Developing a Regional Canopy Fuels Assessment Strategy using Multi-Scale Lidar

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Abstract

Accurate assessments of canopy fuels are needed by fire scientists to understand fire behavior and to predict future fire occurrence. A key descriptor for canopy fuels is canopy bulk density (CBD). CBD is closely linked to the structure of the canopy; therefore, lidar measurements are particularly well suited to assessments of CBD. LANDFIRE scientists are exploring methods to integrate airborne and spaceborne lidar datasets into a national mapping effort. In this study, airborne lidar, spaceborne lidar, and field data are used to map CBD in the Yukon Flats Ecoregion, with the airborne lidar serving as a bridge between the field data and the spaceborne observations. The field-based CBD was positively correlated with airborne lidar observations ($R^2 = 0.78$). Mapped values of CBD using the airborne lidar dataset were significantly correlated with spaceborne lidar observations when analyzed by forest type ($R^2 = 0.62$, evergreen and $R^2 = 0.71$, mixed). Though continued research is necessary to validate these results, they do support the feasibility of airborne and, most importantly, spaceborne lidar data for canopy fuels assessment.

Keywords: GLAS, FlamMap, canopy bulk density, fuels mapping, fire behavior modeling

1. Introduction

Wildland fire can have a significant impact on ecosystems and human populations. To better understand wildland fire occurrence and fire behavior, it is critical to have a thorough understanding of the distribution of fuels in the landscape. Fire behavior models are driven by inputs that describe the three-dimensional distribution of fuels. Canopy fuels are defined as the live and dead biomass located within tree crowns (Keane et al. 2001) and are characterized in part by canopy bulk density (CBD), which is the mass of available canopy fuel per unit canopy volume. The CBD parameter is used by fire modeling systems, such as FlamMap (Finney 2006), and is a key determinant of whether fire will spread from crown to crown as an active canopy fire.

The LANDFIRE project (Rollins 2009; http://www.landfire.gov) has mapped fire behavior model inputs, including CBD, for the entire United States using a set of field data, Landsat imagery, digital elevation models (DEMs) and derivatives, climate gradients, and other ancillary data. The first set of LANDFIRE products was completed in 2009. LANDFIRE is developing a strategy to regularly provide improved and updated data. The updating plan includes the exploration and integration of lidar data for characterizing canopy structure and fuels to address a demonstrated need for better estimates of LANDFIRE fuels products (Krasnow et al. 2009).

Traditionally, fuel parameters are obtained through field observations of vegetation structure. More recently, lidar has also been used to quantify vegetation canopy structure (Dubayah and Drake 2000; Lefsky et al. 2002), which is particularly useful for mapping the fuels complex
While previous studies using lidar to assess fuels have used airborne lidar data, recent work has shown the applicability of the spaceborne Geoscience Laser Altimeter System (GLAS) data for estimating forest canopy structure (Lefsky et al. 2007; Sun et al. 2008; Nelson et al. 2009). Because canopy fuels are defined largely by canopy structure, we wish to explore the utility of GLAS data for estimating CBD, which would promote more accurate mapping of CBD, especially where field data are scarce. The incorporation of GLAS data into a regional fuels mapping effort, while leveraging airborne data acquisitions, will provide detailed vegetation structure metrics over larger areas to inform fuels mapping.

2. Objectives
The objective of this study was to explore how integrating lidar data collected at different scales can contribute to a regional-to-national scale canopy fuels mapping effort. This investigation was conducted in the Yukon Flats Ecoregion (YFE) of interior Alaska (Gallant et al. 1995). We used two lidar data sets: an airborne, small-footprint, discrete-return dataset collected for a subset of the study area; and transects of GLAS data for the entire YFE. Using these two datasets, along with field and ancillary data, we modeled and mapped CBD then used the different CBD products as inputs into FlamMap.

3. Methods

3.1 Study Area
The YFE (Figure 1) is located in interior Alaska and encompasses approximately 33,400 km². Much of the vegetation is short-statured boreal forest. Common tree species are black spruce (Picea mariana), white spruce (Picea glauca), quaking aspen (Populus tremuloides), alder (Alnus sp.), and willow (Salix sp.). Forest stands rarely exceed 20 m except in riparian areas and floodplains. The terrain of the YFE is flat, with 95% of the area at ≤ 3° slope as indicated by the National Elevation Dataset (NED). Access to the area is most practically achieved by float plane.

3.2 Field data
Vegetation sampling was conducted in 2010 in a 2-m-wide transect running north-south through the plot center. Within this transect, we recorded diameter at breast height (DBH), tree height and height to the base of the live crown, and species. We sampled 24 plots at two lake sites. We then generated estimates of CBD for each plot using the tree list data and FuelCalc (Reinhardt et al. 2006). FuelCalc does not calculate CBD for broadleaf species because canopy fire propagation is rare in those species. Six of our plots were in pure willow, alder, or aspen stands, so CBD was not calculated for those sites.

