

geospatial technologies

Applying LiDAR Individual Tree Detection to Management of Structurally Diverse Forest Landscapes

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LiDAR individual tree detection (ITD) is a promising tool for measuring forests at a scale that is meaningful ecologically and useful for forest managers. However, most ITD research evaluates methods over small homogeneous areas, while many forest managers work over large, complex landscapes. We investigated how ITD results varied across diverse structural conditions in California's Sierra Nevada mixed-conifer forests and what this taught us about when and how to apply ITD. Our results suggest that it is advantageous to use ITD when it improves analysis interpretability, when measuring horizontal patterns, or when field data are unavailable. In the latter case, it is best to focus on measures dominated by large trees, like basal area and biomass. Thinking of ITD results as "tree-approximate objects" including one dominant tree and up to a few subordinate tree respects LiDAR's strengths and limitations; we illustrate how this concept keeps analyses consistent across varying structural conditions.

Keywords: LiDAR, individual tree detection, forest landscape management, Yosemite National Park, Sierra National Forest

Airborne LiDAR data is collected by flying a laser scanning instrument over a landscape in back-and-forth flight paths, yielding forest canopy measurements often with complete coverage over hundreds of thousands of acres or more. Because LiDAR data uniquely combine high resolution with large spatial extents, it has proven

useful for measuring and modeling forests at many scales (Hyyppä et al. 2008; Kane et al. 2010a; Kane et al. 2010b). Some widely used LiDAR data products for describing forest structure include direct metrics, such as maps of canopy height, and derived products, such as modeled basal area and volume (Reutebuch et al. 2005).

Raw LiDAR data are stored as a "cloud" of LiDAR returns in 3D space. A common approach to LiDAR data analysis is to use statistics describing the vertical distribution of LiDAR returns to predict traditional forest inventory metrics across a regular grid of pixels. This is referred to as the area-based approach, since the analysis is done over fixed sampling areas (Næsset 1997, 2002). In contrast, a newer approach to LiDAR analysis for forest measurement is individual tree detection. Individual tree detection (ITD) refers to partitioning the raw LiDAR data into objects representing individual trees based on the arrangement of the returns in space (Breidenbach et al. 2010). Typically, the resultant objects are measured for height and crown diameter. These metrics, along with derived metrics such as modeled dbh, are often compiled into a list that is used in much the same way as a field-collected tree list. Individual tree detection has been the topic of much

Received November 2, 2017; accepted May 22, 2018.

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Acknowledgements: The authors wish to thank Luke Dow and Caleigh Shoot for field assistance, Gregory Ettl for guiding advice, especially with respect to sampling design, and Andrew Larson for input on an earlier version of this manuscript. This work was supported by the USDA Forest Service Pacific Southwest Research Station through grants 14-JV-11272139-014, "Using LiDAR to Guide Restoration in Sierra Nevada Forests," and 13-CS-11052007-055, "Using Light Detection and Ranging (LiDAR) to Guide Burned Landscape Recovery and Restoration in Sierra Nevada Forests." This work was performed under National Park Service research permits YOSE-2014-SCI-0092 and YOSE-2015-SCI-0020.

research (Maltamo et al. 2004; Maltamo et al. 2009; Lindberg et al. 2010; Xu et al. 2014; Kankare et al. 2015; Lamb et al. 2017), since accurate detection of individual trees could provide data inputs to existing tree list-based platforms for modeling growth and yield, fire behavior, and habitat classification.

Past studies have applied ITD to estimate standard forest inventory metrics such as density, basal area, or merchantable volume (Maltamo et al. 2004; Bortolot and Wynne 2005; Edson and Wing 2011; Yu et al. 2011), but recent studies have also applied ITD to understanding the ecology and dynamics of forests in ways that are directly applicable to forest management. For instance, ITD has been used to more accurately estimate ecologically relevant parameters of forest structure such as canopy cover, stand structural complexity, aboveground biomass, and the spatial pattern of trees (Huang et al. 2009; Packalen et al. 2013; Tao et al. 2014; North et al. 2017). Individual tree detection can also be used to understand disturbance dynamics, including prediction of fire risk, determination of disturbance extents, and characterization of functional attributes of post-disturbance forests (Morsdorf et al. 2004; Swetnam et al. 2015; Casas et al. 2016). At the same time, the area-based approach has been employed to achieve many of these same ends using generally simpler, less computationally intensive methods (Lefsky et al. 1999; Næsset 2002; Falkowski et al. 2009; Kane et al. 2010a; Kane et al. 2013). Comparisons between ITD and the area-based approach have found similar accuracy when predicting forest inventory metrics (Breidenbach et al. 2010; Lindberg et al. 2010; Yu et al. 2010; Peuhkurinen et al. 2011; Vastaranta et al. 2012) but provide few specific suggestions about when to select one method over the other. Thus, there is an overall lack of guidance for when and at what scales ITD should be preferred over the area-based approach.

One major challenge when using ITD is the under-detection of smaller trees. Many studies have shown that ITD has high accuracy for trees that are visible from above but does not reliably detect trees in lower canopy strata (Maltamo et al. 2004; Vauhkonen et al. 2012; Jakubowski et al. 2013). This suggests that ITD results are only directly equivalent to tree lists in even-aged stands with simple structure

and that the overall accuracy of ITD varies depending on how the dominant trees are configured in space. Many forestlands in the western United States, especially public lands, are managed for structural diversity at both stand and landscape scales, which means that ITD will not behave consistently across these landscapes. While the basic finding that ITD is more accurate for upper-canopy trees is useful, there is a lack of practical understanding of how ITD results might vary with changes in structure from stand to stand.

