

Ground-based LIDAR: a novel approach to quantify fine-scale fuelbed characteristics

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Abstract. Ground-based LIDAR (also known as laser ranging) is a novel technique that may precisely quantify fuelbed characteristics important in determining fire behavior. We measured fuel properties within a south-eastern US longleaf pine woodland at the individual plant and fuelbed scale. Data were collected using a mobile terrestrial LIDAR unit at sub-cm scale for individual fuel types (shrubs) and heterogeneous fuelbed plots. Spatially explicit point-intercept fuel sampling also measured fuelbed heights and volume, while leaf area and biomass measurements of whole and sectioned shrubs were determined from destructive sampling. Volumes obtained by LIDAR and traditional methods showed significant discrepancies. We found that traditional means overestimated volume for shrub fuel types because of variation in leaf area distribution within shrub canopies. LIDAR volume estimates were correlated with biomass and leaf area for individual shrubs when factored by species, size, and plant section. Fuelbed heights were found to be highly variable among the fuel plots, and ground LIDAR was more sensitive to capturing the height variation than traditional point intercept sampling. Ground LIDAR is a promising technology capable of measuring complex surface fuels and fuel characteristics, such as fuel volume.

Additional keywords: fuel sampling, ILRIS, longleaf pine, saw palmetto, wax myrtle, wiregrass.

Introduction

Components of fire behavior, including ignition properties, rates of spread, and intensity are influenced by fuel loading, fuel depth, and thus density (DeBano *et al.* 1998). Fuel volume and loading are not only important in empirically understanding fire behavior and fire effects, but are drivers of models used to simulate fire behavior (Andrews and Queen 2001; Scott and Burgan 2005). Surface fuelbed characteristics have traditionally been quantified by both direct and indirect methods. Direct measurements commonly employed are tallies of down woody fuels along planar transects (Brown 1974), and coupled destructive biomass sampling (i.e. 'clip plots') (Brown 1981). Indirect methods include visual cover estimates in plots or comparisons with photographs of known fuel loads or types (Ottmar *et al.* 2003; Keane and Dickinson 2007). These methods allow for stand level estimation of variables, such as fuel load, bulk density,

and packing ratios that are then used to predict fire behavior (Burgan and Rothermel 1984; Reinhardt and Keane 1998; Andrews *et al.* 2004).

Each method has significant limitations. Direct sampling is labor-intensive, often limiting sample size. Some techniques are not appropriate for all fuel types: planar transects are not efficient at estimating fine fuels such as grasses. Indirect measures can be subjective, resulting in biased estimates. Furthermore, estimating volume for bulk density calculations relies on unrealistic simplifications; shrub or grass volumes are calculated by assuming the plants form simple geometric shapes such as a spheroid or cylinder (Van Wagner 1968) (Fig. 1a). Such traditional volume measurement techniques ignore complex plant architecture. Although these approaches are recognized to have inherent limitations, no alternatives were previously available.

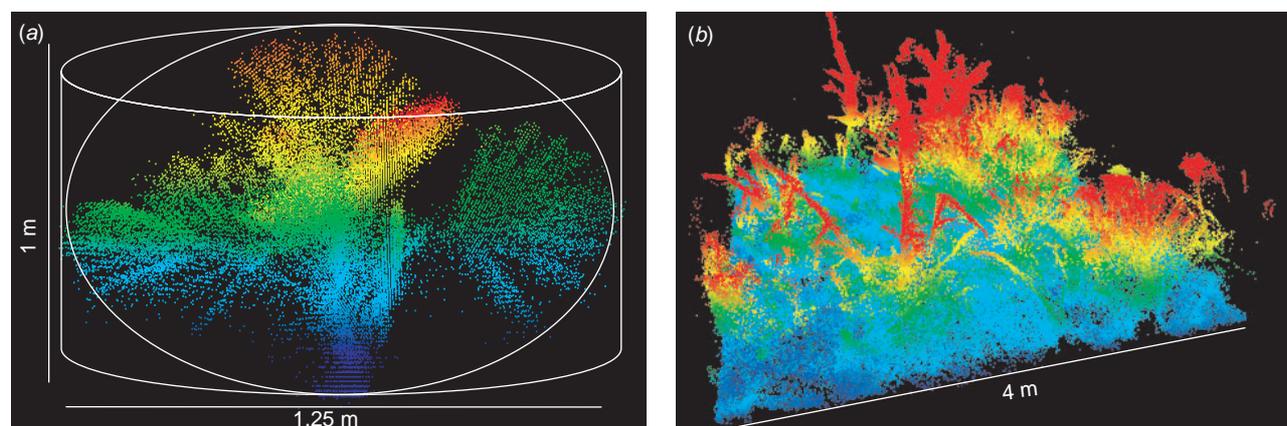


Fig. 1. Output 3-D point-clouds from the ground LIDAR system for: (a) an individual saw palmetto shrub, and (b) a 4 × 4-m plot in a longleaf pine savanna fuelbed (max fuelbed height in plot: 2 m). Note that fuel volume of a plant is commonly measured by assuming a cylindrical or spheroid geometry (a).

Recent advances in laser ranging, or LIDAR, technologies have enabled the successful measurement of complex structures in the field with both high accuracy and precision (Hopkinson *et al.* 2004). LIDAR has been typically used in forestry for large-scale remote sensing of forest canopy structures, estimating tree height distributions, canopy bulk density, and leaf area (Nelson *et al.* 1988; Lefsky *et al.* 1999; Drake and Weishampel 2000; Hall *et al.* 2005; Roberts *et al.* 2005; Lee *et al.* 2009). These airborne LIDAR approaches have been unsuited, however, in measuring understorey vegetation, primarily because of the obstruction from the forest canopy and a horizontal resolution limited to the few-decimetre scale. Modern ground-based LIDAR systems now have some of the strengths of airborne systems (in particular laser pulse rates of a few thousand Hz or more that enable high-resolution sampling), but they can attain subcentimetre resolution and be positioned under the canopy to reduce the shadowing effects of overstorey trees (Slatton *et al.* 2004). The high-density three-dimensional (3-D) point data (more than 10 000 points per m²) obtained from such systems provide the precision needed to characterize fuelbeds, particularly by quantifying fuel height distributions and thus fuel volumes.

