Cattle Weight Estimation from Dense Point Clouds

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Keywords: Structure-from-Motion, 3D Reconstruction, UAV, Livestock Precision.

Abstract: Cattle weight is essential for decision-making in precision livestock farming, directly supporting nutrition management, animal welfare, and production efficiency. Existing methods rely on close-range measurements or manual intervention, limiting scalability. This work proposes an workflow for cattle weight estimation based on point clouds derived from aerial images. RGB images acquired at low altitude were processed using Structure from Motion (SfM) techniques to generate dense point clouds. Individual animals were automatically segmented from the reconstructed 3D scene, and voxel-based volumetric features were extracted for each animal. Body weight was then estimated through linear regression models calibrated with ground truth measurements obtained from individual weighing. The proposed approach was evaluated on Nellore cattle in a feedlot environment and achieved a root mean square error (RMSE) of 8.35 kg, corresponding to an average relative error of approximately 2.29%. The results highlight the potential of UAV-based photogrammetry as a cost-effective decision support tool for digital and sustainable livestock management.

1 INTRODUCTION

Digital systems have become important tools for improving efficiency and sustainability in agricultural production (Wendt et al., 2025). However, considering livestock production, such digital solutions have only gained attention in recent years and still present research gaps to be addressed (Qiao et al., 2021; Besler et al., 2024).

Decision-making processes in livestock production rely on information regarding the physical characteristics of the animals, particularly body weight, which impacts health management and productivity. Traditional manual weight measurement methods are often invasive and labor-intensive, potentially inducing stress in animals and negatively affecting the welfare and growth (Barbedo and Koenigkan, 2018). In addition, these manual techniques are impractical for large-scale or frequent monitoring, limiting their applicability as decision support tools in modern production systems. These limitations have motivated the use of remote sensing technologies combined with artificial intelligence (AI) and computer vision (CV) for contactless animal monitoring (Barbedo and Koenigkan, 2018; Qiao et al., 2021).

Satellite imagery stands out for large-scale applications due to its wide spatial coverage and repeated acquisitions. Recent studies have demonstrated that a very high-resolution (VHR) satellite images enable individual cattle detection and counting when submeter spatial resolution data are available (Torrusio et al., 2024; Ocholla et al., 2025), including applications in remote and inaccessible regions of the Brazilian Amazon (Laradji et al., 2020). These studies show the potential of satellite imagery for large-scale cattle inventory and decision-making processes. However, monitoring animal growth, body condition, or welfare require more detailed spatial and geometric information, which cannot be captured by satellite sensors (Barbedo and Koenigkan, 2018). Images ac-

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Castanheiro, L. F., Tetila, E. C., Furuya, D. E. G., da Silva, J. P., Barbedo, J. G. A., Romani, L. A. S. and Bolfe, E. L.
Cattle Weight Estimation from Dense Point Clouds.
DOI: 10.5220/0014925500004018

In *Proceedings of the 28th International Conference on Enterprise Information Systems (ICEIS 2026) - Volume 2*, pages 1133-1140
ISBN: 978-989-758-834-1; ISSN: 2184-4992

quired using unmanned aerial vehicles (UAVs) have emerged as an alternative for detailed cattle monitoring, offering higher spatial resolution, non-invasive and cost-effective data acquisition (Barbedo et al., 2020). When combined with AI and CV techniques, UAV images enable the extraction of detailed information at the individual animal, becoming a valuable decision support tool for bovine body weight and growth estimation. Shao et al. (2020) showed that deep learning applied to UAV imagery can achieve high cattle detection performance, resulting an F-measure of 0.952 using aerial images of Japanese Brown Cattle acquired at a flight altitude of approximately 50 m. However, image-based detection methods face limitations, such as repeated counting due to image overlap. This issue was addressed by Shao et al. (2020) through 3D reconstruction techniques using aerial images.

