LIDAR PROCESSING SOFTWARE IN SUPPORT OF THE NEWFOUNDLAND FIBRE INVENTORY PROJECT

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ABSTRACT

The Newfoundland Fibre Inventory Project (NFIP) aims to meet the increased emphasis on wood fibre value as a criterion of production rather than volume as traditionally measured by the forest industry. Wood fibre attributes such as wood density, fibre length, coarseness and microfibril angle measured from tree cores at 69 ground sample plots are to be correlated against metrics derived from airborne laser scanner (ALS) data acquired as transects covering ~1193 km^2 of commercial forest area of Newfoundland. The resulting models will in turn be used to support province-wide mapping of forest fibre quality for inclusion into the Newfoundland forest inventory system.

The substantial volume of points (~3.6 billion), large spatial distribution of the transects, number of derived metrics (~200) and the ultimate need to apply the resulting models to new lidar transect collections necessitated the development of a customized suite of tools. This software automatically performs data segmentation of the transects, point processing (filtering and classification), metric extraction (both points and rasters) and model computations (rasters).

This paper discusses the capabilities of the software and how it addresses the needs of NFIP. Of particular interest is the potential of the software to be used by other agencies and stakeholders as a means to produce and maintain more comprehensive forest inventories.

Keywords: forest inventory, wood fibre quality, forest metrics, predictive models, Light Detection and Ranging (LiDAR), Airborne Laser Scanner (ALS), automated processing

INTRODUCTION

The use of Airborne Laser Scanner (ALS) technology for producing and updating forest inventory data has been a topic of research for over a decade. During this time, awareness of the wide variety of information that can be extracted and derived from ALS data has steadily increased.

An emerging technique is to utilize ALS data to construct predictive models from plot-level cloud metrics as an intermediary "calibration" step toward stand-level attributes and regional forest inventories (Hopkinson et al., 2011a). Models are derived to predict attributes such as basal area, gross merchantable volume and above-ground biomass which are then used to estimate inventory variables at the stand and forest scale (Woods et al., 2008).

Recently, the Canadian Forest Service (CFS) under guidance of the Canadian Wood Fibre Centre (CWFC) initiated a research program which aims to expand upon such models to predict wood fibre quality attributes with the goal to provide better forest inventory information for the Newfoundland commercial forest industry (Pitt & Pineau, 2009).

Forestry related prediction models tend to be species and region specific and often require careful selection of predictor variables and regression models. Moreover, the ALS data must be representative of the various height ranges, crown densities and tree species expected to be modelled.

An exhaustive "wall to wall" survey of a region may ensure this but is fiscally impractical when considering provincial-scale mapping. Hopkinson et al. 2011b and Luther et al. 2012 address this by acquiring long sample transects that coincide with a large variety of ground sample plots (Figure 1).

The data processing workflows necessary to translate these large raw ALS datasets into their respective derivative products (classified point clouds, data metrics and attribute grids) often involve multiple software applications, data conversions and manual calculations. Such complex workflows can become barriers to productivity and may impact their adoption by interested organizations.

To address this, Gaiamatics Solutions Inc., in cooperation with the Newfoundland Fibre Inventory Project (NFIP), enhanced their LiDAR processing suite, Pulse, to provide greater capacity for researchers to develop and implement their forest attribute models.

The primary objective of this project was to develop a suite of tools that would (i) streamline and automate ALS point cloud processing; (ii) extract a variety of point cloud metrics for analysis & modelling; (iii) apply derived single and multi-variable models to ALS data to produce grids of predicted forest attributes; and (iv) be flexible in configuration to allow further development of attribute metrics & models to a range of forest-related applications.

PROCESSING WORKFLOW

Overview

The workflow begins with a calibrated but unclassified ALS point cloud organized into strips, typically one per sample transect, stored in LAS format. Through automated tools, the user proceeds to (i) process the point cloud to create preliminary products (classifications, normalized heights & grids); (ii) extract point cloud metrics from the classified points that correspond to sample plots; (iii) analyze metrics to determine optimal predictors and models (performed externally using software such as R); (iv) apply the derived models to the classified point cloud to generate grids of predicted forest attributes outside of the sample plots.

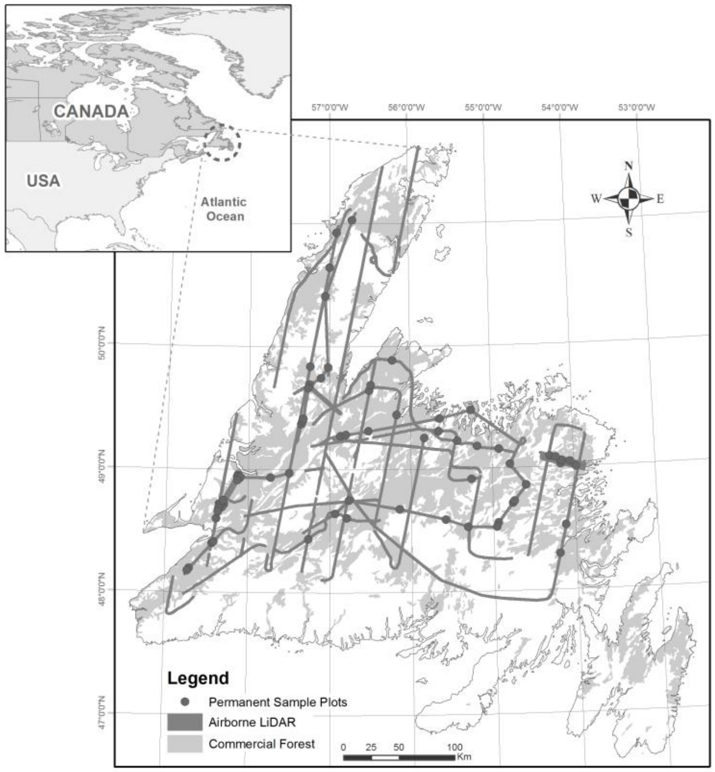

Figure 1. Distribution of ALS survey data for the Newfoundland Fibre Inventory Project. Approximately 1193 km^2 of commercial forest was covered with average point densities from 1 to 4 points/m^2.

