Assessment of Canopy Fuel Loading Across a Heterogeneous Landscape Using LiDAR

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I. ABSTRACT

Our research used light detection and ranging (LiDAR) systems coupled with sequential harvesting of Pitch pine (*Pinus rigida* Mill.) to quantify canopy fuels in three dimensions across a large, heterogeneous landscape impacted by multiple wildfires, prescribed burns and insect defoliation events. We used a three-tiered approach; 1) calibration of upward sensing profiling LiDAR data with sequential harvesting of 20 x 20 meter plots to quantify the mass of foliage, branches and stems in Pitch pine canopies in 1-meter height layers, 2) scaling results to the landscape scale using previously-published relationships between upward sensing and downward sensing scanning LiDAR systems in similar Pitch pine stands, and 3) evaluation of predicted canopy fuel loading using an independent set of 20 x 20 meter field plots.

Five 20 x 20 m plots were harvested, ranging in total live tree biomass from 67 to 108 Mg ha^{-1}. Crown fuel weight (CFW; kg m^{-2}) ranged from 0.83 to 1.16 kg m^{-2}, and maximum canopy bulk density (CBD; kg m^{-3}) ranged from 0.15 to 0.23 kg m^{-3}. Allometric relationships between parabolic bole volume, calculated from height and DBH measurements, and available fuels, needle mass, and 1-hour and 10-hour fuels were highly significant, with regression coefficients ranging from 0.89 to 0.91. Regression coefficients calculated for maximum CBD and its height using biometric data were 0.81 and 0.72, respectively.

Relationships between upward-sensing profiling LiDAR returns and available fuels, needle mass, and 1-hour and 10- hour fuels biomass of canopy fuels were highly significant, and regression coefficients were > 0.9 between crown fuel weight or maximum CBD and LiDAR returns. Across all equations, the poorest fits were for 1000-hr fuels and dead needle mass. Previous research has demonstrated that relationships between upward sensing profiling LiDAR and downward sensing scanning LiDAR are highly significant in Pitch pine – dominated stands, facilitating the scaling of crown fuel estimates across the landscape.

Initial analyses of data from validation plots indicate that biometric and LiDAR-derived estimates of CFW and maximum CBD are not significantly different; CFW estimates were 1.15 ±

0.27 vs. 1.22 ± 0.28 kg m^{-2} (n = 17, Paired-sample T = 0.22, ns) and maximum CBD estimates were 0.22 ± 0.08 vs. 0.22 ± 0.08 kg m^{-3} (n = 17, Paired-sample T = 0.59, ns) for biometric and LiDAR-derived estimates, respectively.

The results of our project will assist state and federal wildland fire managers, because highly accurate canopy fuel maps can be produced for large forested areas in the Pinelands, and for areas in and near wildland-urban interface. Our results can also be used to evaluate the effectiveness of prescribed burns and mechanical canopy fuel reduction treatments. In addition, we can now generate highly accurate estimates of crown bulk density (CBD) and other canopy fuel characteristics, which are appropriate for current fire behavior models such as the FVS-Fire and Fuels Extension, and for the next-generation of fire behavior models such as WFDS, which require high resolution canopy fuel loading information.

Keywords: Canopy fuels, Crown bulk density, Crown fuel weight, Pitch pine, Crown fires, LiDAR.

II. BACKGROUND and PURPOSE

The incidence of stand-replacing crown fires in ecosystems where frequent surface fire regimes have historically occurred is a result of a number of factors, including long-term effects of fire suppression and forest regeneration, insect invasions and subsequent mortality, and large fluctuations in climatic regimes. Crown fires move faster and are more destructive than surface fires. Controlling crown fires is one of the most difficult and dangerous tasks for wildland fire managers. Crowning behavior dictates the type and proximity of suppression activities, and crown fires are much more difficult and expensive to suppress. The impact of crown fires to forest resources, wildland fire personnel, and public safety highlight the importance of quantifying canopy fuels accurately. Despite a strong understanding of the risks and costs associated with crown fires, accurate scaling of three-dimensional canopy fuel estimates across forests with heterogeneous structure is a limitation to our fire modeling efforts, and our ability to improve upon wildfire mitigation strategies.

Metrics used to characterize canopy fuels include crown fuel weight (CFW, kg m^{-2} ground), canopy bulk density (CBD, kg m^{-3}), and canopy base height (CBH, meters)(Wagner 1993, Scott and Reinhardt 2001, Reinhardt et al. 2006, Duveneck and Patterson 2007). Crown fuel weight is defined as the total fuel available within the canopy per unit ground area, typically expressed as kg fuel per m^{-2} ground area. Canopy bulk density is defined as the mass of available canopy fuel per unit canopy volume (kg m^{-3}). It is a stand-level property, although individual tree measurements are frequently used to estimate CBD. CBD is defined operationally for fire behavior models as the available fuel that would be consumed in the

Figure 1. Crown fire burning in a dense Pitch pine scrub oak in the Pinelands National Reserve of Southern New Jersey.

flaming front of a fully active crown fire. It is assumed that live and dead foliage is consumed, and that portions of the live and dead stem wood, typically measured as 1-hour and 10-hour woody fuels, are also consumed. CBD estimates are used in a number of fire behavior models, for example, the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS; Reinhardt and Crookston 2003). Canopy base height (CBH) is the lowest height above the ground at which there is a sufficient amount of canopy fuel to propagate fire vertically into the canopy. CBH is straight forward to measure on individual trees, but is more difficult to quantify at stand to landscape scales. This is especially true in multistory stands or stands where sub-canopy trees and large shrubs comprise ladder fuels. In terms of an operational definition for crown fire initiation, CBH is the lowest height above the ground at which there is sufficient canopy fuel to propagate fire vertically through the canopy. Using this definition, ladder fuels such as draped needles, lichens, dead branches, understory trees and large shrubs are incorporated into available fuel estimates. The FFE-FVS simulator uses this approach, and canopy base height is defined as the lowest height above which at least 0.011 kg m^{-3} of available canopy fuels are present.

Commonly-used techniques to assess canopy fuel characteristics are 1) harvest and biometric or inventory based techniques, 2) indirect, ground-based optical techniques, and 3) remote sensing approaches. Harvest techniques are typically used to develop allometric equations, so that canopy fuel characteristics can be scaled from tree dimensions, usually diameter at breast height (DBH) and tree height (Scott and Reinhardt 2001, Duveneck and Patterson 2007, Reinhardt et al. 2006). Allometric equations can then be used with forest inventory data such as available from the USFS Forest Inventory and Analysis program (http://fia.fs.fed.us/) or other forest census datasets to estimate CBD and CFW over larger areas. Allometric equations from published studies also exist to predict foliar and branch biomass from tree dimensions (e.g., Whittaker and Woodwell 1968, Jenkins et al. 2003, Seo et al. 2012). These estimates can be used with species lists from inventory data to estimate foliage and branch biomass of various diameters to approximate canopy fuels.

Ground-based optical techniques typically employ light attenuation by the canopy to estimate crown fuel characteristics (e.g., Keane et al. 2005). Instruments such as Li-Cor LI-2000

Plant canopy analyzer (Li-Cor Inc., Lincoln, Nebraska USA), AccuPar light ceptometer (Decagon Devices, Inc., Pullman, Washington USA), and hemispherical photography have been used to infer canopy density. These techniques have also been extensively evaluated by the larger ecological community for estimating leaf and branch surface area (e.g., Ameriflux sites; http:/public.ornl.gov/ameriflux/). Typically, calculations are used to first estimate leaf area index (LAI) and branch cover. LAI can then be converted to an estimate of foliar biomass using specific leaf area relationships and approximate canopy fuel loading. Published values for specific leaf area exist for many conifer species, or can be developed rapidly using a leaf area meter (e.g., LiCor LI-3000).

In the past, crown bulk density, crown closure, and canopy height have been estimated from maps based upon aerial photography interpretation and field census data. More recently, satellite-based sensors such as Landsat TM, SPOT, and MODIS have been used to measure NDVI, and estimate leaf area (LAI) at landscape to regional scales (e.g., Pan et al. 2006, Erdody and Moskal 2010). Similar to ground-based optical techniques, LAI can then be converted to an estimate of foliar biomass using specific leaf area relationships and approximate canopy fuel loading.

Benefits of these approaches are that stand-level assessments of canopy fuel characteristics can be highly accurate, and that they provide parameters that can be used directly in current fire behavior models. Both biometric and optical techniques are suitable across large, relatively homogeneous stands, and remote sensing applications can be used to scale estimates to much larger, but relatively homogeneous, areas. However, a major problem arises because it is difficult to scale canopy fuel characteristics accurately across larger landscapes characterized by heterogeneous canopy structure. A second problem arises with optical and remotely sensed techniques, because canopy fuel characteristics are estimated in only two dimensions on a m^2 to km^2 basis, precluding accurate estimates of vertical fuel distributions or the location of maximum CBD in the canopy. Destructive harvest measurements can result in accurate 3-dimensional data (e.g., Duveneck and Patterson 2007), but are highly time-consuming and beyond the scope of most fire management agencies to accomplish. A potential solution for uniform stands is that CBD can be computed as the available canopy fuel load divided by canopy depth, calculated as crown height – crown base height. This method assumes that fuels are distributed uniformly within the canopy, which is highly unlikely even in stands with relatively simple, homogeneous structure. Complex, multistoried stands are likely to be poorly represented using this approach. Thus, plot-based canopy fuel models do not adequately describe site to site variability in CBD at larger scales, and spectral reflectance data cannot accurately describe smaller scale variability in canopy fuel loading, or its 3-dimensional structure. A third major drawback with all of the currently used approaches to estimate canopy fuels is that they largely neglect (or at least undersample) ladder fuels. There is no accepted or operational method to estimate ladder (or transition) fuels formally in fire behavior models. They are often accounted for by adjustment of simulated surface fire intensity, essentially a “fudge factor”.

Collectively, these limitations lead to an inability to accurately assess canopy fuel loading in complex and varied landscapes, particularly those found within the WUI, or in forested landscapes previously damaged by wildfires, insects, windstorms or other disturbances. This inability can impact suppression activities, and reduces our ability to efficiently target and evaluate fuel reduction treatments. Additionally, as numeric wildfire spread models increase in complexity and predictive power, shortfalls in the availability and accuracy of spatially explicit data on canopy fuels have become a serious limitation.

Recently, LiDAR (Light detection and ranging) systems are proving to be indispensible tools for estimating 3-dimensional structure of forest canopies at landscape to regional scales (Riano et al. 2004, Skowronski et al. 2007, 2011, Mutlu et al. 2008a, Erdody and Moskal 2010, Asner et al. 2012, Contreras et al. 2012, Jakubowski et al. 2013). A more accurate approach to quantifying 3-dimensional canopy fuel characteristics across large, heterogeneous landscapes is to combine destructive sampling and allometric relationships with sequential LiDAR sampling. This is often the crucial step that is omitted from fuel inventories using LiDAR technology.

III. STUDY DESCRIPTION and LOCATION

Project Objectives: Our research approach utilizes 1) sequential destructive sampling of Pitch pine (*Pinus rigida* Mill.) in 20 x 20 meter plots to quantify foliage and live and dead 1-, 10-, 100- and 1000-hr fuels in the canopy in 1-meter layers, combined with simultaneous sampling with an upward sensing backpack mounted LiDAR system to develop calibrated CFW and CBD height profiles in 1-meter layers, 2) downward sensing scanning LiDAR data combined with the recently-determined relationships between upward sensing and downward sensing systems to scale estimates over a large, heterogeneous landscape, and 3) a second set of independent, randomly located plots within the scanning LiDAR acquisition to evaluate model predictions of CFW and CBD height profiles in Pitch pine – dominated stands in the Pinelands of New Jersey. Finally, we are producing high-resolution maps to assist suppression activities and to guide fuel reduction treatments, and digital datasets for modeling purposes using WFDS and other models.

Methods

Site Description

Research sites were located in Burlington and Ocean Co. in the Pinelands National Reserve in southern New Jersey (Figure 2). The Pinelands contain the largest continuous forested landscape on the Northeastern coastal plain. The climate is cool temperate, with mean monthly temperatures of 0.3 and 23.8 °C in January and July, respectively (1930-2009; State Climatologist of NJ; http://climate.rutgers.edu/stateclim_v1/data/). Mean annual precipitation is 1142 ± 160 mm. Soils are derived from the Cohansey and Kirkwood Formations, and are sandy, coarse-grained, and extremely oligotrophic (Tedrow 1986). This landscape is also characterized by a high frequency and intensity of wildfires relative to other forest ecosystems in the northeastern US (Little & Moore 1949, NIFC 2013, Figure 3).

