Cataloging and Visualizing Complex Forest Stands Using LiDAR Data

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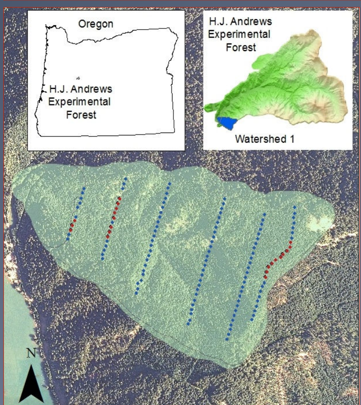
ABSTRACT: Aerial LiDAR data have been used extensively for quantifying canopy cover and forest structure because they provide a scale-invariant estimation of forest biomass, and visualizations from LiDAR data can illustrate forest structure and composition. However, validating remotely-sensed LiDAR metrics against ground-truthed measurements and developing better analytical tools and visualizations are critical for both research and management.

We analyzed tree height and stand composition on long-term plots on a small watershed in the Oregon Cascades. We identified individual trees and tree heights using a LiDAR tree-delineation approach (*TreeVaW*), comparing our results with field catalogued individual trees. *TreeVaW* identified 2,810 of 3,407 observed trees (82.48%). Since landscape simulations can help assess potential impact of land-use decisions, we used *TreeVaW* measurements to visualize LiDAR returns as a simulated landscape at the plot scale, building conical tree models with the *Processing* computer graphics language.

We observed that *TreeVaw* identified more trees and predicted heights more accurately where the overstory is homogeneous and where canopy gaps are present than where stand composition is complex. We conclude that LiDAR data plus tools such as *TreeVaW* and *Processing* produce simple 3D visualizations that could sometimes replace expensive stand-level surveys and might improve communication between researchers and decision-makers. Our findings might help refine analysis software such as *TreeVaW* , and further refinement is needed for complex stands or topography.



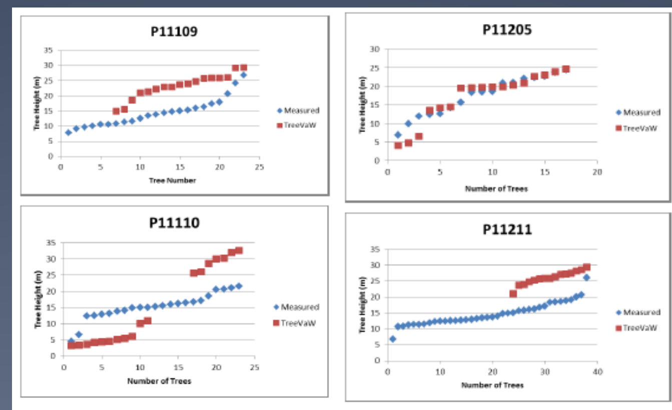
Plot	Observed Trees	Predicted Trees	% Trees Identified
P11108	28	12	42.86
P11109	23	17	73.91
P11110	23	18	78.26
P11205	17	17	100.00
P11206	17	15	88.24
P11207	15	18	120.00
P11208	12	14	116.67
P11209	25	11	44.00
P11211	28	15	39.47
P11212	46	22	47.83
P11213	28	17	60.71
P11608	24	16	70.83
P11609	15	12	80.00
P11610	18	14	77.78
P11611	19	14	73.68
P11612	21	17	80.95
P11613	30	15	50.00
P11614	19	15	78.95
P11615	25	20	80.00
P11616	21	14	66.67
P11617	13	14	107.69

(Left) Watershed 1, H.J. A. Experimental Forest , has 133 sample plots on 6 transects; red plots were categorized and visualized. (Above) % of trees correctly identified varied by plot.

SITE: The H.J. Andrews Experimental Forest is in the Western Cascades range, OR. WS1 is a small watershed (~96 ha) on a first order stream draining to Lookout Creek on the McKenzie River. Minimum elevation on WS1 is 450 m and maximum 1027 m, mean slope measured using ground based clinometry is 59.35%, and the watershed outlet faces a 286^{0} aspect. Mean temperatures: January 35 F (1.6 C) and July 69 F (20.6 C). WS1 has both basaltic and andesitic mineralogy with soils from shallow and stony to moderately deep with well-developed profiles. WS1 was harvested using clear-cut and burn between 1962-1966. Prior to logging, Douglas-fir (*Psuedotsuga menziesii*) was the dominant species, aged 100-500 yrs. Western Hemlock (*Tsuga heterophylla*) was intermixed and generally younger; some western red-cedar (*Thuja plicata*) was also present, mostly in drainage areas. Following logging, WS1 was replanted with Douglas-fir, although hardwood establishment prevailed on poor soils and steep slopes. Re-measurements of DBH began on 133 vegetation plots across 6 transects in 1980, thereafter ~ every 6 years. Trees on each plot are tagged and inventoried, with data converted to height using georegion-specific allometric equations.

