Modelling pasture height and biomass: improving transferability and comparing different UAVs

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Abstract

Photogrammetric and spectral information obtained by Unmanned Aerial Vehicles (UAVs) combined within predictive models can spatially estimate variables of interest for grassland management, such as sward height and biomass. Nevertheless, the models remain highly specific to their calibration environment such as the target grassland, the season, or the sensor employed. The objective of this study was to use a diversified dataset from a multi-species grassland to calibrate height and biomass predictive models. This was done using sensors ranging from low-cost off-the-shelf RGB to top-of-the-range multispectral cameras. Various machine learning models were calibrated with on-field height and biomass samples (n = 64) and evaluated with an independent dataset (n = 24). Results obtained using the top-of-the-range camera show that some models, such as linear regression for height and Principal Components Regression (PCR) for biomass, are transferable, with reduced rRMSE when applied to the validation dataset ($rRMSE_{Height\text{-}Calib.}$ = 25.9%; $rRMSE_{Height\text{-}Valid.}$ = 22.2%; $rRMSE_{Biomass\text{-}Calib.}$ = 45.5%; $rRMSE_{Biomass\text{-}Valid.}$ = 34.2%). A similar performance was observed with mid-range sensors but was not achieved by the low-cost equipment. In conclusion, the models developed here requires improvements, particularly in estimating biomass, due to challenges in assessing cover density. This study nevertheless demonstrated the potential to obtain transferable models using diversified calibration datasets, even with mid-range equipment.

Keywords: biomass, grasslands, sward height, transferability, unmanned aerial vehicles

Introduction

In the context of climate change, it is crucial to ensure grassland stability through sustainable and appropriate management. Field observations are essential for this management, but it is time-consuming when assessing variables, such as sward height or biomass availability. Unmanned aerial vehicles (UAVs) can drastically reduce this workload by providing high-resolution spatial data in a short time (Bindelle *et al.*, 2021). The spectral information derived from Red-Blue-Green (RGB) or multispectral sensors can then be combined in predictive models to estimate variables of interest in grasslands (Assmann *et al.*, 2019). Unfortunately, most models developed so far remain highly specific to their calibration environment (Bindelle *et al.*, 2021). Based on the standardized good practices reviewed by Aasen *et al.* (2018) and by Assmann *et al.* (2019), this study aimed to test the transferability of sward height and biomass predictive models by calibrating them on a diversified dataset from a multi-species grassland and evaluating them on an independent temporary grassland. For this purpose, sensors ranging from low-cost RGB to top-of-the-range multispectral cameras were compared.

Materials and methods

The study was conducted in Gembloux (Belgium) from March to June 2024. The grassland used for calibration (50.565°N, 4.702°E) was a permanent grassland with a diverse botanical composition (*Holcus lanatus* L., *Dactylis glomerata* L., *Poa* sp. L., *Lolium* sp. L., *Trifolium repens* L., *Taraxacum* sp. Weber ex F.H. Wigg) while an independent temporary grassland (50.562°N, 4.728°E) composed of a legumes-grass mixture with a few forbs (*Lolium sp.* L., *Trifolium* sp. L., *Rumex* sp. L.) was chosen for validation. Field reference data were acquired on thirty-two circular (diameter = 0.4 m) sampling units on the calibration grassland on two different dates (10 April and 8 May) to capture different phenological states. Twenty-four units were sampled on the validation grassland on the 3 June. This reference data consisted of eight sward-stick measurements (to calculate the median) per sampling unit for sward height and a cut at 0.05 m followed by oven-drying at 65°C until constant weight for biomass (Kümmerer *et al.*, 2023). Aerial data were collected on the same dates with a DJI Mini 2 (DJI, Shenzen, P.R. China), a DJI Mavic 3M and a DJI M300 RTK equipped with a MicaSense Altum-PT Camera (MicaSense, Seattle, WA, USA) flying at 2 m/s and an altitude of 50 m, with front and side overlapping of nadir images of 80% (Grüner *et al.*, 2020; Kümmerer *et al.*, 2023). Images were processed photogrammetrically using Agisoft Metashape Professional (Agisoft, Saint-Petersburg, Russia). They were radiometrically calibrated with a known-reflectance panel and geometrically processed using eight Ground Control Points of known location. The outputs for each UAV were a Digital Surface Model (DSM), from which an open-source Digital Terrain Model (DTM) (WalOnMap, 2024) was subtracted to derive a Digital Height Model (DHM), and a spectral orthomosaic, used to compute eight vegetation indices. Sward height was directly estimated through simple linear regression using DHM heights as predictors, while DHM information and vegetation indices were combined in various machine learning models (Partial Least Square Regression, Principal Components Regression, Support Vector Machine, and Random Forest), implemented in R (v 4.3.2), to estimate the reference biomass. Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) were computed for each model. Relative RMSE (rRMSE) was also obtained by dividing the RMSE by the mean of the observed values.