Several studies have addressed the problem of under-detecting smaller trees by modeling a separate small-tree list based on the attributes of the dominant trees that were detected (Maltamo et al. 2009; Lamb et al. 2017). A recently suggested alternative approach is to instead accept the reality of small tree under-detection and shift the conceptual object of analysis from trees to “tree-approximate objects” (TAOs, North et al. 2017). The concept of the TAO is that ITD results do not represent just one tree but instead represent clusters of trees including one canopy dominant and possibly a number of smaller subordinate trees. Making this conceptual shift may allow for more robust LiDAR analysis, because the TAO concept explicitly recognizes LiDAR’s inherent strengths—sampling the upper canopy at high resolution—and weaknesses—resolving objects in the lower canopy (Richardson and Moskal 2011). Using TAOs may also help to unify analyses over large, structurally diverse landscapes by maintaining a more consistent unit of analysis even while ITD accuracy varies.

This aim of this study is to develop an improved practical understanding of when

and how to use and apply ITD in forest management, focusing on managing large, structurally variable landscapes for multiple resources. Our specific objectives are as follows:

1. Describe how ITD results and interpretation vary with forest structure across a large, structurally variable landscape.
2. Integrate this understanding with past findings to provide guidelines for how and when it is advantageous to use ITD.
3. Demonstrate how the TAO concept is a practical tool for analyzing ITD results by providing examples illustrating its application at different scales.

Methods

Study Areas

In order to provide descriptions of how ITD results vary with structure, we compared ITD to stem map plots across two areas in the mixed-conifer forest zone of the Sierra Nevada, California (Figure 1): Yosemite National Park (Yosemite) and the Dinkey Landscape Restoration Project on the Sierra National Forest (Dinkey). We selected these areas to capture a wide range of forest structural conditions (Figure 2) representative of the mid-montane Sierra Nevada and incorporating areas with varying fire and management histories.

LiDAR Data

We used three LiDAR acquisitions: Dinkey 2010, Dinkey 2012, and Yosemite 2013 (Figure 1, Table S1). Dinkey 2010 and 2012 were collected by Watershed Sciences, Inc. of Corvallis, Oregon, and Yosemite 2013 was collected by the National Center for Airborne Laser Mapping. Average pulse

Management and Policy Implications

LiDAR is a powerful tool for measuring forests, but relating LiDAR datasets to traditional forestry applications is a challenge. LiDAR datasets are often large and cumbersome, and many commonly produced LiDAR metrics have no clear analogy in field-based forestry. LiDAR individual tree detection is appealing because it brings LiDAR data into a familiar and interpretable context. We found that LiDAR tree detection can be a useful data product but that the accuracy of detection varies with stand structure. Canopy dominants are always detected better than subcanopy trees, and the disparity grows with increasing stand height. Because of this disparity, the interpretation of tree detection results will vary across a structurally diverse landscape. When analyses include patches of high-density and multilayered canopy, many smaller trees will be missed, and ITD results will not be equivalent to tree lists. In these situations, we recommend treating LiDAR-detected trees as “tree-approximate objects” representing one canopy tree, possibly together with a group of obscured smaller trees. Shifting the conceptual unit of analysis from trees to tree-approximate objects is a way to respect the limitations of LiDAR data and maintain a consistent object across varying structural conditions.

