

Automated integration of lidar into the LANDFIRE product suite

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Accurate information about three-dimensional canopy structure and wildland fuel across the landscape is necessary for fire behaviour modelling system predictions. Remotely sensed data are invaluable for assessing these canopy characteristics over large areas; lidar data, in particular, are uniquely suited for quantifying three-dimensional canopy structure. Although lidar data are increasingly available, they have rarely been applied to wildland fuels mapping efforts, mostly due to two issues. First, the Landscape Fire and Resource Planning Tools (LANDFIRE) program, which has become the default source of large-scale fire behaviour modelling inputs for the US, does not currently incorporate lidar data into the vegetation and fuel mapping process because spatially continuous lidar data are not available at the national scale. Second, while lidar data are available for many land management units across the US, these data are underutilized for fire behaviour applications. This is partly due to a lack of local personnel trained to process and analyse lidar data. This investigation addresses these issues by developing the Creating Hybrid Structure from LANDFIRE/lidar Combinations (CHISLIC) tool. CHISLIC allows individuals to automatically generate a suite of vegetation structure and wildland fuel parameters from lidar data and infuse them into existing LANDFIRE data sets. CHISLIC will become available for wider distribution to the public through a partnership with the U.S. Forest Service's Wildland Fire Assessment System (WFAS) and may be incorporated into the Wildland Fire Decision Support System (WFDSS) with additional design and testing. WFAS and WFDSS are the primary systems used to support tactical and strategic wildland fire management decisions.

1. Introduction

Fire behaviour modelling systems such as the Fire Area Simulator (FARSITE; Finney 2004), commonly used for operational fire behaviour simulation, require spatial inputs describing the distribution of canopy structure and fuel across the landscape, among others. The quality of these inputs can significantly impact the utility of the modelled outputs (Stratton 2009). Data quality is assessed in different terms, including the spatial continuity of the data, the scale of the data, and the precision of the data. Data availability, especially at local scales, is often an issue because the vegetation structure measurements needed to derive canopy fuel characteristics are costly to collect on the ground. Remote sensing is an appealing approach for gathering the required vegetation data because it typically can collect data at a useful level of precision over large areas and is relatively inexpensive.

The Landscape Fire and Resource Planning Tools (LANDFIRE) program (landfire.gov) provides consistently developed, spatially continuous vegetation and fuel data for the entire US at a 30 m pixel resolution (Rollins 2009) and relies heavily on the Landsat archive to develop its

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products. LANDFIRE provides an extensive suite of products, including those required to run FARSITE. LANDFIRE is the default data source for government agencies to acquire large-scale data layers. LANDFIRE data are easy to access and periodically updated (Nelson, Connot, Peterson, and Martin 2013; Nelson, Connot, Peterson, and Picotte 2013), drawing on the extensive Landsat archive to detect areas of change. However, other types of remote sensing data can add more detailed information about vegetation structure.

Among remote sensing data types, lidar is uniquely suited for estimating canopy structure and fuel characteristics. Lidar is ideal for estimating canopy height (CH), canopy cover (CC), and canopy base height (CBH, the height at which enough vegetated material exists to propagate fire vertically into the canopy); three of the variables needed to run FARSITE. At present, LANDFIRE does not incorporate lidar because spatially continuous data are not available for the entire US. While various land management agency staff have access to lidar data, there is often insufficient expertise and training among local staff to generate the products of interest from the available lidar data. Additionally, commercial software packages that make the processing of lidar data easier are frequently expensive. Therefore, while local users could update LANDFIRE data with available lidar data, this option is underutilized because of training and data processing constraints.

Airborne laser scanner (ALS) data are commonly used for characterizing forest canopies. ALS data are typically small-footprint, discrete-return, and can provide a great amount of detail about canopy structure. However, ALS data are often collected over relatively small areas with varying acquisition specifications. Many studies employing ALS data have been experimental in design and locally optimize the algorithms used to derive canopy fuel (Andersen, McGaughey, and Reutebuch 2005; Mutlu, Popescu, and Zhao 2008; Riaño et al. 2004) and structure (Dubayah and Drake 2000; Lefsky et al. 2002).

