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RESEARCH ARTICLE

Sustainable livestock farming: Estimating forage biomass with RPAS and 3D modeling

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Abstract

An alternative to support sustainable and technological livestock farming is using aerial images through Remotely Piloted Aircraft Systems (RPAS). This method has demonstrated effective outcomes in assessing agricultural variables including height, volume, and biomass across vegetation and crops like pastures. The study was carried out at Nero farm in southern Ecuador. The objectives of this research were: i) demonstrate the validity of the aerial imagery method with traditional field methods for characterizing grassland agronomic parameters (height, volume, and biomass) and ii) evaluate which of the variables studied (height and volume) is the best predictor of grass fresh mass and dry mass. The first methodology consists of collecting in filed (paddock) height and volume of grass using a frame of 1 m^2, then biomass was measured in laboratory. For the second method, aerial images were obtained through RPAS and processed to generate digital surface model (DSM) and digital terrain model (DTM). Finally, linear models were performed with respective R^2 and error. The height and volume of grass of both methods represent up to 98% of data variability ($p < 0.0001$), also, the measures of central tendency and dispersion were so similar. Regarding the models of fresh and dry mass with height and volume digital of grass representing over 40% ($p < 0.05$), the digital height being the best predictor for dry (R^2: 48%) and fresh mass (R^2: 42%). This research revalidates the effectiveness use of aerial images in important crops from Ecuador.

Keywords: grass height; grass volume; pasture mixture; structure from motion; drone.

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1. Introduction

Livestock farming plays a crucial role in ensuring global food security; nonetheless, grass serves as a vital nutritional component of livestock diets (Hoelzer & Eskin, 2017). In Ecuador, grasslands fulfill the food requirements necessary for the production of meat, milk, and their by-products (Benalcazar-Carranza et al., 2021), and they also constitute a significant element of the national GDP. In Ecuador, according to data from the 2024 Continuous Agricultural Area and Production Survey (ESPAC) of the National Institute of Statistics and Censuses (INEC), the total area used for agricultural activities covered 4,843,461 hectares. Azuay stands out as one of the foremost provinces in terms of livestock production (INEC, 2024).

Nevertheless, the extensive areas of pastures represent a challenge in precisely measuring and sustaining biomass. This value is crucial for assessing available forage and optimizing stocking rates in each pasture, as well as providing information on other parameters such as crop quality and health (Bonin et al., 2023; Segura et al., 2023; Espinosa-Valdez et al., 2024). This information will allow for the development of more economically and technologically efficient livestock farming techniques (Murphy et al., 2021).

A widely employed method to determine the biomass available in a grass crop is the traditional gauging. This approach relies on sampling the vegetation, generally using a wood quadrant or sampling frame, followed by weighing to determine the amount of available forage (Hayatu Ibrahim &

Abubakar Usman, 2021). Sampling involves cutting all the grass within the boundaries of the measurement frame, performing several repetitions, which depends on the grass crop area. This results in the destruction of plant material. This process leads to the destruction of plant material, in addition, is precise solely at the sampling location and requires considerable time and resources, which are frequently constrained, thereby complicating the extrapolation of results to broader regions (Mónaco et al., 2017).

As an alternative to the previous technique, indirect methods are increasingly preferred, such as monitoring with high-temporality aerial images (e.g. satellite images) estimating vegetation parameters to use the photosynthetic absorption fraction (Zhang et al., 2020; Hott et al., 2024), where a diversity of coverage has been evaluated, including pastoral and grass systems (Santos et al., 2024; Gustavo et al., 2025). Likewise, the use of Remotely Piloted Aircraft Systems (RPAS) equipped with RGB and multispectral cameras has not been an exception in determining crop parameters through predictor variables such as the height or volume of the vegetation (Mashraqi et al., 2022; Hao et al., 2025). Prior research recognized that this information can be collected with the use of digital cameras mounted on RPAS to process the data and generate a 3D models (Jang & Kang, 2024; Contreras et al., 2025). Forage biomass has been estimated in winter species such as oats (*Avena sativa*) and alfalfa (*Medicago sativa*) using the technique cited previously (Botello-Aguillón et al., 2019). On the other hand, the construction and prosecution of digital surface model (DSM) or digital elevation model (DEM) and classification analysis of images derived from RPAS, are essential to calculate certain agronomic characteristics, such as plant height and volume (Guth et al., 2021). Actually, the height of the vegetation allows to estimate the biomass and production of the crop applying appropriate mathematical models (Hassnain et al., 2023; Jang & Kang, 2024).

