

Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling

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Abstract

Methods for using airborne laser scanning (also called airborne LIDAR) to retrieve forest parameters that are critical for fire behavior modeling are presented. A model for the automatic extraction of forest information is demonstrated to provide spatial coverage of the study area, making it possible to produce 3-D inputs to improve fire behavior models.

The Toposys I airborne laser system recorded the last return of each footprint (0.30–0.38 m) over a 2000 m by 190 m flight line. Raw data were transformed into height above the surface, eliminating the effect of terrain on vegetation height and allowing separation of ground surface and crown heights. Data were defined as ground elevation if heights were less than 0.6 m. A cluster analysis was used to discriminate crown base height, allowing identification of both tree and understory canopy heights. Tree height was defined as the 99 percentile of the tree crown height group, while crown base height was the 1 percentile of the tree crown height group. Tree cover (TC) was estimated from the fraction of total tree laser hits relative to the total number of laser hits. Surface canopy (SC) height was computed as the 99 percentile of the surface canopy group. Surface canopy cover is equal to the fraction of total surface canopy hits relative to the total number of hits, once the canopy height profile (CHP) was corrected. Crown bulk density (CBD) was obtained from foliage biomass (FB) estimate and crown volume (CV), using an empirical equation for foliage biomass. Crown volume was estimated as the crown area times the crown height after a correction for mean canopy cover.

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1. Introduction

Fuel distribution is critical to determining fire behavior. When fuels are arranged uniformly and continuously, fire will travel uninterrupted, but heterogeneity in canopy cover causes fires to spread along preferential paths. To characterize fuels for wildfire risk, we must consider factors such as

crown bulk density, crown base height, canopy height, percent of canopy cover, surface area-to-volume ratio, vertical and horizontal continuity, dead and live fuel load, and size classes of fuel elements. All these variables are frequently summarized as “fuel types” (Pyne, Andrews, & Laven, 1996), which are groups of fuel categories that have similar fire behavior. For example, fuel types based on fuel height, presence of understory fuels, and fuel load are used for defining fire behavior in the Northern Forest Fire Laboratory (NFFL) system (Albini, 1976).

Aerial photography and extensive fieldwork have been the traditional tools to map these fuel types (Lee, 1941; Oswald, Fancher, Kulhavy, & Reeves, 1999). Satellite remote sensing techniques provide an alternative source of fuel information, since they can provide comprehensive spatial coverage and enough temporal resolution to update fuel maps in a more efficient and operative manner than

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traditional aerial photography or fieldwork. Additionally, satellite sensors provide digital information that can easily be linked to other spatial databases in a Geographic Information System (GIS) environment and imported into fire behavior models. The sensor most widely used for fuel type mapping has been Landsat-MSS (Burgan & Shasby, 1984; Kourtz, 1977; Wilson et al., 1994) and more recently, Landsat-TM (Castro & Chuvieco, 1998; Miller & Yool, 1999; Salas & Chuvieco, 1995; Van Wagendonk, 1998; Vasconcelos et al., 1998); however, newer instrument systems with new capabilities may be able to improve information on fuel types.

The inability to discriminate forest understory is a serious limitation associated with satellite image interpretation and aerial photography despite some attempts (Stenback & Congalton, 1990). This factor is sometimes the only difference between fuel types but other information is also needed to fully characterize the fuel distribution such as canopy cover, tree height, crown base height, and crown bulk density (Scott, 1999).

Photo-interpretation combined with extensive fieldwork has been used to produce these fuel data inputs (Bertolette & Spotskey, 1999), but this is labor intensive and too slow to be used to map these properties for regional fire risk monitoring. Landsat-TM and SPOT-HRV have been widely used to estimate percent canopy cover, canopy height, tree biomass, and tree volume using empirical approaches (De Wulf, Goossens, Deroover, & Borry, 1990; Fazakas, Nilsson, & Olsson, 1999; Oza, Strivastava, & Devaiah, 1996; Spanner, Pierce, Peterson, & Running, 1990). ERS-1, JER-1 and Radarsat data have also been used to predict these forest attributes (Harrell, Bourgeauchavez, Kasischke, French, & Christensen, 1995; Hyypä, Hyypä, et al., 2000; Ranson et al., 1997; Toutin & Amaral, 2000). Ranson et al. (1997) estimated foliage biomass with radar data, which could be used to estimate crown bulk density, a property not easily derived from optical sensors. However, the accuracy of radar satellites to estimate vertical canopy height is limited to 5 m (Toutin & Amaral, 2000). Additionally, they are insensitive to high biomass levels (Kasischke, Melack, & Dobson, 1997; Sader, Waide, Lawrence, & Joyce, 1989).

Satellite Light Detection And Ranging (LIDAR) such as the planned VCL or GLAS missions (Blair & Hofton, 1999) might solve these limitations. These sensors will be able to accurately estimate canopy height (~ 1 m vertical, www.geog.umd.edu/vcl/) and other forest parameters (canopy cover, crown base height, or crown bulk density). LIDAR does not saturate at high biomass and it would be easier to separate tree crown information from other canopy data than with optical data. Airborne LIDAR systems have been tested for estimating these critical parameters for fire behavior, which have produced better results than aerial photography, airborne hyperspectral sensors (e.g. AVIRIS), and airborne profiling radar (Hyypä, Hyypä, et al., 2000; Hyypä, Kelle, Lehtikoinen, & Inkinen, 2001; Lefsky, Cohen, & Spies, 2001).