Where ALS data are not available, data from the Geoscience Laser Altimeter System (GLAS), a spaceborne lidar system that collected data from 2003 to 2009, can be used. GLAS was a large-footprint, waveform-digitizing system that collected data samples with discrete footprints placed along orbital tracks. GLAS footprints are nominally 65 m in diameter and are spaced 172 m apart, centre-to-centre, along track. Because the GLAS data are not spatially continuous, additional geospatial data layers are needed to extrapolate structure observations beyond the footprint locations (Boudreau et al. 2008; Simard et al. 2011). The large size of GLAS footprints makes data over sloping terrain more challenging to interpret and can impact forest height and other canopy structure retrievals. Methods have been introduced to correct this, especially for CH (Pang et al. 2008; Xing et al. 2010). GLAS data have been used to estimate various components of forest canopy structure (Helmer, Lefsky, and Roberts 2009; Lefsky et al. 2007; Rosette, North, and Suárez 2008) and canopy fuel (García et al. 2012; Peterson, Nelson, and Wylie 2013) in various biomes. It is important to note that while GLAS data are no longer being collected, it is worthwhile to include them in mapping for two reasons. First, to date, GLAS data represent the only lidar data set that is available for the entire US, and therefore meet LANDFIRE's objective of national consistency. Second, a follow-on mission to GLAS, the Advanced Topographic Laser Altimeter System (ATLAS), is planned for launch in the near future. While the data from ATLAS will differ from GLAS, the lessons learned from integrating the GLAS data, especially the spatial extrapolation methods, will be valuable for future ATLAS data integration.

Together, airborne and spaceborne lidar provide sources of data that considerably improve estimates of forest structure and fuel. ALS data provide tree-level information about the landscape over relatively small regions, while GLAS data provide samples of canopy-level information for the entire US. These improved estimates are vital for better understanding fire behaviour across landscapes and also inform other science questions in the fields of wildland fire, hydrology, and habitat monitoring. The objective of this study was to build an automated tool

to provide non-expert users with a single, user-friendly application for lidar processing and end-to-end canopy structure and fuel mapping. The Creating Hybrid Structure from LANDFIRE/lidar Combinations (CHISLIC) tool is the resulting application. CHISLIC enables the use of remotely sensed data for the derivation of CH, CC, and CBH through a single, simple-to-use tool, contributing to the wider use of such data within the wildland fire community. While drawing upon lidar processing algorithms previously established in the literature, CHISLIC represents a unique application of these in a large-scale operational capacity rather than in small-scale field experiments. This paper summarizes the background of CHISLIC, reviews the algorithms for deriving the metrics of interest, and reviews the outputs of CHISLIC.

2. Methods

2.1. CHISLIC goals and parameters

The CHISLIC design goals were to provide a simple and easy-to-use interface for users to generate lidar-derived canopy fuel metrics. The intent for CHISLIC was to be fully automated, so that no previous lidar experience would be required. For the initial version of CHISLIC, the algorithms used to generate canopy structure and fuel did not address differences caused by regional diversity in forest structure or variations in lidar data collection strategies. A considerable amount of work has been published regarding the use of lidar for structure and fuels estimation, and therefore the literature was consulted and existing algorithms adapted to use in CHISLIC.

The selected modified data processing algorithms were implemented in CHISLIC as a stand-alone desktop application. This application was developed in C++ and integrated various open-source libraries for reading lidar files, processing lidar data, and handling raster image input and output.