Upland forests comprise ca. 62% of the forested areas in the Pinelands National Reserve, and are dominated by three major forest communities; 1) oak - pine, consisting of black oak (*Quercus velutina* Lam.), chestnut oak (*Q. prinus* L.), white oak (*Q. alba* L.), and pitch (*Pinus rigida* Mill.) and shortleaf pine (*P. echinata* Mill.), 2) pine - oak, consisting of pitch pine with mixed oaks in the overstory, and 3) pine - scrub oak, dominated by pitch pine with scrub oaks (*Q. ilicifolia* Wang. and *Q. marlandica* Muench.) in the understory (McCormick & Jones 1973, Lathrop & Kaplan 2004, Skowronski et al. 2007, FIA data at www.fia.gov, Figure 2). A fourth forest community, the pine plains, consisting of short-statured pitch pine and scrub oaks, is also recognized in the vicinity of Coyle Field, Warren Grove Bombing Range, and Stafford Forge Wildlife Management Area. All stands have ericaceous shrubs in the understory, primarily huckleberry (*Gaylussacia bacata* (Wang.) K. Koch, *G. frondosa* (L.) Torr. & A. Gray ex Torr.) and blueberry (*Vaccinium* spp.). Sedges, herbs, mosses and lichens also are present (Wright et al. 2007). Pitch pine-dominated stands are of major concern to wildland fire managers in the Pinelands because of their propensity to crown during wildfires, and their proximity to WUI areas along the eastern boundary of the Pinelands National Reserve.

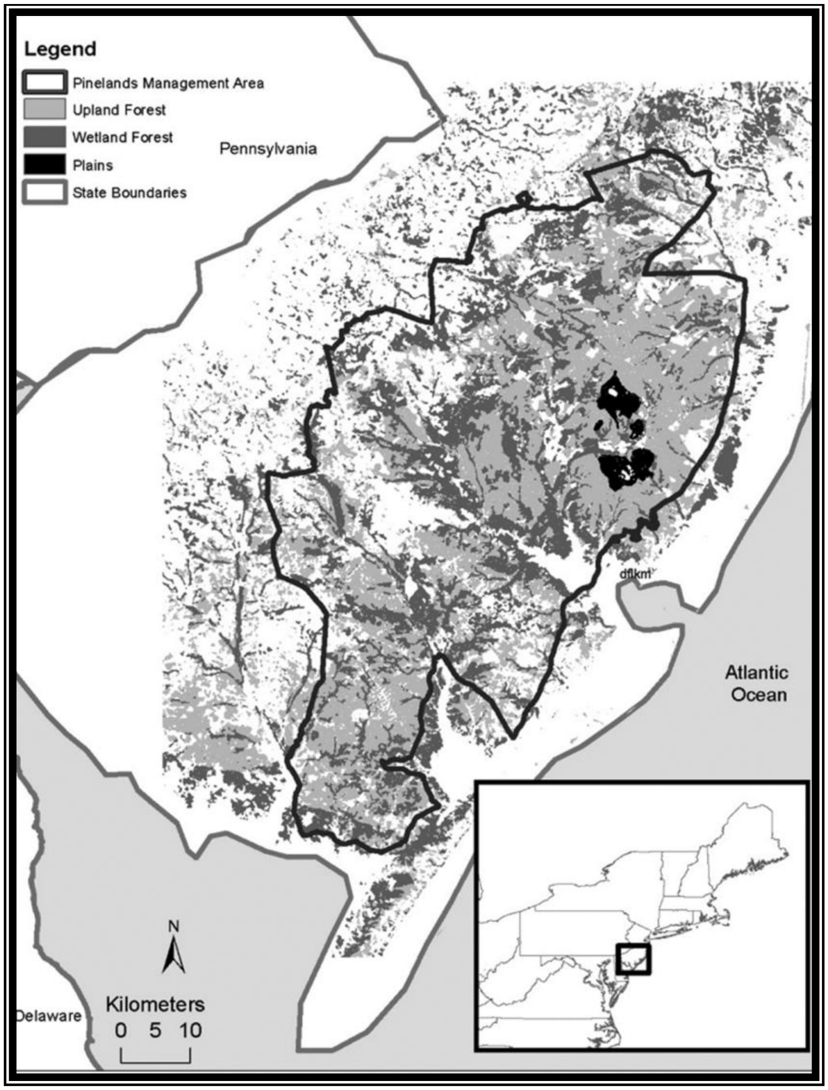


Figure 2. Pinelands National Reserve in Southern New Jersey.

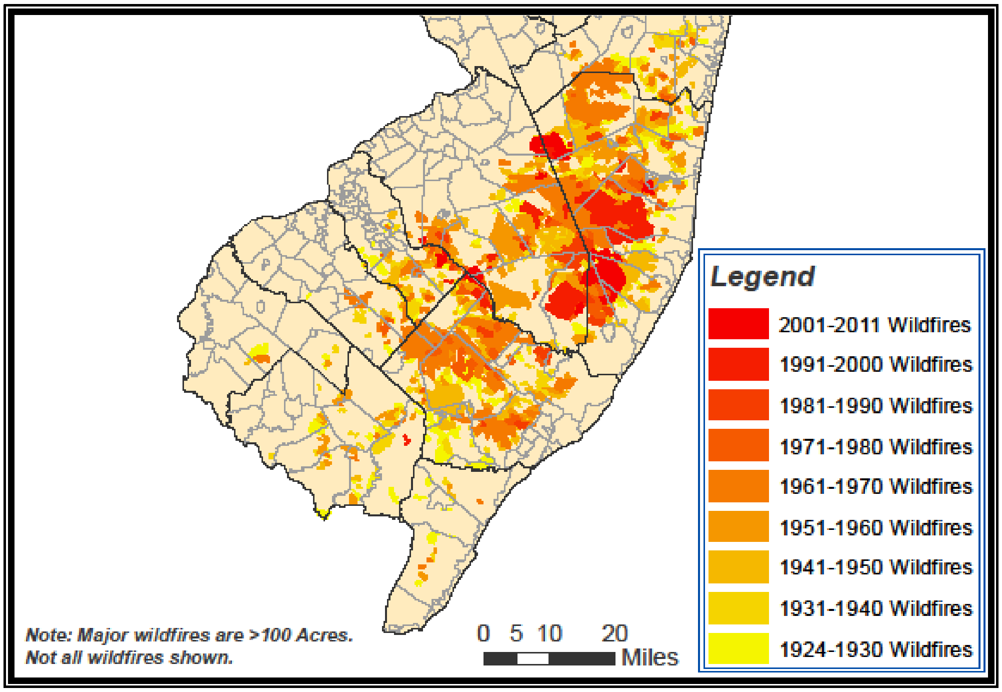


Figure 3. Wildfire occurrence in and surrounding the Pinelands National Reserve. Data are from NJ Forest Fire Service.

Tree harvests plots and biometrics: We selected five 20 m x 20 m plots for sequential harvest and upward sensing profiling LiDAR acquisitions, following the protocol in Skowronski et al. (2011). All plots had been burned repeatedly in wildfires in the past, with the most recent occurring in May 2007. The 2001 NJ Land-Use/Land Change map (Lathrop & Kaplan, 2004) was first used to delimit areas consisting of >75% pitch pine overstory in pitch pine – dominated stands. The UTM co-ordinates of the plot corners were recorded using a high-accuracy, differentially corrected GPS (Pathfinder ProXT, Model # 52240-20, Trimble Navigation Limited, Sunnyville, CA) in order to accurately georeference the scanning LiDAR point clouds to the plot locations. We then recorded tree species, estimated crown class (dominant, co-dominant, intermediate, or suppressed), and measured all trees over 2 meter height (the height at which they would be detected by the upward-looking LiDAR sensor) for DBH and height using a hypsometer (Haglof VL400, Haglof Sweden AB, Langsele, Sweden). Table 1 shows initial plot descriptions and biometric data.

Initial upward sensing LiDAR transects were then laid out and sampled (see below). The first five trees were then harvested one at a time by chainsaw. Tree selection was employed to minimize damage to the tree and to the remaining stand when felling. Each tree was measured on the ground with a loggers tape, 1-meter segments were marked carefully with tree paint, and segments were then cut into 1-meter segments. Live and dead foliage, cones, 1-hour (twigs), 10-hour (stems), 100-hour (stems) and 1000-hour fuels were separated in the field and placed in labeled paper bags. Boles were weighed in the field, and a "cookie" was cut from each 1-meter segment to convert wet, field weight to dry biomass. After five trees were harvested and separated, LiDAR transects were sampled again, and another five trees were harvested. We repeated this process until all trees were removed from the plots. In the five plots, a total of 181 live trees and 85 snags were harvested, separated into 1-meter segments, and weighed.

Figure 4. One of the 20 m x 20 m harvest plots containing wildfire-damaged Pitch pine in the New Jersey Pinelands. This stand was burned in the 2007 Warren Grove wildfire.

Profiling LiDAR data: Upward scanning profiling LiDAR data were collected concurrently with the tree harvests in each plot. The backpack-mounted LiDAR system consisted of a discrete-return Riegl Laser Rangefinder (Model # LD90-3100VHS-FLP, Riegl USA, Orlando, FL) connected to a PDA which collected first returns at 100 Hz via the RS-232 port. The system had a range of 0.1–200 m, and a spot size of 12.4 cm^2 at 1 m to 25.6 cm^2 at 50 m (Parker et al. 2004). The instrument was paced at a constant rate along 21 north–south oriented transects spaced 1 m apart before any trees were harvested, and following the removal of five trees in each plot. Sky shots (laser pulses that passed through the canopy) were recorded as null values. We paced the LiDAR along transects three times per transect, and then averaged the data for each transect.

Sample processing in the Laboratory: For larger samples, we used a wet weight / dry weight ratio calculated from the appropriate sub-sample to estimate dry mass of the sample. All large samples were weighed, and the wet weight recorded. A sub-sample was weighed wet, dried at 70 °C until dried, and then weighed again. Smaller samples were dried at 70 °C until dry, and the final dry mass weight recorded.

Scaling 3-Dimensional CDB estimates to the landscape level: Scanning LiDAR acquisitions and the known relationship between upward profiling and downward scanning LiDAR systems (Skowronski et al. 2011) were used to produce maps of canopy fuel loading across selected pitch pine-dominated forests. A number of scanning LiDAR acquisitions were used to scale estimates up to the landscape level, including an acquisition over a high intensity wildfire (2008, 207 km^2, 4 returns/m^2), and two countywide acquisitions (2010 and 2013). Some of these acquisitions overlap spatially, and can be used to characterize canopy fuel profiles pre- and post- disturbance. Using this approach, we can evaluate the effects of a number of prescribed burns conducted by the New Jersey Forest Fire Service (e.g., Skowronski et al. 2007, see "Management Implications" below). LiDAR data analyses followed Skowronski et al. (2011), and we produced plot, landscape and regional-scale high-resolution (20m x 20m horizontal, 1-m vertical) raster stacks of LiDAR derived canopy fuel profiles, which provide detailed information on canopy gaps, ladder fuels, and three-dimensional canopy structure.

Validation plots: Validation plot locations were generated using random UTM coordinates in Pitch pine – scrub oak stands that were at least 4 ha in size. Plots (n = 20, 20 x 20 m in size) were buffered by a minimum of 100 m from the edge of the stand, and at least 100 m apart from each other. The UTM co-ordinates of the plot corners were recorded, and we then recorded species and crown class, and measured diameter at breast height (DBH) and tree height using a Hypsometer for each tree > 2 m height in each plot. The profiling LiDAR was then paced along 21 transects spaced 1 meter apart, and data were binned to produce 1-meter fuel estimates for each plot.

Statistical analyses: We developed a range of equations to calculate CFW and the mass of individual fuel components, maximum CBD, the height of maximum CBD, and CBD for individual meter layers from the harvest and LiDAR datasets. The first set of equations are based solely on standard forest census data, specifically tree height and DBH measurements, which are recorded routinely during our other research efforts, and are an integral part of FIA datasets and other forest census work conducted by the NJ Department of Forestry. We then developed and present a range of equations for use with upward sensing profiling LiDAR data to calculate canopy fuel characteristics, typically for use with 20 m x 20 m forest census plots (e.g., Skowronski et al. 2011, JFSP project 12-1-03-11). Finally, we are developing and refining a third set of equations to predict CFW, maximum CBD, and CBD in selected meter height bins using downward sensing scanning LiDAR (ALS) datasets.