Airborne profiling radar has provided an estimation of tree height with an error of 1–1.5 m (Hyypä & Hallikainen, 1996), and this could be improved using a larger bandwidth, but this technique is less mature than LIDAR to provide three-dimensional information about vegetation structure.

For current fuel types, the accuracy of vegetation height measurements should be on the order of centimeters. For example, the behave fuel type classification (Albini, 1976) characterizes different shrub fuel types that cause diverse fire behaviors at height intervals of 0.6 m. Discrimination of shrub fuel types could be accomplished with airborne LIDAR of the type described here since it has a recording accuracy of 5–15 cm (Baltsavias, 1999a), which could be sufficient to obtain measured vegetation height accuracies of 0.5–1.0 m.

The validity of airborne laser scanning to retrieve forest parameters has been widely tested using ground validation data (Hyypä et al., 2001; Magnussen & Boudewyn, 1998; Magnussen, Eggermont, & LaRiccia, 1999; Means et al., 2000; Means et al., 1999; Naesset, 1997; Naesset & Okland, 2002; Nilsson, 1996; Rieger, Eckmüllner, Müllner, & Reiter, 1999). This paper proposes a model for the automatic extraction of forest information that is relevant for fire behavior modeling. The spatial dimension of the output data enables it to be used as an input to fire behavior models such as FARSITE (Finney, 1998).

Algorithms are presented to identify crown base height and discriminate laser hits from trees and understory vegetation. Using these data, we present methods to estimate the variables relevant to fire behavior models: tree height, tree cover, surface canopy height, surface canopy cover, and crown bulk density (Scott, 1999).

2. Methodology

2.1. Study area

The test site is located about 2 km east of Ravensburg, in southwestern Germany, bordering the Alps. The landscape is mainly composed of green meadows, conifer, and deciduous forests. Spruce is the dominant conifer species, but in recent years, a mixture of firs and beeches has been introduced. Some original mixed deciduous forest composed of beech, birch, oak, chestnut, and walnut remains. The slopes are gentle within the flight line (mean = 7%, SD = 5%) and elevations range from 572.16 to 603.02 m.

2.2. Data set

The Toposys I system (www.toposys.com) recorded high-density last LIDAR returns (last intercepted return). The Toposys I is a small footprint system that measures the time–distance to an intercepted point on the ground using push broom scanning with a fiber optics array scanner that

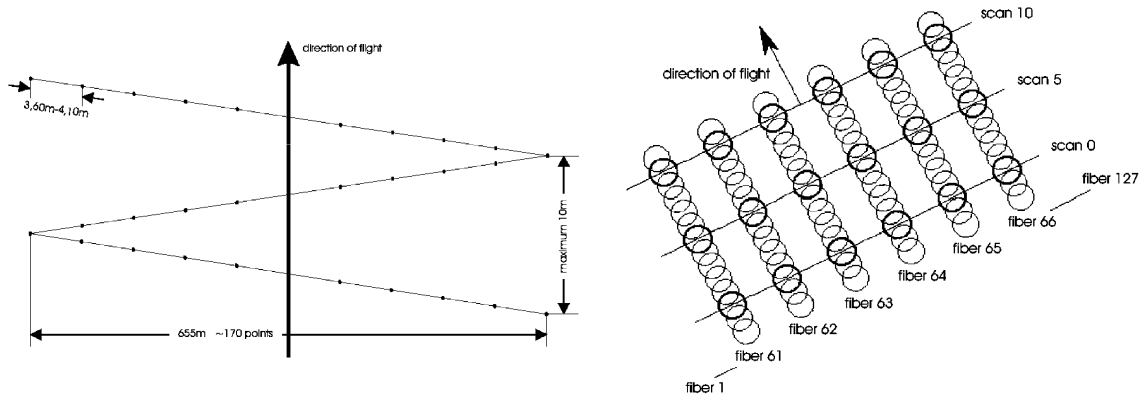


Fig. 1. Typical cross-track (whisk broom) scanning (left), Toposys I scanning (right) (Lohmann & Koch, 1999).

emits a high laser pulse frequency and creates an almost parallel across-track line scan (Wehr & Lohr, 1999) for an under-sampled grid of points (Fig. 1). The footprint size and space between footprints depends mainly on the airborne platform’s altitude and speed (Baltasvias, 1999a). A flight line of about 2 km from North to South (azimuth = 194°) and an approximate width of 190 m was sampled between 23 and 25 April 2001. The flight altitude was between 604 and 759 m. The laser beam divergence was 0.5 mrad, the laser pulse rate was about 83 kHz and the scan rate was 630 Hz. Following calculations of Baltasvias (1999a, 1999b), the diameter of the laser footprint was between 0.30 and 0.38 m. The laser pulse density was between 1.2 and 1.5 m across track and about 0.11 m along track. This configuration rendered a density of about 6.7 points/m², sampling of 20% of the total surface with an over sampling of 200% in the along track direction.