An alternative approach to obtaining 3D measurements is the use of LiDAR sensors, which provide direct 3D point clouds of the environment, and do not depend on lighting condition. Wang et al. (2024) showed that LiDAR data provide consistent geometric features (e.g. waist height, abdomen width, etc.) of Simmental cattle, improving measurement compared to image approaches. Similarly, Los et al. (2023) investigated the use of UAV-based LiDAR for estimating height and weight of Holstein-Friesian cattle in pasture environment, reporting improved accuracy when compared to RGB images. In these works, the use of LiDAR data allowed the direct measurement of geometric features reducing ambiguities and enable data collection during night times (Wang et al., 2024).

The use of 3D data has proven the significance in livestock monitoring. However, LiDAR-based solutions present drawbacks that limit their widespread adoption in operational livestock production systems. The high costs of LiDAR sensors, along with the need for specialized hardware and processing workflows, make such solutions economically unfeasible for many farms. Moreover, achieving suitable spatial coverage and accuracy requires careful selection of LiDAR sensor specifications and flight configurations. These limitations motivate the investigation of alternative approaches that can give 3D information while maintaining lower costs and greater flexibility, such as point clouds generated from multi-view images using photogrammetric and CV reconstruction techniques. For instance, Weber et al. (2020) presented an image-based approach for estimating the body weight of beef cattle using digital images acquired from cameras installed within the feedlot to estimate animal weight. The Bagging algorithm showed the best results, with Mean Absolute Error (MAE) of 13.44 kg, Square Root of the Mean Error (RMSE) of 15.88 kg, and Mean Absolute Percentage Error (MAPE) of 2.27%. In addition to this approach, other studies have similarly relied on close-range digital imagery acquired from cameras installed in feedlot or mobile phone for bovine monitoring (Bai et al., 2025; Giannone et al., 2025). These methods typically use close-range images capturing single view of individual animals and extract morphological features that are used as input for regression or machine learning models. The widespread adoption of close-range images shows its effectiveness for detailed animal-level analysis under controlled acquisition conditions. However, fixed camera limits viewing angle and relies on close-range acquisition of individual animals under controlled conditions, which limits scalability and may induce stress in the animals.

Los et al. (2023) explore the use of dense point clouds generated from UAV images for weight estimation. Individual animals were obtained through manual segmentation, after which the volume of each animal was calculated and converted into body weight though linear regression. This approach was evaluated with spatially separated Dutch cattle in pasture environment, which facilitates the manual segmentation of individual animal. The results showed that estimation accuracy was highly dependent on animal posture and motion: for lying cattle, the mean weight error reached 62 kg, improving to 31 kg after outlier removal, while standing animals achieved a mean error of 38 kg (about 5.5% of the true weight). However, the workflow relied on manual segmentation of individual animals limiting its applicability in large-scale or fully automated monitoring scenarios.

In this work, the objective is to evaluated the performance of cattle weight estimation by integrating 3D reconstruction techniques, automated segmentation based on Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and weight estimation into a processing workflow. The adoption of an automated segmentation technique represents a step toward automation, reducing the need for manual steps commonly reported in Los et al. (2023). Moreover, the proposed approach was evaluated with Nellore cattle in feedlot, where animals are positioned close to each other, increasing the complexity of 3D reconstruction and segmentation due to occlusions and proximity. The proposed approach contributes to the advancement of digital tools for decision support in precision livestock farming, enabling low-intervention monitoring that reduces animal stress, aligning with the United Nations Sustainable Development Goals. In Brazil, this work is also aligned with Embrapa's Semear Digital project, which focuses on developing technological solutions for sustainable agricultural systems.

2 MATERIALS AND METHODS

2.1 Dataset

The field measurement was conducted at the Campanário farm in Laguna Carapã, Mato Grosso do Sul, Brazil (22°47'8" S; 55°3'57" W). The analysis focused on an area containing 70 Nellore cattle (*Bos indicus*). The images were acquired on the same day the animals were individually weighed, ensuring the correspondence between the aerial observations and the ground-based measurements to evaluate the proposed workflow. Each animal was identified by a unique numeric tag, and the correspondence between aerial observations and reference weights was established manually through visual inspection of the images. In contrast to Los et al. (2023), the cattle in this datset were

Data acquisition was performed using a DJI Phantom 4 Advanced UAV (Figure 1.a), in which the camera specifications are presented in Table 1.

