A GIS modelling routine to optimize LiDAR-based effective leaf area index values in a boreal forest watershed

HEATHER MORRISON[1,2], CHRIS HOPKINSON[2,1], LAURA CHASMER[3] & NATASCHA KLJUN[4]

1 *Department of Biology, Acadia University, Wolfville, Nova Scotia, Canada*
morrison.h@gmail.com

2 *Applied Geomatics Research Group, NSCC Annapolis Valley Campus, Nova Scotia, Canada*

3 *Cold Regions Research Centre, Wilfrid Laurier University, Waterloo, Ontario, Canada*

4 *Department of Geography, Swansea University, Swansea, Wales, UK*

Abstract Leaf Area Index (LAI) is an important measure of forest canopy structure that is often employed in physical environmental models as an input to precipitation interception, canopy radiative transfer and evapotranspiration loss computations. As models become more sophisticated and computing power increases, the accuracy and spatial variability of key model inputs like LAI becomes more important. As part of a study investigating hydrological and CO_2 fluxes in the boreal forest ecoregion of northern Saskatchewan, this paper aims to test a method of mapping effective LAI (LAIe) from LiDAR. The model used is based on the assumption that the canopy is considered a turbid medium (analogous to Beers' Law) and utilises the multiple return echo class and vertical intensity profile from LiDAR to simulate canopy gap fraction. However, extinction coefficient (*k*) remains unknown. LiDAR data were collected in 2005 and 2008 over five forested stands ranging from immature to mature jack pine, mature aspen and mature black spruce. Coincident with the LiDAR collection, GPS located field samples of gap fraction were collected using digital hemispheric photography (DHP) for the purpose of training and testing the LiDAR LAIe model. Canopy gap fraction was computed from the LiDAR point cloud for 2 m resolution grids over the five sites, and from this, LAIe was derived. LAIe was first executed without any optimisation of the gap fraction component by assuming an average *k* of 0.5. The predicted LAIe values for the co-located DHP plots were automatically extracted using a python script and cross-correlated with the field estimates to obtain an adjusted *k* for each of the stand types. The purpose of this paper is to examine the applicability of a LiDAR-derived LAI model and to illustrate how *k* effects differences in LAIe between pre- and post-optimisation.

Key words LiDAR; leaf area index; extinction coefficient; DHP; Boreal forest

INTRODUCTION

Leaf area index (LAI) is a metric describing the total leaf surface area per ground area. LAI is an important input to numerous biogeochemical and coupled ecosystem-atmosphere models. Given that many biogeochemical models operate at the stand and landscape scale, tree- and plot-level LAI estimated from high resolution three-dimensional remote sensing data would provide a means for better parameterizing these models. Light Detection and Ranging (LiDAR) data provides spatially contiguous point measurements of the three-dimensional characteristics of vegetation at the tree-, plot- and landscape-scales. The purpose of this study is to examine the applicability of a LiDAR-derived LAI model pre- and post-parameterisation within three dominant boreal forest ecosystems: mature black spruce, chronosequence jack pine, and mature aspen.

In this study, effective LAI (LAIe) is modelled using gap fraction derived from LiDAR (Hopkinson & Chasmer, 2007) and extinction coefficient. Extinction coefficient (*k*), is the fraction of radiation intercepted by the canopy, and varies between species as a result of canopy clumping, leaf angle distribution, and radiation type and direction (Richardson *et al.,* 2009). The objective of this study is to calibrate *k* and improve LAIe within the three boreal forest species types.

METHODS

The data used were collected as part of Fluxnet-Canada (2002-2007) and the Canadian Carbon Program (2007-2011) networks. Located in the Boreal forest of Saskatchewan (Fig. 1) these sites include a three stage chronosequence of Jack Pine stands (mature, ~95 years old) harvested in 1975, harvested in 1994), a mature aspen stand and a mature black spruce stand (Table 1).