2.3. Generation of height above the ground

Raw data contained x , y , and z (above sea level) coordinates. First of all, laser pulses were arranged in 10 by 10 m cells (as recommended by Rieger et al., 1999), keeping x , y , and z coordinates. This cell size provides sufficient statistical significance for the generation of the forest parameters (about 670 points per cell) and assures at least some ground hits per cell. Ackerman (1996) estimates a penetration rate

of 24–29% for conifers and 22–25% for deciduous species in the summer. Therefore, the average number of ground hits should be ~ 178 in a coniferous forest and ~ 157 in a deciduous forest.

The z -value of the laser pulse return may identify either the ground or the canopy elevation. For this study, we used the one percentile return as the ground height for each cell. This value was preferred to using the lowest return value to avoid possible bad data and small local depressions. A digital ground model (DGM) was produced from these data (Fig. 2a). The actual ground height at each of these laser pulses (x , y) was computed using spline function interpolation (Sandwell, 1987) from the DGM. Delaunay linear triangulation (Geometry Center, 1993) was also tested. As a result, another z -value was obtained in reference to the ground elevation above sea level (Fig. 2b). Laser pulse heights (Fig. 2b, filled circles) were subtracted from the interpolated ground heights (Fig. 2b, crosses), which derived the local height above the ground (Fig. 2c).

2.4. Generation of forest height parameters

Surface canopy height of mixed land cover is difficult to estimate from small footprint LIDAR. It is also difficult to measure on steep terrain due to the spreading of the ground return (Means et al., 1999). Fig. 3 shows the methodology for the generation of forest height parameters. These are

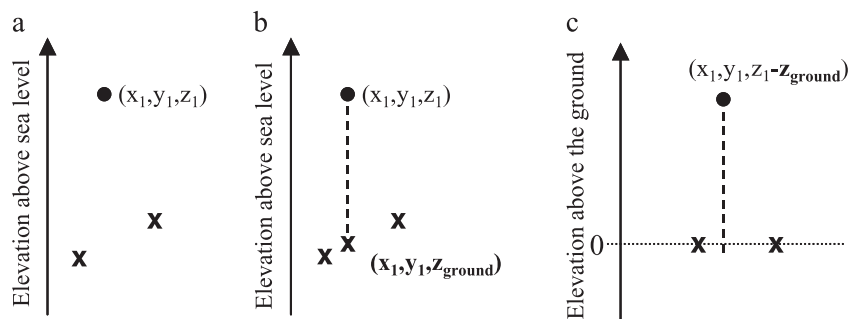


Fig. 2. Algorithm for the generation of above ground height. (a) DGM (crosses) and problem point for the generation of above ground height (filled circles). (b) Ground height of the problem point. (c) Above ground elevation of the problem point.

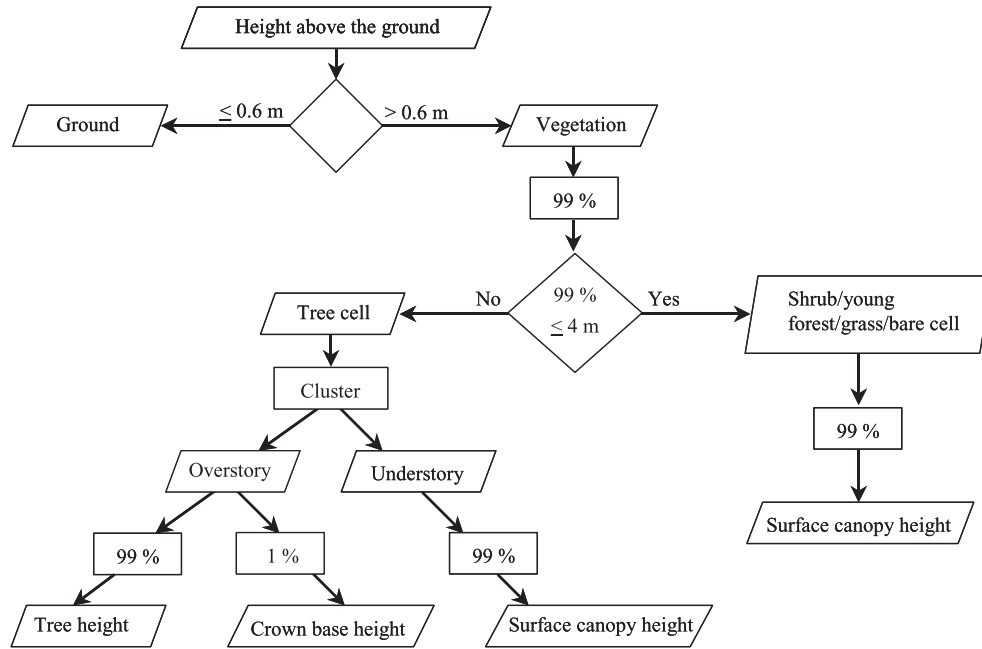


Fig. 3. Flowchart for the generation of tree height, crown base height, and surface canopy height.