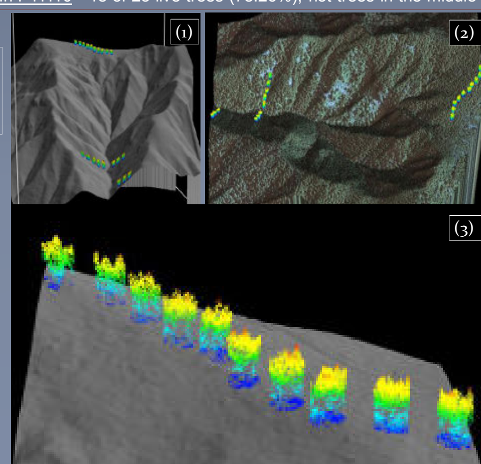
HEIGHT METHODS: Tree heights on 16 WS1 plots were calculated using (1) region specific allometric equations from DBH and (2) difference between first and last LiDAR pulses as calculated with *TreeVaw.* LiDAR was flown in 2008, and the most synchronous forest measurement taken in 2007. The above table displays percent of heights correctly identified by *TreeVaw* on selected plots – 2,810 trees of 3,407 observed trees (82.48%).

Measured vs. calculated height (m) for individual trees in 4 sample plots.



RESULTS OF HEIGHT CATEGORIZATION: We compared heights (m) of identified individual trees with allometric LiDAR/*TreeVaW* predictions across several plots. In general, tall trees were identified more readily than shorter ones, e.g., in plot P11109 *TreeVaW* identified 17 (the tallest in the plot) of 23 live trees (73.91%). We saw 3 categories and believe that complex stand structure and age-dynamics are responsible for these categories: 1) trees were either well-predicted or 2) over-estimated, and/or 3) systematic gaps in the height range were observed. For example, *TreeVaW* identified:

- In P11205 - 100% of live trees; heights identified by *TreeVaW* were very similar to measured tree heights.
- In P11211 - 15 of 38 live trees (39.47%); those 15 were the tallest, and estimated heights were consistently 7-8 m taller than measured heights. Plot 11211 is interesting because a mortality event occurred on the plot P11212 above it.
- In P11110 - 18 of 23 live trees (78.26%), not trees in the middle of the height range.



(Left) *FUSION* software was used to visualize LiDAR returns on our plots over (1) bare earth, (2) the LiDAR return profile, and (3) at high resolution.

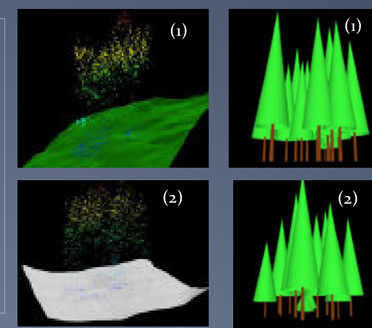
VISUALIZING HEIGHT IDENTIFICATION CATEGORIES: We used *FUSION* to visualize LiDAR height returns of trees on our plots to link (1) height identification categories (well-predicted, over-estimated, or systematic gaps) and (2) field observations of stand structure and age-dynamics.

VISUALIZATION METHODS: After loading raw LiDAR data files into *FUSION*, the stoking technique was used to select circles for the known plots, and the LiDAR Data Viewer (LDV) then visualized the selected data as a colored point cloud based on return density. Using the computer graphics language *Processing*, we developed simplified conical models of the plots; heights of trees were read from *TreeVaW* output files, with DBH calculated as if all trees were Douglas-fir. *FUSION* visualizations were then compared to the *Processing* models which suggested potential biological mechanisms for our 3 tree identification categories.

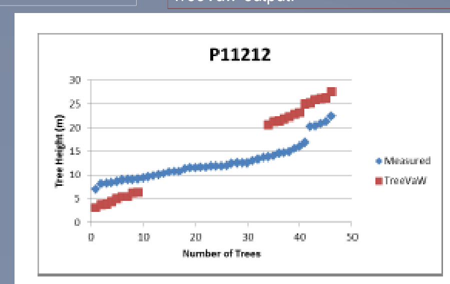
VISUALIZATION RESULTS: We used *TreeVaW* and *Processing* output to visually examine trees identified by*TreeVaW*. With those visualizations, it became clear that where a thick overstory of taller trees is present, *TreeVaw* could identify more trees and predict their heights more accurately than where stand composition is complex and understory trees are present. However, where gaps are present in the taller trees, *TreeVaW* was better able to identify smaller trees found within these gaps. In both cases, we found simplified *TreeVaW* and *Processing* visualizations more "user-friendly" than *FUSION* point clouds.

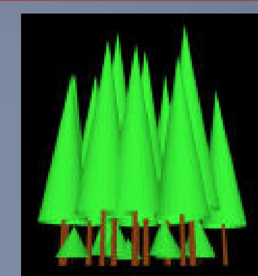
(Right) Visualizations on left are produced with FUSION. On right are *Processing* visualizations of trees identified by *TreeVaW*.

P11109 (1) and P11205 (2) are shown.



RESULTS FROM CATEGORIZATION & VISUALIZATION: An example (below) summarizes the usefulness of our technique. In plot P11212, *TreeVaW* identified 22 of 46 live trees (47.83%). *TreeVaW* identified both tallest and shortest trees in the plot. *TreeVaW* consistently underestimated height for shorter trees and overestimated height of the tallest trees. A local mortality event on this plot had caused canopy gaps, and additionally many trees have poor morphology (broken or leaning). While large and small trees might have survived the event due to structural resilience or flexibility respectively, mid-sized trees might have been damaged to the extent that they are unrecognizable in LiDAR imagery. *Processing* visualizes this structure in a simple cone diagram using *TreeVaw* output.





CONCLUSION: Using *TreeVaW* data and *Processing* visualization, LiDAR forest data can be categorized into meaningful and structurally representative categories. Simplified visualizations provide a basis for easier visual interpretation of LiDAR returns than viewing point clouds.