2.2. ALS algorithm selection

Numerous algorithms have been proposed and tested, in the literature and by the authors, to calculate CH, CC, and CBH from ALS data. For selection into CHISLIC, the team focused on relatively simple algorithms that would likely be applicable across a range of different data acquisition strategies and forest types. The methods CHISLIC uses for deriving CH, CC, and CBH were further evaluated by the authors through comparisons with field data from test sites from across the US (Lubrecht Experimental Forest (LEF), Montana; Grand County, Colorado; Eglin Air Force Base, Florida; and the Yukon Flats Ecoregion, Alaska). Furthermore, while CHISLIC outputs can be used for a variety of applications, the algorithms selected for deriving CH, CC, and CBH were chosen based on the current fire behaviour modelling system requirements. CHISLIC was developed with the capability to implement new algorithms and regional variants easily in the future. The algorithms used in CHISLIC for ALS data processing are presented in [Table 1](#).

Table 1. ALS data processing algorithms used in CHISLIC for estimating canopy metrics.

Canopy metric	ALS algorithm
CH	99th percentile height of vegetation returns
CC	Number of vegetation first returns greater than 2 m divided by the number of all first returns
CBH	Mean height of vegetation returns minus 1 SD of height of vegetation returns

CH is the basic unit of measurement for ALS applications in forestry. The 99th percentile of the CH model was adopted rather than maximum height to filter erroneous data points appearing to be above the forest canopy. These points may be the result of energy intercepting surfaces other than vegetation (e.g. water vapour, dust, or birds) or may be errors in range calculation of received lidar energy. The effect of using the 99th percentile height to derive canopy top is to slightly underestimate height, although Riaño et al. (2004) showed this effect to be negligible. Comparisons of ALS-derived CH with field measurements across 55 plots in the LEF study area produced a linear model (R^2 (coefficient of determination) = 0.89; root mean square error = 1.70 m; bias = -1.1 m). A negative bias of ~1 m is typical due to the reduced probability of laser returns hitting the tops of conical tree crowns.

CC has been estimated from ALS using two types of data: counts of returns and intensity of returns. Floch (2010) compared several CC estimation techniques at the LEF study site. He demonstrated that a model that used the ratio of first returns from vegetation and all first returns showed the strongest correlation with field data (R^2 = 0.74; standard error = 13.31%). Smith et al. (2009) and Hopkinson and Chasmer (2009) also achieved favourable results with this return ratio model. The return ratio model to estimate CC was selected because of its statistical superiority at LEF, its consistent performance in the literature, its simplicity, and to avoid incorporating intensity data into the method. ALS intensity is a difficult metric to work with given a lack of calibration and variation in methods of measurement between different instruments and acquisitions. Using the ratio method, the average difference between field and ALS-derived CC at LEF was 13.48% and a field CC of 0 resulted in an ALS-derived CC of 2.29%. The value of R^2 for this model was 0.78 for Smith et al. (2009) and ranged between 0.58 and 0.75 for Hopkinson and Chasmer (2009) in different forested environments, depending on field measurement parameters. A height cut-off of 2 m to separate points in the canopy from undergrowth is used. Smith et al. (2009) found that the differences in the CC estimates resulting from using either 1 and 2 m as the cut-off height were negligible.

CBH is a more difficult attribute to derive from lidar data as it represents values inside the point cloud. Several methods have been tested in the literature to estimate CBH, including the use of the 1st percentile height (Riaño et al. 2004), the 25th percentile height (Popescu and Zhao 2008), one standard deviation (SD) of height subtracted from mean height (Rowell 2005), dividing in half the range of CHs (Rowell 2005), and multivariate regression modelling (Andersen, McGaughey, and Reutebuch 2005; Erdody and Moskal 2010). We rejected the use of the 25th percentile height because of its poor correlation in Popescu and Zhao (2008) with field measured CBH (R^2 = 0.11). The use of the 1st percentile height showed high correlation with field data (R^2 = 0.68) in Riaño et al. (2004). Multivariate regression models also showed strong correlations with field measurements, but were too site-dependent to use in CHISLIC. Similarly, although Rowell's (2005) first approach, CH divided in half, worked well in a ponderosa-pine-dominated study site in the Black Hills, South Dakota, a method based on one species' crown form may not be applicable in other forests. Rowell's (2005) second approach addressed this concern by introducing the use of SD to tie an estimate of CBH to the variation of heights in the neighbourhood. This second approach ($CBH = \text{mean} - 1 \text{ SD}$) resulted in a higher correlation (R^2 = 0.76) and less bias in the Black Hills (Rowell 2005).

