UAS LIDAR DERIVED METRICS FOR WINTER WHEAT BIOMASS ESTIMATIONS USING MULTIPLE LINEAR REGRESSION

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ABSTRACT

Unmanned Aircraft Systems (UAS) are being used more often in agriculture to provide estimations of important metrics such as biomass because of the potential for improved temporal and spatial resolutions. More recently LiDAR sensor technology has advanced enabling more compact sizes that can be integrated with UAS platforms. Being an active sensor, LiDAR signals are capable of penetrating through the vegetation canopy providing more information on plant structure. Commonly, LiDAR data is used to derive only height information. However, newer studies have shown the retrieval of additional information from the spatial distribution and intensity of LiDAR signals. This study takes a unique look at combining these types of informative products, that are particular to LiDAR, for making biomass estimation with winter wheat.

Index Terms— UAS, LiDAR, Biomass, Drone

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 [1]. The more often AGB is collected and with greater detail, the precision in the overall decision-making increases. When selecting methods of AGB retrieval, it is essential to consider the logistical flexibility and resolution of collection.

Traditional biomass measurement methods are based on manual harvesting and weighing which are time-consuming and difficult to apply over large areas. Satellite remote sensing methods introduced nonintrusive, extensive, and routine collection [2]. However, there is no flexibility on when this data is collected as it is based on the orbital paths of the satellites. This timing is further interrupted depending on cloud conditions. Much of the available satellite data cannot provide sufficient resolution for precision agriculture applications [2]. Vehicle-mounted equipment can provide higher detail and accuracy but comes with poor flexibility and speed [2]. Unmanned aircraft systems (UAS) offer on-demand collection with much less logistical complexity and price than manned airborne methods. Additionally, a UAS is flown below the clouds and close to the ground for higher detail. This comes at the cost of only being suitable for smaller areas with a much lower coverage to time ratio. Yet these systems have great potential in providing the highest spatial and temporal resolutions.

In the last few years, LiDAR systems have been miniaturized thus becoming lighter and capable of being operated on UAS platforms [3]. LiDAR's active signal can pass through gaps in vegetation cover providing information underneath the canopy. Since signals are capable of reaching the ground, accurate height measurements are possible [3] with some studies exploring other understory information such as tree trunk diameters in forests [4]. These ground points can be counted per unit of space for canopy density information and related to leaf area index (LAI) [5]. As opposed to the more common passive spectral sensors used in agriculture that have saturated data in middle to high canopy cover, LiDAR's depth information tends to provide better plant characterization and better biomass accuracy [2].

Linear regression techniques are most often used to relate UAS-derived metrics to biomass [2]. Typically LiDAR height is used to estimate biomass. However, some studies are beginning to use LiDAR density parameters with gap fraction (GF). No studies are using LiDAR intensity for biomass which has shown to be an indicator of green area index (GAI) and chlorophyll status [6]. This study evaluates the combination of LiDAR height, density, and intensity products into a simple multiple linear regression 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 Klein-Altendorf (CKA) in Germany. The area of interest consists of 72 winter wheat plots.

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Figure 1. Overview of the winter wheat plots with destructive samples used for training the model in blue and those used for testing the model in red.

Destructive samples were taken every two weeks including 12 separate plots for the first six dates, then reduced to three different plots for the last two campaign dates. In total, 9 plots were used for training and 3 for testing the model. For the last two flight campaign dates, it was 2 plots for training and 1 for testing. The majority of the destructive sampling took place in the southern half of the winter wield fields as the northern half was primarily used for soil sampling.

2.2 Equipment

A YellowScan Surveyor LiDAR was used onboard a DJI Matrice 600 pro hexacopter UAS. The LiDAR is composed of a Velodyne LiDAR puck for sending and receiving the light signal, inertial measuring units (IMU) for sensor orientation, global navigation satellite system (GNSS) for sensor locations, and an onboard computer where the sensor information is combined and synchronized. A Septentrio Altus NR3 GNSS was used as a base station to provide the needed data for post-processed kinematics (PPK) georeferencing of the scanned scene.