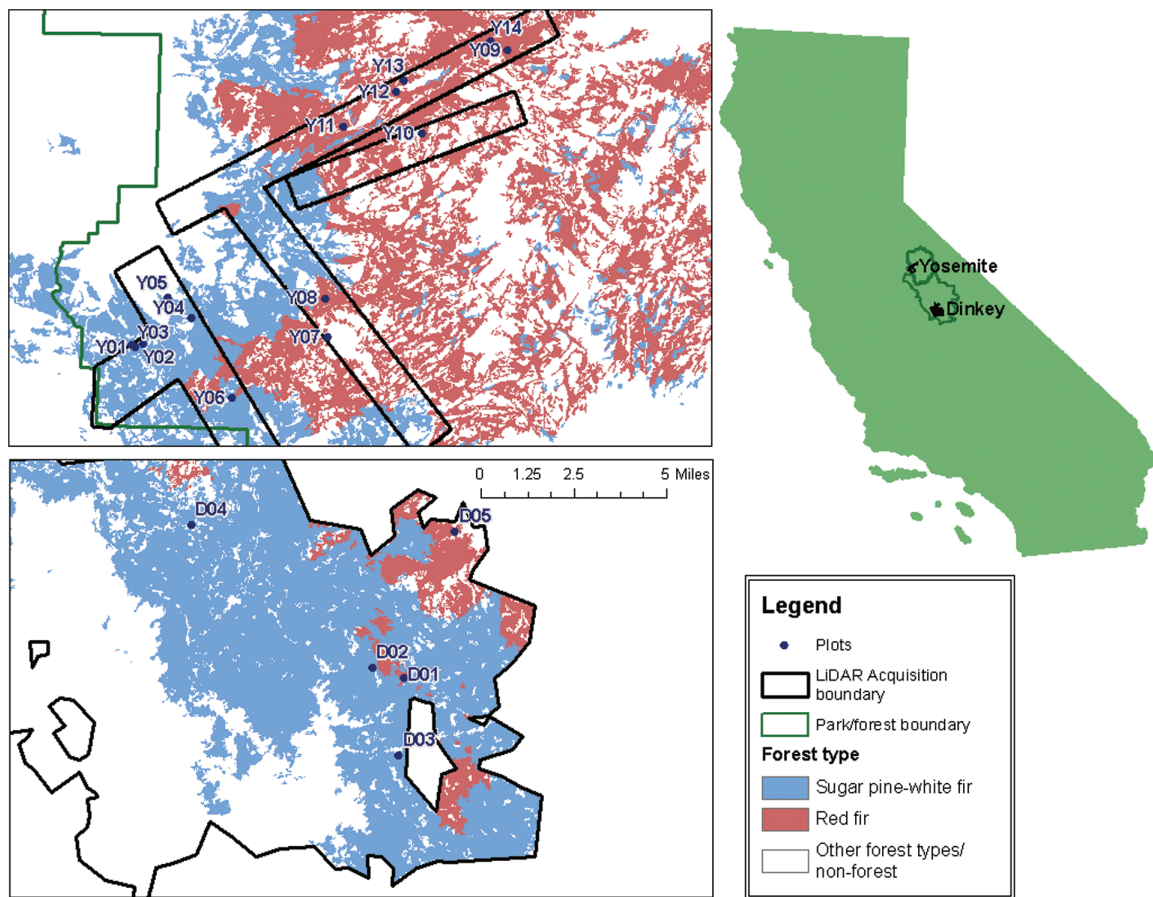


Figure 1. Yosemite and Dinkey study areas within the state of California, showing locations of LiDAR acquisition boundaries, relevant forest types, and stem map plots. Yosemite 2013 acquisition is shown here clipped to match an earlier 2010 Yosemite acquisition, since plots were only located in areas of overlap. For more details about LiDAR acquisitions, see Supplementary Table S1.

density ranged from 0.82 to 1.13 pulses ft^{-2} across the three acquisitions (Table S1).

Field Data

We installed 14 0.5 acre plots in Yosemite in July 2014 and five in Dinkey in September 2014. Sampling was stratified across the eight LiDAR-derived structure classes defined by Jeronimo (2015), which were based on mean height, canopy cover, canopy surface roughness, and the vertical distribution of canopy (Supplementary Figure S1). Plots were randomly located with the number of plots per structure class proportionate to class abundance. Structure class one was not sampled because it did not occur in the mixed-conifer forest type. By spanning the available structure classes, these plots captured the breadth of structural variation across the study areas. More plots were installed in Yosemite since that study area was much more structurally variable. Upon visiting each plot, we ensured that no disturbance had occurred since the time of the LiDAR acquisition.

Plot corners were georeferenced using a survey-grade GPS averaging 300–900 records. GPS positions were differentially corrected using GPS Pathfinder Office version 5.30 (Trimble Navigation Ltd.). All live trees greater than four inches dbh and all snags greater than 10 inches dbh were mapped and measured. Stem mapping was done with a tripod-mounted electronic compass and laser rangefinder.

For each tree measured, we recorded dbh and lean condition (angle from vertical and azimuth of lean). For a random subset of 10 percent of the live trees on each plot, we measured height and crown width. Minimum and maximum crown widths were measured from the tree bole using a clinometer to sight plumb and the two values were averaged. We modeled height and crown widths for remaining trees using linear regression models developed from the measured subset (Jeronimo 2015). We corrected the mapped coordinates of each tree using the height and lean data so

that the coordinates represented the treetop, rather than the breast-height location.

Plot density ranged from 33 trees per acre (TPA) in severely burned plots to 538 TPA in areas without recent fire, while canopy cover ranged from 15–78 percent. Regardless of density, most plots had a substantial large tree component. Quadratic mean diameter (QMD) ranged from 9–30 inches, and 53 percent of plots had a $\text{QMD} \geq 20$ inches. Median basal area was $261 \text{ ft}^2 \text{ ac}^{-1}$, ranging from $31\text{--}527 \text{ ft}^2 \text{ ac}^{-1}$ (Table 2).

Analyzing the Effect of Structure on Tree Detection

We used the TreeSeg tool, an implementation of the watershed transform, from the freely available FUSION LiDAR Toolkit (McGaughey 2018) to identify individual trees from LiDAR. The watershed transform algorithm operates based on one input: the canopy height model (CHM), a raster product where each pixel



Figure 2. Examples of some of the structural conditions within the study area. Included are forests with very recent fire (upper left, burned in 2013), moderately recent fire (upper right, burned in 1989), and no recent fire (bottom row), along with ranges of density, vertical distribution of canopy, and horizontal distribution of trees (i.e., spatial pattern). Photo credits: UL, Cailleigh Shoot; others Sean Jeronimo.

Table 1. Stand structural metrics tested to explain variation in individual tree segmentation accuracy. TPA, BA, QMD, MeanHt, and MaxHt are derived from ground-based measurements. The remaining metrics are derived from LiDAR.

Abbreviation	Description
TPA	Tree density (number ac^{-1})
BA	Basal area ($\text{ft}^2\text{ac}^{-1}$)
QMD	Quadratic mean diameter (in.)
CC	LiDAR-measured canopy cover (%)
MeanHt	Mean tree height (ft)
MaxHt	Maximum tree height (ft)
SD	Standard deviation of all LiDAR return heights: canopy vertical complexity covarying with stand height
Var	Variance of LiDAR return heights: canopy vertical complexity
CV	Coefficient of variation of LiDAR return heights: normalized canopy vertical complexity
Skew	Skewness of LiDAR return heights: bottom-loading or top-loading
Kurt	Kurtosis of LiDAR return heights: narrowness of vertical foliage distribution
P25	25th percentile of LiDAR return heights (ft)
P95	95th percentile of LiDAR return heights (ft)

represents the highest LiDAR return landing in that grid cell. We followed the methods of Jeronimo (2015) and created CHMs using a 2.5-foot resolution with a 3×3 pixel mean smoothing filter.

