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 in the spatial variation of LAI values with the optical method. The LAI values temporally matched closely to ground measurements aside from late in the growing season when the canopy density was at its highest causing an overestimation by LiDAR that was verified with destructive measurements.

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 that are mainly getting top surface information.This study intends to identify the potential use of Unmanned Aerial Vehicle (UAV) LiDAR to estimate LAI of crops as compared to current 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 nine 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. 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). These 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.

DATA PROCESSING

The LiDAR points were classified as ground and non-ground using the Cloth Simulation Formula (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.

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

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

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 LAI using Normalized Difference Vegetation Index (NDVI) and Fractional Vegetation Cover (FVC).

$$FVC_{NDVI} = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \quad (3)$$

$$LAI_{NDVI} = \frac{-log(1 - FVC_{NDVI})}{k(\theta)} \quad (4)$$

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 with two different methods and plot locations. A Sunscan SS1 Ceptometer was used for continuous collection throughout the growing season (08.04, 06.05, 28.05, 22.06, 02.07) and a one time destructive measurement took place near the end of the growing season (07.07).

3 Results & Discussion

Figure 1 depicts LAI derived from NDVI and LiDAR point clouds against RGB composite. Heterogeneity among the crop is clearly visible in the RGB imagery along with senescence starting on the western side of the field as early as late May. LiDAR methodology is able to capture these changes in plant structure whereas the optical method with NDVI fails as the crop gets closer to full senescence.

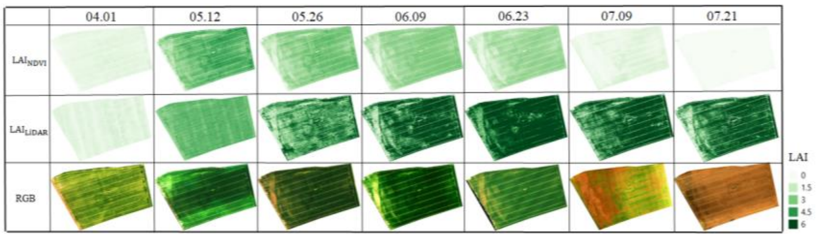

Figure 1. Visualization of the LAI calculated between the two methods with RGB for reference

Sampling was performed using 82 evenly distributed points across both methods. As the 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. There is not a significant correlation early and late in the growing season which can be attributed to optical NDVI's dependence on leaf pigment whilst LiDAR depends on plant structure. The correlations are moderate to high mid-growing season indicating reliable use of LiDAR to estimate LAI.

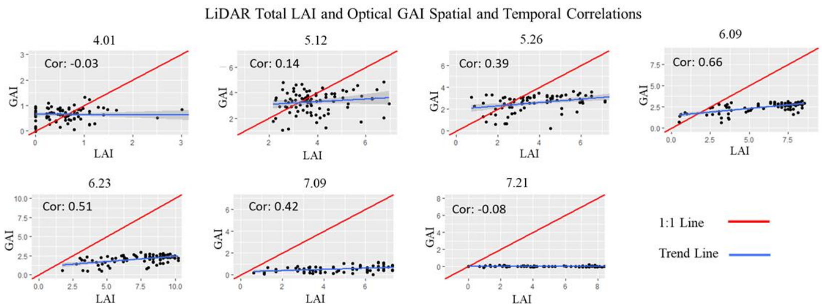

Figure 2. Depiction of correlation amount between LiDAR LAI and Optical LAI NDVI

The results of the ground measurements were used to assess the average LAI derived from the UAV sensors. All three methods show similar results early in the growing season. Ceptometer and LiDAR results remain close in May and early June and vary by 1-2 values from late June till the end.

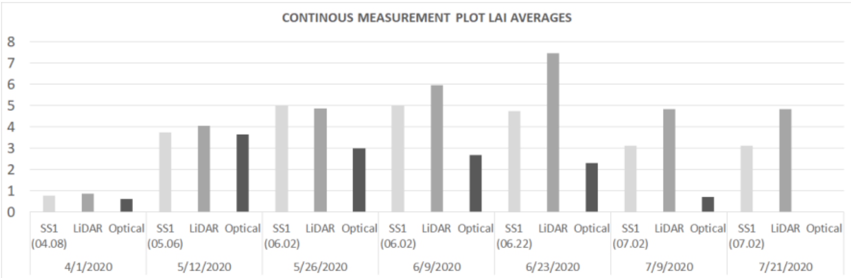

Figure 3. Graph comparing the average LAI measured from the plot locations between the ground truthing with the Sunascent SS1 Ceptometer, the LiDAR method, and the optical method.