One system in particular, the Mobile Terrestrial Laser Scanner (MTLS), is a static, stop-and-scan laser scanner that covers a limited area, but captures data at the sub-cm level. The MTLS consists of Optech's ILRIS 3₆D (Intelligent Laser Ranging and Imaging System) (Vaughan, Ontario, Canada) ground-based laser scanner (Lichti *et al.* 2002; Fröhlich and Mettenleiter 2004), which was mounted on a lift atop a mobile platform (4 × 4 truck) by the National Center for Airborne Laser Mapping (NCALM) at the University of Florida. The MTLS is versatile in capturing details about the terrain at multiple angles. The ability to vary the LIDAR height and pointing angle using the MTLS allows significant reduction in shadowing effects that may be found when using a LIDAR system on a tripod.

Although ground-based LIDAR (also called terrestrial LIDAR) is a relatively new technique, there are several good examples of forestry applications. Accurate tree and canopy metrics (e.g. timber volume, tree height and diameter, gap fraction) have been successfully estimated using tripod-mounted terrestrial LIDAR systems (Hopkinson *et al.* 2004; Watt and

Donoghue 2005; Henning and Radtke 2006). Fine-scale leaf area (Lovell *et al.* 2003; Tanaka *et al.* 2004) and gap fraction (Danson *et al.* 2007) estimates of tree canopies have been correlated with that of hemispherical photographs. Small individual trees were intensely measured using a voxel-based approach to determine leaf area density at the mm³ scale (Hosoi and Omasa 2006). Ground-based LIDAR has also been used to understand the impacts of instrument positioning on shadowing effects that influence tree canopy measurements (Van der Zande *et al.* 2006). Although most terrestrial LIDAR systems used in forestry are stationary, a portable LIDAR system has been developed to record 1-m scale canopy measurements while moving through a forest (Parker *et al.* 2004). To our knowledge, ground-based systems have yet to be reported as a means of surface fuel characterization.

The objective of the present manuscript is to describe a ground-based LIDAR approach to measure fuel volume and loading. We first used LIDAR to measure individual shrubs of two common species with contrasting life-forms found in pine flatwoods of the south-eastern US coastal plain. Specifically, we tested the hypothesis that LIDAR volumes would be significantly less than those obtained from traditional means. We also determined if LIDAR volume measurements were correlated with mass and leaf area. We examined LIDAR characterization of complex fuelbeds, composed of many species of shrubs and herbaceous plants in the field. We compared how LIDAR measurements of fuelbed heterogeneity differed from traditional point intercept measures.

Methods

Ground LIDAR instrumentation

The ILRIS ground-based LIDAR system uses a 1535-nm wavelength (near-infrared) laser with a pulse frequency of 2000 Hz (or points per second), recording first or last returns of each laser pulse (user-defined). The maximum field of view is 40° in both horizontal and vertical planes, although smaller fields of view can be specified for a given scan. It can register laser returns from as little as 5 m away and out to a distance of 1500 m (at 80% target reflectivity). The particular ILRIS used in the current work has a pan-tilt base on the MTLS, which allows for a

Table 1. Manufacturer specifications of the ground-LIDAR instrument (Optech's ILRIS 36D) used in the present research

Note that the beam divergence value corresponds to a circular footprint diameter of 4 mm at an average range of 25 m. IFOV, Instantaneous Field of View; Aux FOV, Auxiliary Field of View, which refers to the range of motion of the tilt and pan mounting for the LIDAR sensor. Texture refers to the radiometric values, which include a relative intensity of the return laser pulse and multispectral (red, green, blue – RGB) values from a co-mounted digital camera

Specification type	Specification value
Range (m)	3–1500 at 80% reflectance; 3–800 at 20% reflectance; 3–350 at 4% reflectance
Range resolution (mm)	4
Azimuth, elevation resolution (°)	0.00115
IFOV (vertical° × horizontal°)	40 × 40
Aux FOV (vertical° × horizontal°)	–20 to 90 × 360
Laser type or color	Infrared
Laser wavelength (nm)	1500
Scan rate (points per s or Hz)	2000
Beam divergence (°)	0.00974
Texture	Intensity and RGB
Weight (kg)	12
Dimensions (L × W × H) (cm)	32 × 32 × 22
Power supply	24 V DC
Power consumption (W)	75

360° rotation in the horizontal plane and roughly $\pm 40^\circ$ in the vertical plane. ILRIS specifications are summarized in Table 1. The lift on the MTLs provides for a vertical adjustment of the scanner up to a height of ~ 9 m. Recording laser data from multiple positions around the target clearly will reduce information lost from shadowing effects, but an efficient imaging geometry is desired to minimize the number of scans required to sample each plot. The ability to adjust the instrument vertically and horizontally to the extent offered by the MTLs allows the user to achieve advantageous scan positions and orientations in spite of constraints posed by the terrain or nearby occluding trees, which is essential to measuring precise fine-scale attributes of intricate plant structures (Hosoi and Omasa 2006).

Point spacing in LIDAR point clouds will vary locally depending on the range from the laser to objects in the field of view and on the angular spacing of laser shots. For the ILRIS sensor, the pulse rate is fixed at 2000 Hz. So it is the angular separation of laser pulses that is used to achieve a desired point density, which is input via the ILRIS Controller software. To achieve this, the ILRIS pre-scans the user-specified field of view at a coarse resolution and acquires an average range. The user then enters a desired linear point spacing into the ILRIS Controller software. This spacing corresponds to the average linear separation between points on a hypothetical plane segment that spans the user-specified field of view, is located at the mean range, and is orthogonal to the sensor's boresight. Given this separation distance and the mean range, the necessary angular shot spacing is automatically calculated by the ILRIS Controller software. Under typical operating conditions, the linear point spacing is chosen to be anywhere from a few cm to 1 mm. High point densities come at the cost of increased memory to hold

the data and increased time to complete the scan. For example, a $20^\circ \times 20^\circ$ field of view centered at boresight with a mean range of 15 m and user-specified linear point spacing of 5 mm will yield an angular separation of 0.0189° , require roughly 9 min to complete, and result in just over 1.1 million points.

The ILRIS collects: (1) x , y , z coordinate values with respect to the position of the laser sensor; (2) intensity values of the return; and (3) true color (RGB – red, green, blue) values for each point obtained from an integrated and calibrated digital camera within the instrument. A more complete description of the technology can be found in Fröhlich and Mettenleiter (2004) and Lichti *et al.* (2002). Once an area is sampled by two or more scans, the point clouds from each scan are merged into a common coordinate frame using software that can accommodate 3-D spatial data (see *Data processing and analysis*). Inside the software environment, the subset of the point cloud that covers the region of interest can be isolated and the remaining points cropped out to minimize the computational burden and obtain statistics representative of the precise region of interest.