Using lidar and field data collected in LEF, we compared three methods of estimating CBH: mean - 1 SD, 1st percentile height, and a method using the mean of the lowest non-ground points in 3 m cells. To filter numerous points just above ground, we applied a minimum height cut-off of 0.5 m. The results of regression analyses of these three CBH techniques are summarized in Table 2. We conclude that the most statistically sound method for CBH estimation was the use of mean - 1 SD, which performed reasonably in both the Black Hills and at LEF. All of the methods over-predict CBH relative to field measurement, resulting in a

Table 2. Results of regression analyses comparing three methods of CBH estimation with field measurements.

	Mean – 1 SD	1st Percentile	Lowest non-ground value
R^2	0.547	0.361	0.470
Standard error	2.019	1.846	1.860
Slope	0.789	0.833	0.858

conservative estimate from a fire behaviour standpoint. Given the ambiguity in defining CBH in the field combined with a lack of data to test the portability of the approach to other sites, we chose to use the mean – 1 SD method in this prototype analysis.

2.3. GLAS algorithm selection

The algorithms used to integrate the GLAS data utilize information from two of the available GLAS products: the GLA01 waveform data and a set of metrics included in the GLA14 product that describe the Gaussians fit to the waveform (Figure 1), including number of peaks, elevation, width, and amplitude of each Gaussian (Harding and Carabajal 2005). CH in areas characterized by low-to-moderate terrain is derived following the methods of Rosette, North, and Suárez (2008), where ground is identified as the elevation of the peak of either the first or second Gaussian characterizing the waveform, whichever has the greater amplitude. This elevation is subtracted from the canopy top height elevation. Canopy top was defined as the first return above a background noise threshold. In areas with high terrain, the height-finding approach of Pang et al. (2008) was adapted. CC was estimated from the GLAS waveform following the approach described in Hyde et al. (2005), where the return waveform is separated into ground and canopy energy components, and the relationship between the canopy energy and the total energy of the waveform is assumed to be correlated with CC. CBH was derived following Peterson, Nelson, and Wylie (2013), where a cumulative energy profile of the waveform is generated and the elevation at which the 30th percentile height of the cumulative energy was reached was identified and from which the ground elevation was subtracted to produce the GLAS-derived CBH value.

The GLAS data extrapolation process in CHISLIC utilizes an open-source regression tree library and custom-developed spatial data appliers. Regression tree models are trained with CH, CC, and CBH metrics obtained from the GLAS data at the footprint locations and with Landsat

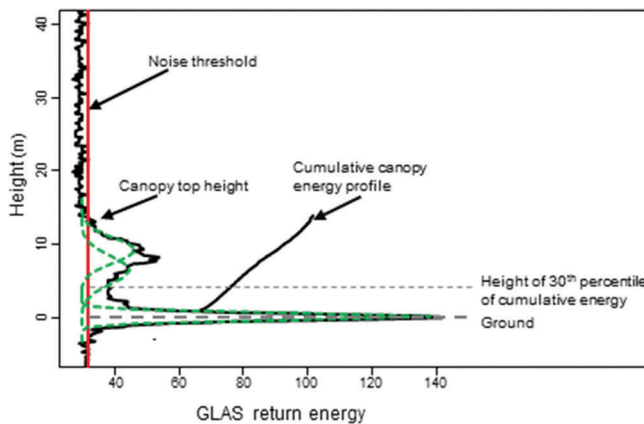


Figure 1. Example GLAS waveform (black curve) shown with Gaussians overplotted (green dashed curves) as well as metrics used for vegetation structure and wildland fuel estimation.

