

## A coupled multitemporal UAV-based LiDAR and multispectral data approach to model dry biomass of maize

Robert Rettig <sup>1</sup>, Marcel Storch <sup>2</sup>, Lucas Wittstruck<sup>3</sup>, Christabel Edena Ansah <sup>4</sup>,  
Richard Janis Bald <sup>5</sup>, David Richard <sup>6</sup>, Dieter Trautz<sup>7</sup>, Thomas Jarmer <sup>8</sup>


**Abstract:** The presented approach attempts to highlight the capabilities of a data fusion approach that combines UAV LiDAR (RIEGL – miniVUX-1UAV) and multispectral data (Micasense – Altum) to assess the dry above ground biomass (AGB) for maize. The combined acquisition of both LiDAR and multispectral data not only supports estimates of AGB when fusing them, but also helps to evaluate phenological stage-specific modelling differences on the individual sensor data. A multiple linear regression was applied on the multisensorial UAV data from two appointments in 2021. The resulting  $R^2$  of 0.87 and RMSE of 14.35 g/plant for AGB was then transferred to AGB in dt/ha.


**Keywords:** LiDAR, multispectral, multisensorial, maize, biomass, MLR

### 1 Introduction


Due to the technological development and advantages of UAV-based remote sensing solutions, new possibilities arise for monitoring agricultural crops while efficiently sensing crop biophysical parameters (CBP) in a close-range scenario [Wa21]. The approach presented here attempts to highlight the capabilities of a data fusion approach that combines UAV LiDAR (RIEGL – miniVUX-1UAV) and multispectral data (Micasense – Altum) to assess the dry above ground biomass (AGB) for maize, which is

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<sup>1</sup> Osnabrück University, Inst. of Computer Sc., Wachsbleiche 27, 49090 Osnabrück, rrettig@uos.de,   
<https://orcid.org/0000-0002-4632-1286>

<sup>2</sup> Osnabrück University, Inst. of Computer Sc., Wachsbleiche 27, 49090 Osnabrück, marcel.storch@uos.de,   
<https://orcid.org/0000-0001-5726-6297>


<sup>3</sup> Osnabrück University, Inst. of Computer Sc., Wachsbleiche 27, 49090 Osnabrück, lwittstruck@uos.de

<sup>4</sup> Osnabrück University, Inst. of Computer Sc., Wachsbleiche 27, 49090 Osnabrück, cansah@uos.de,   
<https://orcid.org/0000-0002-7194-4944>

<sup>5</sup> University of Applied Science Osnabrück, Fac. of Agric. Sc. and Landscape Architecture, Am Krümpel 31,  
49090 Osnabrück, janis.bald@hs-osnabrueck.de,   
<https://orcid.org/0000-0002-0512-7735>

<sup>6</sup> University of Applied Science Osnabrück, Fac. of Agric. Sc. and Landscape Architecture, Am Krümpel 31,  
49090 Osnabrück, d.richard-guionneau@hs-osnabrueck.de,   
<https://orcid.org/0000-0002-9072-7363>

<sup>7</sup> University of Applied Science Osnabrück, Fac. of Agric. Sc. and Landscape Architecture, Am Krümpel 31,  
49090 Osnabrück, d.trautz@hs-osnabrueck.de

<sup>8</sup> Osnabrück University, Inst. of Computer Sc., Wachsbleiche 27, 49090 Osnabrück, tjarmer@uos.de,   
<https://orcid.org/0000-0002-4652-1640>

one of the worldwide most cultivated crops [OF 22]. Due to its canopy structure, it is relatively challenging to assess maize plant parameters, especially at later phenological stages where the crop canopy is almost closed and usable parts such as cobs are hidden, when focussing on non-destructive estimations [Ji20]. The comparison of the individual data to the combination of UAV-based LiDAR- [HBK20] and UAV-multispectral [Ni19] data not only supports estimating AGB, but also helps to evaluate or potentially neglect phenological stage-specific differences [Wa17]. This could help farmers either directly via close-range monitoring or indirectly via Earth Observation missions, powered with close-range UAV-based ground truth models, to improve plant management or crop growth models [ACH21].

## 2 Study site

The study site was a 0.7 ha maize field near Osnabrück in Lower Saxony (DE). It was managed in close collaboration with a local farmer and agricultural experts of the University of Applied Sciences Osnabrück. Various treatment strategies were pursued to create heterogeneous properties: with or without application of chemical herbicides, different sowing densities (7 or 9 plants/m<sup>2</sup>) and two varying degrees of fertilizer use. This results in eight different possible combinations, so that the study area was divided into a total of eight different management zones (see Fig. 1).