We matched ITD results (“candidate trees”) to stem maps (“field trees”) using

methods from (Vauhkonen et al. 2012) and calculated the following evaluation metrics:

1. Error rate of omission (i.e., field trees that were missed by ITD).
2. Error rate of commission (i.e., candidate trees that were “invented” by ITD).

3. The *F*-score, a summary statistic ranging from zero (poor) to one (perfect) that balances omission rates with commission rates (Li et al. 2012).

To understand how different stand structural characteristics affect ITD results, we selected a variety of common structural metrics derived from plot and LiDAR data that we suspected may influence ITD results (Table 1). Because of the high degree of multicollinearity among these variables, we performed a principal components analysis (PCA) to reduce the metrics to a smaller set of orthogonal dimensions (McCune et al. 2002). The PCA was carried out in the R environment (R Core Team 2016) using the *vegan* package’s “rda” function (Oksanen et al. 2016). We scaled all input metrics to equal variance in order to remove the effect of different measures in different units. To analyze the relationship between the structural metrics (i.e., the principal component [PC] axes) and ITD accuracy, we used the *vegan* package’s “envfit” function (Oksanen et al.

Table 2. Plot environmental and biological conditions. For structure class characteristics, see Supplementary Figure S1. Forest type codes: SP/WF = sugar pine/white fir; RF = red fir. Fire severity and fire year refer to the most recent fire on record. Fire severity classified by % overstory mortality: Low = <30%, Moderate = 30–70%, High = >70%. CC = canopy cover, TPA = trees per acre, BA = basal area, and QMD = quadratic mean diameter.

Plot	Structure Class	Elevation (ft)	Forest type	Fire severity	Fire year	CC (%)	TPA	BA (ft ² ac ⁻¹)	QMD (in.)	Max. ht. (ft)
D01	4	6990	SP/WF	None	-	38	77	139	18	105
D02	6	7180	SP/WF	None	-	63	256	240	13	108
D03	7	7090	SP/WF	None	-	69	126	427	25	167
D04	3	6360	SP/WF	None	-	45	260	166	11	108
D05	7	8530	RF	None	-	57	221	466	19	144
Y01	5	6230	SP/WF	Low	2010	75	341	392	14	135
Y02	5	6040	SP/WF	Low	2013	78	238	296	15	144
Y03	5	6270	SP/WF	Mod.	2013	67	155	275	18	128
Y04	7	5380	SP/WF	Mod.	2013	66	139	318	20	164
Y05	7	5150	SP/WF	High	2013	49	33	166	30	200
Y06	8	6040	RF	Mod.	2009	52	57	253	28	187
Y07	2	6530	RF	Low	1988	15	70	31	9	79
Y08	8	6630	RF	Low	2013	52	53	227	28	180
Y09	5	7780	RF	None	-	77	538	527	13	167
Y10	7	7840	RF	None	-	68	218	497	20	203
Y11	4	6860	RF	Mod.	2013	36	46	126	22	144
Y12	6	7220	RF	Low	2006	48	96	261	22	144
Y13	4	7640	RF	None	-	27	34	78	20	121
Y14	6	7810	SP/WF	Mod.	2010	30	51	166	24	157

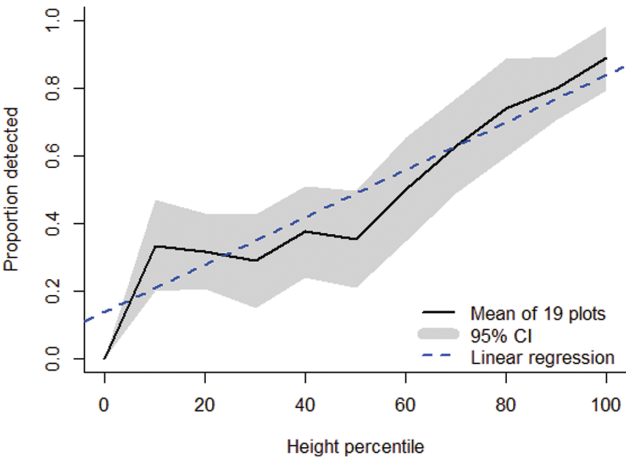


Figure 3. Detection rate by relative tree height aggregated over our 19 sample plots. To normalize between different plots, heights are expressed as percentages of the maximum tree height at each plot. Values on the y-axis are calculated on the basis of 10 percent bins and can be considered as the opposite of omission rates. Detection rate increases quite linearly with relative tree height, a result that is consistent with many past studies (e.g., Vauhkonen et al. 2012; Jakubowski et al. 2012).

2016) to regress the ITD evaluation metrics (omission rate, commission rate, and *F*-score) onto the PCA.

Guidelines for When to Use ITD

We integrated our findings from the section “Analyzing the Effect of Structure on Tree Detection” with findings from prior ITD studies to identify consistent strengths and weaknesses of ITD. We interpreted the strengths and weaknesses of ITD in the context of managing large, structurally

complex forests and compared the tradeoffs of using ITD versus an area-based approach to come up with a set of guidelines for how and when it is best to use ITD.