Harvest plots and allometric equations: We used standard allometric analyses for the sampled trees to produce linear regression equations to predict CFW, maximum CBD, and CBD in 1-meter layers from height and DBH measurements for each tree, following the approaches in Whittaker and Woodwell (1968) and Duveneck and Patterson (2007). Individual tree height and DBH data were used to calculate a parabolic volume (V):

$$V = 0.5\ \pi\ (dbh/2)^2\ h \qquad (1)$$

Where dbh is tree diameter at breast height (m), and h = tree height (m). SigmaPlot (Systat, Inc., Sunnyvale, CA) was then used to calculate regression coefficients for CFW, maximum CBD and the weight of various canopy components.

Upward sensing LiDAR data: All LiDAR returns were summed for each harvest interval, and analyzed against remaining available fuels and fuel components separately. Following Skowronski et al. (2011), upward sensing LiDAR data were then processed to estimate canopy height profiles in 1-meter layers for each harvest interval. Regression equations were then developed to predict CFW, maximum CBD and CBD in 1-meter layers from these canopy height profiles (e.g., Skowronski et al. 2011).

Downward sensing LiDAR data: Downward sensing LiDAR data acquisitions were processed to estimate canopy height profiles in 1-meter layers. Using the known relationships between upward sensing and downward sensing LiDAR in Pitch pine canopies, we developed multiple linear regression equations to predict CFW, maximum CBD and CBD in 1-meter layers from the canopy height profiles (e.g., Skowronski et al. 2011).

Evaluation of model predictions: We evaluated LiDAR-derived estimates of canopy fuels by comparison to biometric predictions from allometric equations in the validation plots. We predicted CFW, maximum CBD, and CBD in 1-meter layers from the biometric data, and compared predictions to the estimates calculated from the upward sensing profiling data. We are currently evaluating estimates using the downward sensing scanning LiDAR data for validation plots and a series of previously sampled plots in the Pinelands.

IV. KEY FINDINGS

Harvest plots and allometric equations: Descriptive statistics for trees in the five calibration plots are shown in Tables 1 and 2. Total tree biomass and basal area ranged between 67 and 108 tons ha^{-1}, and between 19.9 and 23.7 m^2 ha^{-1}, respectively (Table 1a). The greatest number of trees occurred in the shortest stand (HR1). Snag density ranged from none to 39 snags in each 20 x 20 m plot (Table 1b).

Table 1a. Biometric information for live trees in the five calibration plots dominated by Pitch pine that were destructively harvested in 2010-2012.

Plot	Trees (#)	Height (m)	DBH (cm)	Basal area (m^2 ha^{-1})	Biomass (t ha^{-1})	Foliage (g m^{-2})
HR1	57	7.6 ± 1.8	13.2 ± 4.4	21.5	67.0	448.7
HR2	46	10.3 ± 1.2	15.9 ± 4.1	23.7	92.4	573.0
HR3	32	10.2 ± 2.2	17.3 ± 4.3	19.9	78.4	384.1
DH1	19	14.6 ± 3.1	23.0 ± 7.1	21.5	107.9	613.5
DH2	27	12.2 ± 5.3	18.3 ± 9.5	22.4	106.7	579.0
Mean		10.8 ± 2.7	17.5 ± 3.6	21.8 ± 1.4	90.3 ± 17.8	519.7 ± 98

Table 1b. Biometric information for snags in the five calibration plots dominated by Pitch pine that were destructively harvested in 2010-2012.

Plot	Snags (#)	Height (m)	DBH (cm)	Basal area (m^2 ha^{-1})
HR1	32	5.3 ± 1.4	7.8 ± 2.3	4.1
HR2	39	6.2 ± 1.8	9.1 ± 2.4	6.8
HR3	13	6.1 ± 3.1	8.2 ± 2.5	1.8
DH1	1	12.4	14	0.4
DH2	0	---	---	---

Table 2. Contribution of each fuel class to total canopy biomass for all trees in the five harvest plots. Total canopy biomass is defined as all foliage, branches and reproductive material excluding mainstems. Units are kg m^{-2}.

Fuel Class	Mass ± 1 SD (kg m^{-2})	% of Total Canopy Biomass
$Needles_{live}$	0.520 ± 0.098	22.1 ± 4.2
$Needles_{dead}$	0.002 ± 0.002	0.1 ± 0.1
1-hr $_{live}$	0.239 ± 0.043	10.1 ± 1.8
1-hr $_{dead}$	0.126 ± 0.021	5.4 ± 0.8
10-hr $_{live}$	0.369 ± 0.085	15.7 ± 3.6
10-hr $_{dead}$	0.139 ± 0.045	5.9 ± 1.9
100-hr $_{live}$	0.590 ± 0.253	25.1 ± 10.7
100-hr $_{dead}$	0.132 ± 0.159	5.6 ± 2.5
1000-hr $_{live}$	0.069 ± 0.054	2.9 ± 2.2
1000-hr $_{dead}$	0.005 ± 0.003	0.2 ± 0.1
$Reproductive_{all}$	0.164 ± 0.080	7.0 ± 3.4
Total canopy biomass	2.356 ± 0.744	100.0 %

Crown fuel weight of the five destructively-harvested plots ranged between 0.83 and 1.16 kg m^{-2} (Table 3). Crown fuel weight averaged 43.6 ± 5.7 % of total crown biomass. Maximum canopy bulk density in 1-meter height classes ranged between 0.15 and 0.23 kg m^{-3}, and occurred at 7 (HR1) to 13 (DH1) meters (Figure 5). Canopy base height ranged between 4 and 11 meter height (Table 3, Figure 5).

Table 3. Fuel loading characteristics for the five calibration plots dominated by Pitch pine that were destructively harvested in 2010-2012.

Plot	CFW ($kg\ m^{-2}$)	Maximum CBD ($kg\ m^{-3}$)	CBD max height (m)	CBH (m)
HR1	0.953	0.184	7	4
HR2	1.162	0.229	9	6
HR3	0.828	0.165	9	7
DH1	1.110	0.154	13	11
DH2	1.079	0.167	12	10
Mean ± 1 SD	1.026 ± 0.135	0.180 ± 0.030	10.0 ± 2.4	7.6 ± 2.9

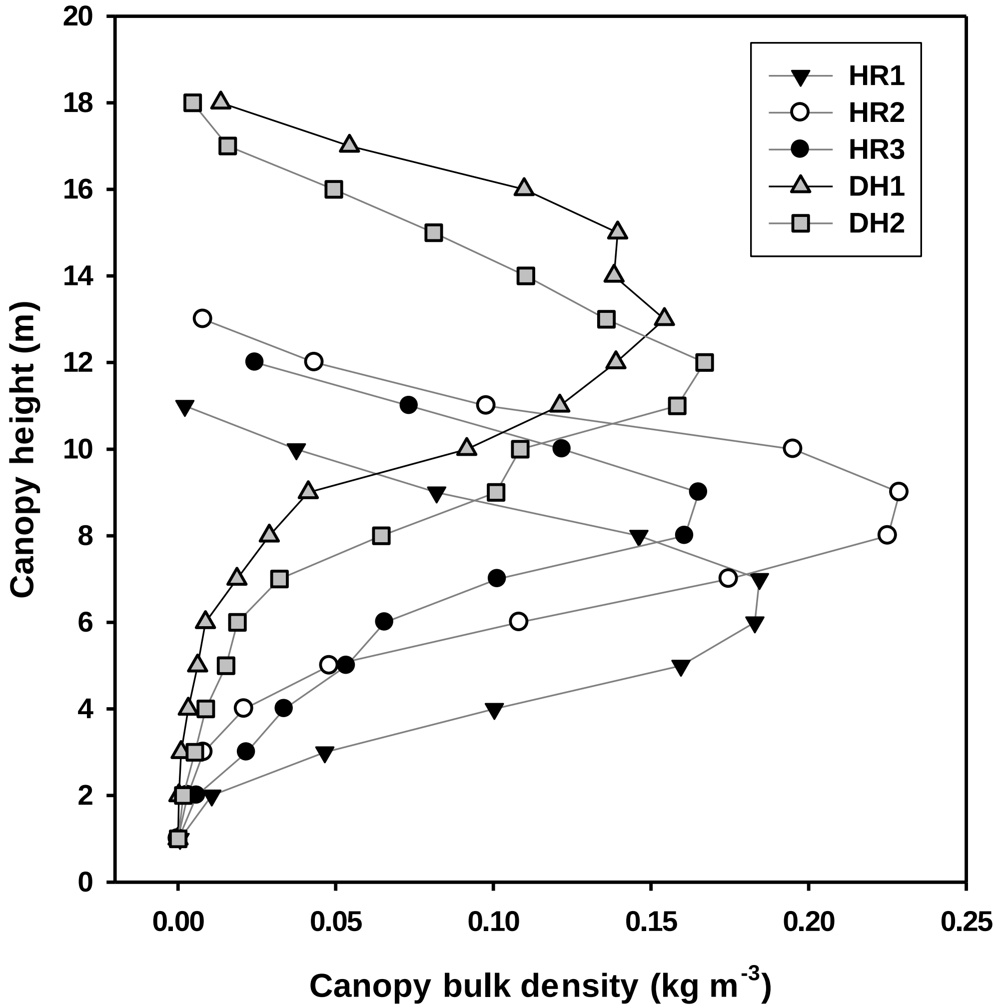


Figure 5. Canopy bulk density profiles for the five harvest plots before harvesting.

Relationships between parabolic volume and available fuel, live foliage, and 1- and 10-hour fuels were all linear (Figures 6-8). Allometric equations to predict available fuels, live foliage, and 1 + 10 hour fuels developed from biometric measurements are in Table 4; equations are highly significant for crown fuel weight and the weight of most individual canopy components that comprise available fuels (needles, 1 – hour live and dead stems, and 10-hour dead stems), with r^2 values generally exceeding 0.8. The poorest fit was for live and dead 1000-hr fuels, which formed very low mass (Table 2). Dead 1-hour fuels, which were abundant in two of the plots that had been burned severely in the 2007 Warren Grove wildfire, but not in the other three plots, were also predicted poorly. These also comprised a low proportion of the overall canopy biomass in all plots (5.4 %). In general, larger, dead woody fuels were more difficult to predict than other fuel types.

Table 4. Selected allometric relationships based on parabolic volume calculated from tree height (m) and DBH measurements (cm). Live trees in all plots were used to develop these equations, and data were fit to $y = \alpha x + \beta$. Units are kg fuel class per tree. SE = standard error of the estimate.

Fuel class	α	β	r^2	F	P	SE
Available fuels[1]	66.12 ± 1.57	1.61 ± 0.35	0.910	1693.5	< 0.0001	3.42
All needles	38.63 ± 0.99	0.41 ± 0.22	0.897	1461.3	< 0.0001	2.15
1-hr and 10-hr	55.27 ± 1.28	1.39 ± 0.29	0.914	1775.0	< 0.0001	2.79
Total canopy[2]	171.29 ± 5.75	0.44 ± 1.28	0.836	845.4	< 0.0001	12.51
Total biomass	676.11 ± 11.08	1.84 ± 2.47	0.955	3547.6	< 0.0001	24.11

[1] Available fuels are defined as live and dead needles, live and dead 1-hour fuels, and dead 10-hour fuels.
[2] Total canopy is defined as needles, branches and reproductive material, but not boles.

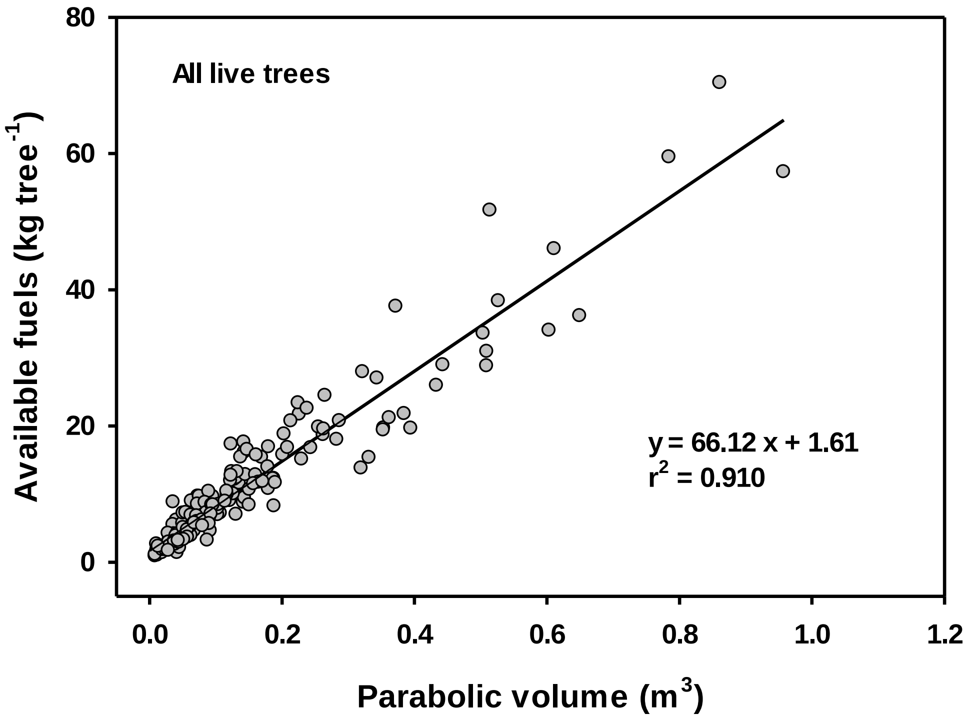


Figure 6. Relationship between parabolic volume calculated from height and dbh measurements and available fuels for live tress on all five harvest plots.