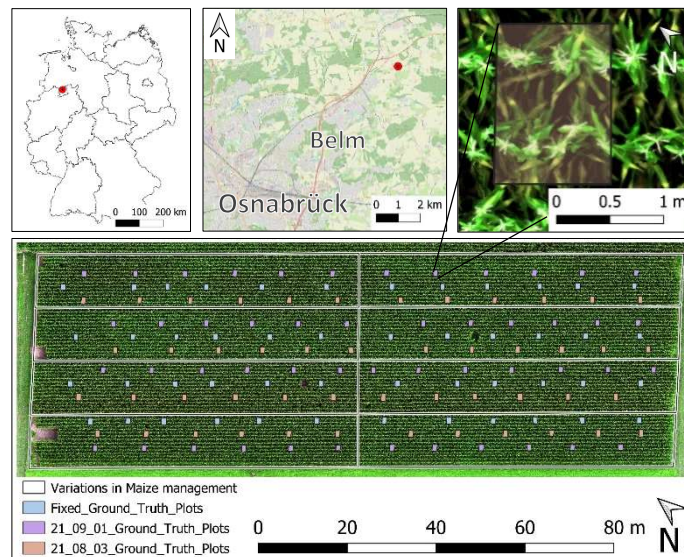


Fig. 1: Maize field with management zones and plots, season 2021

### 3 Materials and methods

The flight with the LiDAR system took place at an altitude of 20 m above ground, resulting in an average point spacing of approx. 0.05 m. A flight altitude of 25 m above ground was chosen for the multispectral system which resulted in a ground sample distance of approx. 0.01 m. The UAV data were acquired either at the day of ground truth data collection or a few days before (see Tab. 1). The data were taken in plots of approx. 1.5 m<sup>2</sup> and georeferenced by RTK-GPS. The plants for each plot were counted and the dry weight was harmonized by plant, summing up to a total of 95 samples of AGB in g/plant (Min = 91.1 g, Max = 236.4 g, SD = 39.4 g, Mean = 155.0 g).

Date of Ground Truth	BBCH	Date of flight	System	n
03.08.2021	67	03.08.2021	LiDAR + MS	47
01.09.2021	85	20.08.2021	LiDAR	48
		30.08.2021	MS	

Tab. 1: Data acquired

The multispectral data was processed with Agisoft Metashape (Vers. 1.7.2.) whereas the RIEGL RiPROCESS software was used for the LiDAR data captured. The LiDAR derived information were the mean range corrected single return intensity, mean return ratio (the number of first returns divided by the number of all returns), and the mean height. An additional correction processing chain, which considered cleaning overlapping LiDAR data, was developed for the LiDAR data. This reduction of overlapping areas was necessary due to the ratio concept: the percentage of first returns in the total number of returns decreases as the number of leaf layers increases. Canopy height was calculated as the median based on the raster data created with PDAL (Point Data Abstraction Library). Subsequently, they were combined with the multispectral bands (B-G-R-RE-NIR-LWIR), vegetation indices (NDVI and EVI [Al20]), and textural parameters (see Fig. 2). Multiple linear regression was then applied onto the individual and combined independent data sources, employing the train function of the caret package (Caret Vers. 6.0-93, R Vers. 4.2.1, RStudio Vers. 2022.07.2), to predict AGB in g/plant and validating it with the Leave-One-Out-Cross-Validation (LOOCV).

## 4 Results

The highest  $R^2$  of 0.87 and RMSE of 14.35 for predicting the AGB of maize was achieved when both data sources were combined (see Fig. 2). However, the sole use of the LiDAR data resulted in an  $R^2$  of 0.79 and an RMSE of 18.07 while the multispectral data alone reached an  $R^2$  of 0.86 and an RMSE of 14.84. The prediction fit shows a good correlation to the ideal 1:1 line resulting in rather low RMSE of 14.4 g/plant, which indicates strong