Tree-Approximate Objects

To demonstrate the merit and practicality of the TAO concept, we selected two examples from our recent work with forest managers that illustrate how the TAO concept can be a valuable tool for analyzing ITD results at operational scales (e.g.,

treatment units), as well as strategic planning scales (e.g., national parks).

Results and Discussion

The Effect of Structure on Tree Detection

The ITD evaluation metrics varied considerably among plots. Across all plots, 38–85 percent (median 68 percent) of trees went undetected (errors of omission), while the number of invented trees ranged from 0–29 percent (median 2 percent) of the actual TPA (errors of commission). The *F*-score, which integrates measures of omission and commission, had a mean of 0.50 and standard deviation of 0.14 and ranged from 0.27 to 0.77 (Supplementary Table S2). As found in past studies, taller trees were detected better than relatively shorter trees (Figure 3). The principal components analysis (PCA) revealed relationships between stand structure and ITD accuracy (Figure 4). The first principal component (PC) explained 54 percent of the variance in the structural data and was strongly associated with dominant tree height. The second PC explained an additional 30 percent of the variance and was strongly associated with tree density.

High rates of omission (more trees missed) at the plot level were most strongly associated with high density, as evidenced

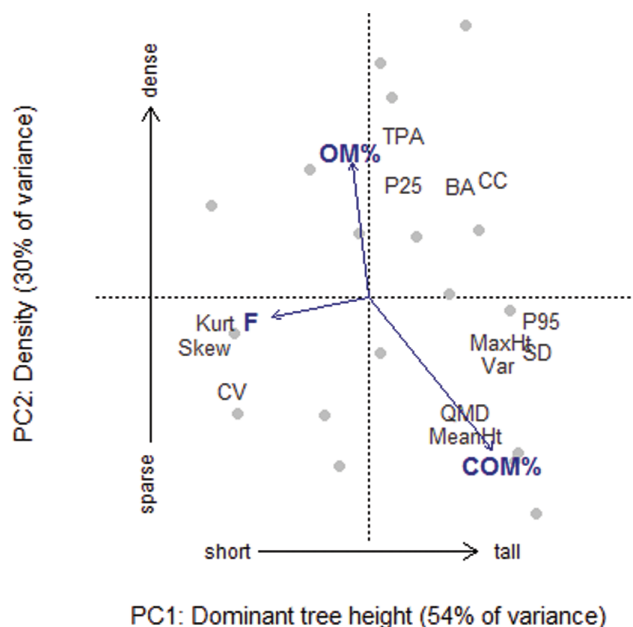


Figure 4. First two principal components (PCs) of ordinated plot-level structural metrics overlaid with fitted vectors of individual tree detection evaluation metrics. Gray dots are individual plots in PC-space. Dark gray text represents the variables that were ordinated on; location of the text in relation to the origin represents the highest gradient of change for that variable. Dark blue text and arrows follow the same concept but for fitted evaluation metrics. Abbreviations: OM%, error rate of omission; COM%, error rate of commission; F, F-score. For definitions of structural metrics, see Table 1.

by positive relationships between omission and TPA ($r^2 = 0.53$, $P < 0.001$), basal area ($r^2 = 0.36$, $P < 0.01$), and canopy cover ($r^2 = 0.25$, $P < 0.05$), but were not related to dominant tree height (Figure 4). This is because increases in density imply a decrease in space between trees and therefore less differentiation and more overlap between crowns (Tao et al. 2014). Additionally, high canopy cover at the stand level creates a physical barrier blocking shorter trees from detection.

Rates of commission (invented trees) increased with dominant tree height and were higher in lower-density plots. These errors were most closely associated with increasing QMD ($r^2 = 0.53$, $P < 0.001$) and mean tree height ($r^2 = 0.49$, $P < 0.001$) (Figure 4), both measures of average tree size. These relationships suggest that ITD invents more trees when the average tree crown is larger and more complex (Ishii et al. 2004; Van Pelt and Sillett 2008) and that open stand conditions lead to spreading crowns that present multiple apparent tops (Jack and Long 1991; Purves et al. 2007).

Overall ITD accuracy as measured by the F-score improved with decreasing dominant tree height ($r^2 = 0.28$, $P < 0.02$) but did not respond to density ($r^2 = 0.12$,

$P = 0.14$), apparently due to cancelling of the opposing effects of density on omission and commission error rates. This relationship was much stronger than relationships between the F-score and measures of vertical structural diversity (i.e., coefficient of variation, standard deviation, skewness, or kurtosis of return heights), indicating that there is something about height *per se* that is related to ITD accuracy. This is an interesting parallel to the common knowledge that taller trees are better detected; it suggests that taller stands are dominated by fewer, larger trees, and so more trees are hidden, and the overall accuracy rate is reduced.

Guidelines for Use of ITD Results

This study and many prior studies have found that the fundamental structural units detected by ITD—regardless of stand structure—are the canopies of trees whose crowns are directly visible from above (Figure 3) (Persson et al. 2002; Popescu et al. 2003; Maltamo et al. 2009; Yu et al. 2011; Kaartinen et al. 2012; Vauhkonen et al. 2012; Kankare et al. 2015). Trees that would typically be defined as intermediates or subordinates can sometimes be detected when occupying an overstory gap, but most detected trees are in the dominant and

co-dominant canopy strata. This becomes especially important across a structurally variable analysis area, since the proportion of trees in different height strata is not consistent, and so ITD detection patterns can vary widely. Thus, across varying structural conditions, ITD can be used effectively to estimate parameters and processes driven by the largest, most dominant trees but is probably not reliable for directly measuring attributes driven by the smaller trees (Lindberg et al. 2010; Xu et al. 2014; Kankare et al. 2015).

