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Optimising prediction of forest leaf area index from discrete airborne lidar

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ABSTRACT

Discrete airborne laser scanning (ALS) data has emerged as a useful tool for mapping forest leaf area index (LAI). Both empirical and physically-based approaches linking pulse penetration to LAI through gap probability theory have been widely used. We contrasted these approaches using field measurements of LAI (n = 135) acquired in stands of pure *Pinus radiata* D. Don in New Zealand. For the empirical approach, we addressed several methodological questions: (1) Identification of important covariates from an extensive list of lidar metrics with empirical or theoretical links to LAI. (2) Evaluation of the impact of lidar plot radius on metric importance and model accuracy by trialling fixed radii and radii based on mean top height (MTH). (3) For ratio metrics, which require selection of a height threshold (HT), identification of the optimum fixed HT and to evaluate a novel variable HT set as a percentage of canopy height. Custom lidar software evaluated all combinations of metric, radius, and HT. For model development, we tested elastic net linear regression for regularisation and variable selection, as well as random forests to explore potential nonlinear relationships and to provide insight into variable importance using conditional importance scores accounting for intercorrelation. For the physically-based model, a proxy for vertical canopy gap fraction was sought from ALS metrics measuring pulse penetration for use in a nonlinear model based on the Beer-Lambert law. Empirical models were strongly impacted by calibration and larger plot radii and higher HTs generally reduced RMSE and highlighted a common set of ratio metrics characterising pulse penetration. Elastic net models performed best with the lowest RMSE = 0.57 LAI at radius = 100% of MTH and HT = 20% of canopy height. Models with low RMSE often had radii in the range of canopy height - supporting theoretical links to instrument view distance. The best fixed-radius model (RMSE = 0.64) had radius = 20 m and HT = 20% of canopy height. Random forests results were similar, with little evidence of nonlinear relationships (lowest RMSE = 0.64). Physically-based models produced results close to the best calibrated empirical models (RMSE = 0.72) using a single metric. This approach offered the potential to estimate forest type coefficients that could allow ALS-LAI mapping without the need for calibration and with greater potential for transferability between ALS campaigns. These results support the use of physically-based models for discrete ALS-LAI mapping.

1. Introduction

Leaf area index (LAI) in coniferous forests is defined as one-half the total green leaf surface area per unit ground area (Chen et al., 1997). Forest LAI is a key ecophysiological parameter with close links to canopy light use, water interception, and a range of biochemical and ecosystem processes (Bréda, 2008). Managers of forests used for production values face increasing pressure to lift output per unit area as resource pressures increase. Precision management approaches are increasingly being sought to achieve this objective. LAI is a good candidate for fine-scale information that may be used to target and monitor silvicultural treatments. Measurable increases in LAI can be obtained with site treatments such as fertilisation or irrigation (Brix and Mitchell, 1983; Raison and Myers, 1992). Defoliating events such as insect attack can also be identified through changes in LAI (Solberg et al., 2006).

1.1. Remote sensing of LAI

Despite the importance of LAI in forest ecosystems, difficulties in measurement have limited the range of practical applications. Forest LAI shows high levels of spatiotemporal variation and direct measurement of LAI is labour intensive and impractical over large areas (Bréda, 2003). Field measurement of LAI usually relies on measurement of gap fraction using either active sensors such as terrestrial laser scanning

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(Zhao et al., 2011) or passive optical methods (Woodgate et al., 2015). Measurements of gap fraction can then be used to estimate LAI by inversion of the Poisson model (Jonckheere et al., 2004; Weiss et al., 2004). Many of these methods cannot discriminate between light blocked by leaf and woody material and the plant area index is measured instead (Woodgate et al., 2015). Optical methods offer rapid, repeatable measurements but are known to underestimate LAI, especially in coniferous forests (Chen et al., 2006; Mason et al., 2012). The relationship between LAI and light interception has been used in reflectance-based techniques to estimate LAI over large areas from multispectral vegetation indices (Myneni et al., 1997; Stenberg et al., 2004). However, sensor saturation in areas of high LAI, interference from background vegetation, canopy gap distribution, and processing difficulties frequently reduce the accuracy of spectral-LAI estimates, restricting the usefulness of these approaches (Carlson and Ripley, 1997; Jensen et al., 2011; Turner et al., 1999).

Light detection and ranging (lidar) has emerged as a valuable tool for measuring forest LAI at large-scales. Lidar is an active sensing technology that uses either pulsed or waveform energy to accurately range targets. Waveform instruments capture a nearly complete record of the reflected waveform that can be decomposed to isolate energy reflected from ground and canopy elements respectively, allowing canopy gap fraction (or usually the opposite value - canopy closure) to be directly estimated (Armston et al., 2013; Tang et al., 2012). Waveform methods have been used to explore the spatial variation of LAI at a range of scales (Tang et al., 2014a) and to retrieve gap fraction and LAI over large areas using the space-borne GLAS instrument (Tang et al., 2014b).

