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Retrieval of narrow-range LAI of at multiple lidar point densities: Application on *Eucalyptus grandis* plantation

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ABSTRACT

Leaf area index (LAI) is an important forest structural parameter that can be used to characterize various biophysical processes such as photosynthesis, evapotranspiration, and carbon flux. Accurate monitoring of LAI therefore is crucial for efficient management of managed and natural vegetation ecosystems. Remote sensing techniques have proved useful in the quantification and monitoring of LAI in different vegetation types; however, most of the focus has been on vegetation with relatively large LAI ranges. This study aimed to investigate the utility of airborne light detection and ranging (lidar) data to estimate narrow-range LAI (min = 0.71, max = 1.56, mean = 1.08 ± 0.18) of intensively-managed *Eucalyptus grandis* plantations. The secondary aim of the study was to assess the effect of lidar point density on LAI retrieval. Reference LAI was quantified in 15 m radius sample plots (n = 46) using hemispherical photography. Akaike Information Criterion (AIC) regression was used to build candidate models that estimate LAI from lidar-derived height and density metrics. The correlations were investigated at different point densities, including the original (> 6 points/m^2) and reduced density levels (0.25–5 points/m^2). Candidate models returned adjusted coefficient of determination (adj. R^2) ranging between 0.65–0.83 (RMSE 7.0-10.0% of observed mean) depending on the number of predicting metrics included in the models. A model that had two non-collinear metrics was selected as a compromise model (adj. R^2 = 0.67; RMSE = 9.7%); this model was comparable to the best model, which had many collinear metrics. Estimation accuracies were similar for lidar densities of the original, 2–5 points/m^2 and less accurate for 0.25–1 point/m^2. These findings demonstrated the capability of lidar in estimating observed LAI with low range and variation. The study also suggests the efficacy of moderate lidar point densities acquired at relatively low-cost surveys in attaining acceptable LAI estimation accuracy.

1. Introduction

Plant leaves play a vital role in driving ecological processes, including photosynthesis, respiration, energy flux, nutrient consumption, and climate cycles (Song, 2012). The amount and spatial arrangement of leaves is a key factor influencing the ecological services sustained by plant foliage (Song, 2012). Knowledge of these characteristics therefore is useful to monitor both the ecosystem services of plants and consumption rate of essential base resources, such as water and nutrients from different environmental spheres. A common quantitative tool that is used to assess foliage levels, is leaf area index (LAI), which measures the ratio of the sum of one-sided leaf area and ground covered by the leaves (Monteith and Unsworth, 1990).

LAI traditionally is measured via direct, contact methods that mainly include scanning live or cut leaves, or collecting and weighing litter falls that are subsequently related to LAI using established models (Eamus et al., 2000; Keith et al., 2000; Jonckheere et al., 2004). These methods provide accurate information for measured leaves and also ensure that only leaves (excluding stems and shoots) are quantified. They are nevertheless labor intensive, time-consuming, relatively expensive, and limited in spatial coverage (Weiss et al., 2004; Zheng and Moskal, 2009). Covering large spatial areas therefore can be compromised by a sampling strategy that fails to characterize the spatial variation in LAI sufficiently. A more practical approach, employed in a variety of vegetation environments, is the use of optical sensors (e.g. Canopy Light Analyzer and hemispherical photography), which measure canopy gaps from which canopy fractions (leaves or branches) are inferred (Jonckheere et al., 2004; Bréda, 2008). Although this approach

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overcomes the problem of destructive sampling, it requires intensive field surveys, thus limiting its utility in terms of spatial coverage. Furthermore, accuracy of the approach is highly dependent upon sky/illumination conditions (Pearse et al., 2016), with overcast sky being the ideal scenario.

The shortcomings of field-based surveys (both contact and optical methods) are largely overcome by using remote sensing techniques (Zheng and Moskal, 2009), which are used to measure and interpret electromagnetic energy reflected from features of interest. Numerous studies have demonstrated the applicability of these techniques to LAI estimation in different vegetation types, including agricultural crops (e.g., Houborg and Boegh, 2008; Hosseini et al., 2015), grasslands (e.g., He et al., 2016), wetlands (e.g., Ghosh et al., 2016), and forests (e.g., Pu and Cheng, 2015; He et al., 2016), among others. One advantage of spaceborne optical (spectral) remote sensing, in particular, is that of extensive spatial coverage. Although imagery available in the public domain (e.g., MODIS, Landsat and ASTER) are suited mostly for coarse scale LAI estimation (e.g., Houborg et al., 2015; Campos-Taberner et al., 2016; Korhonen et al., 2017; Macfarlane et al., 2017), continuous technological advances in sensor performance are improving the accuracies of LAI estimation at finer scales (e.g., Pu and Cheng, 2015; Neinavaz et al., 2016; Tian et al., 2017). However, two problems that are associated inherently with optical remote sensing systems constrain their successful application to LAI estimation. Firstly, the system provides information about plants using picture elements (pixels) that have two dimensions (x/y or latitude/longitude) only; thus, it is unable to profile plants vertically (z-dimension). Such insensitivity to vertical position makes it difficult to differentiate the relative contributions of multi-story plants and plant elements to LAI. For example, imagery is unable to differentiate LAI from large vascular plants and understory herbaceous plants. This does not necessarily constitute a major concern, if the purpose of LAI estimation is for a holistic appraisal of leaf amount in a given area, irrespective of vegetation type (form). However, ecological and biophysical characteristics often are better explained at finer scales or levels, for example, stratification based on vegetation type. Secondly, spectral reflectance in vegetated areas is sensitive to photosynthesis vigor that in turn can be influenced by seasonal or physiological factors. Spectral reflectance of vegetation during low photosynthetic activity can be similar to that of background reflectance (e.g., bare soil or soil covered by organic matter), even with the usage of hyperspectral remote sensing systems that boast high spectral resolutions (Delegido et al., 2015). This lack of differentiation can lead to an underestimation of LAI. A potential solution to these problems is factoring in structural information that can differentiate multi-layered foliage, as well as vegetation vs. non-vegetation land covers during senescence.