The UAS was flown in a crosshatch flight profile with scan overlaps of 50% at scan angles of 18 degrees. The flight altitude was 50 meters above ground level and the speed was 5 m/s.

2.3 Data Processing

The base station data was combined with the LiDAR trajectory files in Applanix's POSPac to produce an SBET file for the precise point positioning (PPP) solution. It was then imported into YellowScan's CloudStation software where the 3D point cloud was extracted from the puck recording and each flight scan was registered with one another.

After preprocessing, the ground was segmented from the vegetation as this is a core step for deriving the metrics used in this study. The cloth simulation filter (CSF) was used to make the classification of ground points parameterized based on the estimated point density [7].

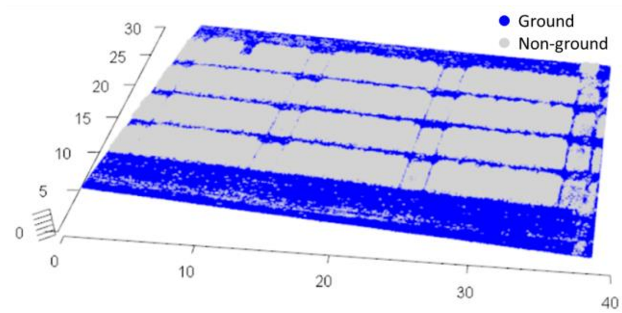

Figure 2. The oblique perspective of the 3D point cloud segmentation of ground and vegetation within the study area.

For information on the vertical extent of the vegetation, canopy height models (CHM) were derived using a difference of digital elevation models (DEM) method. The ground points were rasterized into 15cm grids referred to as the digital terrain model (DTM). The entire point cloud was rasterized into a digital surface model (DSM) with each cell containing the average height. The DTM was then subtracted from the DSM to produce the CHM.

To assess the vegetation density, gap fraction (GF) was incorporated. GF assesses the rate at which the LiDAR signal penetrates through the canopy. This is done by counting the number of points that reach the ground as compared to the entire signal points within a defined area. A rasterized count of ground points and all points within 15cm grids was created where the ground points raster was divided by the all points raster to produce the GF ratio.

To incorporate information about the chlorophyll content of the vegetation, the LiDAR signal was retrieved. The LiDAR signal's wavelength is in the NIR range with a frequency centered on 903nm. Healthy vegetation with high chlorophyll will reflect more NIR and senescence vegetation will absorb more NIR ultimately affecting the resulting intensity of the LiDAR signal. The ground has intensity values that range between that of healthy and dying winter wheat creating noise in the data. Hence, the ground points are removed and the average intensity of the canopy pointes was recorded in a 15cm grid rasterization.

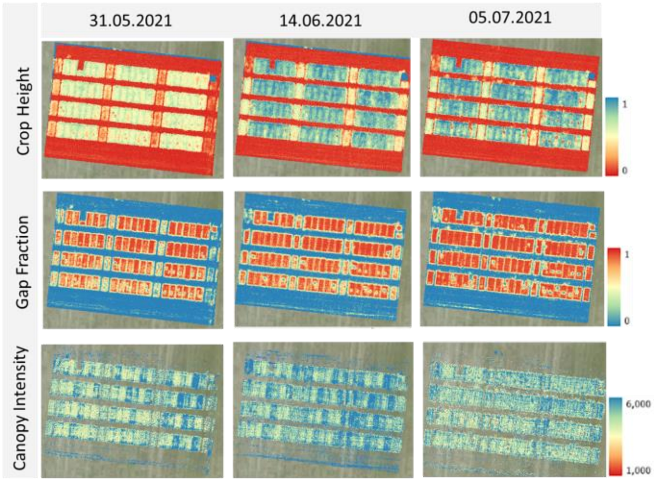

Figure 3. Example visualizations of the resulting derived metrics used for the biomass estimations.