Table 1: Technical specification of the camera embedded in DJI Phantom 4 Advanced.

Parameter	Value
Sensor size	1" CMOS
Field of view	84°
Image resolution	4864 × 3648 pixels
Focal length	8.8 mm
Pixel size	2.609 nm

The UAV flight altitude is also an important factor regarding cattle stress. Wang et al. (2024) showed that cattle can be monitored in their natural environment from distances of approximately 8 m, without inducing behavioral stress. The authors noticed that flight lower than 3 m caused some stress in the cattle. During the data acquisition of this study, it was observed that flight altitudes below 10 m disturbed the animals, indicating that very low-altitude UAV operations may negatively affect animal behavior and welfare. Therefore, the flight was performed at an altitude of 10 m, resulting in approximately 190 nadir-view images (see Figure 1.b) with a Ground Sample Distance (GSD) of 2.96 mm. This altitude was selected to minimize disturbance and stress to the cattle during image acquisition. The UAV was integrated with a real time kinematic (RTK) positioning system, enabling the direct georeferencing of the images within a global reference frame based on Global Navigation Satellite System (GNSS) observations. Figure 1 shows (a) the DJI Phantam 4 Advanced UAV used to collect the images, (b) an aerial image from the test area, and (c) an image of an individual animal. Figure 2 shows the orthomosaic of the test area generated through the aerial images.

Figure 1: (A) UAV platform used for image acquisition, (b) an image of the study area showing cattle, and (c) an image of an individual animal.

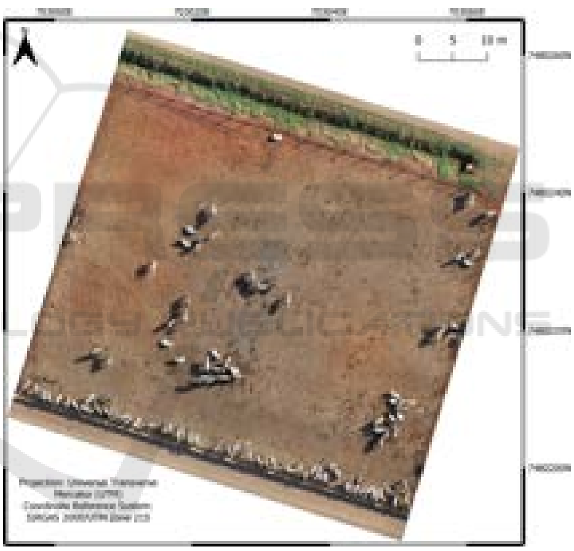

Figure 2: Orthomosaic of the test area, showing the spatial distribution of cattle at the time of data acquisition.

2.2 Workflow Processing

This section describes the methodological framework adopted in this work. An overview of the processing workflow is presented in Figure 3, and each step is detailed sequentially.

The data processing starts with a Bundle Block Adjustment to align all the collected images using a Structure from Motion (SfM)–based photogrammetric approach employed in Agisoft Metashape software. In this step, first, distinctive image features (keypoints) are automatically detected in each image using Scale Invariant Feature Transform (SIFT)

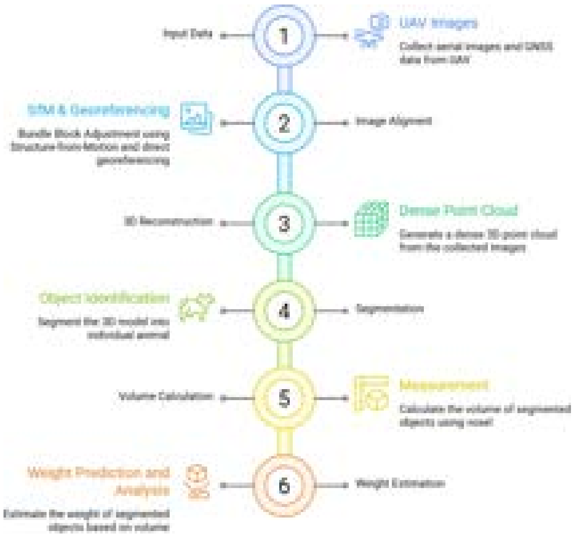

Figure 3: The proposed workflow.