extracted easily if there is a height gap between the ground and the vegetation. The binary classification of laser pulses into ground and vegetation points is the first step. The maximum tolerance of the ground height is 0.6 m, which is appropriate for sites with moderate slopes (Hyypä, Pyy-salo, Hyypä, & Samberg, 2000). Cells were classified as surface canopy if the 99 percentile was equal or less than 4 m. The cell is classified as forest if the 99 percentile was over 4 m. Additionally, a cluster analysis was performed for those cells classified as forest to try to discriminate between overstory and understory layers. The two groups were made based on the smallest Euclidean distance between objects. Once separated, the following parameters were calculated: tree height (99 percentile of overstory group), crown base height (1 percentile of overstory group), and understory height (99 percentile of understory group). These percentiles were chosen to avoid possible outliers. Different criteria could be chosen depending on the size of the output cell and the number of laser pulses.

2.5. Generation of forest cover parameters

Tree cover is inversely related to laser penetration rate (= 1-canopy closure) (Cowen, Jensen, Hendrix, Hodgson, & Schill, 2000; Means et al., 1999). Tree cover (TC) was calculated from the proportion of the laser pulses that hit the tree canopy:

$$TC_{i,j} = \frac{T_h}{Tot_h} \quad (1)$$

where T_h is the sum of laser pulses that hit the trees in cells i, j , and Tot_h is total number of laser pulses (tree, understory, and ground) in cells i, j .

Surface canopy cover (SC) for cells without tree cover is computed similarly:

$$SC_{i,j} = \frac{S_h}{Tot_h} \quad (2)$$

where S_h is the sum of laser pulses that hit the surface canopy cover.

If the surface canopy is near the ground, it is difficult to separate these layers in the pulse return. It is also difficult to discriminate the vegetation layer (understory cover) below the tree crown since the tree cover shades the surface canopy cover. The effect of shading by a taller canopy on returned energy profile can be corrected using a modified exponential transformation (Aber, 1979; Lefsky, Harding, Cohen, Parker, & Shugart, 1999; MacArthur & Horn, 1969; Means et al., 1999) but requires a large footprint, full-digitized waveform (Lefsky et al., 1999; Means et al., 1999). An attempt was made to use this algorithm with small footprint data by modeling the large footprints from the last returns. The full-digitized waveform was simulated as the sum of laser pulses in the 10×10 m cell at 0.3 m intervals. We did not consider vignetting that might have resulted from higher laser beam intensity at the center of the cell and lower toward the edges (Blair & Hofton, 1999; Harding, Lefsky, Parker, & Blair, 2001). This simplification resulted in all small footprint cells having the same weight (importance) regardless of their location in large footprints.

The simulated full-digitized waveform was transformed and corrected for the canopy height profile (Lefsky et al., 1999; Means et al., 1999) in four steps. The correction for relative reflectance of foliage and soil is not needed for the simulated waveform.