The destructive measurement plot (DP) mean values were compared to the LiDAR LAI mean values. Values from the LiDAR data were taken from an adjacent area to the DPs because the closest flight campaign was just after the DP collection. It shows that the values with the LiDAR methods may be overestimating average error of 28%. 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).

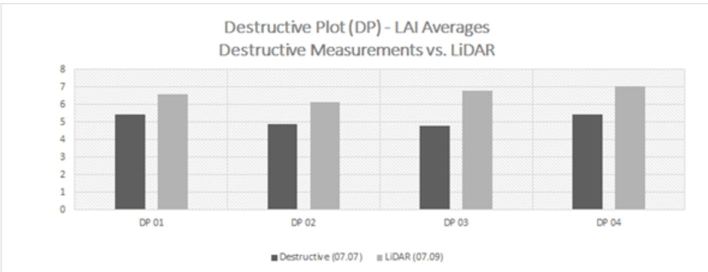

Figure 4 . Graph comparing the destructive measurements and the LiDAR LAI averages.

4 CONCLUSION

LAI results with LiDAR correlated with other accepted methods of calculating LAI and appropriately fluctuates temporally in reference to ground measurements. There are still many factors concerning flight planning and data processing in order 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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References

Brogi, C., Huisman, J. A., Herbst, M., Weihermüller, L., Klosterhalfen, A., Montzka, C., Reichenau, T. G., & Vereecken, H. (2020). Simulation of spatial variability in crop leaf area index and yield using agroecosystem modeling and geophysics-based quantitative soil information. *Vadose Zone Journal*, *19*(1), e20009. https://doi.org/10.1002/vzj2.20009

Delegido, J., Verrelst, J., Rivera, J., Ruiz-Verdu, A., & Moreno, J. (2014). *Brown and green LAI mapping through spectral indices—PDF Free Download*. Kundoc.Com. https://kundoc.com/pdf-brown-and-green-lai-mapping-through-spectral-indices-.html

Huang, Z., & Zou, Y. (2016). Inversion of Forest Leaf Area Index based on Lidar data. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *14*(2A), 44–53. https://doi.org/10.12928/telkomnika.v14i2A.4379

Korhonen, L., Korpela, I., Heiskanen, J., & Maltamo, M. (2011). Airborne discrete-return LIDAR data in the estimation of vertical canopy cover, angular canopy closure and leaf area index. *Remote Sensing of Environment*, *115*(4), 1065–1080. https://doi.org/10.1016/j.rse.2010.12.011

Morsdorf, F., Kötz, B., Meier, E., Itten, K. I., & Allgöwer, B. (2006). Estimation of LAI and fractional cover from small footprint airborne laser scanning data based on gap fraction. *Remote Sensing of Environment*, *104*(1), 50–61. https://doi.org/10.1016/j.rse.2006.04.019

Richardson, J. J., Moskal, L. M., & Kim, S.-H. (2009). Modeling approaches to estimate effective leaf area index from aerial discrete-return LIDAR. *Agricultural and Forest Meteorology*, *149*(6), 1152–1160. https://doi.org/10.1016/j.agrformet.2009.02.007

Sabol, J., Patočka, Z., & Mikita, T. (2014). Usage of Lidar Data for Leaf Area Index Estimation. *GeoScience Engineering*, *60*(3), 10–18. https://doi.org/10.2478/gse-2014-0013

Yan, G., Hu, R., Luo, J., Weiss, M., Jiang, H., Mu, X., Xie, D., & Zhang, W. (2019). Review of indirect optical measurements of leaf area index: Recent advances, challenges, and perspectives. *Agricultural and Forest Meteorology*, *265*, 390–411. https://doi.org/10.1016/j.agrformet.2018.11.033

Yao, X., Wang, N., Liu, Y., Cheng, T., Tian, Y., Chen, Q., & Zhu, Y. (2017). Estimation of Wheat LAI at Middle to High Levels Using Unmanned Aerial Vehicle Narrowband Multispectral Imagery. *Remote Sensing*, *9*(12), 1304. https://doi.org/10.3390/rs9121304

Zheng, G., & Moskal, L. M. (2009). Retrieving Leaf Area Index (LAI) Using Remote Sensing: Theories, Methods and Sensors. *Sensors (Basel, Switzerland)*, *9*(4), 2719–2745. https://doi.org/10.3390/s90402719