Lowe (2004) descriptors. These features are then matched across overlapping images to establish tie points. Based on these correspondences, a bundle adjustment is performed to simultaneously optimize camera positions, orientations, and internal calibration parameters. The camera positions and orientations provided by the RTK system are incorporated into the bundle adjustment as constraints, ensuring accurate alignment of the images block within a global reference system. At the end of image alignment, the camera interior and exterior orientation parameters and a sparse point cloud are obtained, representing the 3D locations of the matched tie points.

Once the cameras are oriented, a dense point cloud using Multi-View Stereo algorithm is generated. For each image, depth information is estimated by comparing pixel intensities across multiple overlapping images with known orientations. Metashape computes depth maps by evaluating pixel correspondences along epipolar geometry constraints, minimizing photometric differences between views. These depth maps are then filtered to remove outliers and noise. The individual depth maps are subsequently merged into a unified 3D representation, producing a dense point cloud at a high spatial resolution.

Based on the dense point cloud, a segmentation procedure was applied to isolate each cattle adapting the segmentation approach presented by Wang et al. (2024), which was developed and tested in LiDAR point cloud. First, the dense point cloud was rotated according to the flight path and cropped to the specific boundaries of the experimental area. To distinguish standing cattle from those lying down, the authors divided the point cloud into two partitions using a horizontal plane ($z=\alpha$) parallel to the ground, where the value of α was defined by the average height from the ground to the bottom of the cattle's abdomen. The DBSCAN algorithm was applied to identify and cluster individual animals, using a neighborhood radius of 0.05 m and a minimum of 10 points for a cluster. Clusters containing fewer than 2000 points were discarded to remove non-cattle. At the end, the individual cattle point cloud was save in a PCD file. To further refine the segmentation, CloudCompare software was used for visual inspection and manual refinement when needed. In this study, only the standing animals were considered.

Each segmented point cloud was discretized into a voxel size of 2 cm, which is compatible with GSD, and the object volume was computed by aggregating the occupied voxels, providing an approximation of the animal's body volume. Then, the animal body weight was estimated from the derived volumetric measurements using an linear regression, a widely applied model (Le Cozler et al., 2019). Model parameters were calibrated using 7 standing animals for which reference weights were available from ground-based measurements. These calibration samples were used to fit the linear model between voxel-derived volume and body weight, establishing a mapping function that was subsequently applied to the remaining animals in the dataset to obtain weight estimates without direct physical measurement.

$$Weight\ (\text{kg}) = \alpha \times V\ (\text{m}^3) + \beta \qquad (1)$$

2.3 Validation

For assessment, each animal was physically weighed on the same day as the UAV image acquisition, and these measurements were adopted as ground truth to validate the proposed approach. Individual identification of the animals was ensured through numeric tags assigned to each animal. This enabled a direct correspondence between the segmented point clouds and the reference weight. Estimated weights were then compared against the ground truth measurements. Validation metrics included the estimation error for each animal, as well as summary statistics such as mean error, standard deviation, and root mean square error (RMSE).

3 RESULTS AND DISCUSSION

The bundle adjustment for image orientation converged successfully, resulting in camera position error of 0.257m and 0.728m for planimetric and altimetric coordinate, respectively. The higher error observed in the vertical component is consistent with the limitations of GNSS-based positioning, for which height estimation is generally less precise than horizontal positioning Meurer and Antreich (2017). Nevertheless, the height error remained low for low-altitude UAV surveys and the reprojection errors of keypoints across the image were lower than 0.6 pixel.

The 3D reconstruction process resulted in a dense point cloud that represents the feedlot and the animals present at the time of image acquisition as shown in Figure 4.

Figure 4: Dense point cloud of feedlot generated using aerial images.

Parts of the scene were not fully reconstructed due to challenges imposed by the scene characteristics and limitations of image-based 3D reconstruction algorithms. Homogeneous areas, such as uniform regions, limited the effectiveness of image matching during the reconstruction process, leading to localized gaps and reduced point density. Figure 5 shows two sequential images and the distribution of detected keypoints in each image and the matched tie points (in blue), highlighting areas (e.g. animal body) with insufficient feature correspondences that directly impact the completeness of the resulting 3D models.

