Generating an automated approach to optimize effective leaf area index by Canadian boreal forest species using airborne LiDAR

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Abstract

Obtaining forest structure data to compute leaf area index (LAI) can be a challenge in remote areas like the Canadian boreal forest. Light ranging and detection (LiDAR) data provides a 3-dimensional view of the forest that can be calibrated with minimal field data requirements relative to other remote sensing data. Our objective is to develop an automated method for combining a limited amount of field data with LiDAR to generate estimates of LAI. To accomplish this we used geographic information system (GIS) tools to expand upon a physically-based gap fraction model by incorporating a process for optimizing extinction coefficient by forest species. In this paper we demonstrate a simple, efficient method for optimizing remote sensing-based estimates of canopy attributes from limited field data. We were able to reduce the RMSE in modelled effective leaf area index by an average of 0.48 across all species. Combining such simple model optimisation approaches with other automated LiDAR-based canopy attribute extraction procedures shows promise as we move towards ever greater levels of LiDAR forestry operationalisation.

Keywords: LiDAR, leaf area index, optimization, extinction coefficient, Boreal forest

1. Introduction

1.1 Rational

Leaf area index (LAI), which is defined as half of the total leaf area per unit ground area (Chen *et al.*, 2006), is an important input parameter used within biogeochemical, biomass, and ecological models. Accurate estimates of LAI are therefore important, as small deviations or biases in could result in sometimes compounded errors within these models. Several studies have used plot-based measurements of gap fraction (used to derive effective LAI (LAIe) and LAI) when scaling to lower resolution spectral imagery (e.g. Fernandez *et al.*, 2003; Fernandez *et al.*, 2004). However, plot measurements often do not represent the full range of vegetation characteristics found within ecosystems, and can be time consuming to acquire. Airborne Light Detection and Ranging (LiDAR) data offers an alternative method for continuously mapping LAI at high resolution. LiDAR provides a three dimensional representation of the canopy, understory, and ground surface topography measured using reflected laser pulses. The basic rationale for LiDAR-based LAI mapping is that the vertical distribution of laser pulse returns within the canopy is related to the foliage profile (Magnussen and Boudewyn, 1998) such that if only ground-level returns occur in a given area then the likelihood of overlaying leaf area is low. Conversely, a greater density of above ground (or canopy level) returns in a given area indicates a higher leaf area. From this basic understanding, LAI can be estimated directly as a function of the canopy gaps thus observed (e.g. Solberg *et al.*, 2006). However, gap fraction-based estimates of LAIe (which must further take into account the canopy clumping, woody to total leaf area ratio, and needle to shoot area ratio in order to estimate true LAI) requires an estimate of extinction coefficient (k). The objective of this study is to investigate model parameter optimization of k to improve LAIe estimates within three boreal forest ecosystems: mature black spruce, a jack pine chronosequence of four sites, and a mature aspen stand.

1.2 LiDAR-based LAI models

A number of LiDAR-based LAIe models have been developed that employ range and echo data provided by discrete-return airborne systems. These include mean return elevation methods (e.g. Lim *et al.*, 2003), fractional canopy return methods (e.g. Riaño *et al.*, 2004; Solberg *et al.*, 2006), and the examination of canopy volume (e.g. Lefsky *et al.*, 1999). Models were developed and tested for a specific forest type but often require calibration. The intensity-based gap fraction (or fractional cover) model of Hopkinson and Chasmer (2007), is one LiDAR-based model that has been shown to require minimal or no calibration. The model divides LiDAR returns into four echo classes (first, single, intermediate, last) and generates grids of intensity by summing returns within a cell. It then accounts for a two-way power transmission loss by intermediate and last return hits using a square root function. First and single hits at and below 1.3 m from the ground surface are subset to represent below-canopy (ground) hits. A ratio of total returns intensity to this below-canopy subset is used to estimate gap fraction:

$$P = \frac{\left(\frac{\sum I_{GroundSingle}}{\sum I_{Total}}\right) + \sqrt{\frac{\sum I_{GroundLast}}{\sum I_{Total}}}}{\left(\frac{\sum I_{First} + \sum I_{Single}}{\sum I_{Total}}\right) + \sqrt{\frac{\sum I_{Intermediate} + \sum I_{Last}}{\sum I_{Total}}}} \qquad (1)$$

Subscripts indicate the echo class and subset of each return. This model has been tested on a variety of study locations across Canada resulting in estimates comparable to ground based (DHP) measures of gap fraction (or fractional cover) without requiring calibration (Hopkinson and Chasmer, 2009). This study uses the intensity-based model of Hopkinson and Chasmer (2007) and an automated plot-based optimisation routine to create a more accurate model of LAIe that can be applied to a broad range of boreal forest types.