Lidar is a remote sensing technology that provides structural information of features at a high spatial resolution. The technology scans a given area by emitting pulsed electromagnetic radiation at a thousand times per second and recording pulses that are reflected from features close to or at the ground (Hyyppä et al., 2008). The time-lapse between emittance and reflectance of each pulse is then multiplied by the speed of light to derive the vertical position of an object that backscattered the pulse. In addition, the coordinates (longitude and latitude) of each pulse in the horizontal plane are recorded. A combination of these three dimensions and a high pulse density within a small spatial area make lidar data suitable for characterization of vegetation structural attributes (Jensen et al., 2008; Thomas et al., 2011; Tang et al., 2014). Several studies have applied lidar data to assess LAI in vegetation environments with heterogeneous morphological and species compositions (e.g., Jensen et al., 2008; Solberg et al., 2009; Béland et al., 2011; Thomas et al., 2011; Tang et al., 2012, 2014; Alonzo et al., 2015; Heiskanen et al., 2015; Luo et al., 2015; Vincent et al., 2017). LAI in such environments generally show a high degree of variation. Although estimation accuracies can be complicated by factors such as scale of data and analysis techniques, the potential of capturing LAI variations using lidar data has been proven. On the other hand, the similarity in species composition and leaf/foliage geometry in homogenous vegetation types is logically expected to make LAI estimation more challenging, particularly in similar growth stage scenarios.

Lidar remote sensing of LAI has been applied in different homogenous vegetation environments, such as boreal (Korhonen et al., 2011), loblolly pine (Peduzzi et al., 2012; Sumnall et al., 2016a, b), tropical (Heiskanen et al., 2015) and Norway spruce forests (Moeser et al., 2014). Solberg et al. (2006) and Solberg (2010) even demonstrated the utility of lidar data for tracking LAI changes that can, in turn, be used for monitoring canopy defoliation, as well as differentiating defoliation from tree harvesting. However, the LAI values in these studies have relatively large ranges that are arguably easy to profile using high density lidar data. Sumnall et al. (2016b), for example, used lidar data to estimate LAI ranging between 0.45 and 5.39 in intensively managed loblolly pine plantations located at different sites. They reported high correlations between certain lidar density-based metrics and LAI ($R^2 > 0.75$). These accuracies were, however, based on a dataset combined from all the sites, each of which had a much narrower LAI range than the combined dataset. The models therefore represented overall variations well, but visual observations show the models' weaknesses in fitting intra-site LAI variations, particularly those with narrower LAI ranges. In contrast, intensively-managed commercial forests are characterized by a great deal of homogeneity, due to the fact that management strategies in these forests are aimed at producing uniform stems within a compartment (a stand). This is achieved by maintaining similarities in site characteristics (e.g., landscape, soil) and silvicultural practices (e.g., planting dates, tree spacing and routine treatments). Such interventions have two implications on foliage structural properties. Firstly, the amount, geometry and arrangement of foliage are generally homogenous within a compartment (Becagli et al., 2016). Secondly, the foliage amount is small relative to stem size, since maximizing wood harvest is the main goal of commercial forests (du Toit et al., 2001; West, 2014). It is therefore important to investigate the utility of lidar data to estimate LAI with relatively small variation. Morsdorf et al. (2006) specifically estimated LAI ranging between 0.1–1.6 using high point density lidar data in a homogenous pine forest. There is a need, however, to extend such an application to vegetation with different morphological characteristics, since foliage assemblage can vary according to vegetation types (Morsdorf et al., 2006). For instance, Riaño et al. (2004) compared LAI estimation accuracies in oak and Scots pine forests, with each characterized by a low LAI variation. They reported consistent differences for the two species, demonstrating the dependence of estimation accuracy on vegetation type. This study therefore aimed to assess the performance of airborne laser scanning in estimating narrow-range LAI (0.71–1.56) in intensively managed *Eucalyptus grandis* plantations. A secondary aim of the study was to investigate the effect of lidar point density (0.25 to > 6 points/m^2) on LAI retrieval. A successful application of lidar data to retrieve LAI through such a study will add value to the forestry industry that is increasingly adopting the technology for accurate characterization of other forest attributes, such as volume/biomass (e.g., Figueiredo et al., 2016; Maack et al., 2016) and carbon monitoring (e.g., Zhao et al., 2018).

2. Methods

2.1. Study area

The study area is located near the town of Richmond in KwaZulu-Natal province, South Africa (Fig. 1). The area falls within the summer rainfall region of South Africa, and experiences cold dry winters and warm wet summers. Plantation forestry dominates the land use in the area, with the *Eucalyptus* and *Pinus* species being predominant. The dominance of these species in the area reflects what is observed at the regional and national levels (Godsmark, 2009). *Eucalyptus* species