Therefore, nowadays, the use of aerial images has become a common and economical method for documenting and presenting images for the technical development of sustainable management of covers such as grasslands (Vafidis et al., 2021; Quille-Mamani et al., 2022; Magar et al., 2025). Moreover, the computational examination of digital imagery for assessing vegetation cover offers considerable promise as a reliable method (Blanco et al., 2020; Song et al., 2025). The application of remotely piloted aircraft systems in agricultural practices has been extensively recommended, because this technique solves problems that frequently are labor-intensive, time-consuming, even are destructive and expensive (Debangshi, 2021).

In Ecuador, studies on the use of these technologies in pastures are still limited. Also, there is a lack about RPAS and pastures application, because most of research are focused on the management of forest areas (Iñamagua-Uyaguari et al., 2022). Consequently, it is important to consider more specific studies that allow determining whether it is possible to estimate the characteristics of the pasture mixtures commonly utilized in southern Ecuador. The hypothesis of this research is to demonstrate that aerial imagery is sufficient for estimating grassland parameters. Therefore, this research was conducted with two objectives: i) demonstrate the validity of the aerial imagery method with traditional field methods for characterizing grassland agronomic parameters (height, volume, and biomass) and ii) evaluate which of the variables studied (height and volume) is the best predictor of grass fresh mass and dry mass. This research reinforces the application of aerial imagery, even in the context of mixed pastures, which will facilitate the advancement of livestock and agricultural practices in southern Ecuador.

2. Methodology

2.1 Study location

The data collection was carried out in Nero, one of the experimental and dairy farms of the University of Cuenca, ubicated in Baños parish, Azuay province, Ecuador, located at 3100 meters above sea level. The farm covers an area of 297.8 hectares, of which 17% is used as pasture for the farm's livestock (Figure 1). Most of the surface area is heterogeneous, with slopes showing signs of degradation. Temperatures vary between 2 °C and 16 °C, while precipitation levels fluctuate from 750 mm to 1000 mm (GAD Baños, 2021).

In this farm, the areas designated for cattle grazing, commonly known as paddocks, consist of a forage mixture of four herbaceous species and one legume: english ryegrass (*Lolium perenne*), italian ryegrass (*Lolium multiflorum*), white clover (*Trifolium repens*) and kikuyu (*Pennisetum clandestinum*).

2.3 Measurement of grass variables

Five variables were measured in the field from the grass mixture described above: grass volume, grass height, biomass, fresh mass, and dry matter. Meanwhile, grass height, volume, and biomass were estimated using aerial images.