Figure 5: Two sequential images and the detected keypoints.

Animal motion during image acquisition also affect the 3D reconstruction of the scene. As shown in Figure 6(a), the displacement of two animals between consecutive images resulted in partially overlapping point to different body positions. Similarly, Figure 6(b) illustrates the case of a single animal whose movement during capture produced double mapping effects. Multi-view 3D reconstruction assumes that the scene remains static during image acquisition. When animals move between consecutive images, tie points are incorrectly matched, leading to the generation of duplicated or inconsistent elements in the dense point clouds. Within the analyzed area, four cases of this double mapping were identified. To reduce this mapping error, strategies should consider animal behaviour, focusing on periods of lower activity. For example, flights conducted during feeding, when animals are typically more stationary at the trough, may help to minimize double mapping errors.

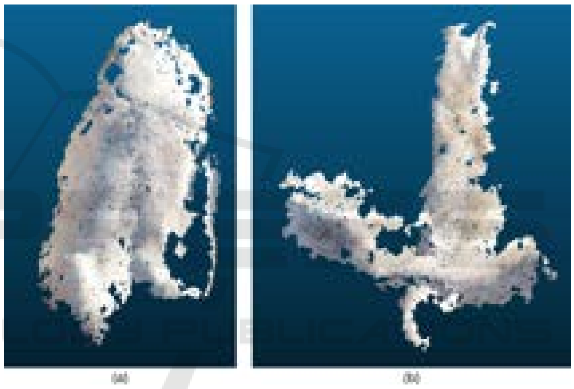

Figure 6: Effects of animal movement on dense point cloud generation: (a) movement of two animals causing partial overlap in the 3D reconstruction; (b) movement of a single animal causing a double mapping.

Another limitation of the 3D reconstruction is occlusions caused by animal proximity, overlapping bodies, and contact with the ground, which resulted in missing or sparsely reconstructed regions, particularly along lateral surfaces and lower body parts. These effects can be observed in the reconstructed point clouds shown in Figures 7(a)–(c), where parts of the cattle are incomplete, mainly lateral and lower belly body parts.

Nevertheless, the reconstructed point clouds consistently captured the upper body geometry of the animals, which is the most visible region from an aerial perspective. As illustrated in Figure 6(b), the dorsal contour of some animals was also reconstructed, providing the animal geometric information for reliable body weight estimation. Moreover, this partial representation was sufficient for subsequent segmentation.

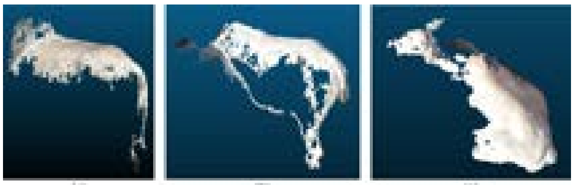

Figure 7: 3D reconstruction of individual cattle (a) and (b) standing and (c) laying, showing the incomplete reconstruction due to occlusions and limited texture.

Segmentation accuracy was affected by reconstruction and scene complexity. In some cases, gaps in the dense point cloud along the animal body led to oversegmentation, where a single animal was divided into multiple segments, particularly when animals were in a lying posture (Figure 8(a)). Such cases were excluded from the analysis. Conversely, undersegmentation occurred in situations where close proximity or physical contact between animals happened, resulting in multiple animals to be grouped into a single segment as illustrated in Figure 8(b). These segmentation challenges are due to aerial perspective and the animal close physical interactions, leading to discontinuities and gaps in the reconstructed point cloud.

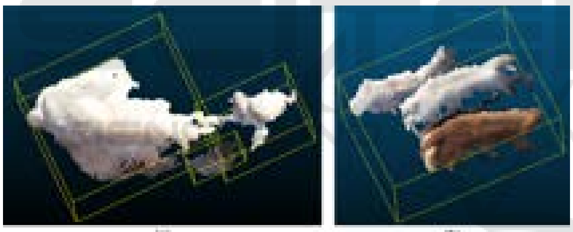

Figure 8: Examples of segmentation errors caused by reconstruction limitations and scene complexity: (a) oversegmentation of a single animal, leading to its division into multiple segments, and (b) undersegmentation resulting from close proximity between animals, resulting in multiple animals to be grouped into a single segment.