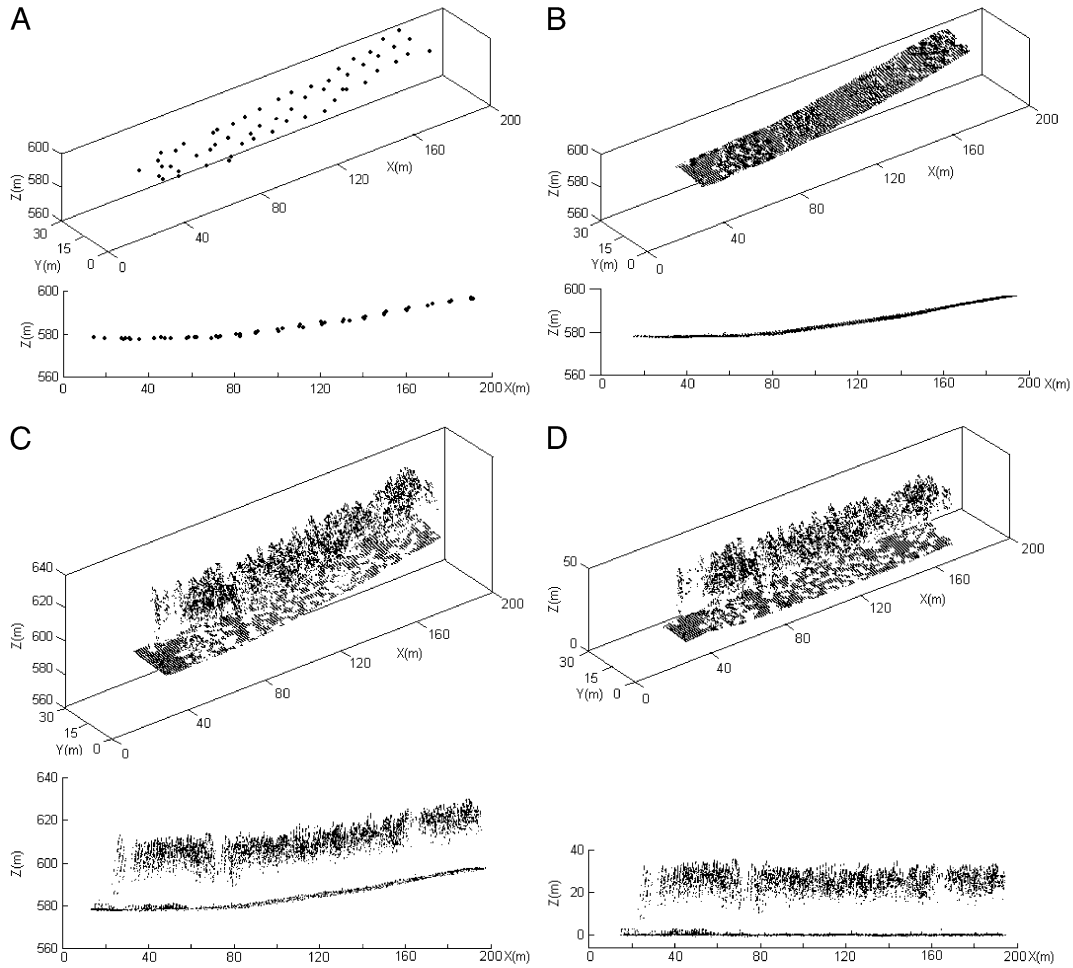


Fig. 4. (A) Laser points selected for the generation of the DGM. A subsample of 180 m in x and 30 m in y directions is selected. (B) Ground height above the sea level of each laser pulse calculated using a spline function interpolation. (C) Laser pulse heights above the sea level. (D) Laser pulse height above the ground.

Step 1: Normalization of the cumulative number of laser returns (NCumL):

$$NCumL(h) = \frac{Lr(h)}{Tot_h} + NCumL(h - 1) \quad (3)$$

where $Lr(h)$ is the number of laser returns at a given height interval (h).

Step 2: Cumulative fraction of total laser pulses returned from the canopy. Therefore, the NCumL of the ground was not considered, although the return energy of the small footprints is higher if the ground is contacted than if foliage is contacted, but it does not effect the total number of pulses that reach each site.

Step 3: Cumulative fraction cover is converted into the corrected cumulative canopy height profile (CHP) (Aber, 1979; MacArthur & Horn, 1969):

$$CHP(h) = -\ln(1 - cover(h)) \quad (4)$$

where $cover$ is the cumulative fraction of total pulses returned from the canopy or fraction of the sky covered by the vegetation canopy at height interval (h). This was obtained in Step 2.

Step 4: Cumulative CHP is differenced and scaled from 0 to 1 to obtain the relative CHP.

Once the correction of the canopy height profile is complete, relative CHP is transformed to generate the corrected simulated waveform:

$$Lr_{cor}(h) = relCHP(h) * (Tot_h - Ground_h) \quad (5)$$

where $Lr_{cor}(h)$ is the corrected number of laser returns at height interval (h) and $Ground_h$ is the number of laser pulses that hit the ground.

Understory cover (UC) is computed then from the corrected number of understory laser hits (Uh_{cor}):

$$UC_{i,j} = \frac{Uh_{cor}}{Tot_h} \quad (6)$$

Table 1
Comparison between both interpolation methods

	Mean height	Minimum height	Maximum height	Standard deviation	Percentage of negative values (%)	Mean height (<0 values)	Standard deviation (<0 values)
Spline function	11.48	-0.65	35.90	13.04	6.20	-0.078	0.084
Delaunay triangulation	11.76	-0.93	35.74	13.08	5.69	-0.090	0.100

Heights are in meters.

2.6. Generation of forest crown bulk density

Crown bulk density (CBD) may be obtained by computing foliage biomass (FB) and crown volume (CV):

$$CBD = \frac{FB \text{ (kg/m}^2\text{)}}{CV \text{ (m}^3\text{/m}^2\text{)}} \left(\frac{\text{kg}}{\text{m}^3} \right). \quad (7)$$

Tree branches are not included in the biomass estimates since they generally do not burn in wildfires unless there is a crown fire. Specific empirical equations are needed to relate laser variables to foliage biomass. Another possibility is to indirectly estimate foliage biomass from allometric equations that use parameters that can be estimated from LIDAR. For instance, Drake et al. (2002) used an allometric equation based on stem diameter to estimate above ground biomass. Here, we use an approximation by extrapolating the empirical equation of Means et al. (1999) for a conifer forest (Douglas-fir and western hemlock). They estimated total biomass (TotBio) as

$$\text{TotBio(kg/m}^2\text{)} = 5.5 + 0.0385 * (\text{meanCH})^2 \quad (8)$$

where meanCH is the mean height of all laser pulses.

Ranson et al. (1997) showed that foliage comprises 5% of the total biomass in the boreal forests of Canada.

