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Machine Learning with UAS LiDAR for Winter Wheat Biomass Estimations

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Abstract.

Biomass is an important indicator in the ecological and management process that can now be estimated at higher temporal and spatial resolutions because of unmanned aircraft systems (UAS). LiDAR sensor technology has advanced enabling more compact sizes that can be integrated with UAS platforms. Its signals are capable of penetrating through vegetation canopies enabling the capture of more information along the plant structure. Separate studies have used LiDAR for crop height, rate of canopy penetrations as related to leaf area index (LAI), and signal intensity as an indicator of plant chlorophyll status or green area index (GAI). These LiDAR products are combined within a machine learning method such as an artificial neural network (ANN) to assess the potential in making accurate biomass estimations for winter wheat.

Keywords. Machine Learning, ANN, LiDAR, UAS, Biomass

1 Introduction

Aboveground biomass (AGB) is important within precision farming for monitoring the growth status of crops, making yield predictions, and enabling the appropriate responses (Lu et al., 2019). The more often and the greater the detail that this metric of information is collected, the timelier and more precise the farming strategies can be.

Unmanned aircraft systems (UAS) offer on demand collection with little logistical complexity. Being able to fly close to the ground and being unaffected by cloud cover, UASs provide some of the greatest temporal and spatial resolutions available. Technology has recently allowed for LiDAR sensor sizes to become compact enough to be mounted on UAS platforms (Harkel et al., 2020). Its signal can pass through gaps in the canopy cover allowing points to reach the ground. This characteristic allows for accurate canopy height measurements (Harkel et al., 2020) and can also provide canopy density metrics in respect to the rate of signal penetration (Bates et al., 2021). The intensity of the LiDAR signal which is often within the near infrared (NIR) bandwidth can also be an indicator for green area index (GAI) (Liu et al., 2017). In this study we evaluate the combination of LiDAR height, intensity, and multilayer density products within an ANN model when monitoring winter wheat over the growing season.

2 Methods

2.1 Study Area

The study was conducted at the PhenoRob Central Experiment at Campus Klien Altendorf (CKA), Germany. The area of interest consists of 72 winter wheat plots (see example: Fig. 1). Destructive samples were taken every two weeks from the 19th of April until the 5th of July 2021. Destructive samples as ground references were taken from 10 separate plots after each flight campaign.

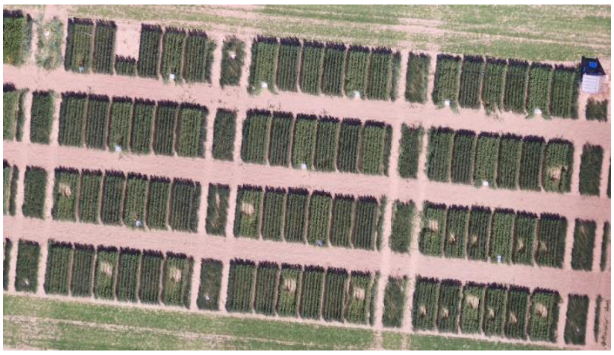

Figure 1. Overhead view of the winter wheat plots at CKA. Cut areas from the destructive measurements can be seen in the southern part of the field.

2.2 Equipment

A YellowScan Surveyor LiDAR was used onboard a DJI Matrice 600 pro hexacopter. A Septentrio NR3 GNSS was used as a base station to provide the needed data for post processing kinematics (PPK) georeferencing of the scanned scene.

Figure 2. The DJI Matrice 600 with the YellowScan Surveyor LiDAR mounted below it.

2.3 Data Processing

3D point clouds were produced using YellowScan's Cloud Station Software. Ground points were segmented from the vegetation points using the cloth simulation filter (CHM) method. The data was then converted into 15 cm raster formats while extracting the respective information needed for each model input.

Canopy height models (CHM) were derived using a difference of digital elevation models (DEM) method (See Eq. 1). The digital terrain model (DTM) is the rasterized ground point elevations and the digital surface model (DSM) is the rasterized elevations of points on top of the canopy.

$$CHM = DSM - DTM \tag{1}$$

Gap fraction uses the count of points (n_{DL}) within the respective density layer (DL) in a ratio to the count of all points (n) defined within the extent of the rasterized grid cell (See Eq. 2). This gauges the signal's rate of penetration through the canopy in relation to the vegetation density.

$$GF = \frac{n_{DL}}{n} \tag{2}$$

This study extracts the points into 5 GF layers of 20 cm vertically long segments. This is to further capitalize on LiDAR point density information throughout the vertical extent of the vegetation.

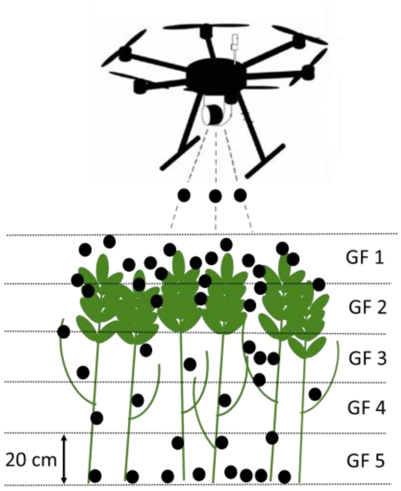

Figure 3. The LiDAR points were segmented into 20 cm layers where GF was used for each layer. GF 5 representing the lowest layer in the canopy and GF 1 representing the highest layer possible.

