristics and measurements, allowing continuous monitoring of body development without the need for direct animal handling. In conclusion, the incorporation of computer vision systems into dairy cattle management can optimize operational efficiency, reduce labor requirements, and promote a more sustainable production system, while enhancing animal welfare through automated monitoring.

Key words: regression model, dairy farming, computer vision.

INTRODUCTION

Dairy cattle farming plays a relevant role in modern agricultural systems, being responsible for the production of a food product with high nutritional value and for income generation across different production scales. Brazil ranks among the world's leading milk producers, highlighting the strategic importance of this activity for the national agribusiness sector (IBGE, 2024). The increasing intensification of dairy production systems has raised the demand for tools that enable continuous monitoring of zootechnical performance and physiological status of animals, with reduced interference in management practices and greater operational efficiency.

One of the main challenges in current Precision Livestock Farming research lies in the development of technologies and tools that combine low implementation costs with feasibility under field conditions. Among the challenges faced by the sector is the development of approaches that enable accurate individual monitoring of body mass (BM) in dairy cows, while reducing financial investment and minimizing the need for invasive management procedures, which may be associated with stress, discomfort, or pain in animals (Cainzos et al., 2022).

Accurate information regarding the BM of dairy cows can contribute significantly to strategic farm management. Such information allows for more precise adjustments in feed supply, reducing waste and minimizing nutritional deficiencies. Consequently, it supports the adequate fulfillment of animals' nutritional requirements (NASEM, 2021; Cainzos et al., 2022). This monitoring is particularly important during the periparturient period, as it aids in identifying changes in body condition associated with excessive mobilization of body reserves, which may be related to an increased risk of metabolic disorders (NASEM, 2021). More precise nutritional management contributes to the overall efficiency of the production system, as adequately nourished animals tend to exhibit better productive performance, resulting in greater efficiency, profitability, and sustainability of the farm. In this context, BM measurement goes beyond a simple growth metric, establishing itself as one of the most relevant biometric indicators for optimizing productive management and supporting health control in dairy herds (NASEM, 2021). From a physiological perspective, BM serves as a fundamental variable for adjusting nutritional models, enabling the estimation of production requirements and supporting the definition of therapeutic protocols, thereby reducing risks associated with underdosing or toxicity. Studies have shown that variations in body-related traits are associated with changes in milk production, reinforcing the importance of continuous monitoring of these indicators in dairy systems (Chlebowski et al., 2020).

Among the most common methods for measuring the BM of dairy cows is the use of conventional floor scales. However, this procedure may cause stress to animals, generating discomfort and even posing a risk of accidents (Weber et al., 2020; Ma et al., 2024; Oliveira et al., 2025).

Therefore, several studies indicate that BM and certain morphological measurements, such as body volume (BV), may be associated, contributing to a strong correlation between these variables (de Oliveira et al., 2025). Accordingly, some studies have sought to develop methodologies that mathematically associate morphological traits – such as dorsal length (DL), thoracic width (TW), abdominal width (AW), rump width (RW), rump height (RH), body depth (BD), thoracic perimeter (TP), and abdominal perimeter – with the BM of dairy cattle (Ruchay et al., 2020; Wang et al., 2021; de Oliveira et al., 2025).

In this context, the use of imaging tools such as LiDAR (Light Detection and Ranging) has emerged as an innovative remote sensing technology that enables the capture of biometric dimensions of the dorsal and lateral regions of cattle with high precision and without any physical contact (Wang et al., 2025).

Previous studies have already demonstrated the potential of different sensors for BM estimation. In dairy cows, Le Cozler et al. (2019) and Xavier et al. (2022) employed the same high-precision full-body scanning system, whereas Oliveira et al. (2025) used a depth camera with lateral acquisition of the animal. More recently, Wang et al. (2025) demonstrated the potential of LiDAR mounted on an unmanned aerial vehicle (UAV) for BM estimation in cattle under different postures. However, these approaches present relevant operational differences. Full-body scanning systems, although highly accurate, usually depend on specific data acquisition systems. In turn, depth cameras with a lateral view may limit descriptor extraction to the body region effectively visible to the sensor. Similarly, UAV-based LiDAR increases data collection mobility, but it remains dependent on factors inherent to aerial acquisition, such as flight height, flight path, and animal posture. In addition, in the study by Wang et al. (2025), this approach was applied to beef cattle. In this scenario, a gap remains regarding the use of short-range handheld LiDAR in lactating dairy cows, in which proximal acquisition may provide greater geometric detail of the trunk and better integration into routine field conditions. Thus, the research problem that motivated this study was to determine whether BV obtained by handheld LiDAR can act as a reliable predictor of BM in these cows under confined operational conditions.