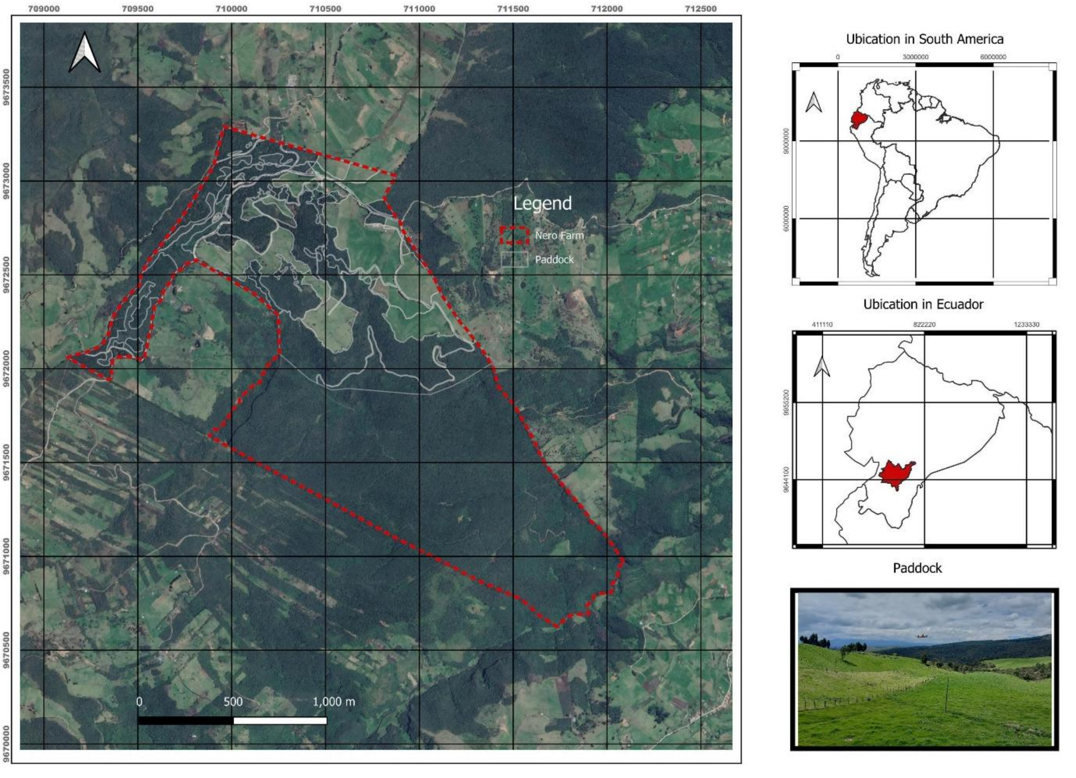

Figure 1. Nero experimental farm where information was collected using aerial and field images.

2.3.1 Grass variables in field

To measure the grass within the experimental farm, a measuring frame (1 m^2) was used for 14 paddocks. Three measurements were made at top, middle and bottom of each paddock. At the same time, the height of the grass was registered within the frame using a tape measure from the soil base to the top of the vegetation. The grass was then cut for weighing and dry matter determination. To calculate the grass volume, the area of capacity was multiplied by the height of the grass contained within the frame (Fenetahun et al., 2020). Finally, the dry matter was measured after the pastures samples were dried in the oven at 60 ºC for 72 hours (Pérez-Harguindeguy et al., 2013).

2.3.2 Grass variables from aerial imagery

A photogrammetric information was conducted using a drone (Autel EVO II RTK) by georeferencing consecutive, homogeneous photographs. Each flight was carried out at 60 m above the grass, obtaining 1171 photographs, and each image had a pixel size of 0.014 m (drone camera 8K 8000 x 6000 pixels). The digital surface model (DSM) was generated using the Structure from Motion (SFM) technique, which consists of forming a 3D image from 2D images. While the digital terrain model (DTM) was formed using Triangulated Irregular Network interpolation (Appendix 1), these two processes were carried out in the Agisoft metashape software (Jacq et al., 2021). The height of the grass (difference between MDS and MDT) and the volume (gauging frame area by grass height) were extracted directly from these images in the Global Mapper and R programs (Lemenkova & Debeir, 2022; Zayed et al., 2023).

2.4 Grass biomass estimation

The biomass was calculated using measures obtained in the field from aerial images applying Equation 1. However, it is important to consider the density factor (DF), which is considered a constant resulting from the amount of dry mass per volume found in each sampling plot to generalize biomass across extensive areas. The procedure used for both methods is summarized in Figure 2.

$$B = V\ x\ DF \qquad (1)$$

Where B: Dry mass of sample area kg/ha; V: Grass volume m^3; DF: Density factor.

2.5 Statistical analysis

To confirm the accuracy of the height, volume, and biomass measurements of grass derived from aerial imagery in comparison to direct field method, simple linear models were employed, although, the same analysis was implemented to find the best predictor for fresh and dry mass (De Rosa et al., 2021).