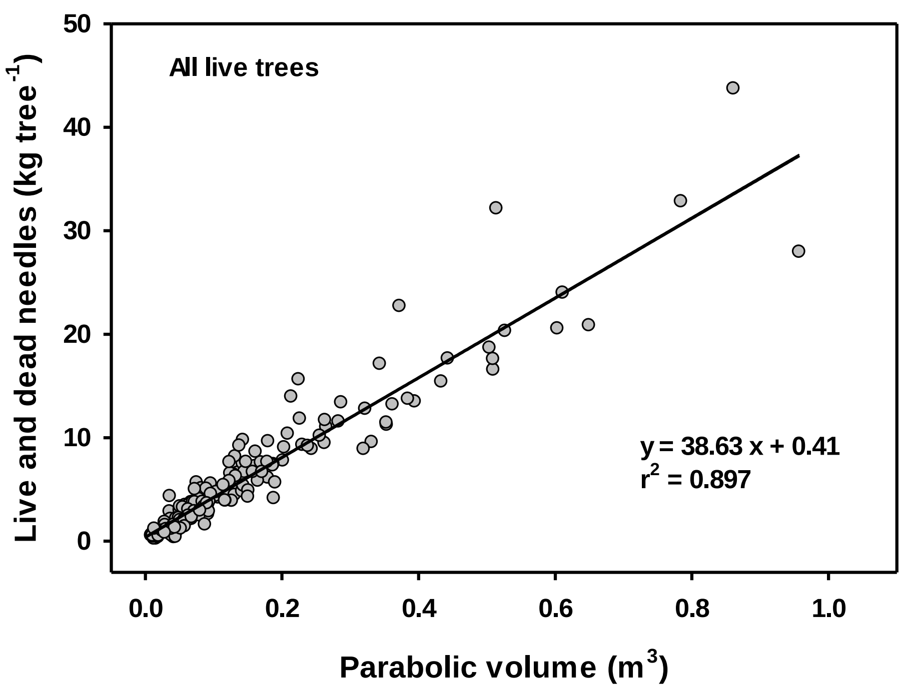


Figure 7. Relationship between parabolic volume calculated from height and dbh measurements and live and dead needle mass for live tress on all five harvest plots.

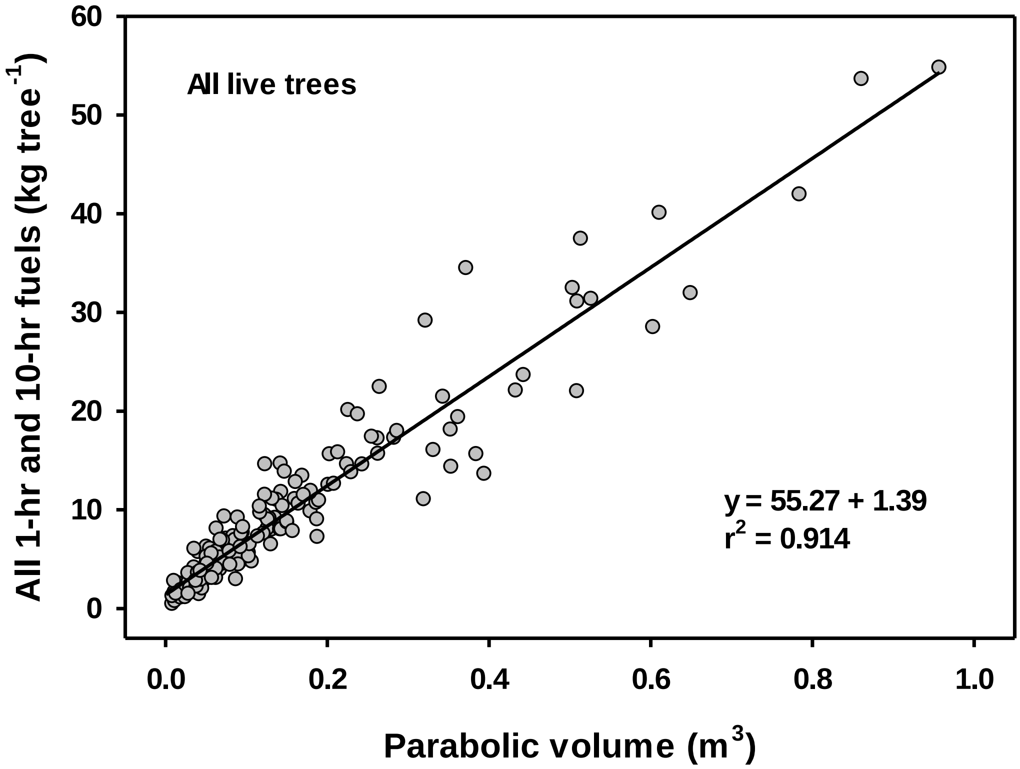


Figure 8. Relationship between parabolic volume calculated from height and dbh measurements and live and dead 1-hour and 10-hour fuels for live tress on all five harvest plots.

Predictive relationships for total biomass using parabolic volume were also highly significant (Table 4). However, if only height data were used, then relationships were non-linear, and not especially strong. Similar results were reported for Pitch pine by Skowronski et al. (2007), who used FIA data to explore the relationship between canopy height and biomass in Pine – oak and Pine – scrub oak stands in Burlington and Ocean Cos. in the Pinelands. They reported a poor relationship existed between canopy height and tree biomass for Pitch pine – scrub oak stands (y = 5.19 x, r^2 = 0.211, n = 26, NS).

Relationships between parabolic volume and calculated maximum canopy bulk density are shown in Table 5 and Figures 7-8. Log-log plots between parabolic volume and CBD_{max} resulted in a slightly better fit than linear equations (Table 5).

Table 5. Relationship between parabolic volume and maximum canopy bulk density for the five harvest plots. Data were fit to linear or log-log plots, where $y = \alpha x + \beta$.

Function	α	β	r^2	F	P
Linear	12.71 ± 0.49	1.08 ± 0.11	0.79	636.7	<0.0001
Log-log	0.679 ± 0.025	1.064 ± 0.029	0.81	744.7	<0.0001

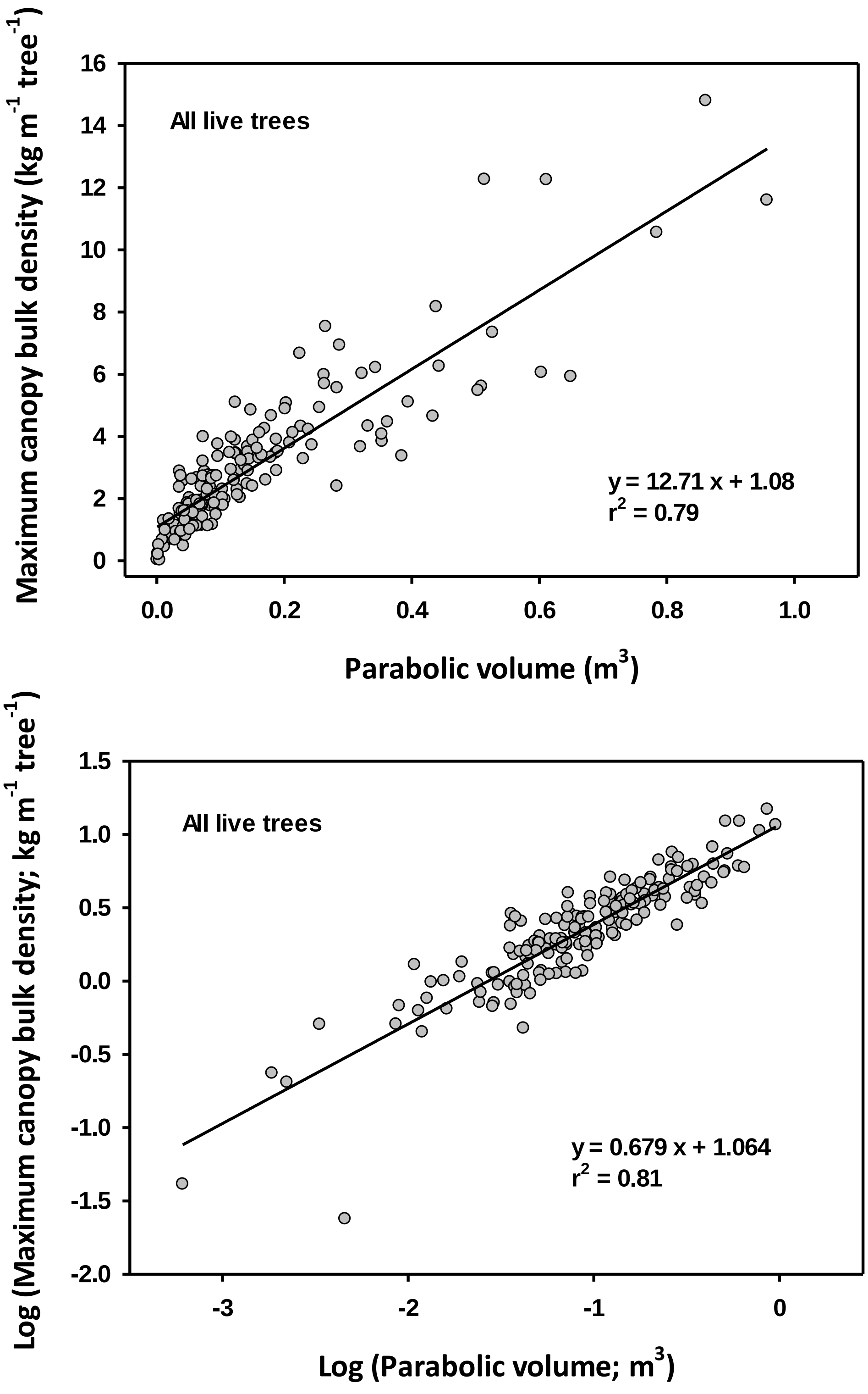


Figure 9a and b. Relationship between parabolic volume and maximum canopy bulk density on a per-tree basis. Data are presented as a) linear and b) log-log relationships.

Equations were also generated for predicting the height of CBD_{max} from the biometric data. This relationship was best approximated as a non-linear power function, and a log-log plot resulted in a slightly better fit (Table 6, Figures 9-10). All relationships were significant, with r^2 values exceeding 0.70.

Table 6. Relationship between parabolic volume and height of maximum canopy bulk density for trees in the five harvest plots. Data were fit to power function, where $y = \alpha + \beta x^{\gamma}$ or a log-log plot, where $y = \alpha x + \beta$.