Individual shrub assessment

In May 2007, we collected ground-LIDAR measurements for two common south-eastern US shrub species: saw palmetto (*Serenoa repens*) and wax myrtle (*Myrica cerifera*). These species are highly flammable and important wildland fuels (Wade *et al.* 1989). Using the ILRIS, we scanned 12 individually potted shrubs in two size classes (i.e. 0.5 and 1 m in height, six for each species) within an enclosed building at the University of Florida. This provided an ideal setting for laser-scanning with flat ground and minimal wind disturbance. Six plants were scanned at a time, using reference targets for subsequent LIDAR data processing (see *Field plot data collection*). Three scans were taken per set of plants (six scans total). After LIDAR acquisition, volume was recorded using traditional field methods, by calculating geometric (cylinder and spheroid) volumes using height and diameter measurements. To more fully analyze the structural variation, we cut the shrubs into three equally spaced vertical sections (or thirds) and measured leaf area using a LI-COR leaf area analyser for each section (LI-COR Biotechnology, Lincoln, NE). Biomass was dried and weighed for each section. The shrub LIDAR point clouds were also divided into thirds for volume estimation (see *Data processing and analysis*) to compare with the biomass and leaf area measurements.

Field assessment of complex fuelbeds

Research site: Ichauway Reserve

The in-field portion of the research was performed at Ichauway, an 11 000-ha reserve of the Jones Ecological Research Center in south-western Georgia, USA. Ichauway is located within the Plains and Wiregrass Plains subsections of the Lower Coastal Plain and Flatwoods section (McNab and Avers 1994). Ichauway has an extensive tract of second-growth longleaf pine and has been managed with low-intensity, dormant-season prescribed fires for at least 70 years, at a frequency of 1 to 3 years. The understory of the study area is primarily composed of wiregrass (*Aristida stricta*), many forb and prairie grass species, as well as interdispersed hardwood shrubs (e.g. *Diospyros* spp., *Prunus* spp., *Quercus* spp., *Sassafras albidum*). With frequent

fires, hardwoods are generally maintained at shrub size, occasionally reaching mature size. The specific study area had not burned for 1 year.

Field plot data collection

In spring 2007, a total of 26 georeferenced 4 × 4-m plots were established to measure fuelbed characteristics. The 4 × 4-m area was chosen because it was large enough to capture heterogeneity at submetre scales, but small enough to support intensive sampling with minimal impact to the vegetation. A ladder was suspended horizontally across the plot to sample the interior with minimal disturbance to the vegetation. Spatially explicit point-intercept (PI) fuel data (169 samples, 0.33-m grid spacing) were recorded using a 5-mm graduated dowel within each plot. Only vegetation in physical contact with the dowel was measured. At each PI sample point, maximum fuelbed and litter depth (or height), as well as presence or absence of fuel and vegetation types were recorded. The georeferencing and sampling intensity were used to capture the spatial variation of the fuelbed found within this small (16 m²) area and to relate to the subcentimetre-scale 3-D laser data collected from the ground-based LIDAR.

Within 2 weeks of field data collection, the MTLs collected ground-LIDAR data on all 26 plots. Prior to laser data collection, reference targets (consisting of a Styrofoam ball on top of a metal rod, 0.5–1 m high) were placed at all four corners of the plot. A double reference target (two Styrofoam balls on one metal rod) was used at the north-west corner of each plot to orient the plot for data processing. The MTLs was restricted to mapped roads and trails, as well as a buffer of 5 m around each plot, to reduce vegetation disturbance. The ILRIS was lifted to a height of 7 m to capture a more aerial view of the plot to reduce shadowing effects and positioned to avoid tree bole or canopy obstruction. The ILRIS was set to a downward angle tilt of 25° from horizontal. A true-color digital photograph was taken by the ILRIS for each plot, and used in the field to delineate the precise field of view for each scan. First-return laser pulses were recorded with an input mean point spacing of 5 mm. Two scans were taken of each plot, from opposite sides, to mitigate shadowing effects and ensure more accurate and complete subcentimetre-scale data for fuel plots. These two scans were merged in the processing stage to a single 3-D point cloud dataset. Data collection with the MTLs took ~20 min per plot. In comparison, field PI data collection lasted an average of 2 h per plot.

Data processing and analysis

Initially, data processing involved converting the collected laser data from binary to ASCII format. These raw data include a four-column text file containing 3-D orthogonal coordinates (x , y , z) and laser return intensity values for each of the sampled laser points. For the present work, the 'Quick Terrain Modeler' (Applied Imagery, Silver Spring, MD) and 'TerraScan' (Terrasolid, Jyväskylä, Finland) software packages were used for processing the laser data, although the 'PolyWorks' software package (InnovMetric, Quebec City, QC, Canada) that is sold with the ILRIS would also have been suitable. Of the two scans taken per plot, the first was horizontally rectified by compensating for the original scanning geometry, as the instrument had a

downward tilt of 25° with respect to horizontal. The reference targets were used to identify common points between the two scans and create a common 3-D coordinate frame for both scans (see Wolf and Ghilani 1997 for details). The second scan was adjusted to fit the same 3-D coordinate frame as the first, which combined them into a single spatially consistent dataset. The digital image and the double target reference for the NW corner of the plot were especially helpful in this merging process and in orienting the plot in cardinal space. Similar procedures were performed for the individual shrub data. The individual shrubs (Fig. 1a) and 4 × 4-m plot areas (Fig. 1b) were clipped from the resulting merged scans using the reference targets. Roughly 600 000 to 700 000 sample laser points were found within each 4 × 4-m plot. Point densities, volume estimates, and height distributions were measured using the merged LIDAR scans of each 4 × 4-m plot and individual shrubs.

It should be noted that when ranging to objects distributed in three dimensions, the actual 3-D point spacing may be larger than the 2-D spacing input by the user into the ILRIS Controller software for an equivalent range because of the added depth component. For example, the specification of a 5-mm linear spacing at the mean range might seem to suggest an average point spacing of 2.5 mm when two similar scans from different viewing directions are merged. But the actual 3-D Euclidian separation distance between points in all such merged scans for the forest plots was found to be roughly 1 cm on average, with a roughly 5-mm standard deviation.