Fig. 1. Map showing location of study area

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

DHPs were collected at each plot (Hopkinson & Chasmer, 2009), using transects and five photograph (N, S, E, W and centre) plot methods. Digital images were analyzed using CAN_EYE software (http://www.avignon.inra.fr/can_eye/). CAN_EYE allows users to classify vegetation and sky, creating a two-tone image from which gap fraction and ultimately LAIe is calculated.

LiDAR data were collected in 2005 (JP chronosequence) and 2008 (JP chronosequence, OA, and OBS) by the Applied Geomatics Research Group coincident with DHP collection (Hopkinson & Chasmer, 2009).

Data Analyses

Gap Fraction (P) was calculated using LiDAR intensity grids for each stand based on the model published by Hopkinson & Chasmer (2007). The model uses the intensity of LiDAR returns divided into 4 echo classes (first, last, single, intermediate) and accounts for two-way transmission loss for intermediate and last returns using a square root function. The ratio of these total returns to a subset of total ground (below canopy) returns is used to estimate gap fraction, which has been shown to compare well with results from DHP without calibration (Hopkinson & Chasmer, 2009):

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

where subscripts denote the echo class and subset of each return. Thus, LAIe is modelled from the Beer-Lambert Law, whereby the canopy is assumed to be a turbid medium with randomly distributed foliage :

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

Extinction coefficient (k) varies due to leaf angle distribution, radiation type and direction, and canopy structure and clumping (Bréda, 2003). Initially, a mid-value k of 0.5 is used because it is an accepted alternative to species specific values (Richardson *et al.*, 2009).

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

The k term in $\mathrm{LAIe}_{\mathrm{LiDAR}}$ (3) is then optimized for each stand type by rearranging the generic equation (2) and using $LAIe_{DHP}$ to train a new estimate of k (k_{NEW}):

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

A GIS-based tool was created to generate P and LAIe raster layers from 1 m LiDAR intensity grids (1). Mean LAIe was automatically extracted from within 11.3 m radius plots surrounding geo-registered DHPs. LAIe estimates from (3) were then compared to $LAIe_{DHP}$ to generate k_{NEW} (4). The optimized k_{NEW} value replaced the initial estimate of 0.5 in (3) to derive a corrected raster image of $LAIe_{LiDAR}$. The model was then tested using independent $LAIe_{DHP}$ data for each stand type as well as all jack pine plots combined (Table 1).

RESULTS & DISCUSSION

LAIe modelled using a mid-value 0.5 extinction coefficient revealed significantly different means when compared to DHP LAIe ($p > 0.05$) for all stands. LAIe for conifer stands was underestimated while the broad-leaved aspen stand was overestimated compared with field measurements (Fig. 2). These results agree with Bréda, (2003) who found that broad-leaved stands experience higher levels of k than conifers. These results also emphasize the need for a more specific k for predicting LAIe from LiDAR data.