Airborne discrete laser scanning (ALS) sensors are more common than waveform sensors in forestry applications and have benefited from rapid advances in technology (Maltamo et al., 2014). These instruments range one or more discrete returns and the penetration rate of pulses through the canopy can be used to provide a measure of gap fraction and hence LAI (Solberg, 2010). Discrete ALS-LAI estimation has emerged as a valuable tool for large-scale assessment of LAI in forested areas. Strong relationships ($R^2 = 0.78$) have been found between field measurements of LAI and ALS data from intensively managed pine plantations, and correlations were observed between the values of lidar metrics and stand silvicultural treatments (Peduzzi et al., 2012). Similar strong relationships between LAI and ALS data have been observed in a range of natural and mixed forest types (Jensen et al., 2008; Morsdorf et al., 2006; Riaño et al., 2004). The strength of ALS-LAI relationships has facilitated detection and monitoring of insect attack in a Norwegian Scots pine (*Pinus sylvestris* L.) forest (Solberg et al., 2006) and large-scale mapping of LAI (Solberg, 2010; Solberg et al., 2009). The improved accuracy of ALS-LAI estimates has also facilitated the validation of large-scale spectral-LAI data products. For example, aggregation of superior ALS-LAI estimates facilitated identification of important deficiencies in GLOBCARBON LAI products (Zhao and Popescu, 2009) and overestimation of LAI in some MODIS products (Jensen et al., 2011).

1.2. Development of ALS-LAI models

The development of ALS-LAI models can be broadly divided into empirical and physically based approaches. Empirical approaches rely on the development of models between ALS metrics and field measurements of LAI. (e.g. Griffin et al., 2008; Jensen et al., 2011, 2008; Peduzzi et al., 2012; Pope and Treitz, 2013). In physically based approaches, gap probability is often assessed using some measure of the penetration rate of pulses through the canopy or measures of reflected pulse intensity are chosen as a proxy for light extinction through the canopy (e.g. Hopkinson and Chasmer, 2007; Korhonen et al., 2011; Morsdorf et al., 2006; Solberg et al., 2009, 2006).

Although the form of these models may vary, all require common methodological decisions that can have significant impacts on model performance (Riaño et al., 2004; Richardson et al., 2009; Zhao and Popescu, 2009). First, lidar data coincident with field measurements of LAI must be extracted to compute lidar metrics. A common choice is to set the lidar plot radius equal to that used to collect field plot data (e.g. Jensen et al., 2008; Peduzzi et al., 2012). However, both physically-based and empirical approaches to ALS-LAI estimation have been shown to be sensitive to the choice of plot radius (Solberg et al., 2009; Zhao and Popescu, 2009). ALS-LAI models have been shown to improve with increasing plot radii, often achieving maximum agreement at radii greater than the defined field plots (e.g. Morsdorf et al., 2006; Richardson et al., 2009; Zhao and Popescu, 2009). In part, this can be explained by the observation that optical instruments used to acquire field LAI measurements may view canopy elements beyond field plot boundaries, and the maximum view distance is partially determined by canopy height and stand density (LI-COR, 2015). In recognition of this, an alternative approach has been to define lidar plot radius as some multiple of canopy height (e.g. Riaño et al., 2004; Solberg et al., 2009). However, the choice of variable radius is not clear, with reported optimum values ranging from 75% of canopy height (Solberg et al., 2009) to 100% of canopy height (Riaño et al., 2004).

After extraction, the lidar data must be described and related to LAI. In the empirical approach, it is common to use a range of descriptive metrics such as height percentiles, descriptive statistics, and distributional statistics for return elevations. These metrics will to some extent capture underlying canopy properties related to LAI and are frequently included in ALS-LAI models (e.g. Beets et al., 2011; Jensen et al., 2008; Pope and Treitz, 2013). Lidar metrics quantifying the rate of pulse penetration through the canopy have been shown to be useful in both empirical and physically-based studies (Morsdorf et al., 2006; Peduzzi et al., 2012; Solberg et al., 2009, 2006). These 'penetration' metrics provide some measure of canopy gap probability, which is nonlinearly related to LAI through the Beer-Lambert law describing the extinction of light through the canopy (Monsi and Saeki, 2005, 1953). Physical differences between the interaction of ALS pulses and solar radiation with canopy elements, such as footprint size, make these models semi-physical at best (Zhao and Popescu, 2009) and ALS proxies for gap probability suffer from limited sampling of the canopy and an inability to resolve smaller gaps (Armston et al., 2013). Other approaches seek to use the ratio of input and reflected pulse energy as a measure of gap probability that can partially overcome resolution issues but still suffer from a lack of calibration and uneven sampling inherent in discrete return data (Hopkinson and Chasmer, 2009, 2007).

A common feature of penetration related metrics is the selection of a height threshold (HT) around which ratios of intensity sums or return counts are computed. The value used for the HT is frequently set at instrument or field measurement height (Peduzzi et al., 2012; Solberg et al., 2009). Where alternatives have been trialled, ALS-LAI models strongly benefited from increased HTs, with the optimum HT found to be well above instrument height (Zhao and Popescu, 2009). Numerous ratio metrics have been highlighted in previous ALS-LAI studies but a comparison of more than a few ratio metrics has seldom been done. In addition, the optimum choice of height threshold has only been examined for a small subset of these metrics.

More sophisticated metrics attempt to increase information content by considering the distribution of returns at the sub-plot level. For example, lidar analogues to ecological complexity indexes and stratified crown closure indices computed from sub-pixels within the plot have all been found to be useful in the development of ALS-LAI models (Griffin et al., 2008; Pope and Treitz, 2013). Theoretically, metrics based on sub-pixels may be able to capture information on structural attributes that drive spatial heterogeneity of LAI, but their value has not been assessed against the many alternative metrics proposed for ALS-LAI estimation.

The final methodological choice requires selection of a modelling approach for ALS-LAI estimation. For empirical approaches, linear methods such as subset regression have frequently been employed (Jensen et al., 2011, 2008; Pope and Treitz, 2013). In the presence of