Volume was calculated using the LIDAR laser data as well as field measurements. LIDAR volume estimates were calculated in two ways. First, volume was calculated by determining the presence or absence of laser points within each cm³ space (similar to the 'voxel' approach in Hosoi and Omasa 2006, and Van der Zande *et al.* 2006) for each whole potted shrub and the three equally spaced vertical sections (or thirds) of each shrub. The process involved using a 1-cm³ 3-D window to move through each point cloud in the horizontal and vertical directions respectively. Every time a point (or points) was found in the 3-D window, 1 cm³ of volume was added to the sum for that shrub or section of shrub. Second, a surface plot (continuous rendering or TIN – Triangulated Irregular Network) was created using traditional kriging techniques for both the LIDAR and PI grid field data (4 × 4-m plots only) using fuel depth (height) values. The total volume (m³) found underneath this surface was calculated for each LIDAR and PI 4 × 4-m dataset. Volume of the whole potted shrubs was also calculated using field measurements (height and diameter) and applying common volumetric formulae for both a cylinder and spheroid.

A paired one-way *t*-test was used to assess differences between whole-plant shrub volumes calculated by LIDAR (LIDAR volume) and by traditional field methods (cylindrical and spheroid volume). We tested the hypothesis that traditional field methods would overestimate individual shrub volume compared with LIDAR and that the cylindrical volume would be larger than the spheroid volume estimates. An ANOVA was used to assess if volume estimates of the whole shrubs differed when affected by the following three factors: (1) volume estimation technique (LIDAR and traditional field methods: cylinder and spheroid); (2) shrub species (saw palmetto and wax myrtle); and (3) size of plant (large and small). Additional ANOVA tests were

Table 2. ANOVA output analyzing individual whole shrub volume (m^3) estimates with three treatments: (A) volume estimation method (LIDAR, cylinder, spheroid); (B) plant size (large, small); and (C) shrub species (wax myrtle, saw palmetto)

Source term	d.f.	Sum of squares	Mean square	F ratio	Probability level	Power ($\alpha = 0.05$)
A: Method	2	0.1557	0.0779	75.59	0.000000*	1.0000
B: Size	1	0.2549	0.2549	247.48	0.000000*	1.0000
AB	2	0.1109	0.0554	53.82	0.000000*	1.0000
C: Species	1	0.0401	0.0401	38.98	0.000002*	1.0000
AC	2	0.0220	0.0110	10.67	0.000483*	0.9791
BC	1	0.0283	0.0283	27.44	0.000023*	0.9989
ABC	2	0.0155	0.0077	7.52	0.002920*	0.9127
S	24	0.0247	0.0010			
Total (adjusted)	35	0.6521				
Total	36					

*Term significant at $\alpha = 0.05$.

used to assess the effects of size, species, and their interactions on whole shrub biomass, leaf area, LIDAR volume, and volume estimated by traditional field methods.

ANOVA was used to assess the differences in LIDAR volume, biomass, and leaf area estimates of the sectional shrub data with shrub volume split into thirds using three treatments: (1) shrub species (saw palmetto and wax myrtle); (2) bottom, middle, top third section of plant; and (3) shrub size (large, small). Least-squares simple linear regression tested the relationships among LIDAR volume, biomass, and leaf area of the sectional shrub data.

A paired two-tailed *t*-test was used to compare the 4×4 -m plot LIDAR volume estimates and PI volume. Regression analyzed how LIDAR and PI volume estimates varied over a range of fuelbed volumes. To analyze the spatial variability within the 4×4 -m plots, we created empirical variograms of the PI and LIDAR datasets. The *Surfer 8* program (Golden Software Inc.) was used to create the variograms with the following settings: omnidirectional lag tolerance, maximum lag tolerance of 3 m, 25 lags, and a 0.4-m maximum lag width for plot smoothing. All statistical assumptions were met and Type I error was set at 0.05 for all tests.

Results and discussion

We found that ground-based LIDAR was able to capture precisely defined volumes of fuels at both the individual shrub scale and within complex herbaceous fuelbeds (Fig. 1). While ground-based LIDAR has been used to accurately define the volume of overstorey trees (Hopkinson *et al.* 2004), this is the first application of ground-based LIDAR aimed downward to assess fuel characteristics. There were discrepancies found between the three volumetric measurement techniques of individual shrubs as well as differences associated with plant size and species (Table 2). Compared with LIDAR, both traditional methods of measuring volume (i.e. cylindrical and spheroid calculations) of individual shrubs were significantly larger than LIDAR estimates (Fig. 2; $P < 0.0038$, $n = 12$). Not surprisingly, the cylindrical measurements were larger than the spheroid measurements ($P = 0.0029$, $n = 12$). The extent of the discrepancy between LIDAR and field measurements varied with species and

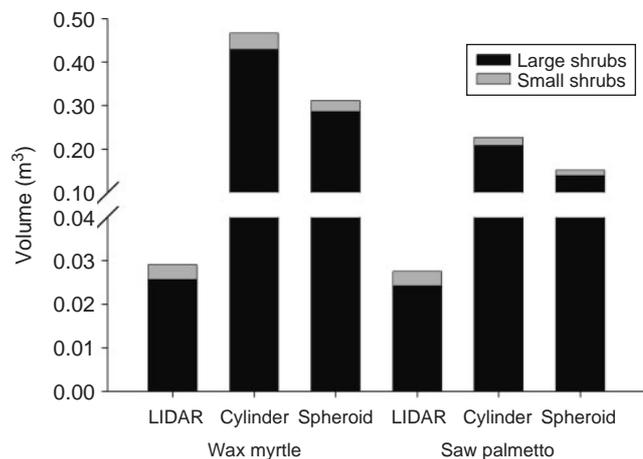


Fig. 2. Variation of volume for two plant species (saw palmetto and wax myrtle), two sizes (large and small) and the methods used to calculate volume (LIDAR v. traditional sampling: cylinder and spheroid). Note the broken y-axis to see smaller changes in LIDAR volume estimates.

size because of variation in the distribution of leaf area. Larger plant sizes resulted in greater differences of volumes between sampling methods (Fig. 2). LIDAR shrub volume did not significantly vary by species. Species was significant for traditional volume methods, biomass, and leaf area ($P < 0.006$, $n = 12$).