Direct use of ITD results can still be useful, since large trees drive several important aspects of ecosystem function. Large trees dominate basal area and biomass (Lutz et al. 2012; Bastin et al. 2015), carbon accumulation and growth (Sillett et al. 2010; Stephenson et al. 2014), and stand spatial heterogeneity (Lutz et al. 2013), and they provide unique structures that are keystone elements of many vertebrate species' habitat requirements (Tews et al. 2004; North et al. 2017). Analysis of ITD results can capture the majority of variation in these processes even while omitting many smaller trees. For example, several studies have predicted biomass and volume directly from ITD results using allometric equations, explaining 67–93 percent of variation in even-aged pine plantations (Bortolot and Wynne 2005; Popescu 2007) and achieving error rates less than about 30 percent for Douglas-fir forests in various successional stages (Edson and Wing 2011).

On the other hand, several aspects of structure and function are driven by smaller trees. For example, the smaller trees dominate stand density (Lutz et al. 2012) and crown fire risk (i.e., ladder fuels; Agee and Skinner 2005) and contribute greatly to hiding and thermal cover for various wildlife species (Millsbaugh et al. 1998; Zielinski et al. 2004). In these cases, ITD can be augmented by modeling the small tree component using Weibull distributions or imputation (Maltamo et al. 2004; Maltamo et al. 2009; Lindberg et al. 2010; Lamb et al. 2017). Small-tree augmentation is effective and is especially desirable when an unbiased estimator is required, for example, in forest inventory and growth modeling (Breidenbach et al. 2010). However, it does not provide actual locations for smaller trees and so cannot be applied to analyses of horizontal structure at fine scales such as might be required for spatially parameterized

tree-mortality models or physics-based fire models (Das et al. 2008; Burke 2017).

For many forest management applications, the area-based approach is a better choice than ITD. The area-based approach provides accuracy comparable to ITD and augmented ITD for estimates of density, basal area, biomass, and merchantable timber volume (Breidenbach et al. 2010; Lindberg et al. 2010) but require less processing and simpler workflows. However, ITD does provide some key advantages, and we recommend using it strategically to capitalize on these. First, ITD deals with elements that are ecologically relevant and easily conceptualized, namely, individual trees. Individual tree detection should be used when reliability or interpretability of analysis is improved by thinking in terms of individual trees. The object-based nature of ITD can also be an advantage when field data are not available. The area-based approach requires ground-truth calibration, while ITD can make many structural measurements without the need for ground truthing (Vastaranta et al. 2012). Lastly, ITD associates areas in xy space with certain trees, and so ITD can be used to characterize horizontal structure, as well as horizontal configuration of vertical structure. This is not possible with the typical area-based approach.

Another important consideration when deciding whether to use ITD is species composition. Some studies have investigated predicting species of detected trees based on canopy structure (Holmgren and Persson 2004; Barilotti et al. 2009; Yao et al. 2012), but in general, ITD results are not resolvable

to the species level. When composition data are required, they must be obtained through some other means such as area-based imputation (Breidenbach et al. 2010), modeling from multi- or hyper-spectral imagery (Koukoulas and Blackburn 2005; Dalponte et al. 2014), or field surveys.

Tree-Approximate Objects

On sites with high-density, multi-story canopy, or large trees with individualistic crowns, ITD results have higher error (Figure 4) and are not in one-to-one correspondence with actual trees. In these cases, the detected objects can be thought of in terms of connected canopy units called tree-approximate objects (North et al. 2017), which are composed of one larger tree and zero or more subordinate trees (Figure 5). TAOs are useful because they are the conceptual common denominator of what ITD objects represent, regardless of stand structure: a larger tree that is visible to LiDAR with an uncertain body of canopy hidden under its foliage. Thinking about ITD results this way respects the strengths and weaknesses of LiDAR measurements by accepting the reality that the lower canopy is very difficult to parse. It also allows the same unit of analysis, the TAO, to be used across a variety of structural conditions, even while ITD accuracy varies.

There is a strong theoretical basis for considering TAOs as ecological units. In many forests—especially frequent-fire forests—trees tend to arrange themselves as a mosaic of clumps, individuals, and open space (Franklin and Van Pelt 2004; Kane et al. 2011; Larson and Churchill 2012;

Churchill et al. 2013 and references therein; Kane et al. 2014). Trees within a clump share carbohydrate and water resources through root grafting and mycorrhizae (Warren et al. 2008; Simard 2009) and often act as a single entity in terms of functions such as habitat provision, snowmelt and hydraulic regulation, and determination of fire behavior (Larson and Churchill 2012). In these forests, the tree group, rather than the tree, can be thought of as the fundamental structuring element of the forest.

Here we provide two examples from our recent work with forest managers demonstrating how the TAO concept can improve analysis of ITD results at different scales.

Anchoring Restoration Prescriptions Around Backbone Trees. We worked with Crater Lake National Park to develop restoration prescriptions for mechanical treatments in the Annie Creek Extension area (Jeronimo et al. 2017). The area is occupied by dry mixed-conifer forest with a substantial legacy of old ponderosa pine (*Pinus ponderosa*) and sugar pine (*Pinus lambertiana*). Treatment goals were to improve survivorship of old pines, reduce the risk of high-severity fire, increase structural diversity, and promote pine regeneration. We had high-resolution LiDAR data (0.78 pulses ft^{-2}) for the project area, which was split into treatment units of 10–40 acres.