Despite incomplete 3D reconstruction in the dense point cloud, voxel-based volumetric analysis was performed. First, a visual inspection of the segmentation results was carried out, in which some animals were excluded from the weight estimation procedure. This included cases of double mapping caused by animal motion during image acquisition as presented in Figure 6. Cases of undersegmentation (Figure 8(b)) and segments containing residual points were manually refined through segmentation correction in CloudCompare software. A total of seven segments required this manual refinement step. Only standing animals with correct segmentation were retained for subsequent step.

The volumetric estimation step was then performed on the validated segments using a voxel-based discretization of each point cloud into a three-dimensional grid. As a result, the overall body volume could be approximated even in the presence of missing lateral or lower-body parts, enabling volume estimation for subsequent weight estimation.

The volume-weight model was calibrated using a subset of seven animals, resulting in a root mean square error (RMSE) of 6.03 kg, corresponding to an average relative error of 1.66%. During calibration, the mean absolute error was 1.87 kg, with a standard deviation of 6.19 kg. When applied to the remaining animals, the estimated weight achieved an RMSE of 8.35 kg, with a standard deviation of 8.52 kg and an average relative error of 2.02%, demonstrating consistent estimation performance beyond the calibration set.

Although the reconstructed point clouds do not fully represent the complete body surface of the animals, the achieved accuracy is consistent with reported errors in the literature for non-invasive weight estimation approaches, which typically range between 2% and 5% of the animal body weight (Barbedo and Koenigkan, 2018; Weber et al., 2020; Los et al., 2023). Considering an average cattle weight of approximately 360 kg in test feedlot in this work, the observed RMSE is within the expected errors, demonstrating that voxel-derived volumetric information provides a reliable basis for indirect weight estimation even under partial geometric reconstruction conditions.

The proposed methodology is not dependent on site-specific characteristics of the study area. It is based on a processing pipeline that integrates aerial image acquisition, 3D reconstruction, segmentation, and volumetric analysis, which can be transferred to other livestock production areas, including Agrotechnological Districts (DATs) established under Embrapa's Semear Digital program. DATs are areas across different regions of Brazil where digital technologies, data integration, and innovation ecosystems are jointly implemented to support agricultural production, sustainability, and decision-making processes. Within this framework, the transferability of the proposed system support its integration into decision support infrastructures for digital and sustainable livestock management.

4 CONCLUSION

This work evaluated the feasibility of estimating cattle body weight through dense point cloud generated from UAV images acquired in a feedlot. The proposed approach achieved an relative errors below 3%. These values are consistent with reported accuracies of existing non-invasive weight estimation approaches, while requiring lower-cost sensors and reduced animals stress.

The results further indicate that voxel-derived volumetric features provide a robust basis for weight estimation even when complete body surface reconstruction is not available, as long as the upper body is captured. This characteristic is particularly advantageous for UAV-based monitoring, where the upper body of the animals are most presented in an aerial images

Nevertheless, further advances are required to improve the scalability of the workflow. Future research should focus on enhancing 3D reconstruction algorithms as well as automated segmentation strategies capable of minimizing oversegmentation and undersegmentation errors. Improvements in these stages are expected to increase model generalization, reduce manual intervention. Future studies should also evaluate the performance under different cattle production systems, such as pasture-based environments, and across distinct breeds.

ACKNOWLEDGEMENTS

This study was financed by the São Paulo Research Foundation (FAPESP), Brasil, process number #2022/09319-9, #2025/05985-2, #2023/03870-8, #2024/05205-4, #2025/22552-2, and Foundation for Support to the Development of Education, Science and Technology of the State of Mato Grosso do Sul (FUNDECT) under Grants #83/029.295/2024 and #83/044.460/2024. We also thank the management and staff of Fazenda Campanário for providing access to feedlot facilities and confined cattle. We also express our appreciation to the farm's veterinary team for their valuable collaboration and technical support during data collection and animal handling.