The discrepancy between LIDAR and traditionally estimated volume resulted from two factors. This disparity can be attributed to variation in shrub structure and the assumed geometry used to calculate traditional volume (Fig. 1a), as well as uneven distribution of leaf area within a shrub (Table 3). By segregating individual shrubs into thirds ($n = 36$) and using LIDAR, we were able to capture the distribution of leaf area. As such, section-specific volume estimations of each species were evident (Fig. 3). Subsequent analysis shows that species, plant size, and plant section significantly interacted to influence LIDAR volume, biomass, and leaf area (Table 3). Using the section data across all species and sizes, we were able to show a strong linear relationship between LIDAR volume and biomass ($R^2 = 0.83$) and leaf area ($R^2 = 0.70$, Fig. 4, Table 4). This suggests that

Table 3. ANOVA output analyzing sectional shrub (1) LIDAR volume (m³); (2) biomass (\sqrt{g}); and (3) leaf area ($\sqrt{m^2}$) estimates with three treatments: (A) plant species (wax myrtle, saw palmetto); (B) plant section (bottom, middle, top); and (C) plant size (large, small)

Source term	d.f.	Sum of squares	Mean square	F ratio	Probability level	Power ($\alpha = 0.05$)
(1) LIDAR volume						
A	1	4.70×10^{-7}	4.70×10^{-7}	0.28	0.602874	0.080
B	2	8.83×10^{-5}	4.42×10^{-5}	26.12	0.000001*	1.000
AB	2	1.81×10^{-5}	9.07×10^{-6}	5.36	0.011881*	0.791
C	1	4.68×10^{-4}	4.68×10^{-4}	276.55	0.000000*	1.000
AC	1	2.58×10^{-7}	2.58×10^{-7}	0.15	0.699738	0.066
BC	2	5.45×10^{-5}	2.72×10^{-5}	16.11	0.000037*	0.999
ABC	2	1.60×10^{-5}	8.01×10^{-6}	4.74	0.018454*	0.737
S	24	4.06×10^{-5}	1.69×10^{-6}			
Total (adjusted)	35	6.86×10^{-4}				
Total	36					
(2) Biomass						
A	1	2.15	2.15	4.51	0.044130*	0.532
B	2	50.53	25.27	53.10	0.000000*	1.000
AB	2	4.11	2.06	4.32	0.024934*	0.695
C	1	67.34	67.34	141.51	0.000000*	1.000
AC	1	0.39	0.39	0.82	0.374606	0.140
BC	2	8.64	4.32	9.08	0.001159*	0.956
ABC	2	2.35	1.17	2.47	0.106045	0.447
S	24	11.42	0.48			
Total (adjusted)	35	146.93				
Total	36					
(3) Leaf area						
A	1	1199.63	1199.63	40.28	0.000001*	1.000
B	2	4544.19	2272.09	76.29	0.000000*	1.000
AB	2	191.04	95.52	3.21	0.058288	0.557
C	1	4840.19	4840.19	162.52	0.000000*	1.000
AC	1	21.10	21.10	0.71	0.408241	0.128
BC	2	757.72	378.86	12.72	0.000171*	0.992
ABC	2	272.65	136.32	4.58	0.020702*	0.721
S	24	714.78	29.78			
Total (adjusted)	35	12 541.30				
Total	36					

*Term significant at $\alpha = 0.05$.

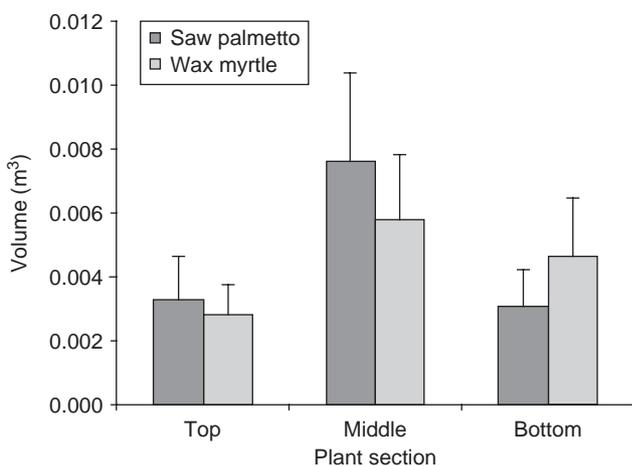


Fig. 3. Mean volume and standard errors of vertical sections (equal thirds) of two pine-flatwood shrub species ($n = 36$; 12 plants, three sections each).

knowledge of the vertical arrangement of the plant as well as size is critical for accurately estimating plant volumes. The accuracy of the LIDAR volume calculations (using a 3-D moving window, see *Data processing and analysis*) can be supported by the fact that the laser point-density distributions are directly impacted by plant structure and size (Fig. 1) when shadowing effects are minimized (i.e. using multiple scan angles). Shrub 3-D spatial variability (related to volume, biomass, and leaf area) typically increases with size. This stresses the need for more accurate volume estimates of complex understory fuelbeds, where shrub or other plant sizes vary and where volumes of larger shrubs (>0.5 m in height) may be more severely overestimated than smaller shrubs when using traditional methods. These results could be critical for the successful application of ground-based LIDAR for surface fuels assessments and represent a unique capability of LIDAR relative to traditional methods. For example, applying this ground-based LIDAR approach for estimating volumes at a larger plot or management unit level is foreseeable with the versatility of the MTLs (e.g. truck and instrument

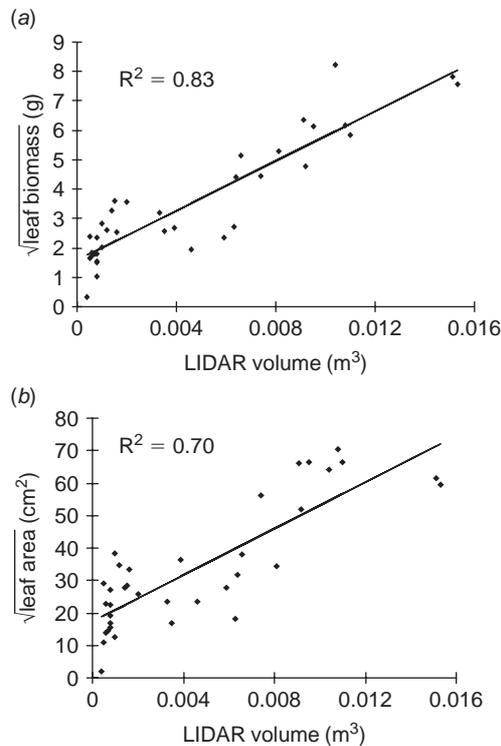


Fig. 4. Linear relationships of LIDAR volume estimates with (a) leaf biomass, and (b) leaf area measurements of all 12 individual shrubs, divided into three equal vertical sections ($n = 36$).

mobility, vertical and horizontal angular positioning, ranging up to 1500 m), especially within the open mid-storey of this savanna-type woodland.