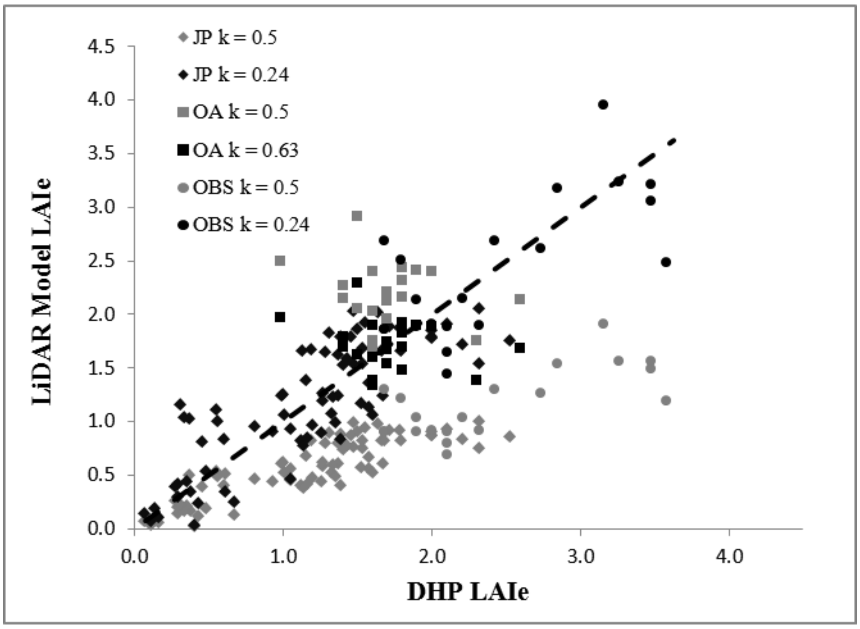

Fig. 2. $LAIe_{LiDAR}$ compared with $LAIe_{DHP}$ for the training data subset. Grey symbols are estimated from $k = 0.5$. Black symbols use k_{NEW}. Dashed line is 1:1.

The inclusion of k_{NEW} improved the LAIe model fit, reducing the RMSE by an average of 0.43 across all stand types (Table 2). The greatest improvement was observed in the OJP model while the lowest RMSE occurred in the HJP75 stand (Table 2). The average LAIe values also shifted, between -1.25 (OBS) and 0.43 (OA) with an average absolute shift of 0.43 across all stand types within the training subset after optimization. This magnitude of change is similar to the difference in LAIe between conifer and deciduous stands, suggesting a notable difference in canopy structure.

Test plot LAIe results calculated using k_{NEW} demonstrated no significant difference at the 95% level of confidence between $LAIe_{LiDAR}$ and $LAIe_{DHP}$ for all stands except HJP75 ($p = 0.28$). This indicates a significant improvement in model predictions using $k_{NEW.}$ Figure 3 is an example of a high resolution map that can be produced by this model.

Table 2. Pre and Post-optimization statistics

Stand	Mean $LAIe_{DHP}$	Optimized $LAIe_{LiDAR}$	k_{NEW}	RMSE pre-optimized Training plots	RMSE post-optimized Training plots	RMSE post-optimized Testing plots
JP	1.17	1.17	0.24	0.71	0.35	0.32
OJP	1.35	1.34	0.21	0.79	0.26	0.34
HJP75	1.70	1.59	0.27	0.91	0.39	0.30
HJP94	0.46	0.46	0.30	0.25	0.21	0.43
OBS	2.42	2.42	0.24	1.34	0.49	0.56
OA	1.71	1.71	0.63	0.67	0.44	0.42

Fig. 3. Estimates of $LAIe_{LiDAR}$ using k_{NEW} within the 2008 OJP stand.

CONCLUSIONS

These results indicate that improvement and optimization of *k* when modelling LAIe from LiDAR data will improve results, which are important for ecosystem model parameterisation using spatially continuous remote sensing data. The model and optimization procedure presented offers the potential to improve spatially explicit parameterisations of rainfall interception, evapotranspiration and below canopy snow melt within GIS-based physical hydrological models by providing a high resolution map of LAIe.

ACKNOWLEDGEMENTS

Dr. Harry McCaughey, Queen's University and the Canadian Carbon Program and Fluxnet-Canada for subsidizing LiDAR data collection and field work in 2005, Chris Beasy and James Churchill for assistance with DHP data collection in 2005 and 2008. Applied Geomatics Research Group, NERC (Natural Environment Research Council UK), Grant NE/G000360/1 grant provided to Dr. Natascha Kljun and Trevor Milne for guidance with Python coding.

REFERENCES

Bréda, N.J.J. (2003) Ground based measurements of leaf area index: a review of methods, instruments and current controversies. *J of Exp Bot* **54**(392), 2403-2417.

Hopkinson, C. & Chasmer, L. (2007) Using discrete laser pulse return intensity to model canopy transmittance. *Photogrammetric J. of Finland* **20**(2), 16-26

Hopkinson, C. & Chasmer, L. (2009) Testing LiDAR models of fractional cover across multiple forest ecozones. *Remote Sens. Environ.* **113,** 275-288.

Richardson, J.J., Moskal, L.M. & Kim, S-H. (2009) Modeling approaches to estimate effective leaf area index from aerial discrete-return LIDAR. *Agri. & For. Meteor.* **149,** 1152-1160.