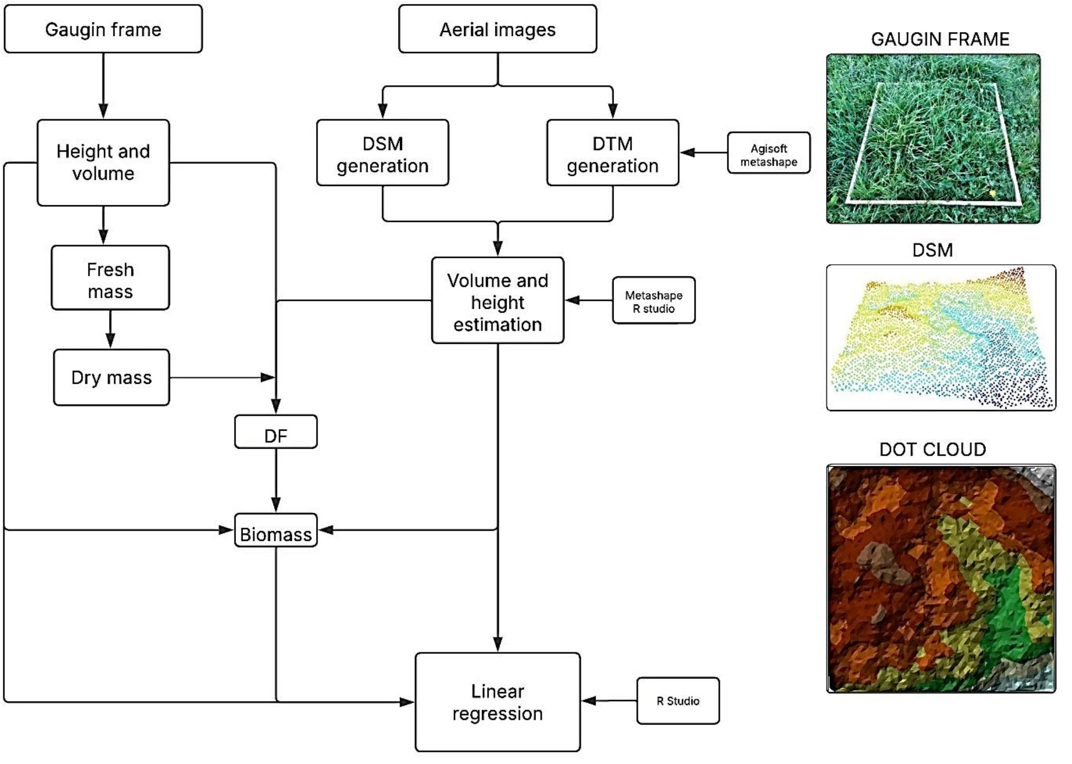

Figure 2. Diagram of the processes carried out to obtain results for the methodology obtained in the field and with aerial images. DSM: Digital surface model; DTM: Digital terrain model; DF: Density factor.

Subsequently, the R^2 values and root mean square error (RMSE) were assessed, in addition, variables per method were illustrated through scatter plots. Furthermore, metrics of central trend and dispersion were calculated for each variable and method. Statistical analysis and graphics were performed in R software (R Core Team, 2024).

3. Results and discussion

The findings demonstrated that utilizing aerial photography acquired via RPAS for estimating grass volume and height is a feasible alternative. This approach allows for the estimation of grass biomass, volume, and height, thereby preventing the need for unnecessary mowing of the grass, which is an invasive and destructive survey methodology. Previous research has successfully modeled biomass from aerial imagery, demonstrating an explanation of 80% to 90% of the data variability (Tang et al., 2022; Vahidi et al., 2023), results that closely align with those found in the present study.

According to Table 1, the variables of grass obtained through the two methodologies are so similar, because the means and medians are close. The height in field registered the larger mean compared to the height achieved following image post-processing; the filed measurement was only 0.002 m different from the digital estimated. The same pattern we found for the volume of the grass, for this variable the field volume was also greater.

Similarly, it is observed that the biomass obtained through the digital process is very close to the variables of field; the difference between them was approximately 4 kg/ha, which is barely perceptible in terms of biomass per hectare. When analyzing dispersion metrics, it can be inferred that the amount of biomass varies widely between pastures, for this reason, the variance and coefficient of variation reach values of up to 40%.

The models generated to validate the height, volume and biomass between the methodology in the field and through aerial images, indicate adjustments greater than 0.97 ($p < 0.0001$), this means that variability of the data was explained until 97%, as is the case of the height in the field with digital height and, volume in the field with digital volume, also the RMSE of these models in relation to their measurement unit is small, which indicates that the error between the two methods is very low. These results confirm the validation of aerial images, in addition, this technology has made it possible to avoid intervention in the crop, just obtaining heights and volume of the plant is enough to know its biomass (Batistoti et al., 2019).