In this study, the LiDAR signal wavelength is in the NIR range with a frequency centered on 903 nm and having potential to indicate variation in vegetation vigour. LiDAR penetration index (LPI) is derived using the mean intensity values of ground points (Int_{ground}) in comparison to the mean intensity of all points within that particular raster cell extent (See Eq. 3) (You et al., 2017).

$$LPI_{intensity} = \frac{Int_{ground}}{Int} \tag{3}$$

The variables are plotted for correlation to dry mass (DM) of the crop as can be seen in Figure 4. Height has the highest correlation. Intensity is negatively correlated with DM considering that this can be due to senescence later in the growing season. The GF layers between the top and bottom layer hold the highest correlation to resulting biomass.

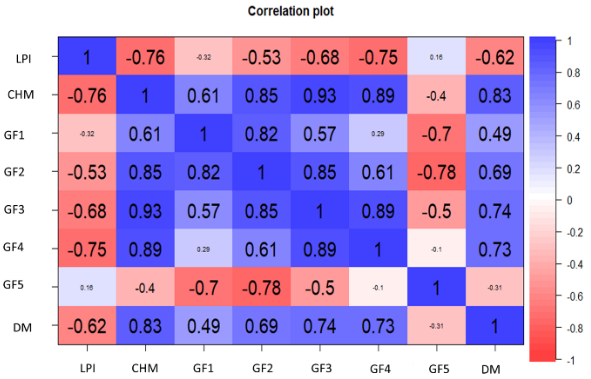

Figure 4. Correlation of model inputs to sampled dry mass (DM)

2.4 ANN Model

ANNs combine the input with interconnected neurons to best match the output values over a training database. Out of the 10 winter wheat destructive plots data, 7 were used for training the model. The network architecture was defined by trying a combination of hidden layers and nodes that provided the best results. In our case, this was one hidden layer consisting of 4 nodes. (Liu et al., 2017). The model training and implementation with raster data was done in RStudio with the neuralnet package.

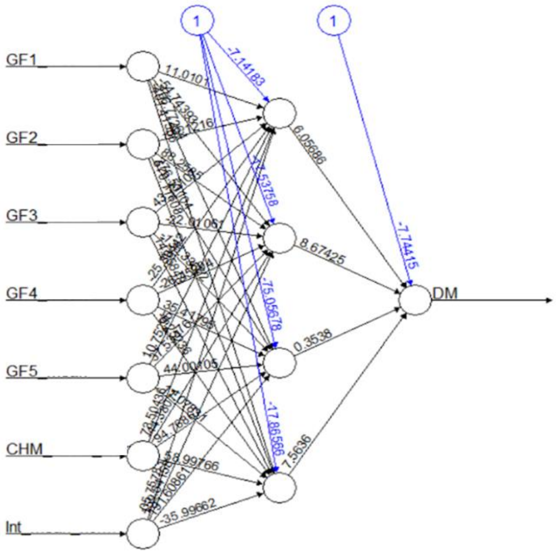

Figure 5. Graphical representation of the model with the weights on each connection. The black lines show the connections between each layer and the weights on each connection while the blue lines show the bias term added in each step. The bias can be thought as the intercept of a linear model.

3 Results

An example visualization of the resulting biomass estimations from the trained model can be seen in figure 6.

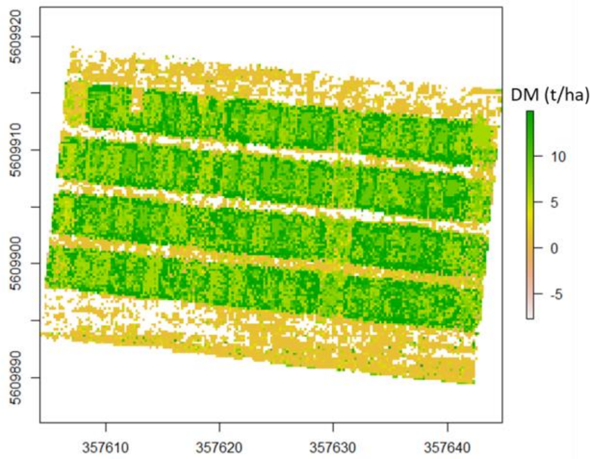

Figure 6. Example of visualized dry mass (DM) biomass map produced using the trained ANN model from raster inputs using RStudio with the neuralnet package.

Root mean square error (RMSE) and R2 were selected as the statistical metrics used to evaluate the performance. The results achieved a RMSE of 1.94 t/ha and an R2 of 0.87 throughout the entire growing season (see example: Fig. 7).

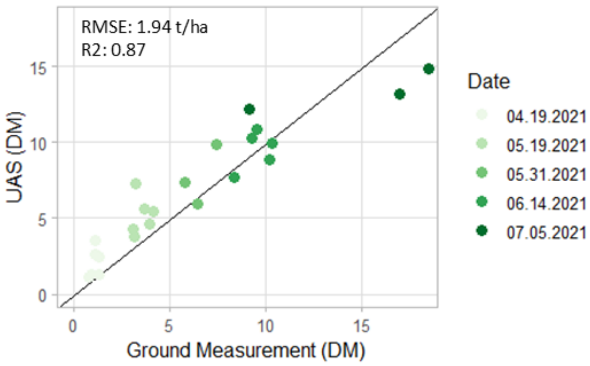

Figure 7. Results of LiDAR UAS dry mass (DM) biomass estimations as compared to the ground measurements in tons per hectare (t/ha) using the 3 winter wheat plots allocated for accuracy testing for each date.

4 Conclusion

This study provides an example of the versatility of LiDAR data when deriving various vegetation parameters that can be used in combination to provide accurate biomass estimations. Furthermore, it provides evidence that machine learning methods such as ANN can utilize and bring forth the benefits from the combination of these metrics that are particular to LiDAR.

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