3.3 Airborne Lidar
The airborne lidar data were collected in summer 2009 for a sub-area (2605 km²) of the YFE (Figure 1). The data were collected by Aero-Metric, Inc. with an airborne Optec ALTM Gemini. The dataset has a horizontal accuracy of 1.15 m, with a nominal point spacing of 2.3 m and a vertical positional accuracy of 0.10 m. The raw data were processed and delivered as 2.5-m resolution raster datasets that include the bare-Earth digital surface model (DSM) and first-return DSM. Height above ground (HAG) was derived by differencing the bare-Earth DSM and the first-return DSM.
Various metrics were derived from the airborne lidar dataset to predict CBD. The maximum, mean, and minimum HAG were calculated for each plot. All other airborne lidar metrics were derived from a 10 × 10 m grid of the point cloud data using the vertical distribution of return elevations within the grid cell. For each 10 × 10 m grid cell at six different height thresholds (>1 m, >2 m, >3 m, >4 m, >5 m, and >6 m), the ratio of canopy returns above the threshold to the total number of canopy returns was calculated. The maximum, minimum, and mean of these ratios were calculated for each plot, which described the vertical distribution of canopy material between and the lower, middle, and upper portions of the canopy.

We used a stepwise linear regression procedure in R (http://www.r-project.org/) to identify models for estimating CBD. Our goal was to identify a parsimonious yet predictive regression model. The final model was then applied to the entire set of airborne lidar data where the National Land Cover Database (NLCD; Selkowitz and Stehman 2011) indicated evergreen or mixed forest. Focal statistics (maximum, minimum, and mean) were generated from the HAG layer and 10 ×10 m ratio data. The resulting map was gridded to 30 m to match the spatial resolution of LANDFIRE products. Also in accordance with LANDFIRE methods, the CBD for hardwood forests was set to 0.01 kg m⁻³. For all other NLCD classes, the CBD was set to 0.

### 3.4 GLAS

We obtained GLA01 (waveform data) and GLA14 (land/canopy elevation data and footprint locations) GLAS products (http://nsidc.org/data/icesat/index.html) from the Laser L3F acquisition (release 31) for the entire YFE. Included in the GLA14 product is a set of metrics describing Gaussian curves fit to the waveform, including number of peaks, elevation, width, and amplitude of each Gaussian (Harding and Carabajal 2005). L3F acquisitions occurred during leaf-on conditions (May 24 through June 26, 2006). The GLAS footprints are nominally 65 m in diameter and 172 m apart along-transect.
The GLA01 and GLA14 products were processed to derive quartile and decile heights of waveform energy following Sun et al. (2008), as well as canopy depth, total waveform energy (Peterson et al. 2007), and canopy height, which is the difference between the ground elevation and the elevation of the signal beginning. We used these derived metrics plus the GLA14 Gaussian metrics as independent variables in a regression analysis.

We filtered the GLAS returns based on four criteria: we eliminated footprints 1) which were located on slopes > 3° as indicated by NED; 2) where the NLCD land cover was not uniform; 3) which were cloud contaminated according to GLA14; and 4) with waveforms for which only a single Gaussian was identified assuming that no distinct canopy could be inferred. This filtering resulted in 718 usable footprints for the YFE with 115 falling in the airborne lidar subset area.

None of the GLAS footprints were coincident with the field plot locations. Therefore, we used the CBD values from the airborne lidar-based map as our dependent variable in the regression. For each of the 115 GLAS footprints, we extracted the CBD value at the footprint center. In R a stepwise linear regression procedure was used to identify a model for estimating CBD. This model was applied to the GLAS footprints in the YFE to estimate CBD for those locations.

Because the GLAS data are sampled at discrete locations, we used a regression-tree approach for mapping CBD from GLAS. We used seven Landsat Thematic Mapper spectral bands and the DEM, slope, aspect, and NLCD land cover as independent variables. These values were extracted at each footprint center. We used Cubist (http://www.rulequest.com) to develop the regression tree and a spatial applier to map CBD for the YFE. NLCD land cover was used to assign CBD values to hardwood forests and non-forested pixels.

3.5 FlamMap Fire Behavior Modeling

To assess the impact of mapping CBD using airborne lidar and GLAS data, the CBD maps were used to conduct fire behavior analyses. Analyses were completed at two scales, the entire YFE and the sub-area covered by the airborne lidar data. FlamMap was used with input layers from LANDFIRE and the lidar-derived CBD maps. In the sub-area, a baseline model run was completed using the LANDFIRE CBD layer. The airborne- and GLAS-derived CBD layers were each then substituted for the LANDFIRE CBD, and FlamMap was re-run keeping all other data and settings the same. In the full YFE run, the baseline LANDFIRE data were again used as a baseline, and the CBD layer was then replaced with the GLAS-derived CBD layer, keeping all other data and settings constant. Thus, a total of five FlamMap runs were made.