In light of this, the objective of this study was to develop a regression model to estimate BM in dairy cows from body volume obtained from images captured by handheld LiDAR. From a scientific perspective, the study aimed to evaluate the relationship between BV and BM, as well as to verify the predictive ability of this variable in a regression model. From a practical perspective, the study sought to contribute to the development of a non-invasive and operationally feasible alternative for BM estimation in dairy herds.

MATERIALS AND METHODS

Ethical procedures

This research was conducted in full compliance with the guidelines established and approved by the Institutional Animal Care and Use Committee (CEUA) of the Federal University of Lavras (UFLA), under approval protocol no. 8093310125.

Experimental design and data acquisition

The experiment was carried out on a commercial dairy farm specialized in Holstein dairy cattle production, located in the municipality of Ijaci, Minas Gerais State, Brazil, at the geographic coordinates 21°09′52.3″ S and 44°55′52.1″ W. Experimental data collection was conducted between September 15, 2025, and December 10, 2025.

Animals, housing, and feeding

During the experimental period, 145 sample records were collected from lactating Holstein dairy cows aged between 2 and 6 years. Fig. 1 illustrates the tie-stall confinement system in which the animals were housed. The facilities measured 36.0 m × 12.0 m and consisted of 42 individual stalls, each measuring 1.20 m × 2.40 m, equipped with sand bedding and with a total capacity of 42 animals. The sand bedding was regularly maintained to ensure cleanliness and provide adequate comfort for resting.

The barn was equipped with continuous mechanical ventilation, monitored by automatic thermal sensors to regulate airflow intensity and ensure thermal comfort. In addition, a sprinkler system was activated during daytime hours (from 7:00 a.m. to 5:00 p.m.), operating in intermittent cycles, particularly during periods of elevated ambient temperatures, thereby enhancing thermal comfort for the animals.

Figure 1. Confinement facilities - Tie Stall System.

Feed was provided along the feed alley according to the farm's standard management practices, typically following a total mixed ration (TMR) system. The diet was primarily composed of corn silage and soybean meal, with occasional inclusion of other ingredients such as soybean hulls, depending on management conditions. Water was available ad libitum through individual drinkers positioned between stalls, with one drinker serving two animals and equipped with a float-controlled system to ensure continuous water supply. Additional water access was also available during milking periods. Routine management procedures, including milking and feeding, followed established practices aimed at minimizing animal stress.

Milking was not performed in the tie-stall barn; instead, cows were routinely moved to a dedicated milking parlor located approximately 70–100 m from the housing facility. Milking was carried out using a pipeline milking system, in which teat cup clusters were attached to the animals, allowing the simultaneous milking of small groups of cows. The tie-stall system allowed animals to stand and lie down comfortably within their stalls, supporting normal postural adjustments. Additionally, animals were visually monitored during daily management activities to ensure adequate health status and general condition throughout the experimental period. Bedding management included the periodic addition of lime to improve hygiene conditions and reduce moisture.

Data acquisition

Body mass (BM) data collection was initiated after the completion of the first morning milking at 05:30 h. The animals were individually guided to a handling and restraint chute (Fig. 2) equipped with a precision electronic scale, model EziWeigh5 (Tru-Test, Auckland, New Zealand), which was used to measure body mass. Measurements were recorded in kilograms (kg), with a resolution of 5 kg increments, as configured in the scale at the time of data collection.

Figure 2. Handling chute equipped with an electronic scale.

After BM measurement, the animals were returned to their individual stalls in the tie-stall confinement system, where they received feed and three-dimensional image acquisition was performed.

Three-dimensional images were acquired using a portable LiDAR sensor, model GS-100G (Geosun Navigation, Guangzhou, China). The device features a 360° field of view in the horizontal plane and 270° in the vertical plane, a data acquisition rate of 320,000 points s^{-1}, and point cloud accuracy of $\leq$ 5 cm at a distance of 100 m.