A traditional approach would have been to sample a grid of plots in each unit to meet a certain margin of error, compile stand tables, and design prescriptions based on the trees to be removed. This same process could have been accomplished using

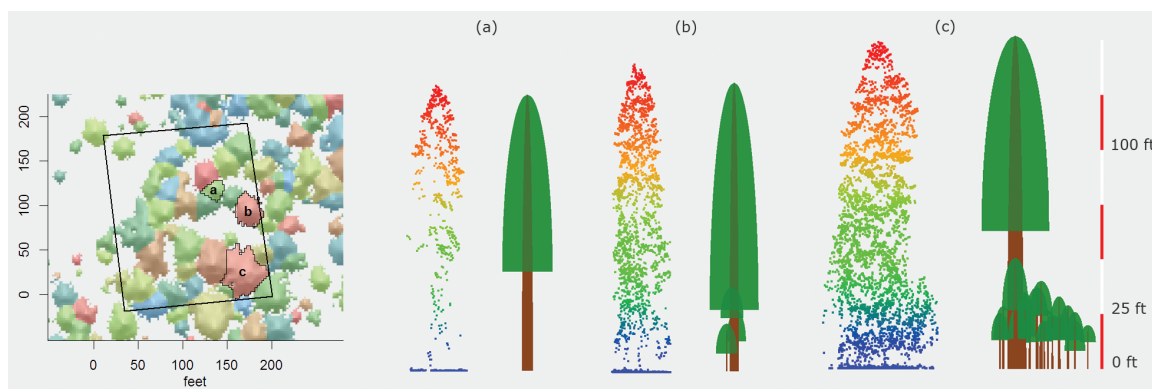


Figure 5. Examples of what a tree-approximate object (TAO) might represent. Inset shows plot Y10, with TAOs represented by unique colors and the three example TAOs outlined. Left column shows the point cloud associated with each of the example TAOs. Right column shows renderings of the stem-mapped trees landing within the footprint of each example TAO. These examples demonstrate how an individual TAO is composed of one canopy tree that is well-resolved by LiDAR, plus zero or more smaller subcanopy trees. Note also that although the subcanopy trees are not individually resolvable they maintain a signature in the point cloud.

LiDAR with an area-based approach and field calibration plots. Instead, we used an ITD approach, thinking of the ITD results in terms of TAOs. Instead of focusing on small trees to be removed, we focused on large trees to be retained, since the TAOs primarily represent the canopy trees. This was compatible with the treatment objectives because, as a restoration treatment, the residual stand conditions were more important than the wood removed.

We estimated which TAOs were dominated by a legacy tree and defined

prescriptions that were anchored around those “backbone” trees. Using the TAO concept allowed us to assess the spatial patterns of backbone trees and identify opportunities for creating fuel breaks and regeneration gaps that did not conflict with retention of legacy trees. It also allowed us to simulate different prescriptions and assess post-treatment structural diversity under different scenarios. All of this could be done without the need for ground truthing, since we were analyzing objects that we were confident ITD detected well.

In stands where structure was simple—with even spacing, shorter canopy heights, and a low degree of vertical complexity—TAOs were more equivalent to individual trees. Where stand structure was more complex—with tall trees, vertical and horizontal heterogeneity, and individualistic nonmodel-conforming crowns—TAOs represented small groups of trees (Figure 6). Using the TAO concept allowed us to treat ITD results the same way across a diversity of structural conditions.