Thematic Mapper (TM) imagery, topographic data, and LANDFIRE surface fuel data layers. Providing additional inputs increases the available output options. The optional landscape file is a multiband raster format used by wildland fire behaviour models and fire effects simulation models that assimilate the characteristics of the topography, vegetation structure, and fuels of a landscape. When building the updated landscape file, outputs from the ALS algorithm and GLAS/Landsat algorithms are merged spatially to provide a seamless data set that can be used with existing LANDFIRE products. GLAS data layers will only be calculated if sufficient GLAS footprints are located within the area mapped by ALS.

2.4. CHISLIC testing

CHISLIC was tested for functionality and accuracy. The tool interface was assessed for clarity and usability by potential end-users. CHISLIC results were also compared to products generated manually outside of the application environment. Furthermore, CHISLIC was tested by a pool of potential end-users to ensure it could handle different data types and volumes. Thus far, feedback has been positive with considerable enthusiasm for potential opportunities to process additional ALS data sets. It is clear from this limited evaluation that there is interest on the user side for tools that will improve fuel layer geospatial products (e.g. CH) and provide access to previously inaccessible ALS data sets.

3. Results and discussion

The current CHISLIC application presents a simple interface that provides users with a step-by-step series of selections which guide the user through the application to generate meaningful results. The processing steps within CHISLIC are completely automated and require no user input (Figure 2). The interface provides information about each of the steps; additionally, a brief user’s guide is distributed with CHISLIC.

The primary purpose of CHISLIC is to infuse LANDFIRE products with lidar data to improve spatial and informational detail. The current results indicate that CHISLIC delivers more detail, compared to LANDFIRE, which can be used in fire behaviour applications. This greater detail is illustrated in Figure 3, showing a subset of the Grand County study area. Figure 3 shows both the standard LANDFIRE product for CH and the CHISLIC CH output upon

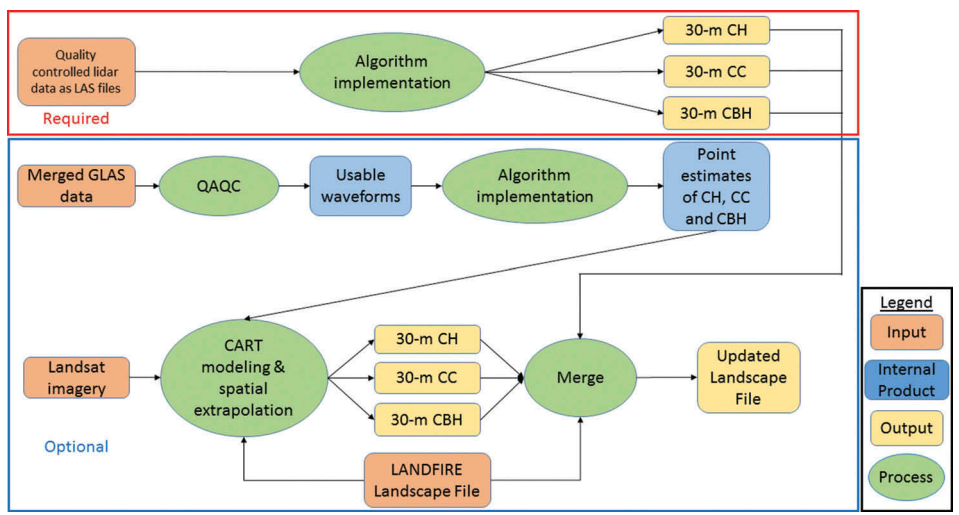


Figure 2. Diagram showing the flow of data through the CHISLIC process. The minimum input data required are the LAS files, from which 30 m CH, CC, and CBH are derived.