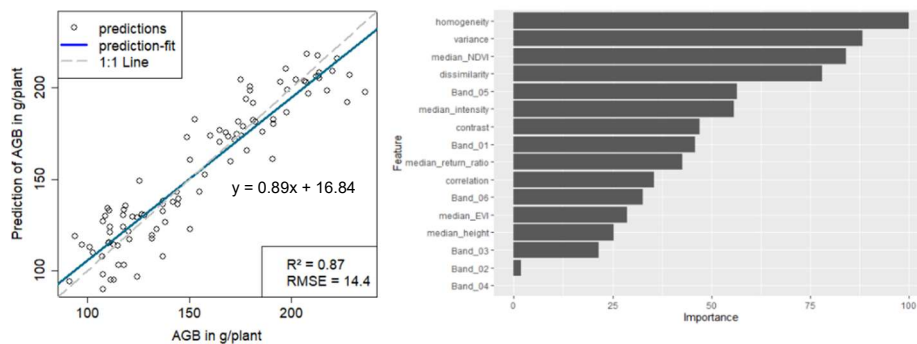
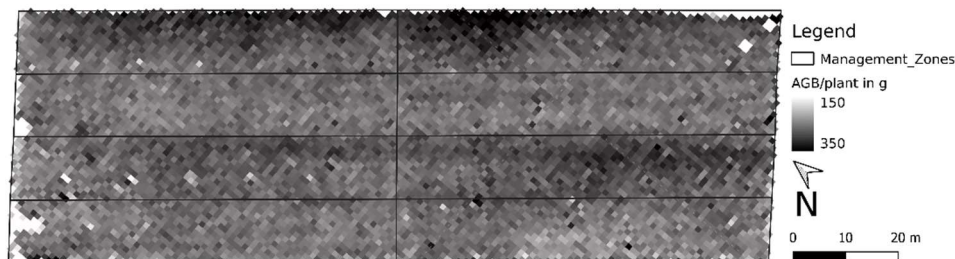


Fig. 2: Prediction of the MLR model and importance of variables

model performance. The model slightly overestimated lower AGB, while it underestimated highest AGB. Most important variables for the multitemporal prediction were textural parameters, including homogeneity, variance and dissimilarity, followed by NDVI, the NIR band and the intensity of the LiDAR derived data. Lowest explanation power was achieved by single bands (G, R, RE), the height and the EVI.

In the next step, the prediction of AGB per plant was transferred to the spatial domain by deriving AGB on the raster stack. To convert the data into comparable agronomic units, the results were multiplied by the assumed number of plants per  $m^2$  resulting from the predefined sowing density (see Fig. 3).

Prediction of AGB per plant - 30.08.2021



Prediction of AGB in dt/ha - 30.08.2021

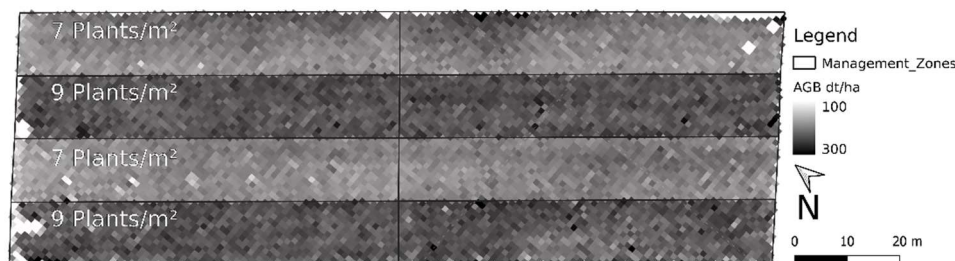


Fig. 3: Spatial prediction of AGB per plant (upper map), the results are multiplied with the sowing density for the spatial prediction of AGB in dt/ha (lower map)

## 5 Discussion and conclusion

Combining multiple data sources and merging multitemporal ground truth data increased the prediction capability comparable to other related research, see e.g. [Wa17]. LOOCV was used for validation of the model predictions due to the small sampling amount. We gathered ground truth data from two field campaigns with different growth stages and respectively, different reflectance patterns. This has to be considered for comparing the results of both, multisensorial derived data and the sole use of LiDAR information. The explanatory power while adding the LiDAR derived information did not increase the prediction accuracy significantly. However, testing the LiDAR data alone proves the spectral independence of growth stage-dependent reflection differences. This makes the prediction model potentially more robust for later growth stages when biomass is accumulated and the plants reach senescence. Ground truth data collected more frequently through the entire phenological cycle while matching with multisensorial data, may lead to more reliable predictions on a wider range of growth stages. Including the plant density (plants/m<sup>2</sup>) as information for extrapolating the AGB prediction to the field is prone to errors since the field emergence is not always optimal or other effects cause differences in

the initially planned plant density. This is taken into account and can be improved by detecting field emergence with UAV-based LiDAR [Ga22] and/or RGB neural network approaches [Pa20]. This research is intended to serve as a basis for more detailed observation.

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