Although the proportion is obviously species dependent, we used this relationship to provide a first approximation of foliage biomass:

$$FB = 0.05 * \text{TotBio}. \quad (9)$$

Crown volume (CV) is calculated from the volume between tree height and crown base height. Since the entire volume is not occupied by canopy, this value was corrected by the sum of the relative CHP (relCHP) between both heights:

$$CV \left(\frac{\text{m}^3}{\text{m}^2} \right) = \frac{(\text{TH} - \text{CBH}) * 10 * 10}{10 * 10} * \sum_{h=\text{CBH}}^{\text{TH}} \text{relCHP}(h). \quad (10)$$

3. Results and discussion

A small area of 180 by 30 m was selected to illustrate the generation of canopy height above the ground. The digital elevation (ground) model was first generated using the one percentile of all laser pulses in each cell (Fig. 4A). The ground height at each of these laser pulses (x, y) was computed using spatial interpolation from the DGM, and the ground height above sea level was determined (Fig. 4B). Laser pulse heights

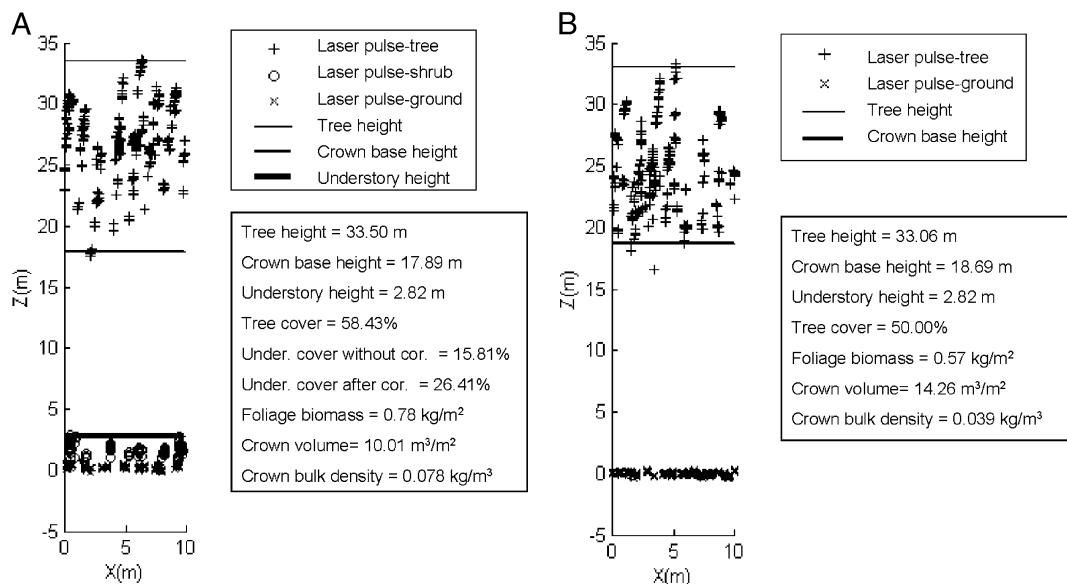


Fig. 5. (A) Estimation of forest parameters in a cell with understory. (B) Estimation of forest parameters in a cell without understory.

(Fig. 4C) were subtracted from the interpolated ground heights (Fig. 4B) yielding the local height of the vegetation above the ground (Fig. 4D) after the terrain height was removed. Small footprint systems typically underestimate tree height rather than overestimate height (Magnussen & Boudewyn, 1998; Magnussen et al., 1999; Naesset, 1997), and this error is reduced using high-density measurements. For example, Hyypä, Pyysalo, et al. (2000) reach this conclusion with at least 9 points/m² and up to 24 points/m² when overlapping flight lines.

The two methods applied for spatial interpolation (spline function and Delaunay linear triangulation) were tested (Table 1) but did not show large differences between methods according to mean, maximum, minimum, and stan-

dard deviation values. These methods each produce a good estimate of the terrain since average negative values are less than 0.10 m, being slightly better for spline interpolation. The Delaunay interpolation could process only 89.33% of the data due to points at the border being located outside of the triangles. Spline interpolation did not have this limitation but computation was three times slower. The algorithm proposed works fairly well for this data set, since gentle slopes are well modeled when one measurement every 10 by 10 m is used in the interpolation. In case of larger slopes and greater local height variations, an algorithm more sensitive to slope changes should be used.

Following the generation of canopy heights above the ground, the classification of laser pulses was performed.