Each FlamMap run produced flame length (FL), rate of spread (ROS), and crown fire activity (CFA) output layers. FL and ROS are continuous outputs measured in meters and meters per minute, respectively. The CFA layer separates the landscape into unburned (water, barren, etc.), surface fire only, passive crown fire (individual tree torching), and active crown fire (fire spreading from tree to tree) classes. The CBD layer is used only for calculating crown fire properties so that the amount of unburned and surface fire areas are consistent between runs, only the amount of active versus passive crown fire varies in the CFA outputs. The amount of active and passive crown fire for each run is summarized, as are descriptive statistics of the FL and ROS outputs for each model run.

4. Results

4.1 Airborne Lidar

The final model identified through stepwise regression analysis for estimating CBD from the airborne lidar is shown in Equation 1.
CBD = 0.11 + 0.05 * hagsd + 1.19 * meanrat1 – 0.93 * meanrat2 – 0.26 * maxrat2 – 0.26 * maxrat4 + 0.26 * maxrat5, \hspace{1cm} (1)

where hagsd is the standard deviation of the HAG; meanrat1 and meanrat2 are the mean ratios at 1 and 2 m above ground, respectively; and maxrat2, maxrat4, and maxrat5 are the maximum ratios at 2, 4, and 5 m, respectively. This model had a coefficient of determination (R^2) of 0.78, an adjusted R^2 of 0.67, and a residual standard error (RSE) of 0.05 kg m\(^{-3}\) and was used to generate the airborne lidar-derived map of CBD.

### 4.2 GLAS

The model generated using all 115 GLAS footprints in the YFE sub-area resulted in a weak relationship, with an R^2 of 0.30. To develop a model with more predictive power, we split the 115 GLAS footprints into two sets by NLCD forest class: evergreen forest or mixed evergreen/deciduous forest. We also eliminated footprints where the standard deviation of the mapped CBD value within a 60 m radius of a footprint center was > 0.05 kg m\(^{-3}\).

The final regression model for estimating CBD from GLAS data for footprints falling within evergreen stands (N = 30) is shown in Equation 2.

CBD = 0.156 – 0.003 * r90 – 0.079 * r40 + 0.063 * r30 + 0.068 * r20 – 0.053 * r10 + 0.00002 * tenergy – 0.298 * numpeak + 0.009 * height, \hspace{1cm} (2)

where r10, r20, r30, r40, and r90 are the decile heights at 10, 20, 30, 40, and 90% of waveform energy, respectively, tenergy is the total waveform energy, numpeak is the number of Gaussian peaks, and height is the canopy height. This model had an R^2 of 0.61, an adjusted R^2 of 0.46 and an RSE of 0.03 kg m\(^{-3}\) and was used to generate CBD values for the GLAS footprints in evergreen forest.

The final regression model for estimating CBD from GLAS waveform data for footprints falling within mixed stands (N = 29) is shown in Equation 3.

CBD = 0.161 – 0.012 * r90 – 0.028 * r70 + 0.051 * r40 + -0.138 * r25 + 0.212 * r20 – 0.091 * r10 + 0.023 * depth + 0.104 * numpeak, \hspace{1cm} (3)

where r25 and r70 are the 25th and 70th percentile heights of waveform energy, respectively, and depth is the canopy depth. This model had an R^2 of 0.80, an adjusted R^2 of 0.72, and an RSE of 0.06 and was used to generate CBD values for the GLAS footprints in mixed forest stands.

The Cubist regression-tree modeling initially resulted in a correlation coefficient (R) of 0.31. This was caused by an underrepresentation of the tails of the CBD distribution. To improve the predictive power of the model, we adjusted the sample to ensure an even distribution of CBD values. This resulted in a stronger model with an R of 0.90, and predicted values that represented the entire range of CBD values in the training data.

### 4.3 FlamMap

In the study sub-area, there were three runs using LANDFIRE, airborne lidar-derived, and GLAS-derived CBD. There were 61923 ha of surface fire and 77948 ha of crown fire. Using the LANDFIRE CBD, 22% of the crown fire was active, whereas when using airborne lidar- and GLAS-derived CBD layers, 74% and 79% of the crown fire was active, respectively. The
ROS using the LANDFIRE CBD ranged from 1 to 47 m/min with a mean of 21 m/min. When using both airborne lidar- and GLAS-derived CBD, the ROS ranged from 1 to 49 m/min with a mean of 23 m/min. FL ranged from 1 to 26 m with a mean of 11 m using the LANDFIRE CBD. With the airborne lidar-derived CBD, the FL ranged from 1 to 46 m with a mean of 15 m. The FL from the GLAS-derived CBD ranged from 1 to 38 m with a mean of 14 m. Both the increased FL and ROS using the lidar-derived CBD reflect the increase in active crown fire modeled from these data.

