Winter Wheat LAI Estimation Using UAV Mounted LiDAR

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Abstract

Leaf Area Index (LAI) is used to understand and predict crop health and potential yield for farm management. Several remote sensing methods use optical sensors that rely on spectral reflectance to calculate LAI. This can be problematic with cereal crops like winter wheat that lose greenness with decreased chlorophyll and increase in visible browning as they approach senescence stages. Methods with LiDAR have started to emerge using gap fraction to estimate LAI based on canopy density. These methods have been applied to forest cover with Airborne LiDAR Systems (ALS) and have yet to be used with crops such as winter wheat using Unmanned Aerial Vehicle (UAV) LiDAR. This study helps to better understand the potential of LiDAR as a tool to estimate LAI in precision farming.The method proved to have a high to moderate correlation (0.66) in the spatial variation of LAI values with the passive optical method. The LiDAR LAI values were compared to Sunscan SS1 ceptometer ground measurements where it was found to have possibly been overestimated by 18%. There are several flight collection parameters that can be changed to potentially increase the accuracy. This study sheds light on the potential of LiDAR to contribute to LAI metrics in precision farming.

Keywords: LiDAR, UAS, LAI, drone, winter wheat

1 INTRODUCTION

Leaf Area Index (LAI) is a dimensionless variable describing the ratio between the amount of leaf area per unit of ground surface area. LAI is an important metric in vegetation monitoring as a key indicator for plant health and yield estimations (Yan et al., 2019). Majority of remote sensing methods use optical sensors with ratios of different spectral reflectance to calculate LAI (Delegido et al., 2014; Yao et al., 2017). Essentially this often becomes a measurement of Green Area Index (GAI) or response to chlorophyll content (Delegido et al., 2014). Cereal crops such as winter wheat begin browning as they approach senescence, making it harder to distinguish from the soil. An alternative method with Light Detection and Ranging (LiDAR) sensors has started to appear. There are several cases of Airborne Laser Scanning (ALS) being used to calculate LAI for forests (Huang & Zou, 2016; Korhonen et al., 2011; Morsdorf et al., 2006; Richardson et al., 2009; Sabol et al., 2014). This method bases its estimation on the laser signal's ability to penetrate through gaps in the vegetation cover, using Gap Fraction (GF) thus making it reflective of canopy density (Zheng & Moskal, 2009). It is suggested to be a better indicator of the plant structure as opposed to passive optical methods..This study intends to identify the potential use of Unmanned Aerial Vehicle (UAV) LiDAR to estimate LAI of crops as compared to current passive optical methods.

2 METHODS

2.1 STUDY AREA

The study area was located in Selhausen, Germany (50◦51′ 56″ N 6◦27′ 03″ E) with a winter wheat field of approximately ten hectares. The west side of the field has increased sand and gravel amount at shallower depths which has shown to cause heterogeneity among the crops during periods of water scarcity (Brogi et al., 2020).

2.2 DATA ACQUISITION

The UAV used was a DJI Matrice 600 outfitted with a YellowScan Surveyor LiDAR system and a Micasense Rededge-M for two separate flights on the 9th of June 2020. The LiDAR integrates a Velodyne LiDAR puck with an embedded computer, Inertial Measuring Units (IMU), and Global Positioning System (GPS). The UAV was flown at an altitude of 50 m and at a ground speed of 5 m/s establishing an average 85pts/sqm Point density with an accuracy of 5cm. The multispectral camera has five bands consisting of Blue (465 - 485 nm), Green (550-570 nm), Red (663-673 nm), Rededge (712-722 nm), Near Infrared (NIR) (820-860 nm). The multispectral flights were conducted at an altitude of 100 m and at a speed of 6 m/s. The parameters were set for a forward and side overlap of 90%. Before each flight spectral calibration was performed with a reflectance panel.

Figure 1. DJI Matrice 600 carrying the YellowScan Surveyor LiDAR sensors that was used in this study

DATA PROCESSING

The LiDAR points were classified as ground and non-ground using the Cloth Simulation Filter (CSF) module in CloudCompare. Three different rasters were created for average scan angle, ground and total point population with 15 cm grid spacing. The following formulae were then used to calculate the gap fraction (GF) and LAI.

$$\boldsymbol{GF} = \frac{\boldsymbol{n}_{\boldsymbol{ground}}}{\boldsymbol{n}} \quad (1)$$

$$\boldsymbol{LAI_{LiDARl}} = -\frac{\boldsymbol{cos(ang)} \times \boldsymbol{In(GF)}}{\boldsymbol{k}} \quad (2)$$

Where:

- n_{ground}, n – ground and total point population,
- ang – average scan angle,
- k - extinction coefficient,

The multispectral imagery was processed into orthomosaics and were manually aligned and resampled to 15 cm. The following formulae were used to calculate the GAI using Normalized Difference Vegetation Index (NDVI) and Fractional Vegetation Cover (FVC).