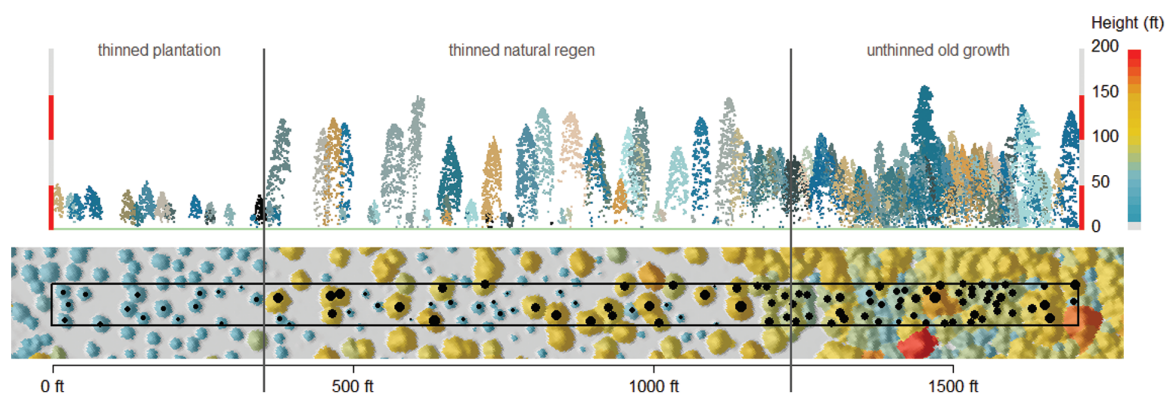


Figure 6. A transect exemplifying some of the characteristics of individual tree detection in different stand structural conditions. The transect is located in a mixed conifer forest in the Oregon Cascades and begins in a heavily thinned plantation on the Fremont-Winema National Forest (left), crossing into a mature naturally regenerated stand thinned under the same prescription (center), then crossing into Crater Lake National Park, in a patch of unthinned old growth. The upper panel is a side view of the LiDAR point cloud, with the points associated with each detected tree colored in unique contrasting colors. The lower panel shows an overhead view of detected trees, in which each tree canopy is colored by the tree’s height and black dots represent the treetop location, size scaled by tree height. The thinned plantation is characterized by small conical trees with wide spacing. In this stand, LiDAR tree detection results correspond to individual trees. The thinned natural regeneration demonstrates some of the effects that tall trees can have, even on a lower density stand: the large crowns of the dominant trees block out lower strata, hiding smaller trees. The unthinned old growth stand is difficult to parse, even visually, due to a combination of large trees and higher density. Shorter trees are discernible only in overstory gaps. Thinking of ITD results as tree-approximate objects instead of individual trees can help when comparing different structural conditions like these, since it represents a consistent and comparable unit of analysis.

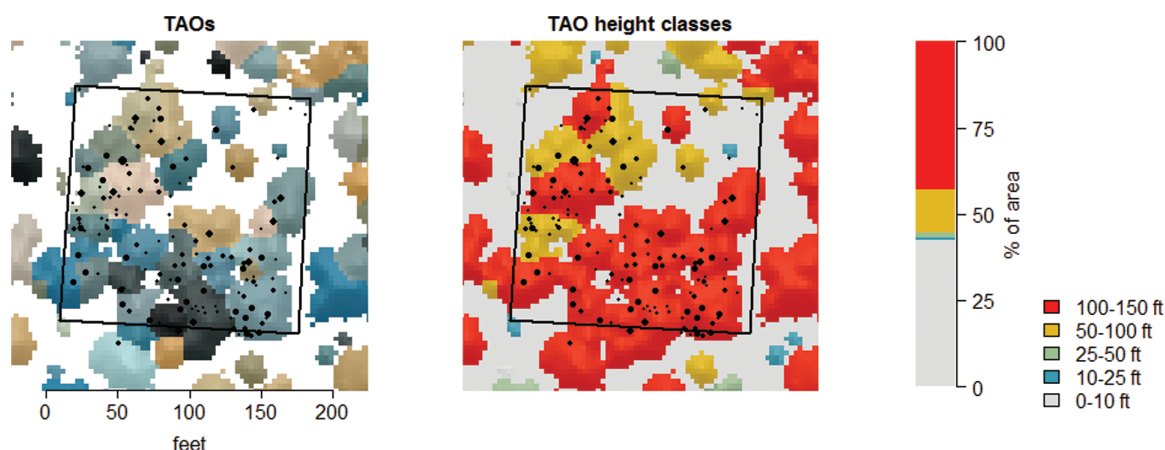


Figure 7. A height strata classification approach to tree-approximate object (TAO) quantification. The left panel shows mapped trees (circles, scaled by $\sqrt{\text{dbh}}$) at plot D05 superimposed on top of ITD results, with detected objects shown as contrasting colors. Note that mapped points represent tree top locations accounting for lean, and so do not all land within the plot boundary. The right panel shows the same map with TAOs classified into height strata. Summarizing proportions of area in each of these canopy classes can be an effective way to integrate the horizontal pattern measurements that ITD affords with the analytical efficiencies of the area-based approach.

Mapping Spotted Owl Habitat Across the Sierra Nevada. We studied structural habitat preferences of the California spotted owl (CSO, *Strix occidentalis occidentalis*) using nest location data and LiDAR measurements of structure across the Sierra Nevada (North et al. 2017). We classified LiDAR-measured structure on a pixel basis and were able to associate certain structure classes with CSO nesting, activity, and territory areas. A typical area-based approach would have created structure classes based on vertical distributions of LiDAR returns over each pixel (e.g., Lefsky et al. 1999; Zimble et al. 2003; Kane et al. 2013). Instead, we used the TAO concept to include horizontal pattern information gained from ITD into the area-based analysis.

We classified TAOs into height classes and summarized the proportion of canopy area in different classes over 295 ft (90 meter) pixels (Figure 7), then used these proportions as inputs into the structure classification. This allowed us to simultaneously account for vertical and horizontal elements of pattern, including openings. Because we considered ITD results to represent TAOs, we did not need an exhaustive tree list but instead were comfortable dealing with connected areas of canopy dominated by a tree of a given height class. An added benefit of this approach is that any large, complex tree crowns that were split up were likely to have been grouped back together in the same height class, reducing the overall impact of commission errors.

In this case, using ITD and area-based analysis together resulted in a stronger result than using either approach individually. The ITD data, conceptualized as TAOs, provided important data about the horizontal arrangement of structural elements, while the area-based analysis framework allowed us to easily synthesize these results over more than one million acres across the Sierra Nevada.

Conclusions

Individual tree detection is a powerful and interpretable way to analyze LiDAR data, but like any data source, it has strengths and limitations. We explored some of these tradeoffs using one tree detection method across one small part of the western United States. There are many other ITD methods, but comparative tests show that all methods provide results that vary by forest type, and

no one method is clearly superior in all conditions (Kaartinen et al. 2012; Vauhkonen et al. 2012). Furthermore, the limitations we found in this study are similar to limitations found by others using different methods in different forest types (Richardson and Moskal 2011; Eysn et al. 2015). For these reasons, we believe that the guidelines for using ITD presented here can be applied for many different ITD methods and forest types.

Supplementary Materials

Supplementary data are available at *Journal of Forestry* online.

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