Point Cloud Processing

The first step is to optimize the ALS data from its original strip form and prepare the point cloud for additional processing. As an automated process the following tasks are performed with the outputs being organized into a rigorous folder structure:

(i) *Segmentation*. Long sample transects are typically too large to load into memory and thus are segmented spatially into regions containing approximately 10 million points. A small amount of overlap is maintained between segments to avoid classification and gridding seamlines.

(ii) *Data Cleaning*. Several commonly used point filtering routines (e.g. isolated, low points, high points, etc.) are applied to remove errors such as atmospheric scattering or multi-path through the canopy.

(iii) *Ground Classification*. A variant of a widely adopted ground filtering algorithm (Axelsson, 1999) is applied which iteratively adds points to a Triangulated Irregular Network (TIN) to identify “ground” and “non-ground” points.

(iv) *Elevation Normalization*. A TIN derived from the identified ground points is used to derive “height from ground” elevations for each LiDAR point. Both the original points and normalized points are output.

(v) *Gridding*. Digital Terrain Models (DTM), Digital Surface Model (DSM), Canopy Height Models (CHM), hillshades and data density grids (points/m^2) are generated from the classified points.

Metric Extraction

After the ALS data has been prepared, data metrics for sample plots can be extracted from the classified points. The user provides a set of polygons delineating the regions to query along with a list of which metrics to compute. It is expected that the user will extract metrics multiple times as they progress through their analysis and refine their choice of predictors.

For each metric, the user is able to precisely describe the calculation to perform and which points are to be used (e.g. “Mean Normalized Height of First Returns above 2m”) by combining the following parameters:

(i) *Source*. Metrics can be computed on normalized heights, DTM elevations, CHM elevations, or intensity values.

(ii) *Selection Criteria*. Points can be filtered according to echo (first, last or all returns) and thresholds (above the ground, mean, mode, or a constant value). The filtered points can also be organized into multiple bins according to height ranges (e.g. 2m to 5m above ground), deciles (i.e. 10 bins of equal intervals) or percentiles (e.g. points between the 70^{th} and 80^{th} percentile).

(iii) *Metric*. Points meeting the above criteria are then used to compute a particular metric. A variety of metrics are supported including number of returns, basic statistics (mean, mode, standard deviation, etc.), moments (skewness & kurtosis), L-moments (L1 to L4, L kurtosis, L skewness, etc.), percentiles, return ratios (e.g. % of first returns), volume/area ratio and rumple index.

Grid Modelling

When predictive models have been derived from the metrics, they can be applied to ALS point cloud data to generate? attribute? grids. A coarse grained grid (e.g. 20m cells) is overlaid upon the data with the points of each cell being used to compute the model’s respective metrics.

Predictive (attribute?) grids are then created by evaluating (implementing?) the equations for each model. For example, to implement the regression model:

[Biomass] = -19.761 + (16.091 x [Hgt_P95]) + (-14.292 x [CHM_Rumple])

the software computes the 95^{th} percentile of normalized heights and the rumple index for the canopy height model elevations; then combines these grids with the model coefficients to produce an estimate of “biomass”.

Multiple models can be defined and computed together with output grids being generated for all corresponding predictor variables and model results.

NFIP RESULTS

The NFIP transects (3.6 billion points) were processed (in 16 hours) with 1524 summary grids (DTM, DSM, CHM & point density) output. A total of 201 metrics were computed from 69 permanent sample plot locations.

Ten preliminary models for coniferous strata were derived from 11 metrics (Height max, mean, standard deviation, 95th percentile, and % first returns above 2m; DTM min, max and rumple; CHM mean, standard deviation and rumple) to predict attributes such as DBH, average height of dominant trees, stem density, basal area, gross merchantable volume and above ground biomass with R^2 values ranging from 0.496 to 0.850 (Luther et al., 2012).

These plot-level models were applied to the entire ALS dataset and in 8 hours of processing 4191 metric grids (11 metrics for each ALS data segment) and 3180 attribute grids (10 models per ALS data segment) at the cell-level (20m x 20m area) were produced. These attribute grids will be further used to derive fibre quality information at the stand-level ultimately leading to an enhanced forest inventory for the province.

CONCLUSIONS

The suite of tools presented herein tightly integrate and automate the complex workflow associated with ALS-based forest model development. The need for such automation is evident when considering the number of outputs generated during these preliminary stages of the NFIP project. By streamlining this workflow, the complications and limitations experienced by Woods (2011?) and Hopkinson et al. (2011a, 2011b) are reduced enabling other organizations and initiatives such as the NFIP to adopt and expand upon the methodology.

Support for forest type and species specific models is planned to further refine this new workflow. This will incorporate a GIS forest type or species layer to determine which of the multiple predictive models is to be applied to each output grid cell; eliminating the need for the user to integrate the individual output grids.

Finally, a plug-in architecture for the metric generation tool is under consideration. Users would be able to add their own customized metric calculations enabling them to expand the scope of their projects with a minimum of effort.

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