$$FVC_{NDVI} = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \tag{3}$$

$$GAI_{multispectral} = \frac{-log(1 - FVC_{NDVI})}{k(\theta)} \tag{4}$$

Where:

- $NDVI_v$ - value representing max NDVI / vegetation for time series,
- $NDVI_s$ - NDVI value representing soil,
- $k(\theta)$ - extinction coefficient with solar zenith angle

2.3 GROUND MEASUREMENTS

Ground testing took place at four plot locations near the center of the field. A linear Ceptometer (SS1 SunScan Canopy Analysis System, Delta-T Devices Ltd, Campbridge, UK) was used. A total of 36 ceptometer measurements distributed over three sub locations were carried out for each plot and subsequently averaged to a single LAI value.

3 RESULTS & DISCUSSION

Figure 2 visualizes the result with LAI derived from LiDAR and GAI derived using multispectral methods with passive optical sensors. Heterogeneity among the crop is clearly visible in both results. It proves the potential of the LiDAR methodology to capture these variations in plant canopy structure.

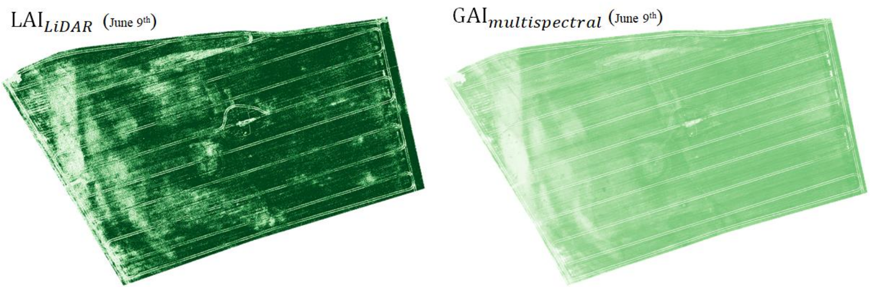

Figure 2. Visualization of LiDAR LAI and the passive optical GAI multispectral method used

The results of the ground measurements were used to assess the average LAI derived from the UAV sensors. The ceptometer and LiDAR values are close but with LiDAR appearing to overestimate by 18%. This overestimation could have resulted from the flight parameters and incident angles used that may have failed to accurately depict the gaps in the canopy. It has been mentioned in studies with ALS and forestry that when the canopy is too dense for the LiDAR to find gaps, the values may become saturated (Richardson et al., 2009). It is recommended to increase flight overlap and directions of the flight paths to gain better perspectives of the vegetation canopy (Richardson et al., 2009). However, this could also be from lack of accuracy with the ground methods. The GAI values are much lower as senescence had already begun appearing in the western side of the field and the overall leaf pigment was decreasing at this point in the growing season. Further testing needs to be applied with flight parameters and additional ground validation methods.

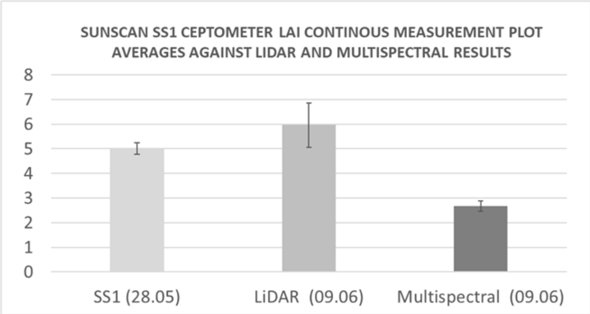

Figure 3. Comparison of the Sunscan SS1 ground measurements to the UAV methods used

Sampling for correlation testing was performed using 82 evenly distributed points across both methods. As the passive optical methods are proven in past studies it is meant to provide credibility to the LiDAR's ability to detect the spatial variation of LAI. The correlations are moderate to high mid-growing season indicating possible reliability when using LiDAR to estimate LAI.

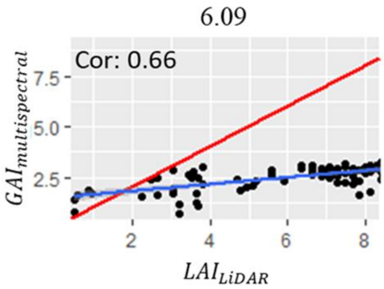

Figure 4. Correlation between the LiDAR LAI and the passive optical GAI multispectral method used.

4 CONCLUSION

The LiDAR LAI results correlated well with an accepted method of calculating GAI with passive optical methods and has comparable values to measurements taken on the ground. There are still many factors concerning flight planning and data processing to understand and increase this method's accuracy and feasibility. However, this study provides supporting evidence that there is potential with UAV mounted LiDAR to derive LAI values.

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