3. RESULTS & DISCUSSION

The CHM, GF, and intensity metrics derived from the LiDAR and the destructive biomass measurement data for the entire growing season were compared for correlations. The strength of each of the LiDAR predictors was able to then be evaluated. The CHM has the strongest correlation of 0.89 with GF closely following with a negative 0.70 correlation. Intensity still has an influence as it has a negative correlation of 0.35.

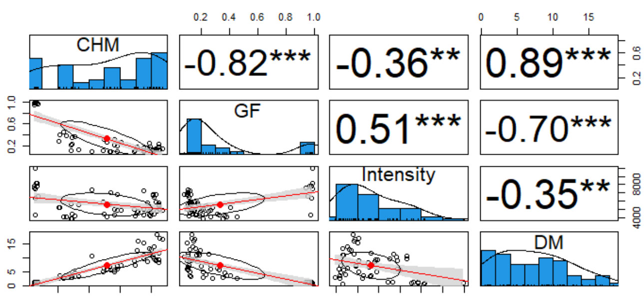

Figure 4. Correlations and histograms of crop height model (CHM), gap fraction (GF), and signal intensity from LiDAR and dry biomass from destructive sampling.

An example visualization of the resulting biomass estimations using the multiple linear regression model derived can be seen in Figure 5.

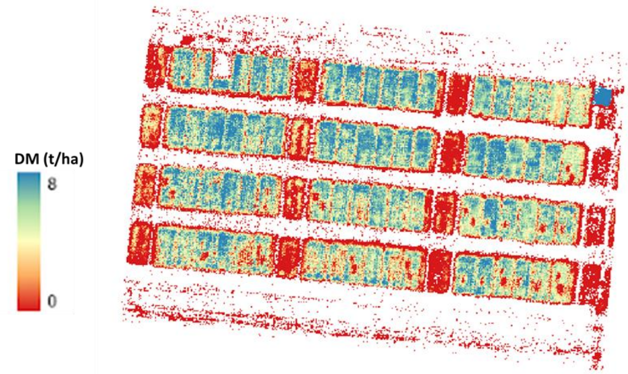

Figure 5. Example visualization of the 14th of July data with resulting dry mass (DM) biomass estimations using multiple linear regression utilizing LiDAR height, density, and intensity metrics.

Destructive samples not used in the training were reserved for the testing of the model created. The results using the testing data from the entire growing season provided a root mean square error (RMSE) of 1.89 t/ha and R2 of 0.84. A graph of these data points can be seen in Figure 6. These results show that the model has promise in estimating the biomass with low error and good replication of its variability.

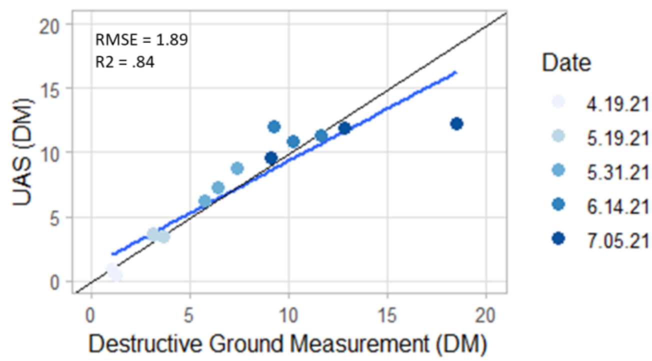

Figure 6. Comparison of UAS LiDAR dry mass (DM) biomass estimations to the ground destructive measurements throughout the growing season.

These results are acceptable concerning similar studies with UAS LiDAR biomass estimations for winter wheat. In one instance, using only LiDAR derived height (H) metrics such as Hmax, Hmajority, and Hvariety in multiple regression an R2 of 0.82 was achieved [8]. In another study, using a recently developed methodology called 3DPI that incorporates a multilayered gap fraction approach from a Beer-Lambert methodology an R2 of 0.82 was also achieved [3].

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. Typical biomass retrieval in remote sensing is done in association with reflectance values. Being an active sensor, LiDAR expands beyond this. Height (CHM), density (GF), and greenness (intensity) information from LiDAR used within a multiple linear regression model is showing promise in its effectiveness and in addition to its simplicity.

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