Table 1
Measures of central tendency and dispersion of the three variables measured in the field and estimated through post-processing of aerial images

Variable	Mean	Median	Max	Min	SD	Coef. Var.
Dig. H. (m)	0.236	0.222	0.466	0.137	0.079	0.33
Fie. H. (m)	0.238	0.220	0.470	0.140	0.077	0.32
Dig. V. (m^3)	0.235	0.221	0.466	0.137	0.078	0.33
Fie. V. (m^3)	0.237	0.220	0.471	0.135	0.077	0.32
Dig. B. (kg/ ha)	2902.9	2883.1	4771	628.6	12.05.5	0.41
Fie. B. (kg/ ha)	2906.1	2915.5	4884	646	1175	0.40

Dig. H.: Digital height, Fie. H.: Field height, Dig. V.: Digital volume, Fie. V.: Field volume, Dig. B.: Digital biomass, Fie. B.: Field biomass. Max: maximum, Min: minimum, SD: standard deviation, Coef. Var.: coefficient of variation.

A similar trend is observed in the estimated grass biomass measured in kg/ha. Based on its R^2 value, this linear model exhibited the highest performance among all analyzed models, as it accounts for 98% of the data variability and demonstrates a low error relative to its scale. Sinde-González et al. (2021) suggest that achieving explain over 90% is optimal for estimating vegetation biomass; however, this trend has been documented in numerous prior studies (Bazzo et al., 2023).

Conversely, the models that estimate fresh and dry mass from the digital volume and height of the grass did not explained even greater errors than the first two models, however, these were estimated with an average of samples per paddock (14 paddocks), since, when working by sampling unit, their adjustments are lower (Appendix 2), although other investigations use paddocks as an experimental unit (Botello-Aguillón et al., 2019), even, the study by plot is recommended (Rueda-Ayala et al., 2019). It has been shown that obtaining grass height is very difficult, because of the morphology differs greatly between leaves. In this study, we used a forage mixture and could be the reason why height as a predictor of fresh and dry mass did not obtain high R^2, so the use of high-resolution aerial images can solve this problem (Rueda-Ayala et al., 2019; Rose et al., 2023).

Although these models were significant ($p < 0.05$), the models' R^2 did not exceed 50% of explanation for variables. Likewise, among these, dry mass with height was the one that obtained a R^2 of 0.48. A comparable situation is observed between dry mass and volume, this model explains the 41% of data variability ($R^2 = 0.41$), this trend may be a suggestion that dry mass can be estimated from these two variables, however, it is necessary to use another processing with aerial images (Table 2). These findings differ from the results reported by (Botello-Aguillón et al., 2019), in this research, the models explain around 70% for fresh mass and less than 40% for dry mass, this can be answered because in the cited study the covers were analyzed individually, in the present study four species were analyzed together, being able to influence the phenotype of this mixture (Rueda-Ayala et al., 2019).

Figure 3a shows the height values measured in the field within the gauging frame and the values extracted from the images after post-processing indicate a high linearity, since the points are on the trend line or have values very close to it. Additionally, the linear equation produced from the model is reported ($y = 0.01 + 0.97x$). Most of the data are grouped between 0.1 and 0.2 m of grass height, while there are few data that reach and exceed 0.4 m.

A similar behavior is evident in the dispersion graph of the volume obtained in the field and through aerial images (Figure 3b); however, in this one, a greater adjustment of the points on the trend line is observed. The model equation has also been described ($y = 0.01 + 0.98x$). This variable is very similar to the previous one, because the area of the gauging frame was a unity of area (1 m^2), although in the aerial image, the area of the frame could be extracted from the same frame and recorded an area close to 1 m^2. Finally, the values of two methodologies to obtain biomass are mostly adjusted to the trend line, besides, this is reflected in R^2. This graph confirms the presence of biomass levels below 1000 kg/ha and others nearing 5000 kg/ha; however, most of the biomass data fall within the range of 2500 to 4000 kg/ha of grass (Figure 3c).