Function	α	β	γ	r^2	F	P
Power	-0.027	15.288	0.262	0.70	203.3	<0.0001
Log-log	0.268 ± 0.013	1.181 ± 0.015	---	0.72	447.8	<0.0001

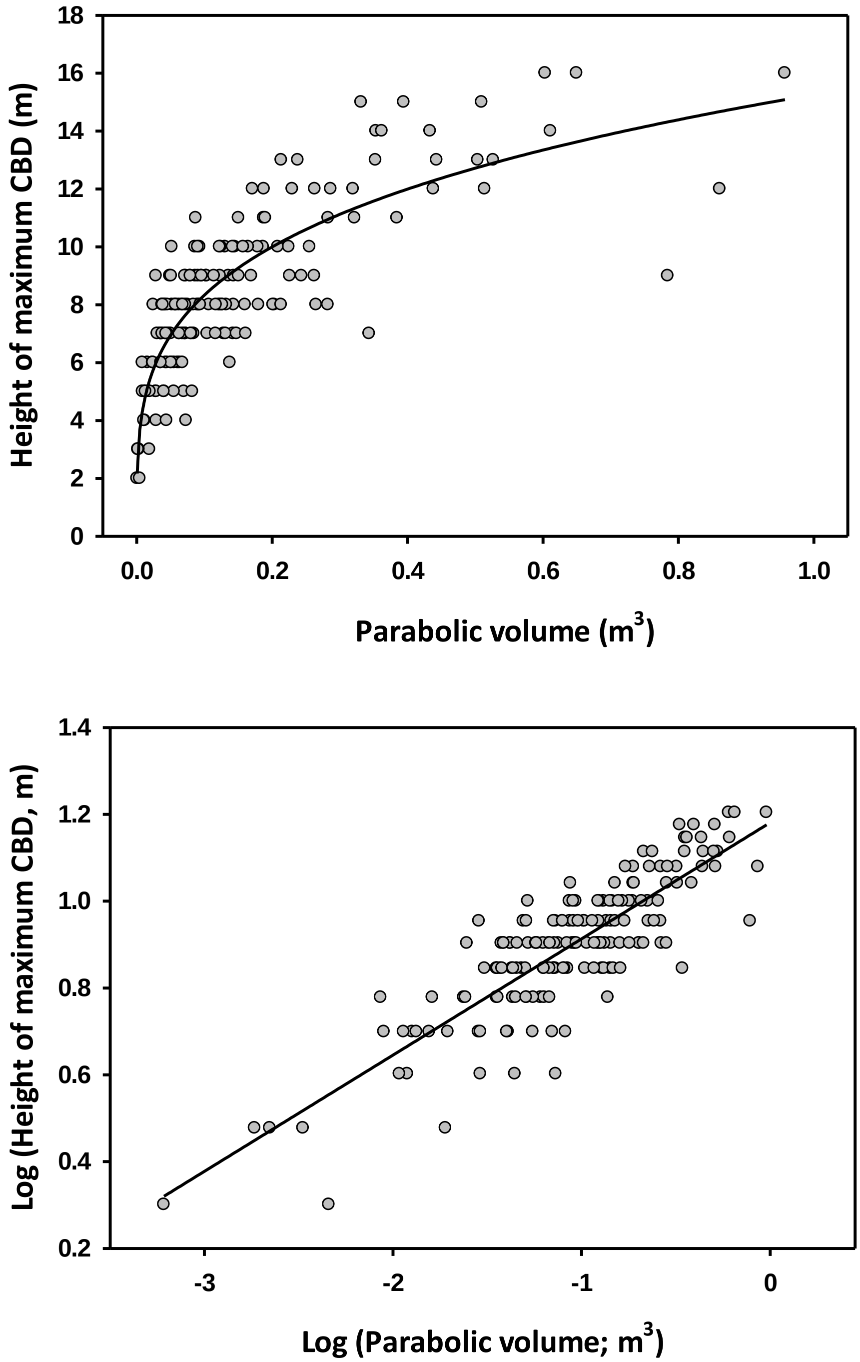


Figure 10 a and b. Relationship between parabolic volume and the height of maximum canopy bulk density on a per-tree basis. Data are presented as a) power function and b) log-log relationships.

Profiling LiDAR data for calibration plots: Parameter values and statistics for the relationships between upward sensing profiling LiDAR data and crown fuel weight, and for selected fuel components during harvesting were all linear and highly significant (Figures 11-13). For example, crown fuel weight and fuel loading variables were linearly related to the ratio of intercepted to total LiDAR returns in the HR3 plot as trees were sequentially harvested; regression equations had r^2 values < 0.9, and all equations are significant at P < 0.0001 (Table 7).

Table 7. Linear regression parameters and statistics for the relationships between crown fuel weight, live and dead needles, or 1-hour and 10-hour fuels and LiDAR returns, expressed as the ratio of intercepted to total pulses from the upward sensing profiling LiDAR above 2 meter height for one of the harvest plots (HR3) during sequential harvesting. Data were fit to $y = \alpha x + \beta$. Parameter values are ± 1 SE, and units are kg m^{-2}. Examples of these relationships are shown in Figure 11 for available fuels, Figure 12 for live needles, and Figure 13 for 1-hour and 10-hour fuels.

Fuel class	α	β	r^2	F	P
Available fuel	1.426 ± 0.057	0.030 ± 0.023	0.986	635.4	< 0.0001
Needles	0.669 ± 0.041	0.035 ± 0.017	0.967	261.5	< 0.0001
1-hr and 10-hr	1.279 ± 0.042	0.017 ± 0.017	0.990	924.3	< 0.0001

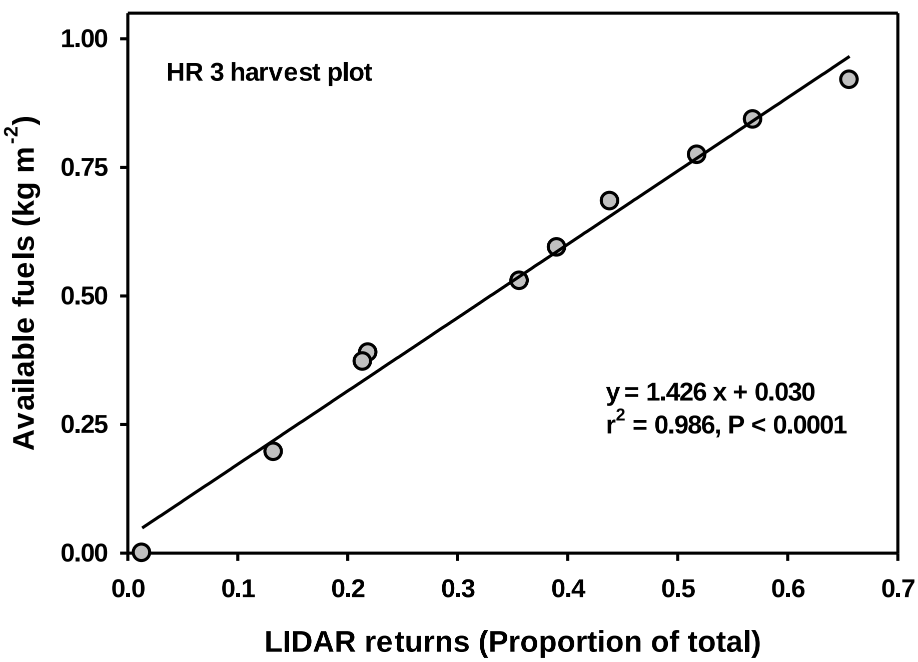


Figure 11. The relationship between upward sensing profiling LiDAR returns (expressed as the ratio of intercepted to total pulses) and crown fuel weight as the HR3 plot was sequentially harvested. Five trees were harvested between each point in the 20 m x 20 m plots.

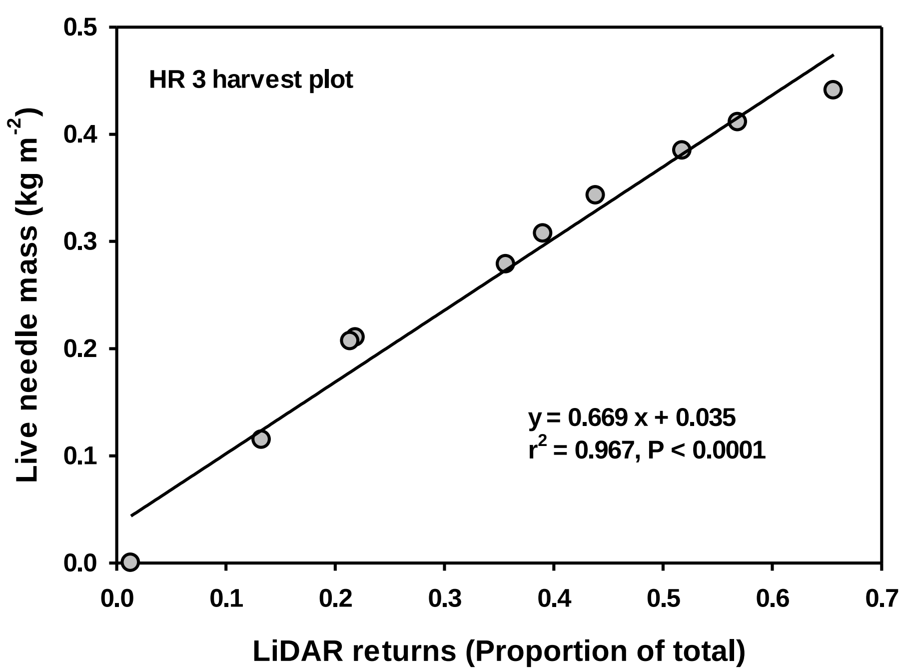


Figure 12. The relationship between upward sensing profiling LiDAR returns and live needle mass as the HR3 plot was sequentially harvested.

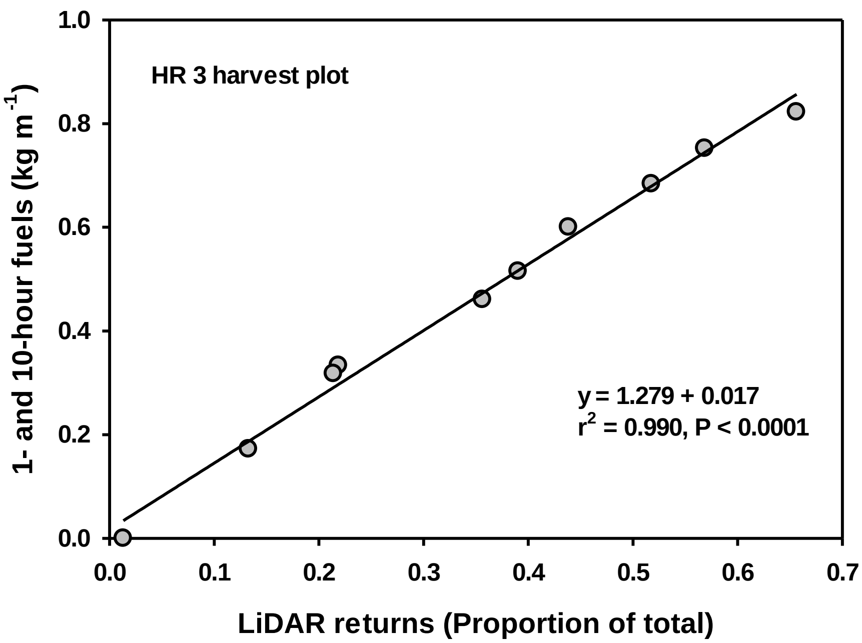


Figure 13. The relationship between upward sensing profiling LiDAR returns and 1-hour and 10-hour fuels as the HR3 plot was sequentially harvested.

We then compared canopy height profiles derived from upward sensing profiling LiDAR data with biometric measurements of canopy bulk density for each plot. An example of LiDAR data collected in one of the 20 m x 20 m plots before initial harvest in shown in Figure 15, with canopy height color-coded by height bin. Figure 16 shows a comparison of a canopy height profile of apparent cover calculated from the upward sensing profiling LiDAR data, and canopy bulk density (kg m^{-3}) derived from destructive harvests of three of the five harvest plots. A set of regression equations were then developed to predict crown fuel weight and canopy bulk density in all 1 meter canopy layers together for all five harvest plots (Figure 16, Tables 8 and 9). Although a polynomial equation provided the best fit, estimates based on this equation tended to lead to erroneous values because LiDAR apparent cover tends to saturate in dense canopies. We used the linear equation for all further analyses here.