2. Study Area

The study area is located in the Boreal forest of Saskatchewan, Canada (Fig. 1) on a number of sites being monitored as part of Fluxnet-Canada (2002-2007) and the Canadian Carbon Program (2007-2011) networks. A variety of stand types were sampled including a three stage chronosequence of jack pine (mature ~95 years old, harvested in 1975, harvested in 1994); a mature aspen stand and a mature black spruce stand (Table 1). The total number of plots examined within each stand type were randomly divided into training and testing categories for modeling and validation.

Figure. 1. Map showing location of study area within Canada

Table 1. Forest plot descriptions and stand type

Stand	Description	LAIe/DHP Training Plots	LAIe/DHP Testing Plots
JP	All Jack Pine Sites	75	56
OJP	Old Jack Pine	25	27
HJP75	Jack Pine harvested in 1975	25	17
HJP94	Jack Pine harvested in 1994	25	12
OBS	Old Black Spruce	20	8
OA	Old Aspen	20	11

3. Methods

3.1 DHP collection and analysis

Ground-truth data were collected August 10-20, 2005 and July 29-August 3, 2008. Five digital hemispheric photos (DHP) were collected per geographically located plot (dGPS), one at the center and four located 11.3 m from the center in each cardinal direction (N, E, S, W) using a compass bearing and tape measure. All images were captured using a Nikon Coolpix 8.0 Megapixel camera positioned 1.3 m off the ground (at mature sites, 0.5 m at HJP94), facing north, fitted with a 180° fisheye lens with the exposure set one 'f stop' lower than normal exposure to improve contrast between foliage and sky. DHPs were processed using CAN_EYE software (http://www.avignon.inra.fr/can_eye/) which utilizes user enhanced automated image classification to calculate gap fraction and LAIe from two-tone images.

3.2 LiDAR data collection and preparation

LiDAR data were collected by the Applied Geomatics Research Group (AGRG) coincident with DHP collection on August 12, 2005 and August 2, 2008 using an ALTM 3100 laser scanner. The 2005 LiDAR data collection was flown at a height of 950 m a.g.l, with a laser pulse repetition frequency (PRF) of 70 kHz, and a scan angle of $\pm 19^{o}$ (with 50% overlap of scan lines). The 2008 LiDAR data collection was flown using the same sensor at a height of 700 m a.g.l., with a PRF of 70 kHz and a scan angle of $\pm 20^{o}$ (with 50% overlap of scan lines). The point data were classified using *Terrascan* (Terrasolid, Finland) into ground, canopy and echo code classes then gridded using *Surfer* 8 (Golden Software Inc., USA) by assigning summed intensity values to each cell based on points that fell within 2.5 m to generate 1 m resolution grids. Classification and gridding was also performed by the AGRG in preparation for modeling (Hopkinson and Chasmer, 2009).

3.3 Optimization process

Gap fraction (*P*) grids were calculated using the intensity-based model published by Hopkinson and Chasmer (2007) described above. If the canopy is assumed to be a turbid medium with randomly distributed foliage then the Beer-Lambert Law can be applied:

$$LAIe = -\ln(P) \,/\, k \qquad (2)$$

where extinction coefficient (*k*) is a function of leaf angle distribution, radiation type and direction, and canopy structure and clumping (Bréda, 2003). Initially, a mid-value *k* of 0.5 is used in this study because it represents a spherical (random) projection coefficient for leaves of any shape, (Chen *et al.*, 1997) and is an accepted alternative to species specific values (Richardson *et al.*, 2009).

$$LAIe_{LiDAR} = -\ln(P) \,/\, 0.5 \qquad (3)$$

The *k* term in equation (3) is then optimized for each species by rearranging the general equation (2) using measurements of LAIe from captured DHPs ($LAIe_{DHP}$), to train new estimates for *k* based on species (k_{NEW}):

$$k_{NEW} = LAIe_{LiDAR}/(2 * LAIe_{DHP}) \qquad (4)$$

LAIe raster layers were generated for the entire study area by equation (3) using an automated GIS-based tool as a baseline for optimization. Mean LAIe values were extracted for 11.3 m radius plots at the geo-located photo positions and the training subset were compared to coincident LAIe measured using DHPs to generate k_{NEW} for each species (4). LAIe raster layers were then regenerated using the *P* layers and substituting k_{NEW} for 0.5 in equation (3). Model quality was determined using the testing subset of plots for each species (Table 1).

