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# Estimating wheat green area index from ground-based LiDAR measurement using a 3D canopy structure model

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A B S T R A C T

The use of active remote sensing techniques based on light detection and ranging (LiDAR) was investigated here to estimate the green area index (GAI) of wheat crops. Emphasis was put on the maximum GAI development stage when saturation effects are known to limit the performances of standard indirect methods based either on the gap fraction or reflectance measurements. The LiDAR provides both the three dimensional (3D) point cloud from which the vertical distribution (Z profile) of the interception points is computed, as well as the intensity of the returned signal from which the green fraction (GF) is derived. The data were interpreted by exploiting the 3D ADEL-Wheat model that synthesizes the knowledge accumulated on wheat canopy structure. A LiDAR simulator that accounts for the specific observation configuration used was developed to mimic the actual LiDAR measurements. The in-silico experiments were conducted to generate training and validation dataset. Neural network were then used to estimate GAI from the Z profile and GF derived from the LiDAR measurements. Performances of GAI estimates by the several methods investigated were evaluated using either experimental data with $3 < \text{GAI} < 6$ and data simulated with the 3D structure model with $1 < \text{GAI} < 7$.

Results confirm that using only the GF provides poor estimates of GAI ($0.89 < \text{RMSE} < 1.28$; $0.22 < \text{rRMSE} < 0.31$), regardless of turbid medium or realistic assumptions on canopy 3D structure. The introduction of the Z profile information improved significantly the GAI estimation accuracy ($0.48 < \text{RMSE} < 0.55$; $0.12 < \text{rRMSE} < 0.13$). This study demonstrates the interest of using the third dimension provided by LiDAR to better estimate GAI in crops under high GAI values. However, this requires the use of a realistic 3D structure crop model over which the LiDAR data could be simulated under the observational configuration used.

## 1. Introduction

Green area index (GAI) is defined as the total one-sided area of green vegetation elements per unit ground horizontal surface. GAI is here preferred to leaf area index (LAI) since it includes other green organs such as stems and ears (Baret et al., 2010; Verger et al., 2014) that significantly contribute to the canopy photosynthesis, respiration and transpiration (Bonan, 1993; Weiss et al., 2004). Thus, GAI excludes the senescent leaf parts that are no more functioning. GAI is commonly estimated in-situ using green fraction measurements (the fraction of green elements seen from a given direction) derived from downward looking hemispherical digital photography (Weiss et al., 2004) or imagery acquired with longer focal length (Baret et al., 2010). The canopy is generally assumed to be a turbid medium to ease the derivation of the GAI using a well-established theory (Nilson, 1971). However, these GAI estimation methods are limited due to their prohibitive cost (Zheng and Moskal, 2009) when repeated a large number of times, and the associated accuracy may be compromised by the

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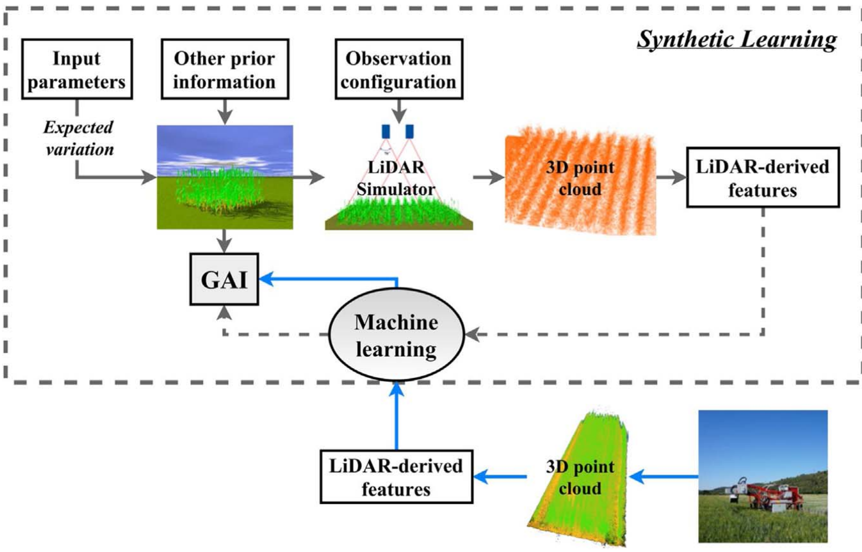


**Fig. 1.** Diagram showing the principles of the synthetic-learning methodology developed to estimate GAI from ground-based LiDAR measurements.

possible violation of the turbid medium assumption. Further, in the case of field phenotyping applications where the GAI dynamics along the growth cycle is highly desired (Araus and Cairns, 2014), structural differences between genotypes that are not well represented by the turbid medium assumption may degrade the accuracy of the GAI estimates.