For the full YFE runs, there were 1,774,107 ha of surface fire and 1,321,264 ha of crown fire. Using the LANDFIRE CBD, 23% of the crown fire was active, whereas 64% of the crown fire was modeled as active using the GLAS-derived CBD layer (Figure 2). The FL using the LANDFIRE CBD ranged from 1 to 21 m with a mean of 9 m, compared to a range of 1–34 m with a mean of 10 m using the GLAS-derived CBD. The ROS using both CBD maps ranged from 1 to 39 m/min with a mean of 16 m/min.

Figure 2: FlamMap Crown Fire Activity output maps using LANDFIRE CBD (left) and GLAS-derived CBD (right)

5. Discussion

The regression model derived from the airborne lidar and field-based CBD explains nearly 80% of the variability in the dataset. This is somewhat lower than those reported by others, using more parsimonious models (Andersen et al. 2005; Riaño et al. 2004; Skowronski et al. 2007). Several factors likely affected these results: 1) the allometries that FuelCalc uses to derive CBD are not well developed for some boreal species and could produce invalid results, 2) our limited plot sample is not representative of the full range of CBD values present within the YFE, and 3) the landscape in the YFE is very heterogeneous and the vegetation type changes across relatively small scales (10s of meters). The other studies conducted their work in more homogeneous landscapes of evergreen forest, which simplifies both the calculation of field-based CBD and the derivation of lidar metrics.

The results of the GLAS-based CBD prediction are comparable to previous work using airborne waveform data to derive CBD in the Sierra Nevada Mountains of California (Peterson et al. 2007). Once we split the GLAS footprints into forest classes, we were able to predict 61% (evergreen), and 72% (mixed) of the variability using GLAS metrics. The splitting into forest types likely resulted in a stronger relationship because of the way CBD is assigned to hardwood species. Two waveforms may be described by similar parameters, but one falling in an evergreen stand will have a much higher CBD associated with it than one falling into a mixed stand with a large percentage of hardwoods.
Both of the lidar-derived maps indicate CBD values for the YFE that are higher than those produced by LANDFIRE. Given the lack of field data, the LANDFIRE CBD layers for much of interior Alaska are based on expert opinion of expected fire behavior under historical weather conditions. In contrast, the airborne lidar-derived CBD map is based on field measurements. Because this map is then used to train the GLAS-derived CBD map, it is also related to the field data. By using field measurements, the resultant CBD maps capture more of the range of values and spatial variability of the landscape. Higher CBD values are expected from the lidar-derived CBD maps because the CBD calculated from the field data was generally higher than the coincident LANDFIRE CBD values. The LANDFIRE CBD values ranged from 0 to 0.15 kg m\(^{-3}\) for the field plot locations, while the calculated values ranged from 0.02 to 0.29 km m\(^{-3}\). The average CBD value was 0.05 kg m\(^{-3}\) higher when calculated from the YFE field data than the corresponding LANDFIRE CBD value.

The FlamMap outputs confirmed the significance of the higher CBD values in the lidar-derived maps with the higher incidence of active crown fire and corresponding increases in FL and ROS. This also confirms the sensitivity of fire behavior models to changes in CBD since there were significant changes in the FlamMap outputs and other fire behavior modeling systems such as FARSITE (Finney 1998) are based on the same underlying fire behavior models as FlamMap. The outputs of these models are used operationally for both strategic and tactical resource management decisions which have significant societal, ecological, and financial consequences. Therefore, the model inputs must be based on the best available source data and methods, which are constantly evolving, to ensure the most reasonable outputs.

6. Conclusions

This study highlights a multi-scale approach to regional canopy fuels mapping using airborne and spaceborne lidar data. These methods can leverage all available lidar collections from across the United States, and their inherent ability to characterize vegetation structure, to map canopy fuel parameters. While canopy fuels have been previously mapped with airborne lidar, we have demonstrated a novel approach to mapping canopy fuels with GLAS data. There are some issues to consider prior to adapting this approach nationally. For example, the flat terrain of the YFE allowed us to reasonably ignore the effects of terrain on the GLAS waveform. For other regions with steeper slopes, this effect needs to be addressed (Lefsky et al. 2007). Additionally, while GLAS data are no longer being collected, spaceborne lidar data are scheduled to continue. NASA is scheduled to launch the Advanced Topographic Laser Altimeter System (ATLAS) in 2016, which will provide additional global lidar observations.

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References