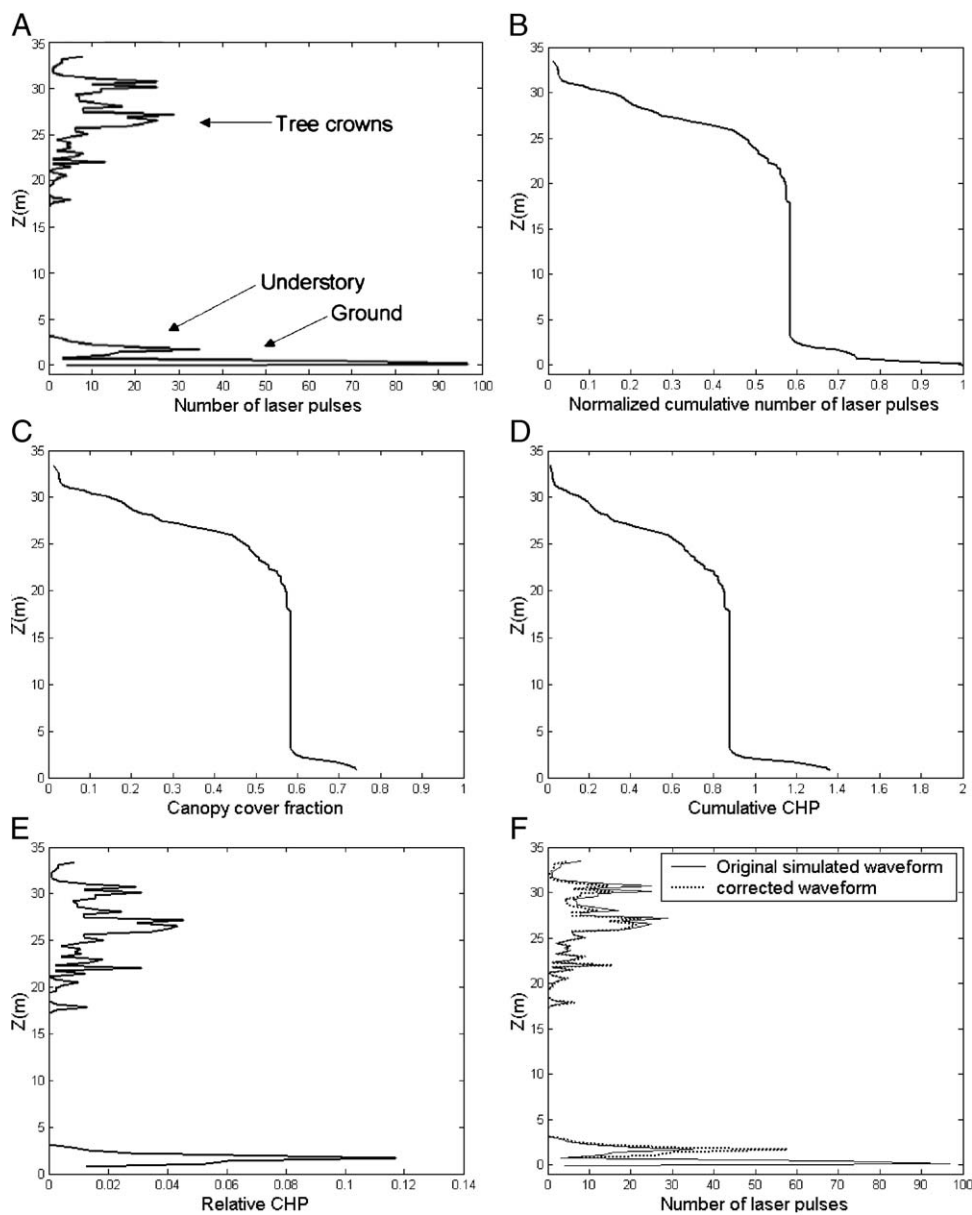


Fig. 6. (A) Simulated waveform (same cell as Fig. 5A). (B) Normalized cumulative number of laser returns. (C) Cumulative fraction of total pulses returned from the canopy. (D) Corrected cumulative CHP. (E) Relative CHP. (F) The corrected waveform versus simulated one.

Fig. 5 shows two examples of the results using the algorithm described above for automatically generating forest height parameters. The cluster algorithm used to separate overstory from understory canopy cover works well and has an advantage over empirical estimations that it can be extrapolated to other study areas. The algorithm can be applied even when there is no gap between forest overstory and understory canopies, that is, when there is almost no separation between crown base height and understory height. The main disadvantage appears to be that if there are more than two layers, for example, mature trees, young trees, and shrubs, then another cluster needs to be added.

The one percentile was selected as the crown base height and the 99 percentile as the understory height to determine whether a connection exists between the two layers, in which a low branch could act as a fuel ladder and produce a crown fire. The same issue applies to tree height (99 percentile) for establishing possible connectivity with adjacent cells.

Tree cover estimation has been already validated in other LIDAR studies, which show that it can be directly retrieved from the number of laser pulses that hit the canopy. The canopy height profile was corrected by modeling the large footprints from the last return of the small footprints (Fig. 6A). The algorithm applied produced NCumL (Fig. 6B), NCumL from the canopy (Fig. 6C), the corrected cumulative CHP (Fig. 6D), and finally, the relative CHP (Fig. 6E). Once the relative CHP was transformed using Eq. (5), the corrected simulated waveform was generated. This transform corrected the shading effect by the surface canopy on the overstory (Fig. 6F). The understory cover estimate increased from 15.81% to 26.41% (Fig. 5A).

The same correction of the waveform can be applied to the model to estimate crown bulk density. Empirical equa-

tions specific to each species should be generated to estimate foliage biomass. It would be also possible to estimate foliage biomass from an empirical estimate of above ground biomass, if the proportion of foliage to total biomass is known for that species and location (controlling for variation in drier versus wetter sites). In terms of crown volume, the main advantage of the direct retrieval of crown volume proposed here over empirical equations is that the method is site independent. The main disadvantage appears when crown base height cannot be clearly delimited.