The application of 3D modeling from aerial images has proven to be very powerful when seeking to obtain vegetation cover heights such as grasslands in different land uses (Gillan et al., 2019). This suggests that employing these methodologies for measuring vegetation height and volume produces values that closely align with actual conditions. Furthermore, biomass of vegetation such as pastures, crops, and scrub has been obtained from aerial images (Varela et al., 2017). Han et al. (2018), in their study, report that models generated with corn plant heights measured in the field and aerial images obtained with hang-gliding, reached R^2 above 80% and RMSE below 1. Similar coefficients for models presented in this research have been documented in the context of modeling the biomass of english ryegrass, which constitutes a component of the forage mix on the farm (Lussem et al., 2020).

In summary, the primary predictor for both fresh and dry mass was identified as grass height; however, the variable yielding the most accurate model was dry mass (Table 2 and Figure 4). As illustrated in Figure 4a, most data points near the trend line are located at heights around 0.20 m with a corresponding mass of 1.7 g. This pattern is similarly observed at heights exceeding 0.30 m, where the mass approaches 2.5 g of fresh mass. Figure 4b indicates a higher concentration of points near the trend line; it was confirmed that heights around 0.30 m and above correspond to dry mass values ranging from 0.3 g to 0.4 g. Consequently, a more accurate correlation between the variables and the dry mass of grass was demonstrated. Meanwhile, the volume exhibits a higher degree of data dispersion, with a significant quantity of data points lying beyond the standard error (represented as a gray band surrounding the trend line). However, within this model, only a single data point is in proximity to the trend line (refer to Figure 4c). The relationship between volume and dry mass demonstrates a resemblance to the height model that utilizes the same dry mass variable; nevertheless, the R^2 in this instance is less satisfactory (see Figure 4d). Even, another study applied the same methodology using the height of the corn plant as a predictor to estimate crop yield, the training models have managed to explain up to 74% of variability (Geipel et al., 2014; Matsuura et al., 2023; Pun Magar et al., 2025), This supports the application of aerial imagery via RPAS and the incorporation of variables like crop height to assess agricultural parameters.

Rueda-Ayala et al., (2019) confirm that it is feasible to estimate the volume, height, and biomass of a forage mixture using images captured by RPAS and RGB technology, along with their subsequent analysis. They further assert that higher image resolution leads to improved outcomes (Wang et al., 2022), which will save resources, cuts and unnecessary waste of grass.

In addition, models derived from aerial images and grass biomass using Machine Learning and Deep Learning with different algorithms have demonstrated exceptional performance (Guevara-Escobar et al., 2023; Ogungbuyi et al., 2023; Huang et al., 2024).

Table 2
Error coefficients (RMSE), R^2 and p-value (p) of the linear model performed for height, volume, biomass and models between these with dry and fresh mass

	Height Dig. & Fie.	Volume Dig. & Fie.	Biomass Dig. & Fie.	Height dig. Fresh mass	Height dig. Dry mass	Vol dig. Fresh mass	Vol. dig. Dry mass
RMSE	0.013	0.009	137.1	1.87	0.06	0.070	1.87
P	< 0.0001	< 0.0001	< 0.0001	< 0.01	< 0.01	< 0.05	< 0.01
R^2	0.97	0.97	0.98	0.42	0.48	0.30	0.41
n	44	44	44	14	14	14	14

RMSE: root mean square error, Dig: digital, Fie: Field, Vol: volume.

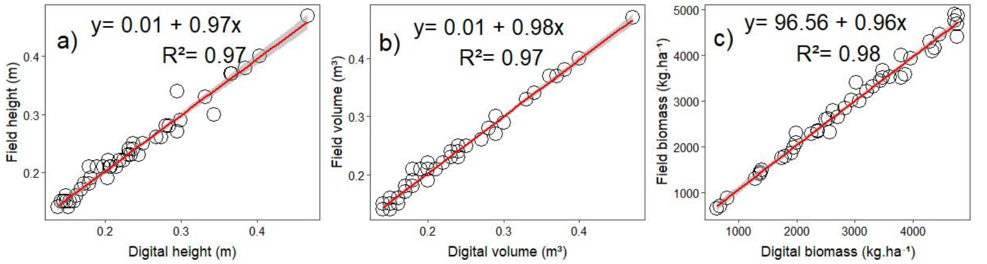

Figure 3. Scatter plots between the two methods analyzed with their respective linear equations, R^2, trend line and standard error.