Overall, the use of this small cubic space (1 cm^3) to calculate volume for the individual shrubs proved advantageous for several reasons. First, the voxel approach minimized the possibility of overestimating volume because the overlapping laser points that may have been collected from the same plant canopy element (i.e. from merging of scans) were represented as a single volumetric unit (cm^3) rather than a raw point count. Hosoi and Omasa (2006) concluded that the ability to capture all of the plant canopy elements fully and evenly through the use of several scans and scanning angles outweighs the possibility of overestimating volume, and such overestimation is minimized by using a small voxel. Without multiple scans, volume may be severely underestimated because of the significant loss of laser data on the 'shadowed' side of the plant, which may require further statistical procedures to correct (Van der Zande *et al.* 2006). This technique also provided the ability to measure volume at various scales of plant size as well as estimate volume, leaf area, and biomass for various portions of the plant. This is especially useful when plants are larger or highly complex in structure or shape and assumptions about plant geometry (i.e. cylinder, spheroid) become less reliable.

At the fuelbed scale ($4 \times 4\text{-m}$ plots), the volume estimates from traditional point-intercept sampling and LIDAR were linearly correlated ($R^2 = 0.48$; Fig. 5) and were not significantly

Table 4. Linear regression relating LIDAR volume (m^3) to biomass (g), and leaf area (m^2) from sectional shrub data
Model used: $f(x) = b_0 + b_1(\text{LIDAR volume})$

Dependent variable	n	R^2	RMSE
$\sqrt{\text{leaf biomass}}$	36	0.83	0.87
$\sqrt{\text{leaf biomass, large shrubs only}}$	18	0.78	0.96
$\sqrt{\text{leaf biomass, small shrubs only}}$	18	0.60	0.56
$\sqrt{\text{leaf area}}$	36	0.70	10.51
$\sqrt{\text{leaf area, large shrubs only}}$	18	0.62	12.02
$\sqrt{\text{leaf area, small shrubs only}}$	18	0.33	8.03

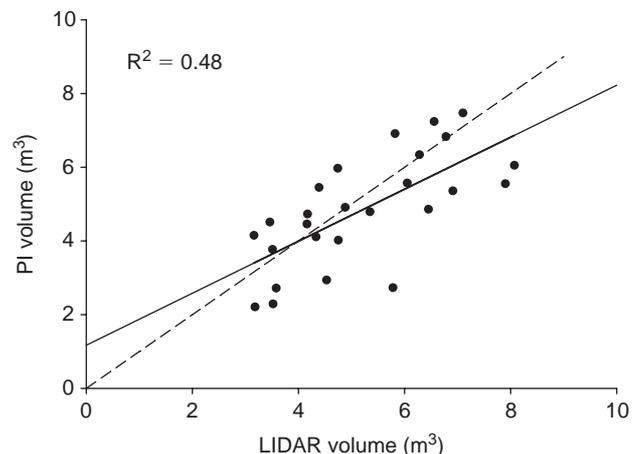


Fig. 5. Linear correlation between kriged surface volumes calculated from ground LIDAR and point-intercept (PI) field sampling. Solid line: calculated regression line. Dotted line: 1 : 1 line.

different from one another ($P = 0.12$). The slope of the regression line was not significantly different from a 1 : 1 relationship (CI – confidence interval – for slope ranged from 0.39 to 1.01; CI for intercept ranged from -0.5 to 2.87). This suggests that fuelbed volume may be estimated at submetre scales using either method with similar results. The lack of variation captured in the model may be explained by the difference in sampling intensity (0.33 v. ~ 0.005 m) between the PI data and LIDAR data respectively.

The aggregation of fuels within a fuelbed (and thus variance) influences the relative accuracy of traditional point-intercept sampling when compared with LIDAR. The empirical variograms of the $4 \times 4\text{-m}$ plots illustrated that the spatial distribution of fuelbed heights within a relatively small area (16 m^2) is highly variable at multiple scales. This is illustrated by the changing slope within the variogram plot (Fig. 6). High spatial variation at very small scales was observed (< 1 m lag distance). These small-scale patterns in variation can be observed within the variograms and were more evident within the LIDAR data compared with the PI data (Fig. 6a, d). Some plots displayed a more bi-modal distribution of spatial variance (e.g. Fig. 6b), indicating abrupt changes in fuelbed heights. These plots consisted of a very low continuous fuelbed of grasses and forbs,