The output of our model was a raster layer with a cell size of 10 × 10 m containing the following forest parameters: tree height (Fig. 7), crown base height, tree cover, surface canopy height, surface canopy cover, and crown bulk density. The model for the automatic extraction was carried out using the scheme presented in Fig. 3 and Eq. (1) (TC), Eq. (2) (SC), Eq. (6) (UC), and Eq. (7) (CBD). These parameters are ready to be used as input data in a fire behavior model such as FARSITE (Finney, 1998).

4. Conclusions and future research

This paper proposed a model for the automatic extraction of forest information critical to assessing fire behavior from LIDAR data. The output data is provided in a spatial framework. An algorithm based on a cluster analysis allows discrimination between overstory and understory canopy and we used height percentiles to extract tree height, crown base height, and understory height. Tree cover and surface canopy cover parameters were obtained from the fraction of laser pulses that hit each canopy. A correction of the canopy height profile was performed for the understory canopy. The

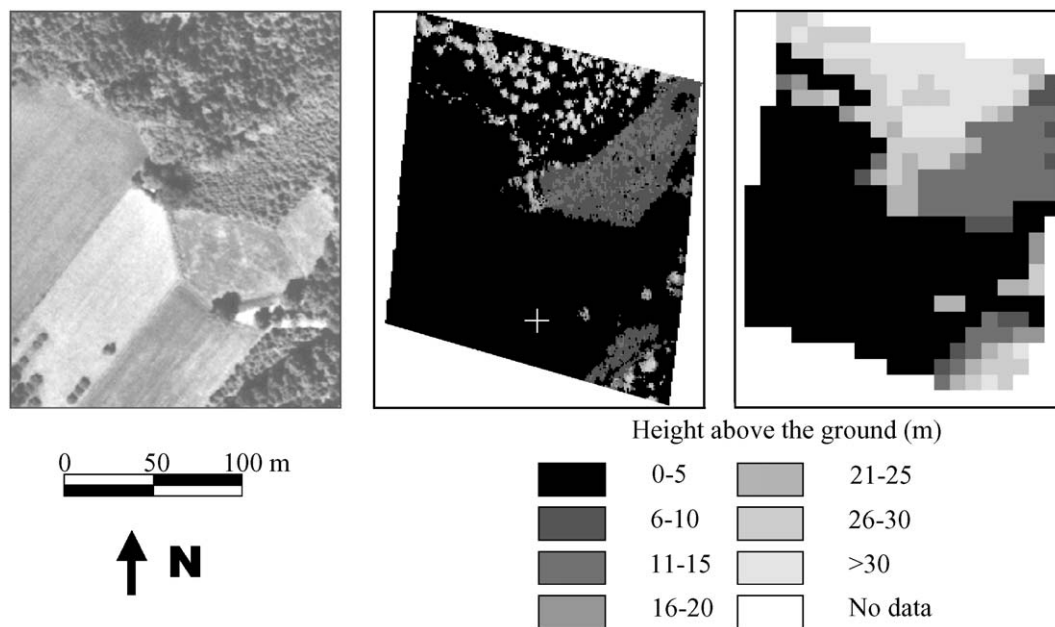


Fig. 7. Aerial photograph (left), estimated tree height, cell size=1 m (center), and estimated tree height, cell size=10 m (right).

estimation of crown bulk density is difficult but essential for fire behavior modeling. Crown volume can be directly retrieved, but foliage biomass also might be modeled from empirical equations. Specific empirical equations for the estimation of this parameter are needed.

LIDAR technology should help accomplish a precise characterization of fuels. Sandberg, Ottmar, and Cushon (2001) developed a new comprehensive system of 192 stylized fuel classes for which all of these forest parameters are crucial to the fuel classification. The generation of accurate forest inventories using the LIDAR methodology we describe is expensive, but traditional methodologies are at least twice as expensive and 3.5 times more time consuming to produce (Means et al., 2000).

Fusion of LIDAR data with other optical sensors will help in identifying the type of tree species or surface canopy types (shrubs, young forest, grassland, etc.) when they are not shaded by tree canopies. Fusion could also be valuable to assist in the spatialization of forest variables when LIDAR data are not available (Dubayah, Knox, Hofton, Blair, & Drake, 2000). Airborne LIDAR surveys are now conducted only in local areas, and the upcoming spaceborne LIDARs will sample only 2% of the total surface (www.geog.umd.edu/vcl/), hence there will be continued need for data fusion methods.

In terms of the output data structure, knowing the exact position of the lowest branch of a tree within a cell is achievable, but it is necessary to obtain the entire crown base height as well. Fire behavior models should be ready to implement such accurate measurements. The next step in advancing wildfire models should be the generation of 3-D forest models. In order to do this, new data formats are needed (Hill, Graham, & Henry, 2000). A good example of the type of new data formats that are needed to achieve 3-D reconstructions is a voxel, a flexible layer describing a volume using multiple attributes (Marschallinger, 1996).

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