Remote sensing techniques including optical passive sensors and active light detection and ranging (LiDAR) provide efficient ways to estimate GAI over larger spatial domains. Passive optical methods are generally based on the calculation of vegetation indices such as the Normalized Vegetation Difference Index (NDVI) (Baret and Guyot, 1991) or the green fraction when high enough spatial resolution is available (Baret et al., 2010). These methods are generally showing a degradation of their performances for the larger GAI values because of the saturation of the signal. Further, these techniques may be sensitive to the variation in the illumination conditions that affect vegetation indices (Stark et al., 2016) as well as the separation between the green elements and the background (Baret et al., 2010). Conversely to these passive remote sensing techniques, LiDAR is an active method independent from the illumination conditions. Further, LiDAR observations offer a more detailed description of the canopy structure by providing the third dimension from which more canopy traits of interest could be potentially retrieved. Recent work has demonstrated its capability for GAI or LAI estimates over a wide range of values on both homogenous and heterogeneous forest stands (Béland et al., 2014; Griebel et al., 2015; Ilangakoon et al., 2015; Korhonen et al., 2011; Richardson et al., 2009; Zhao and Popescu, 2009) and orchards (Arnó et al., 2013). However, little work has been dedicated to the application of airborne or ground-based LiDAR systems for GAI estimates for staple crops.

The relatively little use of LiDAR over crops was mainly due to the significant footprint of the available systems that were limiting the description of the fine structure. This limitation is now partly overcome by some of the current LiDARs as the reduction of footprint size and the increase of scanning frequency (Eitel et al., 2014; Lin, 2015; Saeys et al., 2009). Further, the interaction of the laser beam with the canopy structure is complex (Kukko and Hyyppä, 2009) and specific interpretation algorithms need to be developed to reach the expected level of accuracy and precision required (Baret and Buis, 2008; Zhao et al., 2009; Zhao and Popescu, 2009).

Empirical based methods have been derived from available datasets acquired under specific conditions and instruments (Richardson et al., 2009). Although these methods are tractable and may perform well for the cases similar to those prevailing during the calibration experiments, they will provide uncertain performances outside the calibration conditions. Alternatively, laser–canopy interactions could be described using physically based models. The turbid medium assumption has been exploited recently by Zhao et al. (2015) to estimate GAI from the gap fraction measured by LiDAR. Although this approach does not require any calibration process, the LiDAR-derived gap fraction, hence the estimated GAI, may be greatly affected by LiDAR intrinsic setup and extrinsic scanning pattern (Morsdorf et al., 2006; Van der Zande et al., 2006; Zheng and Moskal, 2009). Moreover, GAI estimates using the turbid medium assumption provide an effective GAI. Possible clumping effect has to be corrected to get the actual GAI (Chen et al., 1997).

The limitations of the two approaches to estimate GAI from LiDAR measurements may be overcome using machine learning techniques trained over simulations of the LiDAR signal achieved with a realistic 3D description of the canopy structure. The turbid medium assumption will therefore be no more necessary allowing accessing the true GAI, because model simulations allow considering the whole range of possible cases corresponding to what is currently achievable using actual experimental observations. Afterwards, GAI estimation from synthetic dataset can be achieved using either a Look-Up-Table (LUT) or a machine learning method that are both proved to be computationally efficient as compared with other methods (Baret and Buis, 2008). In this work, machine learning technique was selected due to its efficiency for solving problems of high level complexity given a small dimensionality of inputs (Atzberger, 2004).

The objective of this study is to propose a synthetic learning approach to estimate the true GAI from ground-based LiDAR measurements as sketched in Fig. 1. The synthetic learning dataset is generated using the 3D ADEL-Wheat model (Abichou et al., 2013; Fournier et al., 2003) coupled to a LiDAR simulator mimicking the actual LiDAR measurements. Machine learning techniques were then trained over the synthetic dataset to estimate the true GAI corresponding to the LiDAR measurements. For this purpose, the LiDAR observations were described by few features. Further the space of canopy realization may be reduced to speed up the computation using the available prior information on the range of possible cases. Finally, the performances of the method were evaluated over both an independent synthetic dataset as well as over actual field measurements.