Results and discussion

As expected, the best models for height estimation were obtained using the MicaSense Altum-PT (see Table 1). The methodology applied appears to lead to partially transferable models as the RMSE only increases by less than 0.03 m with this material. The corresponding decrease in rRMSE can be attributed to the higher mean height on the validation grassland ($\text{mean}_{\text{Height-Calib.}}$ = 0.265 m; $\text{SD}_{\text{Height-Calib.}}$ = 0.121 m; $\text{mean}_{\text{Height-Valid.}}$ = 0.406 m; $\text{SD}_{\text{Height-Valid.}}$ = 0.101 m).

Concerning biomass estimation, the best models presented in Table 2 indicate that similar performance was obtained with mid- (Mavic 3M) and top-of-the-range (MicaSense Altum-PT) materials while RMSE was significatively higher for the DJI Mini 2. Antagonistic increase of RMSE and

Table 1. Performance of the simple linear regressions for the three UAVs in height estimation.

	DJI Mini 2		DJI Mavic 3M		MicaSense Altum-PT	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
R^2	0.726	0.113	0.774	0.731	0.672	0.547
RMSE (m)	0.061	0.233	0.057	0.172	0.069	0.090
rRMSE (%)	22.9	57.4	21.5	42.3	25.9	22.2

Table 2. Performance of the best machine learning models for the three UAVs in biomass estimation.

	DJI Mini 2[1]		DJI Mavic 3M[2]		MicaSense Altum-PT[3]	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
R^2	0.066	0.159	0.504	0.166	0.633	0.369
RMSE (kg DM/ha)	1335	1120	973	933	836	935
rRMSE (%)	72.5	41.0	52.9	34.2	45.5	34.2

[1] Random Forest (500 trees); [2] PCR with one component; [3] PCR with three components.

decrease of rRMSE can here also be explained by a higher mean biomass in the validation dataset ($\text{mean}_{\text{Biomass-Calib.}}$ = 1840 kg DM/ha; $\text{SD}_{\text{Biomass-Calib.}}$ = 1392 kg DM/ha; $\text{mean}_{\text{Biomass-Valid.}}$ = 2730 kg DM/ha; $\text{SD}_{\text{Biomass-Valid.}}$ = 863 kg DM/ha). Thus, it seems that the use of a multi-species grassland, which results in a wide range of values for vegetation indices, height, and biomass, led to a certain transferability of the models. Nevertheless, even if model generalization seems beneficial, it must be balanced, as broader applicability often comes at the cost of reduced accuracy compared to a specific model (Grüner *et al.*, 2019).

Despite this partial transferability, results should be viewed with caution, given the overall quality of the models, which remains barely acceptable due to the consistently high residual error. In terms of prospects, it could be worthwhile to improve these models by incorporating additional information such as textural data as suggested by Grüner *et al.* (2020) or by exploring more advanced Deep Learning techniques (Alves Oliveira *et al.*, 2022).

Conclusion

In conclusion, this study has shown the potential to achieve transferable models using diversified calibration datasets, even with mid-range equipment. Nevertheless, attention should be paid to the trade-off between accuracy and generalization, depending on the research objective.

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