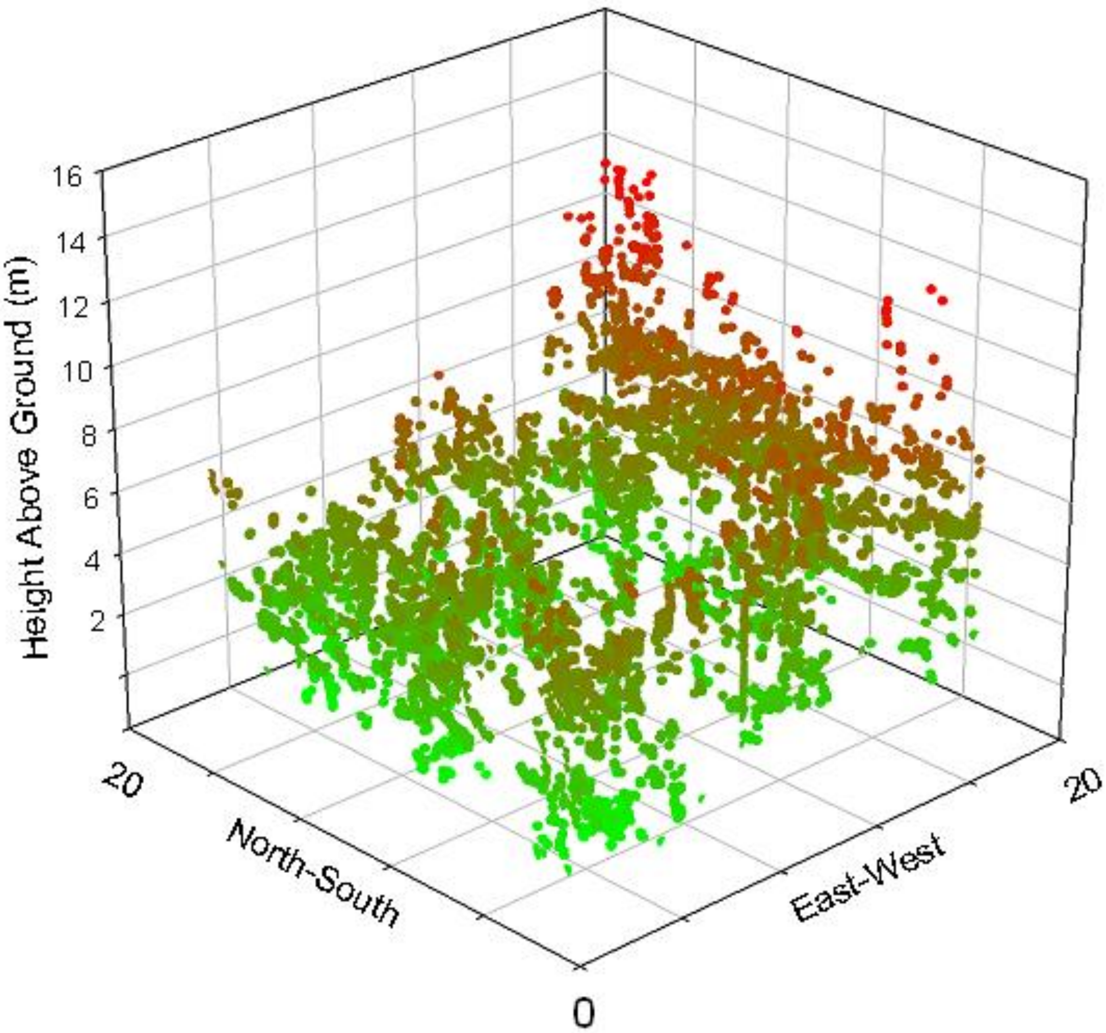


Figure 14. Upward profiling LiDAR data expressed as a color-coded canopy height profile for a 20 m x 20 m plot before initial harvest.

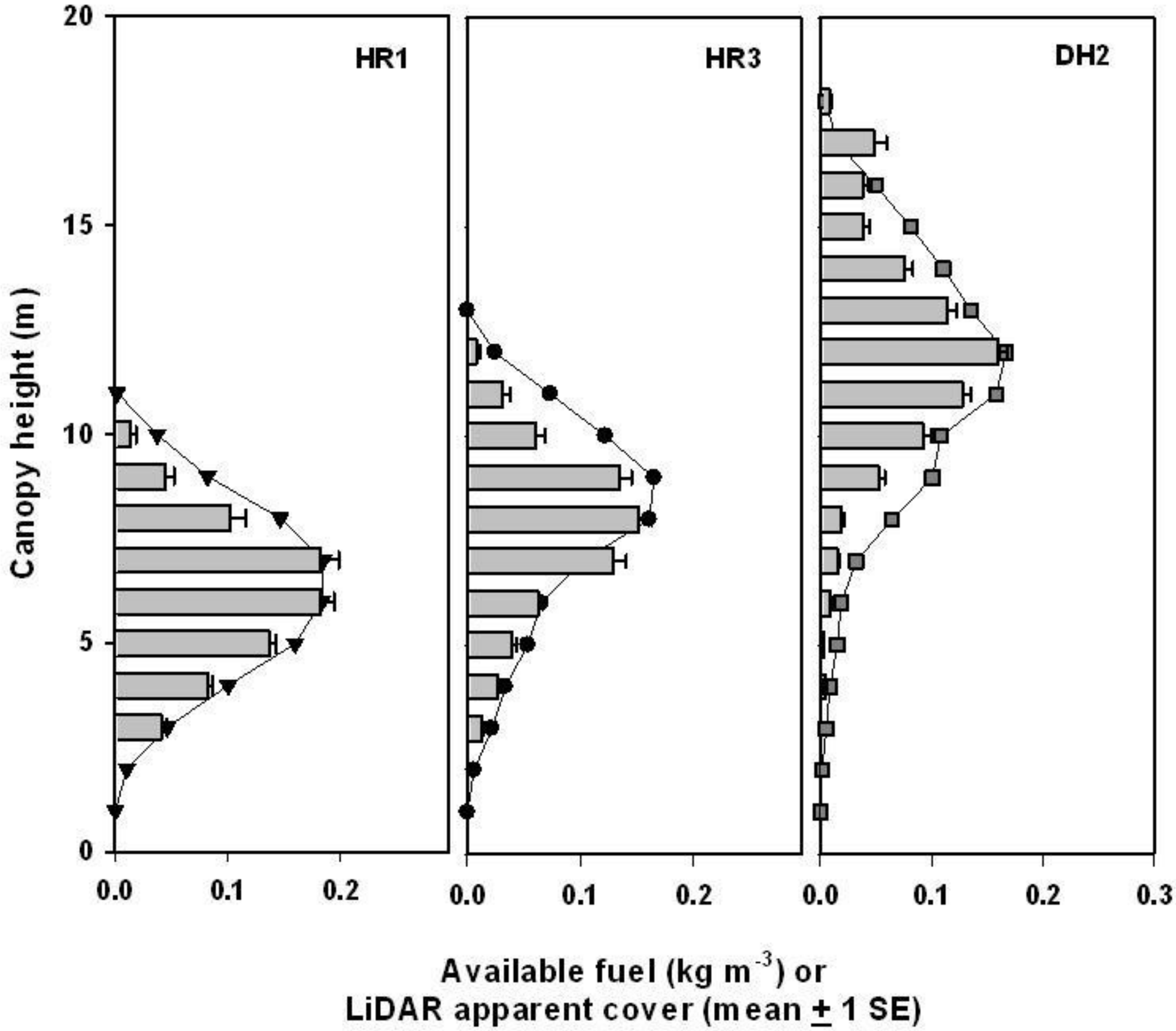


Figure 15. Available fuel (solid symbols) and LiDAR apparent cover (horizontal bars) by meter height in three of the harvest plots. LiDAR apparent cover was calculated as a ratio of intercepted to total LiDAR returns for each 1-meter height bin. Values are means of the 20 profiling LiDAR sampling lines ± 1 SE before harvest. Available fuels were calculated from harvest data (shown in Figure 5).

Table 8. Statistics and parameters for the relationship between available fuels and LiDAR apparent cover by 1-meter heights before harvesting of the five calibration plots. Values are given for linear ($y = \alpha * x + \beta$) and polynomial ($y = \alpha + \beta*x + \gamma*x^2$) equations.

Function	α	β	γ	r^2	F	P
Linear	0.917 ± 0.004	-0.009 ± 0.004		0.887	567.9	<0.0001
Polynomial	0.003 ± 0.004	0.304 ± 0.103	3.371 ± 0.537	0.927	457.3	<0.0001

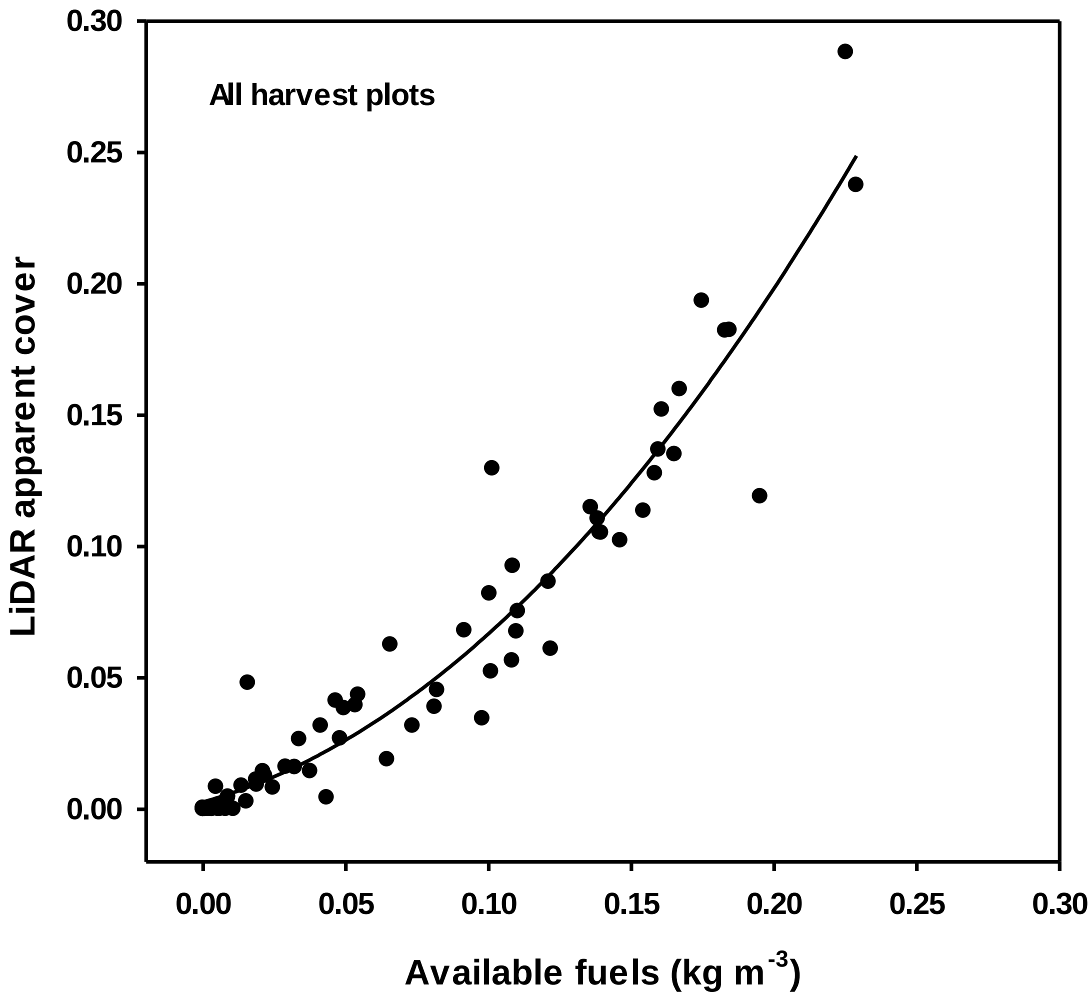


Figure 16. The relationship between available fuels and apparent cover derived from LiDAR data in 1-meter height bins. Data were fit to a polynomial equation, $Y = \alpha + \beta*x + \gamma*x^2$.

Table 9. Linear regression equations and statistics to predict crown fuel weight for available fuels and canopy fuel classes from LiDAR returns, expressed as the proportion of intercepted pulses divided by the total pulses emitted in all five plots. Units are kg m^{-2}.

Fuel Class	Equation	r^2	F	P
Available Fuels*	y = 2.012 x + 0.009	0.94	901.9	<0.0001
Needles $_{live}$	y = 0.998 x + 0.013	0.89	451.6	< 0.0001
Needles $_{dead}$	y = 0.008 x – 0.001	0.36	31.0	< 0.0001
1-hr $_{live}$	y = 0.426 x + 0.007	0.87	363.6	< 0.0001
1-hr $_{dead}$	y = 0.255 x – 0.001	0.93	727.8	< 0.0001
10-hr $_{live}$	y = 0.662 x + 0.001	0.82	257.9	< 0.0001
10-hr $_{dead}$	y = 0.326 x – 0.009	0.92	613.4	< 0.0001
100-hr $_{live}$	y = 0.930 x + 0.056	0.53	62.1	< 0.0001
100-hr $_{dead}$	y = 0.248 x + 0.009	0.56	70.8	< 0.0001
1000-hr $_{live}$	y = 0.056 x + 0.016	0.08	4.5	0.0382
1000-hr $_{dead}$	y = 0.042 x + 0.001	0.08	4.5	0.0370
Reproductive $_{all}$	y = 0.355 x + 0.012	0.63	93.5	< 0.0001

Table 10. Linear regression equations and statistics to predict available fuels or the mass of individual fuel components from binned LiDAR data for all height bins (i.e. as a proportion of intercepted and total LiDAR returns by 1-meter height bin). Units are kg m^{-3}.