The portable LiDAR sensor was operated at an approximate distance of 1.5 m from the animals and at a height of 1.2 m above the ground.

Data processing and preprocessing

CloudCompare® software (version 2.14) was used to process the LiDAR point clouds, including noise removal, animal segmentation, and spatial alignment, resulting in datasets exported for subsequent analysis.

Individual animal segmentation was performed on the three-dimensional point clouds acquired by LiDAR in order to isolate the geometric representation of each bovine for subsequent body volume (BV) estimation.

Initially, the point clouds underwent a pre-processing step aimed at noise reduction and the removal of points associated with confinement system structures. Animal individualization was carried out through manual segmentation based on geometric criteria, enabling the independent extraction of the point cloud corresponding to each animal. The adopted procedure ensured the preservation of body morphology required for volumetric estimation while minimizing environmental interference.

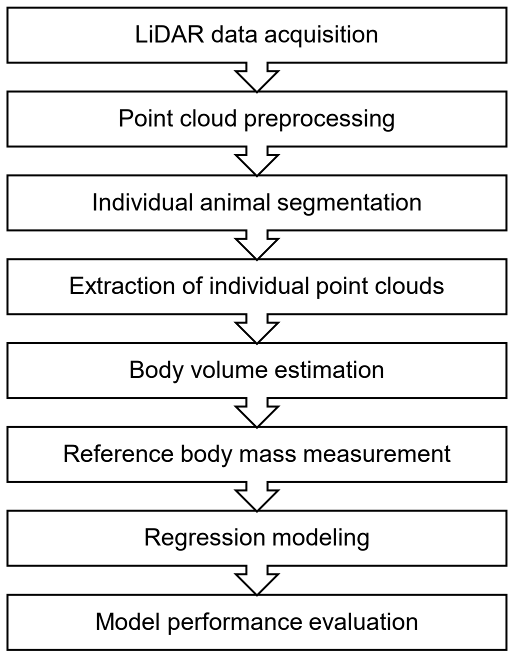

Figure 3. Operational flowchart for animal segmentation.

The general steps of the segmentation and individual point cloud extraction procedure are summarized in the flowchart presented in Fig. 3.

Fig. 4, a illustrates a segmented point cloud obtained from the original full-body image of the animal. To normalize the point clouds, extremity removal was performed according to the methodology proposed by Weber et al. (2020), Menesatti et al. (2014), and Cominitte et al. (2020), as a criterion to optimize the manipulation of the thoracic region. Once isolated, the region of interest was converted into a new image and subjected to a refinement process (Fig. 4, b).

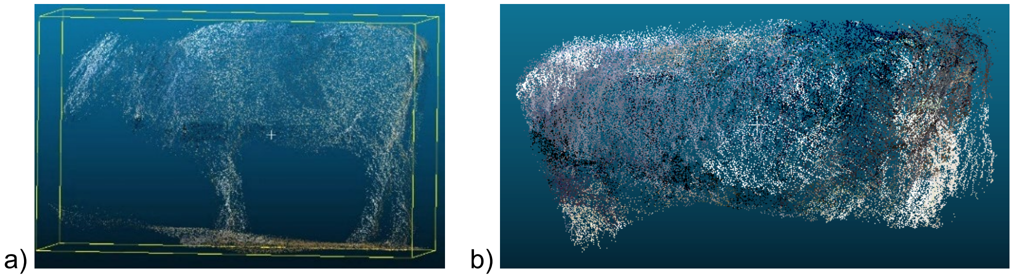

Figure 4. a) Three-dimensional point cloud of an isolated animal; b) isolated and refined region for volume analysis.

The data cleaning and processing protocol consisted of the systematic elimination of noise points generated by the infrastructure and physical installations of the rural property, as can be seen in detail in Fig. 5.

The point cloud filtering protocol began with the extraction of noise (isolated points) that showed deviations from the average density of the sample. Subsequently, the dataset was subjected to point filtering processes. The concluding step of the cloud processing was the quantitative determination of the animal's BV, as illustrated graphically in (Fig. 6).