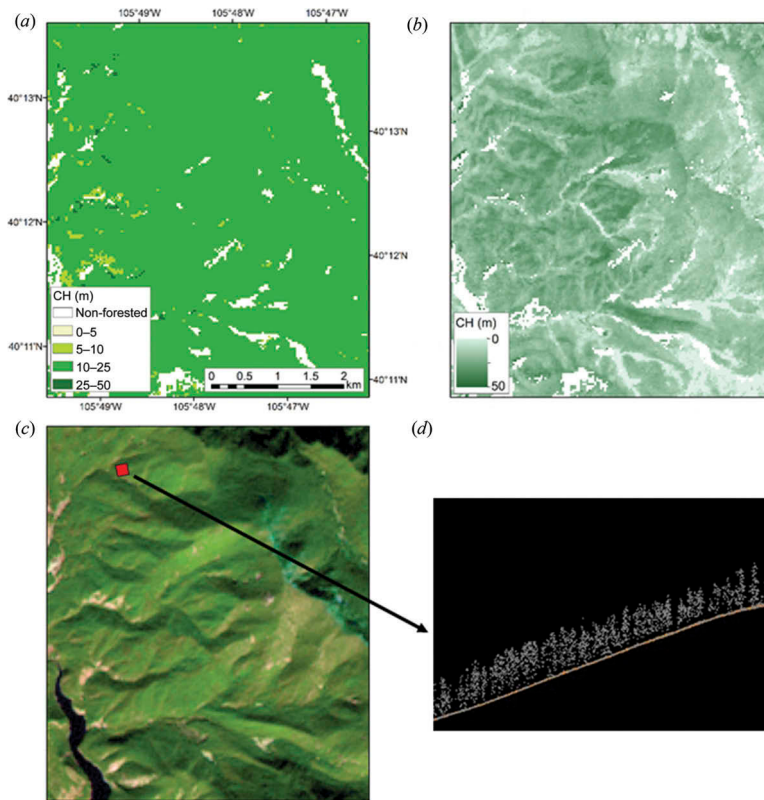


Figure 3. CH products from LANDFIRE (a) and CHISLIC (b) and primary remote sensing data types used to develop them from the Grand County, Colorado, study site. Panel (c) shows the Landsat TM (bands 5, 4, and 3) imagery used to generate LANDFIRE products, and panel (d) shows the airborne lidar used to produce the CHISLIC outputs for the point marked in (c).

integrating ALS data, as well as the primary sources of remote sensing data used to derive them. Mapping CH as a continuous variable, the lidar-infused CHISLIC output depicts more spatial heterogeneity across the landscape as opposed to the binned Landsat TM-based LANDFIRE product. The greater informational detail in the CHISLIC products, as compared to the LANDFIRE layers, is shown in Figure 4. Here, the CH distributions for the CHISLIC and LANDFIRE CH products for the same subset area as shown in Figure 3 are presented. At the gross scale, the two products are consistent, with the majority of the values falling in the 10–25 m CH range. However, the CHISLIC product represents far greater variability within the LANDFIRE class bins.

The impacts of using CHISLIC products as opposed to those obtained from LANDFIRE are demonstrated by a modelling exercise that was conducted near Coeur d'Alene, Idaho, using FARSITE (Figure 5). In this example, CC increased significantly in many places when using CHISLIC products. This increase affected the modelled fire behaviour significantly by increasing the wind reduction factor, which slowed fire spread (Albini and Baughman 1979). Also, the values of CH and CBH were increased in the CHISLIC products when compared to the LANDFIRE data. The change in CBH reduced torching potential, resulting in a shift from significant torching (yellow) when using the LANDFIRE data to increased surface fire (green) with CHISLIC. This example indicates that the fire behaviour modelling systems