Fuel Class	Equation	r^2	F	P
Available Fuels	y = 1.0084 x + 0.0187	0.82	2736.9	<0.0001
Needles $_{live}$	y = 0.6280 x + 0.0055	0.89	4271.1	<0.0001
Needles $_{dead}$	y = 0.0064 x – 0.0001	0.25	202.9	<0.0001
1-hr $_{live}$	y = 0.2725 x + 0.0022	0.84	2850.1	<0.0001
1-hr $_{dead}$	y = 0.1612 x + 0.0008	0.87	4144.0	<0.0001
10-hr $_{live}$	y = 0.4195 x + 0.0036	0.84	2929.5	<0.0001
10 –hr $_{dead}$	y = 0.2058 x + 0.0003	0.84	3215.8	<0.0001
100-hr $_{live}$	y = 0.6299 x + 0.0075	0.71	1455.8	<0.0001
100-hr $_{dead}$	y = 0.1977 x + 0.0002	0.65	1077.8	<0.0001
1000-hr $_{live}$	y = 0.0378 x + 0.0017	0.10	64.6	<0.0001
1000-hr $_{dead}$	y = 2E-05 x + 0.0002	0.00	0.0	0.9808
Reproductive $_{all}$	y = 0.2497 x + 0.0016	0.70	1286.8	<0.0001

Canopy fuel loading predicted from calibrated scanning LiDAR datasets:

The relationship between upward sensing profiling LiDAR and downward scanning LiDAR developed from an independent set of Pitch pine-dominated plots is shown in Table 11. To evaluate this comparison for estimating canopy fuels, Skowronski et al. (2011) derived canopy bulk density estimates from upward sensing profiling LiDAR (n = 5 20m x 20m plots, n = 480 bins, r^2 = 0.827) and compared to downward scanning LiDAR (n = 5 plots 20m x 20m plots, n = 380 1-meter bins, r^2 = 0.818) (Figure 17). Figure 18 shows an example of a calibrated maximum canopy bulk density map for the Cedar Bridge area in the Greenwood Wildlife Management Area in the Pinelands.

Table 11. The relationship between LiDAR parameters derived from upward sensing profiling LiDAR to downward sensing scanning LiDAR for n = 19 20 m × 20 m plots dominated by Pitch pine in the New Jersey Pinelands. Means and standard deviations from upward and downward senors and equations for their relationships are presented. Correlation coefficients (r^2) are Pearson's product moments. Correlations are all significant at P <0.01 with the exception of the equation indicated with a "*". Adapted from Skowronski et al. 2011.

Parameter	Profiling LiDAR	Scanning LiDAR	Equation	r^2
Standard LiDAR-derived parameters				
Mean return height, h_{mean}	6.54 ± 1.48	7.71 ± 1.66	y = 0.735 x + 0.940	0.98
Maximum return height, h_{max}	12.04 ± 3.07	12.40 ± 2.29	y = 1.288 x − 3.599	0.82
90th percentile height, h_{90}	8.85 ± 1.83	10.00 ± 2.00	y = 0.746 x + 1.451	0.96
75th percentile height, h_{75}	7.80 ± 1.72	9.00 ± 1.88	y = 0.692 x + 1.652	0.94
25th percentile height, h_{25}	5.51 ± 1.43	6.51 ± 1.54	y = 0.662 x + 1.276	0.94
10th percentile height, h_{10}	4.41 ± 1.23	5.36 ± 1.31	y = 0.713 x + 0.640	0.90
Canopy density, D(%)	44.5 ± 17.9	87.8 ± 9.61	y = 1.262 x − 62.1	0.86
Coefficient of variation, CV	0.26 ± 0.03	0.24 ± 0.43	y = 0.540 x + 0.128	0.67
Canopy height bins				
All height bins (n=475)	0.04 ± 0.06	0.14 ± 0.19	y = 0.320 x − 0.001	0.85
Selected 1-m height bins (n = 5 for each bin)				
3-4 m height	0.01 ± 0.01	0.05 ± 0.06	y = 0.081 x + 0.009	0.38*
8-9 m height	0.16 ± 0.09	0.40 ± 0.20	y = 0.398 x − 0.016	0.86
13-14 m height	0.03 ± 0.04	0.11 ± 0.11	y = 0.224 x − 0.001	0.93

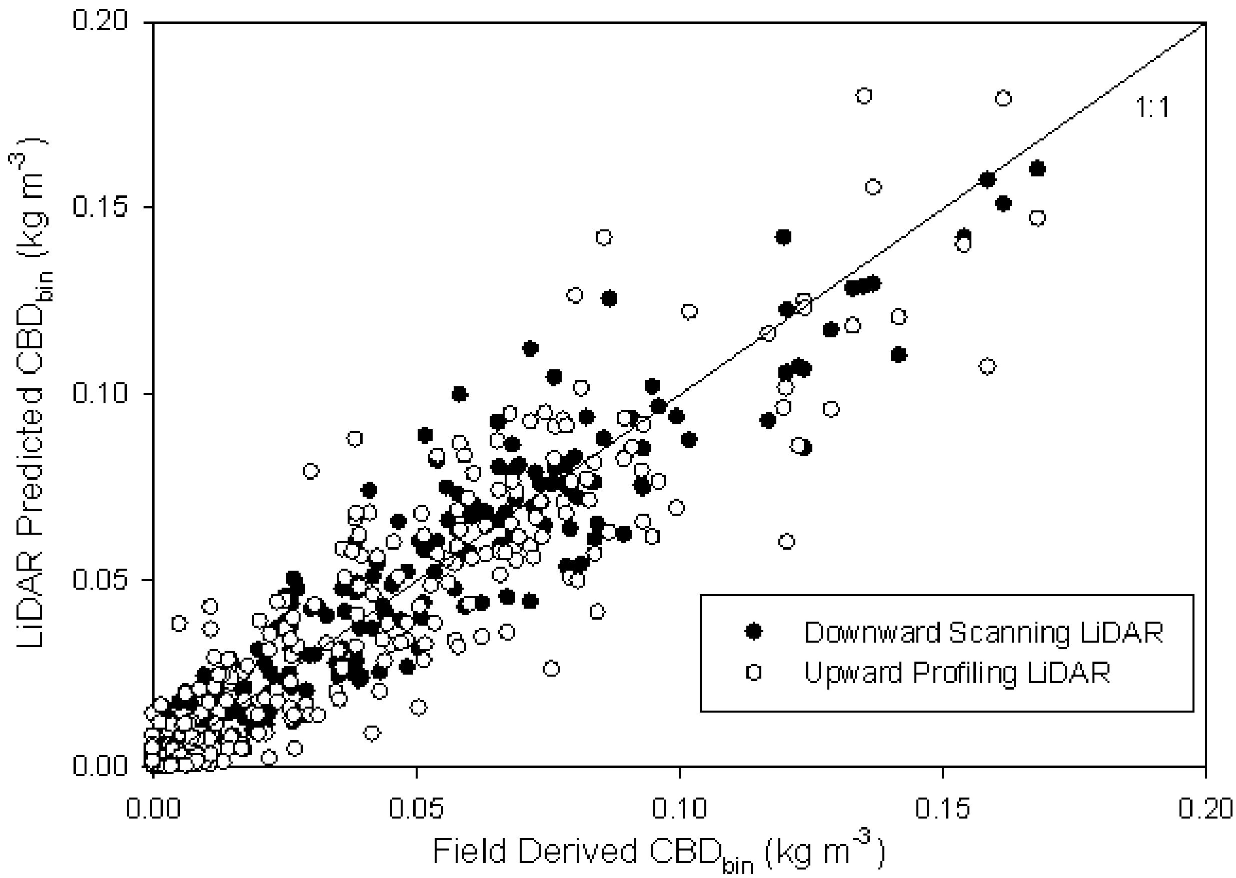


Figure 17. Predicted values of CBD_{bin} from equations for upward profiling LiDAR (open symbols) and downward scanning LiDAR (closed symbols), plotted against biometric estimates of CBD_{bin} in 1-meter layers. From Skowronski et al. 2011.

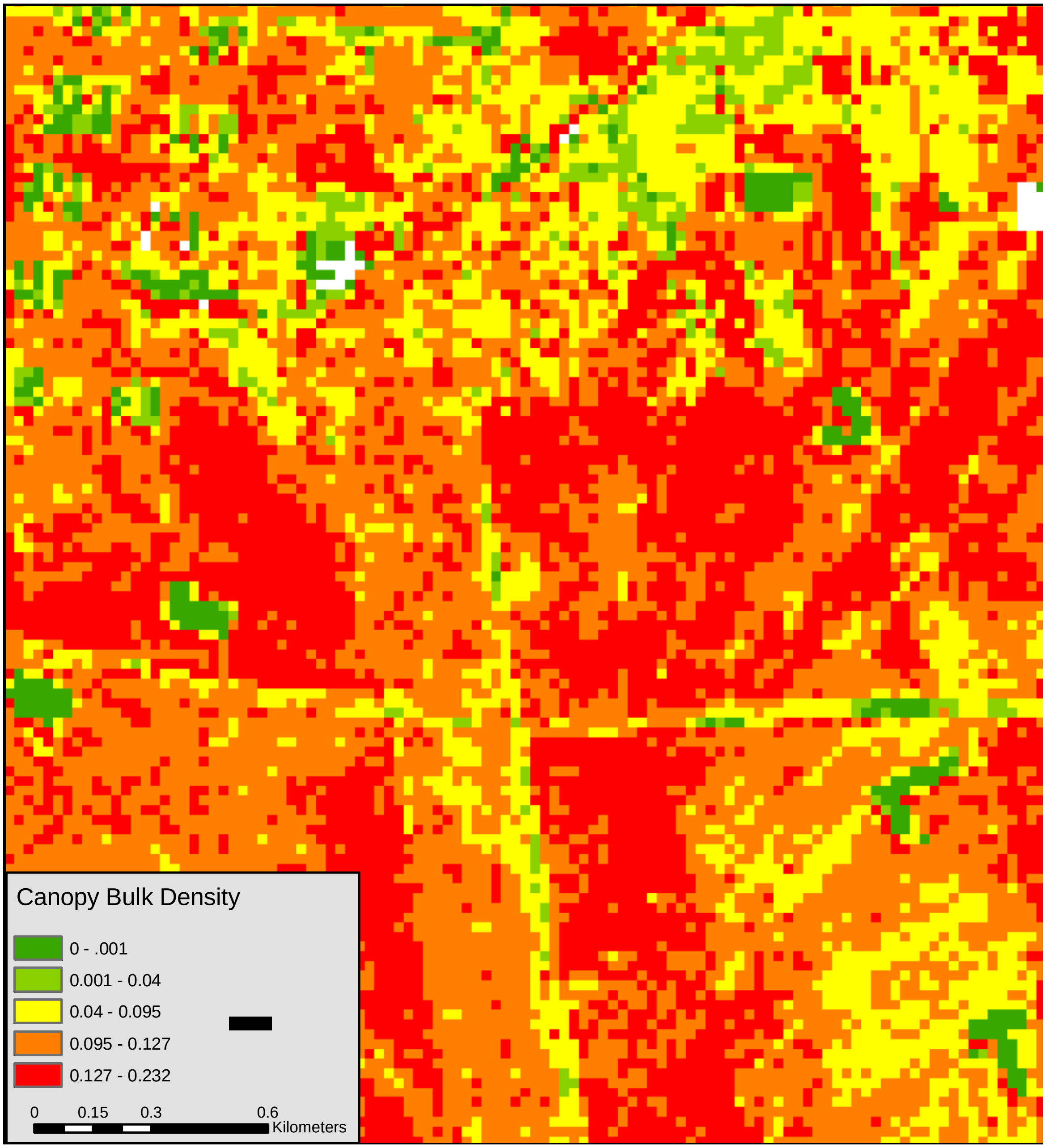


Figure 18. Calibrated maximum canopy bulk density map for the Cedar Bridge area in the Greenwood Wildlife Management Area in the Pinelands (from Skowronski et al. 2011).

Evaluation of LiDAR predictions with independent field plots:

We sampled an additional 20 20 x 20 meter plots throughout Pitch pine dominated forests to evaluate LiDAR-derived estimates of selected canopy fuel parameters. Descriptive statistics for trees in the validation plots are in Table 12, and canopy fuel characteristics are shown in Table 13.

Table 12. Summary of biometric information for the (n = 20) validation plots dominated by Pitch pine.

Variable	Number	Snags	Height (m)	DBH (cm)
Mean ± SD	67.8 ± 38.8	11.5 ± 8.6	9.4 ± 2.0	13.9 ± 3.1
Minimum	30	1	6.1	9.0
Maximum	195	34	13.6	20.3

Table 13. Canopy fuel characteristics predicted for the n = 20 validation plots. Total tree biomass and available fuels were calculated from biometric equations in Tables 2-4.

Statistic	Biomass (t ha^{-1})	CFW (kg m^{-2})	Maximum CBD (kg m^{-3})
Mean ± SD	97.8 ± 32.0	1.170 ± 0.386	0.211 ± 0.082
Minimum	19.6	0.238	0.043
Maximum	142.6	1.930	0.347

Seventeen of the 20 plots had complete LiDAR data, and biometric vs. LiDAR-derived estimates of crown fuel weight and maximum canopy bulk density were compared using pair-sample T-tests (Table 14). We have collected upward sensing profiling LiDAR data and downward sensing scanning LiDAR at and above these plots, and are currently comparing predictions to biometric estimates.