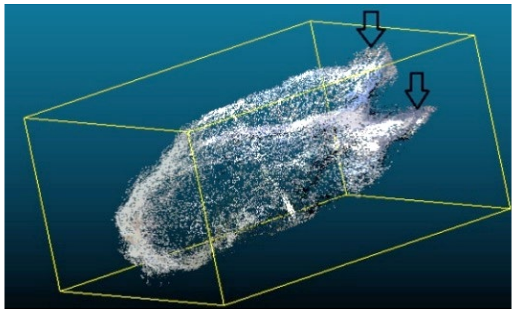

Figure 5. Image with noise due to angle distortion in the frontal region of the animal.

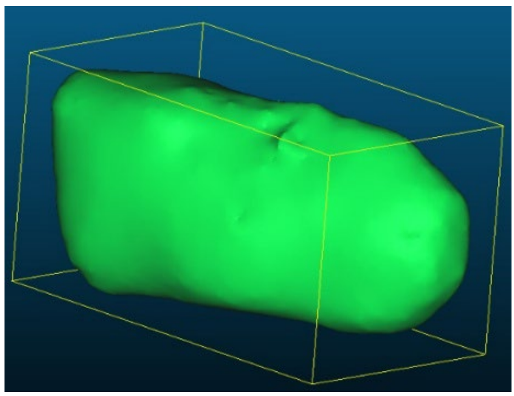

Figure 6. Image of the mesh for calculating the animal's BV (body volume).

Statistical analysis

The relationship between body mass (BM) and body volume (BV) was assessed using Spearman's correlation coefficient (Zar, 2005). This nonparametric method was adopted because it does not require assumptions of data normality and is suitable for identifying monotonic associations between variables, even when the relationship is not strictly linear.

A simple linear regression model was fitted to estimate BM as a function of BV, aiming to evaluate the potential of BV as a predictor variable for body mass in dairy cattle. For model development and performance evaluation, the dataset was randomly divided into two subsets: 80% of the observations were used for model training, while the remaining 20% were reserved for predictive validation.

Model performance was evaluated using the coefficient of determination (R^2) and the correlation coefficient (r), which were employed to analyze the agreement between observed and estimated values. The mean absolute percentage error (MAPE) and the root mean square error (RMSE) were used to quantify deviations between predicted and observed values.

RESULTS AND DISCUSSION

The descriptive statistics of the BM of the dairy cows analyzed are presented in Fig. 7, highlighting the distribution of the observed values in the dataset.

According to Fig. 7, the body mass (BM) of the dairy cows ranged from 423 to 854 kg, indicating high data variability and the presence of individuals with heterogeneous physical characteristics within the sample. The median BM was636 kg, with an interquartile range defined by 600 kg (Q1) and 700 kg (Q3), indicating that most individuals in the sample exhibited BM values within this interval. The lower and upper limits were 454 kg and 826 kg, respectively.

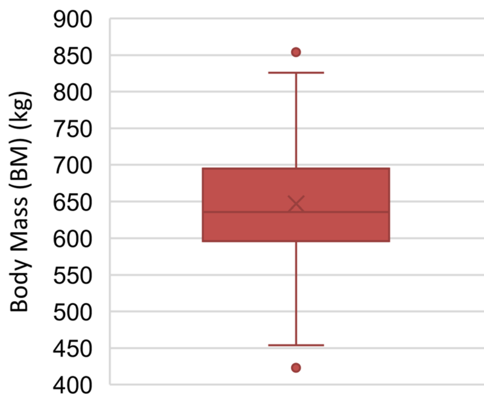

Figure 7. Boxplot of BM in kg of the animals evaluated.

Table 1 details the minimum, maximum, and mean values of BM and body volume (BV) for the evaluated cows.

When comparing the mean BM with the boxplot distribution (Fig. 7), it can be observed that the mean is very close to the median, suggesting an approximately symmetric distribution, although two extreme values are present. The coefficient of variation (CV) for BM was 12%, a value below 15%, indicating low relative dispersion of the data and suggesting that the dataset is homogeneous and that the mean is a reliable representation of the sample (Zar, 2005).