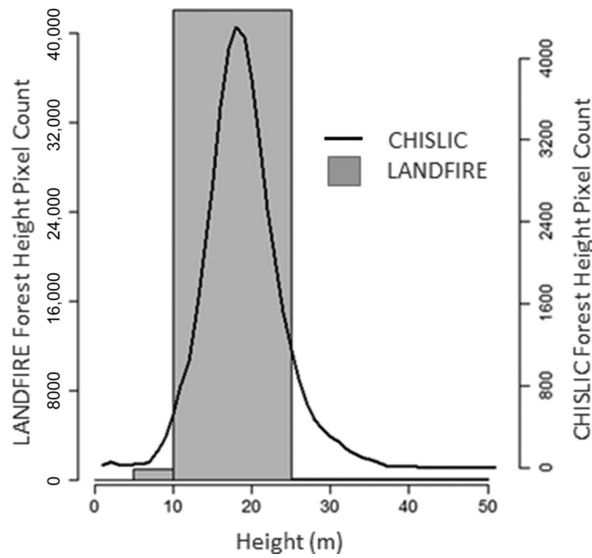


Figure 4. Histograms showing the distribution of LANDFIRE and CHISLIC canopy height products for area of the Grand County, Colorado, study site shown in Figure 3.

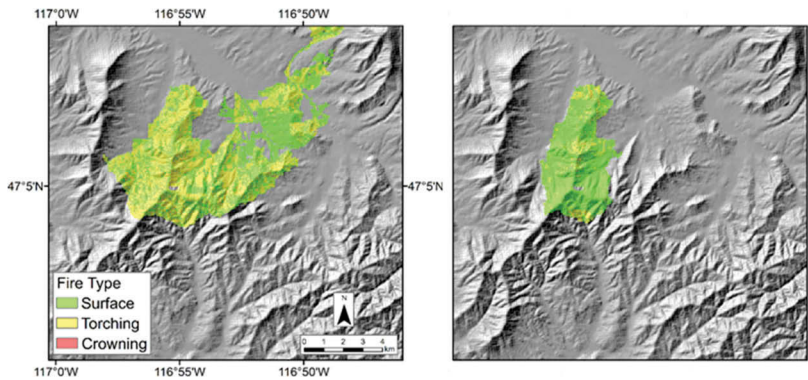


Figure 5. FARSITE-predicted crown fire type and fire perimeter using canopy fuels layers from LANDFIRE (left) and CHISLIC (right) for an area near Coeur d'Alene, Idaho.

currently used for operational incident support are sensitive to changes in canopy fuel data and that different results are obtained when using locally derived fuel layers compared to the national LANDFIRE data. Similar results were found in other study areas, for example Yukon Flats, Alaska (Peterson, Nelson, and Wylie 2013).

CHISLIC benefits from partnerships with the Wildland Fire Assessment System and the Wildland Fire Decision Support System. These two systems are widely used by federal, state, and local wildland fire managers to support a variety of tactical and strategic decisions and both plan to support CHISLIC as it becomes operational. Future plans for CHISLIC include adding canopy bulk density (CBD) derived from biomass modelling and lidar data. CBD is a key input to operational crown fire spread models and is correlated to the distribution of biomass within the canopy. Deriving CBD from lidar data is challenging because, unlike the CH, CC, and CBH metrics, it cannot be directly inferred. In addition, the ability to generate all other layers needed

for fire behaviour modelling – elevation, slope, aspect, and surface fuel models – will be included. The processing of GLAS data and the extrapolation methods used to generate the spatially continuous GLAS-based products are still being refined. A repository of GLAS data metrics with a web interface will be developed where users will be able to input their area of interest and download preprocessed GLAS data that will be directly usable by the desktop CHISLIC version. There are also plans for CHISLIC to transition from solely a desktop application to a web-based interface. By providing a web interface, the lidar processing can be accomplished on server hardware rather than the end-user systems and will enable more efficient data transfers and prevent data storage issues for end-users.

4. Conclusions

The CHISLIC application has been developed to allow for easy, automated integration of lidar data into standard LANDFIRE data products. Its ease of use will foster the incorporation of lidar data by fire behaviour analysts to develop locally refined maps, drawing upon the best remote sensing data available to define forest canopy structure and fuel characteristics of interest. CHISLIC will be made available to end-users through partnerships with the U.S. Forest Service. As lidar data become increasingly available, application of the CHISLIC tool will provide additional benefits to land managers by providing quantitative assessments of fuel changes arising from fuel treatments or disturbances such as insect outbreaks, windthrow events, or wildfires.

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