4. Results

LAIe estimated using a generic 0.5 extinction coefficient (equation 3) resulted in means that were significantly different from DHP LAIe ($p < 0.05$) across all species. The generic model underestimated LAIe for both conifer species while overestimating the broad-leaved aspen compared with measurements gathered in the field (Fig. 2). These results are comparable to those published by Bréda (2002) who indicated that coniferous stands trended towards extinction coefficients less than 0.5. The need for a more specific *k* for predicting LAIe from LiDAR is also highlighted by these results.

Including k_{NEW} improved LAIe model fit, reducing the RMSE by an average of 0.48 across all species (Fig. 2, Table 2). The greatest improvement was observed in the OBS model which translates to a shift in average LAIe values from 1.17 to 2.42. The lowest RMSE occurred across the JP stands at 0.35 after optimization. The average absolute shift in LAIe across all species is 0.79, which is greater than the difference observed between coniferous and deciduous species, signifying a change in canopy structure.

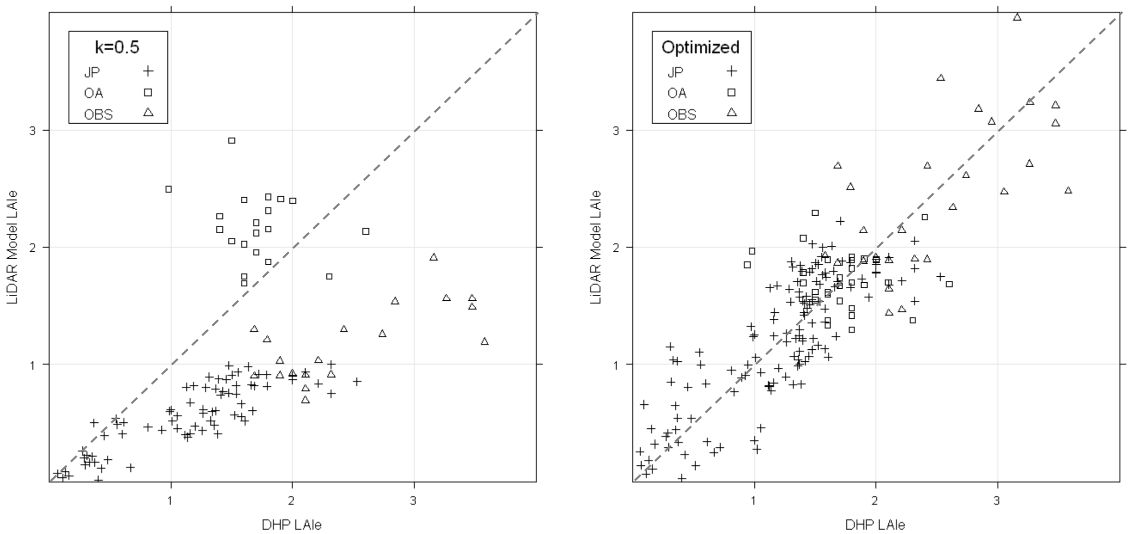

Figure. 2. $LAIe_{LiDAR}$ compared to $LAIe_{DHP}$ for all data (n=190). k=0.5 represents pre-optimization results (left) and optimized (right) represents estimates using k_{NEW} . Dashed line is 1:1.

LAIe for plots set aside for testing calculated using k_{NEW} revealed no significant difference at the 95% confidence level between LiDAR modelled and DHP measured LAIe for all species, indicating a significant improvement over the generic model.

Table 2. Pre and Post-optimization statistics

Stand	Pre-optimized mean $LAIe_{LiDAR}$	Post-optimized mean $LAIe_{LiDAR}$	k_{NEW}	RMSE pre-optimized Training plots	RMSE post-optimized Training plots	RMSE post-optimized Testing plots
JP	0.57	1.17	0.24	0.71	0.35	0.32
OBS	1.17	2.42	0.24	1.34	0.49	0.56
OA	2.17	1.71	0.63	0.67	0.44	0.42

5. Conclusion

An automated optimization model such as the one presented here creates opportunities to gain knowledge of forest structure over large areas using limited field data. The adjustment of k when modelling LAIe from LiDAR intensity data will improve results that will be reflected in environmental applications based on remote sensing data. Further investigation including more species and age classes would benefit from model optimization of this type including investigating optimal intensity gridding parameters (Morrison *et al.*, 2011). This work is part of a larger effort to operationalize forest structure modelling routines through the generation of automated tools.

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