REFERENCES

Bai, L., Guo, C., and Song, J. (2025). Cattle weight estimation model through readily photos. *Engineering Applications of Artificial Intelligence*, 143:109976.

Barbedo, J. G. A. and Koenigkan, L. V. (2018). Perspectives on the use of unmanned aerial systems to monitor cattle. *Outlook on agriculture*, 47(3):214–222.

Barbedo, J. G. A., Koenigkan, L. V., Santos, P. M., and Ribeiro, A. R. B. (2020). Counting cattle in uav images—dealing with clustered animals and animal/background contrast changes. *Sensors*, 20(7):2126.

Besler, B. C., Mojabi, P., Lasemiimeni, Z., Murphy, J. E., Wang, Z., Baker, R., Pearson, J. M., and Fear, E. C. (2024). Scoping review of precision technologies for cattle monitoring. *Smart Agricultural Technology*, 9:100596.

Giannone, C., Sahraeibelverdy, M., Lamanna, M., Cavallini, D., Formigoni, A., Tassinari, P., Torreggiani, D., and Bovo, M. (2025). Automated dairy cow identification and feeding behaviour analysis using a computer vision model based on yolov8. *Smart Agricultural Technology*, page 101304.

Laradji, I., Rodriguez, P., Kalaitzis, F., Vazquez, D., Young, R., Davey, E., and Lacoste, A. (2020). Counting cows: Tracking illegal cattle ranching from high-resolution satellite imagery. *arXiv preprint arXiv:2011.07369*.

Le Cozler, Y., Allain, C., Xavier, C., Depuille, L., Caillot, A., Delouard, J., Delattre, L., Luginbuhl, T., and Faverdin, P. (2019). Volume and surface area of holstein dairy cows calculated from complete 3d shapes acquired using a high-precision scanning system: Interest for body weight estimation. *Computers and Electronics in Agriculture*, 165:104977.

Los, S., Mücher, C. A., Kramer, H., Franke, G. J., and Kamphuis, C. (2023). Estimating body dimensions and weight of cattle on pasture with 3d models from uav imagery. *Smart Agricultural Technology*, 4:100167.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110.

Meurer, M. and Antreich, F. (2017). *Signals and Modulation*. Springer International Publishing, Cham.

Ocholla, I. A., Heiskanen, J., Karanja, F., Boitt, M., and Pellikka, P. (2025). Towards monitoring livestock using satellite imagery: Transferability of object detection and segmentation models in kenyan rangelands. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, page 100106.

Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D., Eiffert, S., and Sukkarieh, S. (2021). Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation. *Computers and electronics in agriculture*, 185:106143.

Shao, W., Kawakami, R., Yoshihashi, R., You, S., Kawase, H., and Naemura, T. (2020). Cattle detection and counting in uav images based on convolutional neural networks. *International Journal of Remote Sensing*, 41(1):31–52.

Torrusio, S., Gonzalez, J., Errázquin, M., Cereceda, A., Cassano, M. J., Morales, N., and Saucedo, R. (2024). Counting cattle in argentina with ai and satellite images. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 48:459–464.

Wang, Y., Mücher, S., Wang, W., and Kooistra, L. (2024). Automated retrieval of cattle body measurements from unmanned aerial vehicle-based lidar point clouds. *Computers and Electronics in Agriculture*, 227:109521.

Weber, V. A. M., de Lima Weber, F., da Silva Oliveira, A., Astolfi, G., Menezes, G. V., de Andrade Porto, J. V., Rezende, F. P. C., de Moraes, P. H., Matsubara, E. T., Mateus, R. G., et al. (2020). Cattle weight estimation using active contour models and regression trees bagging. *Computers and electronics in agriculture*, 179:105804.

Wendt, R., Tiadoro, E., Basso, F., and Bernardino, M. (2025). Bridging the gap in agricultural sharing economy: A systematic review for evaluating information systems for machinery efficiency. In *Proceedings of the 27th International Conference on Enterprise Information Systems (ICEIS)*, volume 2, pages 320–327. SCITEPRESS.