Table 14. Comparison of biometric and LiDAR derived estimates of crown fuel weight and canopy bulk density for n = 17 validation plots. Comparisons were made with paired sample T-tests.

Variable	Biometric	LiDAR derived	T	Significance
CFW (kg m^{-2})				
Mean ± 1 SD	1.153 ± 0.272	1.217 ± 0.279	0.216	ns
Maximum	1.914	1.619		
Minimum	0.582	0.606		
Maximum CBD (kg m^{-3})				
Mean ± 1 SD	0.223 ± 0.078	0.217 ± 0.079	0.587	ns
Maximum	0.470	0.398		
Minimum	0.101	0.081		

Summary of Key Findings

Our study focused on the quantification of canopy fuels across a heterogeneous landscape in the Pinelands of New Jersey. We improved estimates of canopy fuel loading in Pitch pine (*Pinus rigida* L.) stands by integrating destructive harvests with sequential upward sensing profiling LiDAR data, and then used extensive scanning LiDAR data to scale data to the landscape. We provide a wide range of equations, from both the biometric and the LiDAR datasets, to calculate CFW, maximum CBD and CBD in 1-meter bins. Using previously sampled plots reported in Skowronski et al. (2011), we determined the relationship between upward sensing profiling LiDAR and downward sensing scanning LiDAR in 20 x 20 m plots dominated by Pitch pine. We can now produce accurate maps of canopy fuel characteristics throughout Pitch pine dominated stands in the Pinelands, and have developed a sampling framework that is appropriate for determining canopy fuels in other forested ecosystems.

We note that LiDAR data has been used frequently for fuel assessments in forests and shrublands. Calibrated LiDAR has the advantages over allometric, plot-based approaches because: 1) Large, landscape to regional scale inventories can be accomplished in a systematic manner, 2) Processing time is limited by data-processing time, not by field crews, access and scheduling, and 3) Damaged, non-uniform crowns can be quantified accurately. However, for an accurate determination of canopy fuel loading, it is essential to evaluate LiDAR signals against destructively harvested data, preferably with sequential harvesting and concurrent LiDAR data collections, following the approach developed here.

V. MANAGEMENT IMPLICATIONS

This research provides important, useful information for the New Jersey Forest Fire Service, and will directly inform their decision-making during wildfire suppression activities, and for evaluating the effectiveness of prescribed burns as they move forward with their extensive fuels management program. We have worked extensively with NJFFS to provide fuel loading and fuel consumption data, with an eye on providing estimates of fuels treatment effectiveness (e.g., Skowronski et al. 2007, 2011, Clark et al. 2009, 2010). For example, we are currently linking the information derived from this research with an evaluation of a series of prescribed burns conducted in March 2013 over much of the area shown in Figure 19a-c. We now have the ability to provide well-calibrated, accurate canopy fuel maps of areas like this.

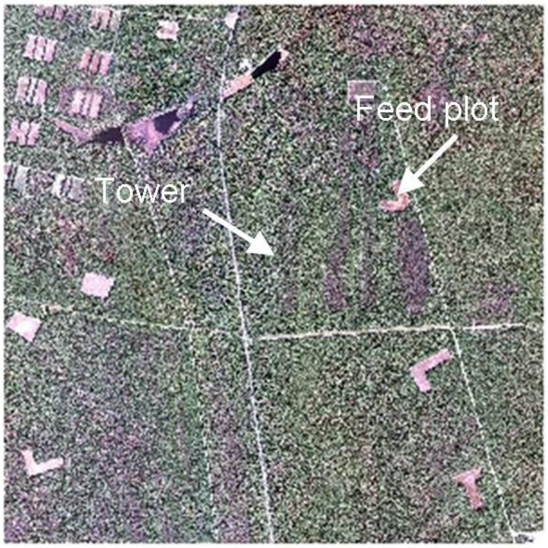
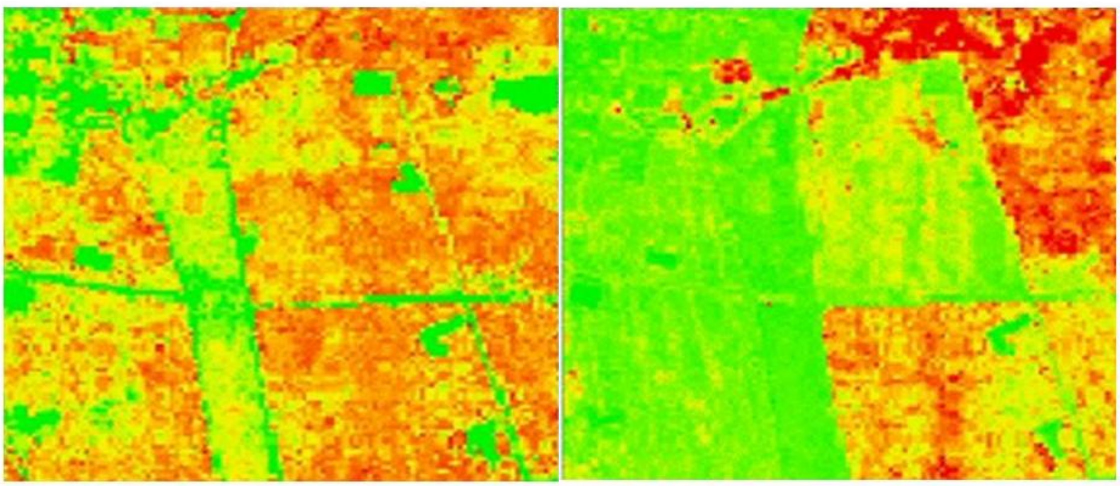


Figure 19a. An aerial photo of the Cedar Bridge area. 19 b and c. Scanning LiDAR estimates of understory fuel density, showing the effect of a series of prescribed burns conducted in March 2008. Green indicates low fuel loading density, and red indicates high density.



LIDAR 1-2 m, pre-burn   LIDAR 1-2 m, post-burn

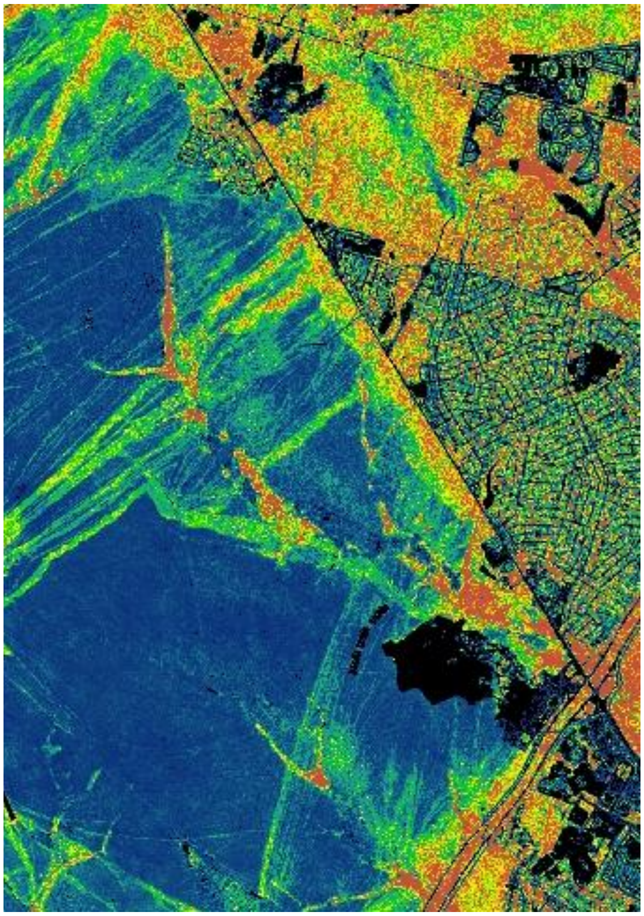


Figure 20. Canopy fuel loading estimated from scanning LiDAR following the 2007 Warren Grove wildfire. Extensive WUI is in the center right portion of the image.

We are also using these data to provide calibrated maps of fuels and wildfire hazard within WUI areas at the margins of the Pinelands National Reserve. In addition, we are also working the New Jersey Department of Forestry and USFS Forest Inventory and Analysis program to provide biometric information for fuel loading and biomass of Pitch Pine, based on the harvest data collected during this research.

VI. RELATIONSHIP TO ONGOING RESEARCH EFFORTS

Our results and products are directly applicable to JFSP 12-1-03-11, "Evaluation and Optimization of Fuel Treatment Effectiveness with an Integrated Experimental and Modeling Approach", Nicholas Skowronski, PI. This research will integrate LiDAR measurements of three-dimensional canopy structure and field consumption measurements, using both a space-for-time and remeasurement approaches, with fire intensity and spread simulated with the

Wildland-Urban Fire Dynamics Simulator (WFDS; Mell et al. 2007). Our project contributes to the characterization of three-dimensional canopy fuel loading across a heterogeneous landscape, and to the characterization of the physical changes to the canopy that occur during fuel reduction treatments. Accurate canopy fuel estimates will be used to parameterize WFDS for simulating fire behavior, thus the integration of treatment-dependent canopy structure derived from the LiDAR with WFDS simulations will be used to evaluate realistic treatment scenarios over a wide range of fire weather conditions. The integration of remote sensing, extensive field sampling and modeling in this research will provide a powerful approach for evaluating fuel treatment effectiveness in a variety of other forest and shrub-dominated systems.

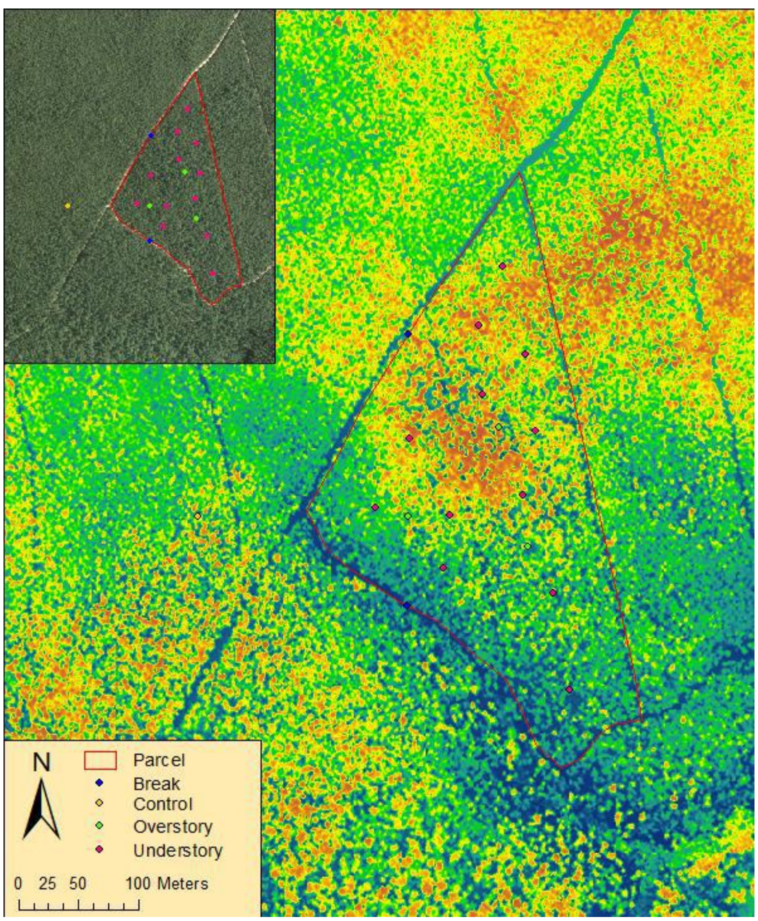


Figure 21. Canopy height profile derived from scanning LiDAR data near the Warren Grove Bombing Range. This stand was burned in a highly instrumented fire in March 2013.

Our project results are also well-integrated with JFSP 09-1-04-1, "Development of Modeling Tools for Predicting Smoke Dispersion from Low-intensity Fires", Warren Heilman, PI. They evaluated several state-of-the art, fine-scale atmospheric dispersion models and CFD models, with an emphasis on their performance in simulating local-scale flows and near-surface conditions. Their overall goal is to improve our understanding of the influence of forest vegetation layers and local terrain-induced circulations on smoke emissions, dispersion, and transport within and above forest canopies. The LiDAR-derived estimates of canopy fuel loading can be used to improve the accuracy of modeling of atmospheric turbulence within and above vegetation layers. For example, Heilman et al. (2013) show the importance of interactions between the forest canopy and turbulence in the fire environment, further stressing the importance of accurate estimates of canopy structure.

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