Descriptive analysis of body volume (BV) revealed a CV of 13.42%, indicating moderate variability among animals. For biological experiments involving large animals, this BV variability may may reflect the natural biological variation in body size and body mass within the evaluated herd. The BV exhibited a total range of 0.37 m^3 between the minimum and maximum values within the group of 145 samples.

Table 1. Descriptive statistics of body mass (BM) and body volume (BV) of the evaluated dairy cows (n = 145)

Variables evaluated	Min.	Max.	Average	Coefficient of variation (CV) %
BM (kg)	423	854	647	12
BV (m^3)	0.44	0.81	0.62	13.42

Fig. 8 shows a strong positive linear association between BV obtained from the portable LiDAR sensor and BM, with a Pearson correlation coefficient of $r = 0.88$, indicating that body volume captures a substantial proportion of the variation in body mass within the evaluated herd. This interpretation is consistent with the three-dimensional imaging literature. Le Cozler et al. (2019) reported a strong association between BM and BV derived from three-dimensional shapes, with correlation coefficients of 0.93 for total volume and 0.92 for truncated volume, highlighting that volume estimation is particularly relevant due to its high correlation with body weight.

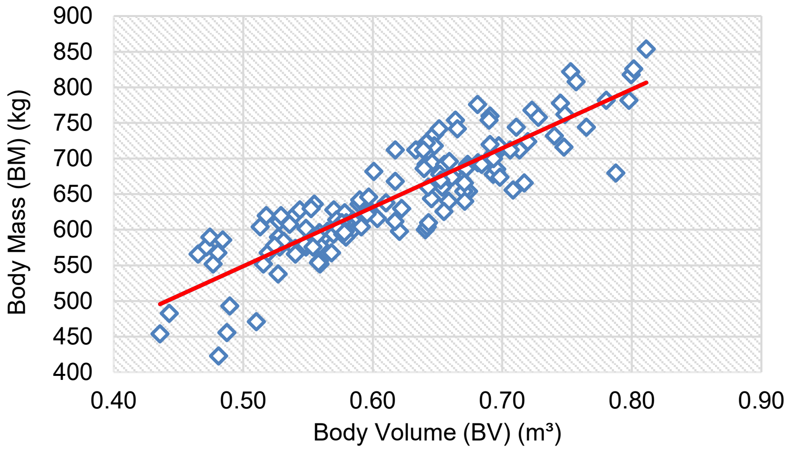

Figure 8. Data dispersion and global linear regression between BV and BM in dairy cows, used for exploratory analysis of the relationship between the variables.

The positive correlation observed between BM and BV supported the fitting of a linear regression model for exploratory purposes using the complete dataset. This analysis aimed to evaluate the overall strength of the relationship between the variables and to assess the potential of BV as an explanatory variable for BM prior to the predictive modeling stage with training-testing data partitioning.

The linear regression model fitted to estimate BM as a function of BV yielded a coefficient of determination (R^2) of 0.7861 and a mean absolute percentage error (MAPE) of 4.43%, indicating a strong association between the variables and reinforcing the potential of LiDAR-derived BV as a predictor of BM. Nevertheless, the estimation still presents a non-negligible error, which may be considered acceptable depending on the intended application, particularly in large herds where absolute accuracy is often of lower priority (de Oliveira et al., 2025).

The global linear regression model fitted to estimate BM as a function of BV is expressed by Eq. 1:

$$\mathrm{BM} = 134.57 + 828.46\,\mathrm{BV} \tag{1}$$

The results obtained were comparable, although slightly lower, than those reported by Le Cozler et al. (2019), who used total body volume as a predictive variable in a dataset of 64 Holstein cows and achieved an R^2 of 0.85. The discrepancy observed in R^2 between studies may be related to factors such as sample size and specific characteristics of the evaluated populations, including differences in body conformation, body condition, and data acquisition conditions. Despite the lower accuracy, the present study corroborates that body volume is a relevant and effective predictor of body mass in cattle (Oliveira et al., 2025).