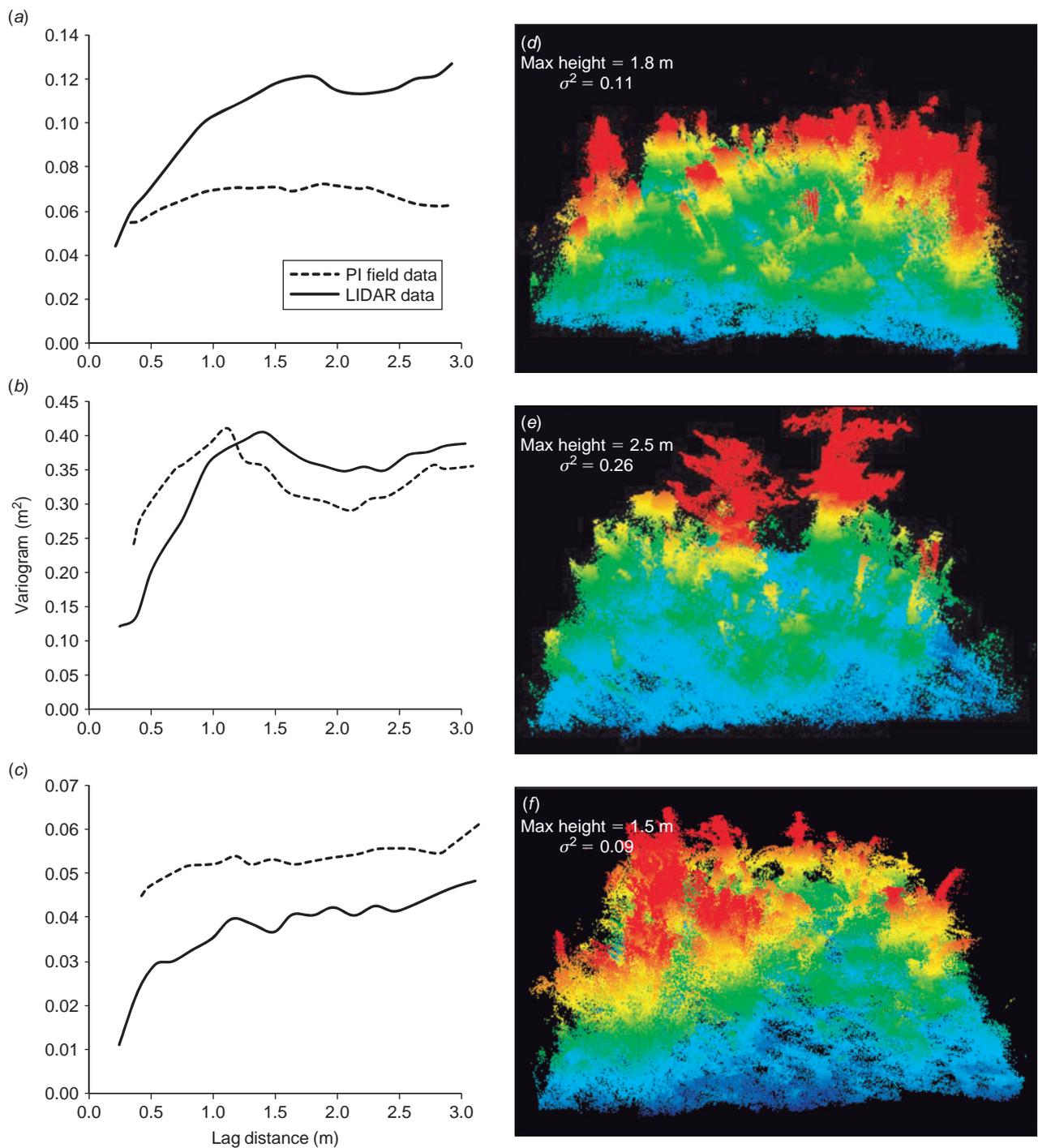


Fig. 6. Examples of spatial variation (empirical variogram) of fuelbed heights found within three 4 × 4-m plots recorded by point intercept (PI) field sampling and ground LIDAR. Here we illustrate: (a) how multiple scales of spatial variation (~0–1.5 m and 2–3 m) may only be evident with the LIDAR data; (b) how strong correlations between LIDAR and field sampling may be found with high spatial variation (compared with a, c) and strong fluctuations of spatial continuity (i.e. low fuels with interdispersed shrubs) across the plot; and (c) how a linear distribution of overall low height variation (compared with a, b) may be found, representing a more random distribution of low fuelbed depths and possibly fuel types. LIDAR imagery (d–f) provides a 3-D visual representation of fuelbed height distributions and height (m) statistics associated with each variogram (a–b) respectively. Note scale is different between graphs, and color gradients in the LIDAR imagery are relative to vertical height distributions within each plot.

with a few large interdispersed shrubs (Fig. 6e). Other plots had a more linear distribution of spatial variance (Fig. 6c), suggesting more consistently independent heights within the dataset. These fuels were more randomly distributed with clustering only found within fuels found near the ground, namely forbs, some grasses and pine litter (Fig. 6f). We determined that the LIDAR data were more reliable than the PI data for measuring surface fuel height distributions for two reasons. First, the LIDAR data create a much lower nugget effect (errors of spatial variation or measurement) than the PI data. Second, the LIDAR data were more sensitive to subtle changes in spatial heights at fine scales. This was seen by comparing the (non-spatial) variance (σ^2) and spatial variance (variogram) of fuelbed heights within a plot. The higher the σ^2 , the more likely the PI data detected spatial changes in height, whereas the LIDAR data continued to detect changes at smaller σ^2 values (e.g. compare Fig. 6b (larger variance) with Fig. 6a, c (smaller variance)). Not surprisingly, this discrepancy is mainly because of the high concentration of LIDAR points compared with those that can be obtained through PI methods. It is important to note that the field effort to obtain this degree of accuracy through LIDAR was considerably less than that of point intercept for all plots in this study.

Application

Ground-based LIDAR efficiently captured fine-scale fuelbed characteristics related to plant structure, specifically height and volume. Its precision compared with traditional methods is explained by LIDAR's ability to capture the actual vegetation structure *v.* an assumed geometry. For discrete shrubs, we demonstrated that ground-based LIDAR can accurately measure volumes that can be used to derive biomass and leaf area. This is particularly useful in shrubby fuelbeds, such as pocosin, chaparral or south-eastern pine flatwoods, where destructive harvesting of fuels for biomass is logistically difficult. In similar ecosystem types where prescribed burning is less frequent (hence larger fuel buildup) or in larger plots or management units, this laser-technology may still be applicable for estimating fuelbed volume. The surface grid technique of estimating volume beneath a 3-D rendering (used for the 4×4 -m plots) would be especially useful. The size of the area that can be captured with the MTLs is only bound by time for data collection and processing and hard drive space. Shadowing effects, however, seem to be the limiting factor when capturing distinct spatial plant structure and may become more difficult to obtain where fuels are thicker or denser. This can be minimized with multiple scans (particularly from elevated positions), careful positioning of the MTLs, and thorough processing techniques (merging of scans and removing trees).

Fire behavior prediction system software is sensitive to fluctuations in parameters associated with fuelbed height measurements, such as calculating volume and fuel density (Andrews and Queen 2001; Scott and Burgan 2005). Volume is especially difficult to measure, compared with mass estimates in many fuelbeds, because of the complex structure. As shown in the present study, LIDAR provides an opportunity for improving measurements of fuelbed properties that drive fire behavior and possibly enhance the accuracy of fire behavior prediction models. Moreover, LIDAR has the capacity to measure those

characteristics with a precision and at a finer scale than is afforded by traditional methods. The degree to which such fine-scale heterogeneity is critical to fire behavior and fire effects is not currently known but can only be tested by the development of methods with the capacity for such measures. This approach to using ground-based LIDAR is promising in this aspect, as both measurements of the physical structure of fuelbeds and discrete fuel types can be sampled non-destructively and analyzed in a spatially explicit context. By understanding how fuel structure and fine-scale volume vary among fuels, we hope to better understand how other fuel characteristics, such as surface area-to-volume ratios, packing ratio, fuel continuity, and patchiness affect fire behavior.