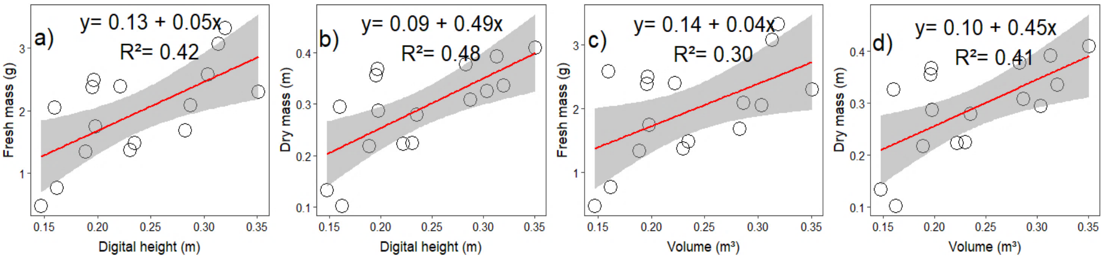

Figure 4. Scatter plots of volume and height with fresh and dry mass with their respective linear equations, R^2, trend line and standard error.

Recent research has indicated a coefficient of determination over 90% through the use of vegetation indices and supervised classification to estimate the fresh mass of vegetation cover (Castillo et al., 2017; Sharma Banjade et al., 2024). The findings of the present study differ slightly from those mentioned above, since the methodologies and algorithms for obtaining results are different.

4. Conclusions

After descriptive metrics of the grass variables obtained in the field and with aerial images, in this study similar values were found, suggesting the use of aerial images to obtain volume and height of passage, as well as biomass. After generating linear models with their respective R^2 and error metrics, the models captured values close to 100% variability, which demonstrates the similarity between the two methods used in this study. Conversely, estimating dry and fresh mass using volume and height from aerial images is not recommended, especially for fresh mass, because their adjustments are below 40% variability. This limitation probably responds to the morphology of the vegetation within the forage mixture, which could pose a challenge. However, alternative methods, such as employing vegetation indices to assess the same grass parameters, could be explored. Therefore, a digital methodology is recommended to estimate height, volume, and biomass of pastures as an alternative to support sustainable and technological livestock farming.

Authors' contribution

E. Tacuri-Espinoza: Conceptualization, Supervision, Methodology, Writing - Review & Editing Original Draft. M. López-Espinoza: Methodology, Writing - Review & Editing Original Draft. A. Macancela-Herrera: Formal Analysis, Visualization, Writing - Review & Editing Original Draft. L. Lupercio-Novillo: Conceptualization, Supervision, Writing - Review & Editing Original Draft.

Declaration of conflict of interest

The authors declare that they have no conflicts of interest that could influence the work presented in this article.

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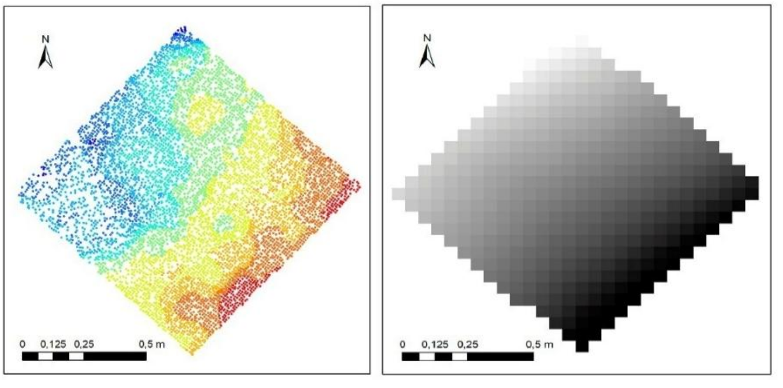
Appendix

Appendix 1

Results of Digital surface model (left) and Digital terrain model (right) from pastures plot



Appendix 2

Error coefficients (RMSE), R^2 and p-value (p) of the linear model performed for height, volume, with dry and fresh mass considering 44 sampling units

	Height dig. Fresh mass	Height dig. Dry mass	Vol dig. Fresh mass	Vol. dig. Dry mass
RMSE	0.14	2.06	2.06	0.15
P	>0.05	>0.05	>0.05	>0.05
R^2	0.03	-0.01	0.12	-0.01
n	44	44	44	44