Additionally, Xavier et al. (2022), using three-dimensional images to estimate the body mass of Holstein cows, reported that BM could be estimated from BV with an RMSE of 25.4 kg, a value very close to that previously reported by Le Cozler et al. (2019) (24.9 kg). They further observed that incorporating animal-specific intercepts and slopes increased R^2 to 0.98 and reduced RMSE to 12.1 kg, indicating that part of the prediction error arises from inter-individual variability in the volume–weight relationship throughout lactation. Similarly, Costigan et al. (2021) fitted equations to predict the BM of Holstein Friesian and Jersey heifers in pasture-based systems and reported high performance for BV-based models, with R^2 of 0.96 and RMSE of 15.06 kg for Holstein Friesian and R^2 of 0.95 and RMSE of 13.37 kg for Jersey. They also concluded that, from a practical standpoint, BV-based equations are the most suitable for routine farm use, as they require fewer measurements and allow growth monitoring in the absence of a weighing scale.

Taken together, these results reinforce that volumetric variables are robust predictors of BM, while also highlighting relevant methodological differences among studies. Whereas Xavier et al. (2022) derived variables from three-dimensional images acquired automatically by a dedicated imaging device, the present study estimated BV using LiDAR scanning, i.e., laser-based acquisition. This represents a distinct source of three-dimensional data compared with camera-based approaches and strengthens the potential for application under operational conditions in which LiDAR capture may offer greater geometric detail of body contours.

Following the exploratory analysis of the relationship between variables, the dataset was partitioned at an 80:20 ratio for calibration (training) and external validation (testing), respectively. This strategy ensured that the test data remained fully independent from model fitting, allowing an unbiased assessment of model generalization capacity (de Oliveira et al., 2025).

Model performance and the graphical analysis of the training data are presented in Fig. 9.

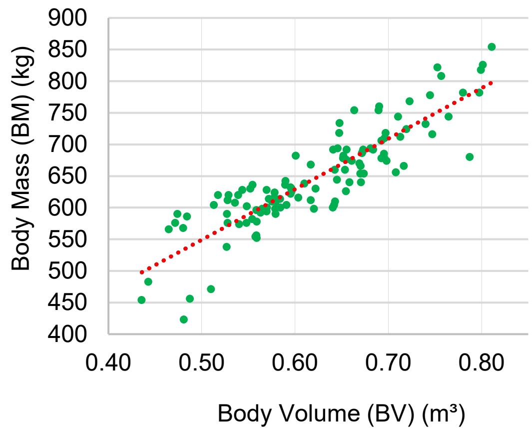

Figure 9. Dispersion of training set data (80%) and fitted linear regression between BV and BM in dairy cows.

The graph presented illustrates the adjustment and training process of a predictive model, in which simple linear regression was used to describe the relationship between BV (m^3) and BM (kg). From the training data, the model expressed in Eq. 2 was obtained:

$$\mathrm{BM} = 799.73\,\mathrm{BV} + 149.3 \quad (2)$$

The fit resulted in $R^2 = 0.776$, indicating that BV explains 77.6% of the variation observed in BM in the training set, which shows a consistent positive linear association (Zar, 2005; Gomes, 2009).

The results of the model fit validation can be seen in detail in the graphical analysis of Fig. 10.

The results of the linear regression models obtained in the different stages of the analysis – exploratory global regression, calibration (training), and external validation (testing) – are presented in Table 2. The model equations, the coefficient of determination (R^2), and the MAPE and RMSE error metrics were considered, allowing for a comparison of the model fit and its generalization capacity.

The coefficient of determination obtained during validation was $R^2 = 0.869$, which is higher than that observed in the training dataset, indicating high statistical reliability and reinforcing the predictive capability of BV for BM estimation. This performance is corroborated by Fig. 10, in which R^2 expresses the proportion of observed variability explained by the model, demonstrating satisfactory agreement between observed and estimated values. Taken together, the numerical and graphical consistency supports the suitability of simple linear models to describe the relationship between the predictor variable BV and BM, even in the presence of morphological variability among the evaluated individuals.

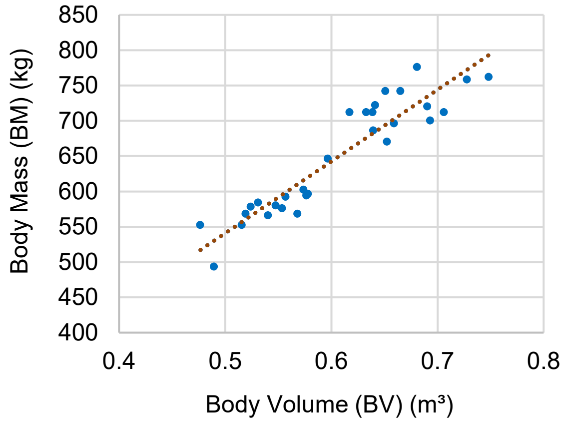

Figure 10. Relationship between BV and BM of dairy cows during the validation phase (20%) of the regression model.