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References

- Andrews P, Bevens C, Seli R (2004) BehavePlus fire modeling system, version 3.0: user's guide. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-106WWW. (Ogden, UT)
- Andrews PL, Queen LP (2001) Fire modeling and information system technology. *International Journal of Wildland Fire* **10**, 343–352. doi:10.1071/WF01033
- Brown JK (1974) Handbook for inventorying downed woody material. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report GTR-INT-16. (Ogden, UT)
- Brown JK (1981) Bulk densities of non-uniform surface fuels and their application to fire modeling. *Forest Science* **27**, 667–683.
- Burgan RE, Rothermel RC (1984) BEHAVE: fire behavior prediction and fuel modeling system – FUEL subsystem. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-GTR-167. (Ogden, UT)
- Danson FM, Hetherington D, Morsdorf F, Koetz B, Allgower B (2007) Forest canopy gap fraction from terrestrial laser scanning. *Geoscience and Remote Sensing Letters, IEEE* **4**, 157–160. doi:10.1109/LGRS.2006.887064
- DeBano LF, Neary DG, Ffolliott PF (1998) 'Fire Effects on Ecosystems.' (Wiley: New York)
- Drake JB, Weishampel JF (2000) Multifractal analysis of canopy height measures in a longleaf pine savanna. *Forest Ecology and Management* **128**, 121–127. doi:10.1016/S0378-1127(99)00279-0
- Fröhlich C, Mettenleiter M (2004) Terrestrial laser scanning – new perspectives in 3D surveying. In 'Laser-Scanners for Forest and Landscape Assessment'. pp. 7–13. (International Archives of Photogrammetry, Remote Sensing and Spatial Sensing: Freiburg, Germany)
- Hall SA, Burke IC, Box DO, Kaufmann MR, Stoker JM (2005) Estimating stand structure using discrete-return Lidar: an example from low-density, fire-prone ponderosa pine forests. *Forest Ecology and Management* **208**, 189–209. doi:10.1016/J.FORECO.2004.12.001
- Henning JG, Radtke PJ (2006) Ground-based laser imaging for assessing three-dimensional forest canopy structure. *Photogrammetric Engineering and Remote Sensing* **72**, 1349–1358.
- Hopkinson C, Chasmer L, Colin Y-P, Treitz P (2004) Assessing forest metrics with a ground-based scanning lidar. *Canadian Journal of Forest Research* **34**, 573–583. doi:10.1139/X03-225

- Hosoi F, Omasa K (2006) Voxel-based 3-D modeling of individual trees for estimating leaf area density using high-resolution portable scanning Lidar. *IEEE Transactions on Geoscience and Remote Sensing* **44**, 3610–3618. doi:10.1109/TGRS.2006.881743
- Keane RE, Dickinson LJ (2007) The photoload sampling technique: estimating surface fuel loadings from downward-looking photographs of synthetic fuelbeds. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-190. (Fort Collins, CO)
- Lee H, Slatton KC, Roth B, Cropper WP (2009) Prediction of forest canopy light interception using three-dimensional airborne LiDAR data. *International Journal of Remote Sensing* **30**, 189–207.
- Lefsky MA, Cohen WB, Acker SA, Parker GG, Spies TA, Harding D (1999) Lidar remote sensing of the canopy structure and biophysical properties of Douglas-fir western hemlock forests. *Remote Sensing of Environment* **70**, 339–361. doi:10.1016/S0034-4257(99)00052-8
- Lichti DD, Gordon SJ, Stewart MP (2002) Ground-based laser scanners: operation, systems and applications. *Geomatica* **56**, 21–33.
- Lovell JL, Jupp DLB, Culvenor DS, Coops NC (2003) Using airborne and ground-based Lidar to measure canopy structure in Australian forests. *Canadian Journal of Remote Sensing* **29**, 607–622.
- McNab WH, Avers PE (Eds) (1994) 'Ecological Subregions of the United States: Section Descriptions.' USDA Forest Service. (Washington, DC)
- Nelson R, Krabill W, Tonelli J (1988) Estimating forest biomass and volume using airborne laser data. *Remote Sensing of Environment* **24**, 247–267. doi:10.1016/0034-4257(88)90028-4
- Ottmar RD, Vihnanek RE, Mathey JW (2003) Stereo Photo Series for Quantifying Natural Fuels. Volume VIa: Sand Hill, Sand Pine Scrub, and Hardwood with White Pine Types in the South-East United States with Supplemental Sites for Volume VI. National Interagency Fire Center, National Wildfire Coordinating Group, PMS 838, NFES 1119. (Boise, ID)
- Parker GG, Harding DJ, Berger ML (2004) A portable LIDAR system for rapid determination of forest canopy structure. *Journal of Applied Ecology* **41**, 755–767. doi:10.1111/J.0021-8901.2004.00925.X
- Reinhardt E, Keane RE (1998) FOFEM – a first order fire effects model. *Fire Management Notes* **58**, 25–28.
- Roberts SD, Dean TJ, Evans DL, McCombs JW, Harrington RL, Glass PA (2005) Estimating individual tree leaf area in loblolly pine plantations using LiDAR-derived measurements of height and crown dimensions. *Forest Ecology and Management* **213**, 54–70. doi:10.1016/J.FORECO.2005.03.025
- Scott JH, Burgan RE (2005) Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-153. (Fort Collins, CO)
- Slatton KC, Coleman M, Carter W, Shrestha R, Sartori M (2004) Control methods for merging ALSM and ground-based laser point clouds acquired under forest canopies. In '4th International Asia-Pacific Environmental Remote Sensing Symposium', 8 November 2004, Honolulu, HI. (Eds Bevis M, Shoji Y, Businger S) pp. 96–103. (SPIE: Bellingham, WA)
- Tanaka T, Park H, Hattori S (2004) Measurement of forest canopy structure by a laser plane range-finding method: improvement of radiative resolution and examples of its application. *Agricultural and Forest Meteorology* **125**, 129–142. doi:10.1016/J.AGRFORMET.2004.02.008
- Van der Zande D, Hoet W, Jonckheere I, van Aardt J, Coppin P (2006) Influence of measurement set-up of ground-based LiDAR for derivation of tree structure. *Agricultural and Forest Meteorology* **141**, 147–160. doi:10.1016/J.AGRFORMET.2006.09.007
- Van Wagner CE (1968) The line intersect method in forest fuel sampling. *Forest Science* **14**, 20–26.
- Wade DD, Lunsford JD, Dixon MJ (1989) A guide for prescribed fire in southern forests. USDA Forest Service, Southern Research Station, Southern Region Technical Publication R8-TP 11. (Atlanta, GA)
- Watt PJ, Donoghue DNM (2005) Measuring forest structure with terrestrial laser scanning. *International Journal of Remote Sensing* **26**, 1437–1446. doi:10.1080/01431160512331337961
- Wolf PR, Ghilani CD (1997) 'Adjustment Computations: Statistics and Least Squares in Surveying GIS.' (Wiley: New York)

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