Table 2. Linear regression models for estimating body mass (BM) from body volume (BV) and their respective performance metrics

Equation	Model	R^2	MAPE (%)	RMSE (kg)
(1) Global model	$BM = 828.46\,BV + 134.57$	0.786	4.43	36.25
(2) Training model	$BM = 799.73\,BV + 149.3$	0.776	4.50	36.51
(3) Test model	$BM = 799.73\,BV + 149.3$	0.869	3.96	35.27

To assess predictive accuracy in the validation (test) model, residual error indicators were calculated. The RMSE of 35.27 kg quantifies the average deviation between estimated and observed values in the validation dataset, while the MAPE was 3.96%. According to Gomes (2009), MAPE values below 10% classify model performance as excellent, thereby confirming the technical feasibility of using BV as a predictor of BM within the studied context.

In comparative terms, Xiong et al. (2023) estimated BM from projected BV obtained using depth images and adopted an 80% training and 20% testing data split, with five-fold cross-validation applied to the training set. During training, the authors reported a strong correlation between BV and BM ($r = 0.9166$) and a linear fit with

$R^2 = 0.8255$, as well as a mean absolute error (MAE) of 19.20 ± 13.50 kg and a MAPE of 4.80% ± 3.50. When applying the test dataset, they observed an increase in error to MAE = 22.7 ± 13.44 kg and MAPE = 5.5% ± 3.88%, while maintaining an R^2 of 0.8661, indicating good model generalization to external data. These results reinforce that volumetric variables derived from three-dimensional sensing maintain consistent predictive capability across training and validation stages, despite relevant methodological differences relative to the present study. Specifically, Xiong et al. (2023) employed a time-of-flight depth sensor and projected volume derived from a top view, whereas in this study BV was estimated using LiDAR.

The use of univariate models, such as the BV-based model adopted in this study, is notable for its methodological simplicity and operational feasibility under real field conditions. Relying on a single explanatory variable reduces data collection and processing complexity, thereby facilitating practical application and scalability in dairy production systems. Previous studies have demonstrated consistent results when exclusively using chest circumference as a predictor of BM, reinforcing that univariate approaches can effectively capture biologically relevant relationships (Heinrichs et al., 2017; Pereira et al., 2021).

From a practical standpoint, the results indicate that the proposed approach has potential to be applied as a support tool for routine BM monitoring on dairy farms. In confined systems, BM estimation using handheld LiDAR may reduce dependence on frequent weighing with scales, decreasing interference with management practices and making animal monitoring faster and less invasive. For producers, monitoring BM and its variation over time may help identify body losses or gains, adjust nutritional management, track productive and reproductive performance, and support decisions related to herd health and welfare. Although large-scale application still depends on standardized acquisition and processing procedures, the results obtained reinforce the potential of handheld LiDAR as a support tool for body monitoring in dairy herds.

Despite the promising results, some limitations should be considered. The study was conducted under specific conditions, including a single farm, confined housing system, and a limited number of animals, which may restrict the generalization of the findings to other production systems. In addition, the accuracy of BV estimation may be influenced by factors such as animal posture, movement during data acquisition, and variability in LiDAR scanning conditions. Furthermore, the use of manual segmentation may introduce operator-dependent variability. Future studies should explore automated processing approaches and validate the methodology under different environmental and management conditions.

CONCLUSIONS

The results of this study demonstrate that BV can be used as a predictive variable for BM in lactating Holstein cows, confirming the potential of handheld LiDAR as a non-invasive tool for body monitoring in dairy cattle. The developed model showed that the relationship between BV and BM can be satisfactorily represented by a simple regression approach, which reinforces its applicability under field operational conditions. In this way, the technology shows potential to support routine animal monitoring and contribute to more objective management practices in dairy production systems.

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