

Estimating forest canopy fuel parameters using LIDAR data

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Abstract

Fire researchers and resource managers are dependent upon accurate, spatially-explicit forest structure information to support the application of forest fire behavior models. In particular, reliable estimates of several critical forest canopy structure metrics, including canopy bulk density, canopy height, canopy fuel weight, and canopy base height, are required to accurately map the spatial distribution of canopy fuels and model fire behavior over the landscape. The use of airborne laser scanning (LIDAR), a high-resolution active remote sensing technology, provides for accurate and efficient measurement of three-dimensional forest structure over extensive areas. In this study, regression analysis was used to develop predictive models relating a variety of LIDAR-based metrics to the canopy fuel parameters estimated from inventory data collected at plots established within stands of varying condition within Capitol State Forest, in western Washington State. Strong relationships between LIDAR-derived metrics and field-based fuel estimates were found for all parameters [$\sqrt{\text{crown fuel weight}}$: $R^2=0.86$; $\ln(\text{crown bulk density})$: $R^2=0.84$; canopy base height: $R^2=0.77$; canopy height: $R^2=0.98$]. A cross-validation procedure was used to assess the reliability of these models. LIDAR-based fuel prediction models can be used to develop maps of critical canopy fuel parameters over forest areas in the Pacific Northwest.

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1. Introduction

The use of remote sensing for the acquisition of accurate, spatially-explicit estimates of canopy height, canopy base height, canopy bulk density, and total canopy fuel weight would significantly improve the data layer creation process for wildfire simulation models such as FARSITE (Finney, 1998). Previously, these data layers [typically formatted as GIS (Geographic Information System) coverages] were generated using the output from stand-level growth models such as the Forest Vegetation Simulator (FVS), which use a tree list to drive the simulations (Wykoff et al., 1982; Teck et al., 1996). Since the stand-level estimates generated from these models are (typically) based upon a relatively limited

inventory of stand attributes, they will be subject to sampling error and will be unable to capture variability in stand structure at fine spatial scales over the landscape. If canopy structure metrics could be accurately estimated using high-resolution remotely-sensed data, the application of fire spread models to landscapes would be significantly improved, resulting in an increased efficacy of fuel management programs in general.

The emergence of a new generation of active, high-resolution remote sensing systems has the potential to allow for more accurate and efficient estimation of canopy fuel characteristics over extensive areas of forest. In particular, the capability of active infrared laser scanning (LIDAR) systems to acquire direct, three-dimensional measurements of canopy structure could significantly improve estimates of the quantity and distribution of canopy biomass and fuels. Previous studies have shown that LIDAR can be used to estimate a variety of forest inventory parameters, including biomass, stem volume, stand height, basal area, and stand

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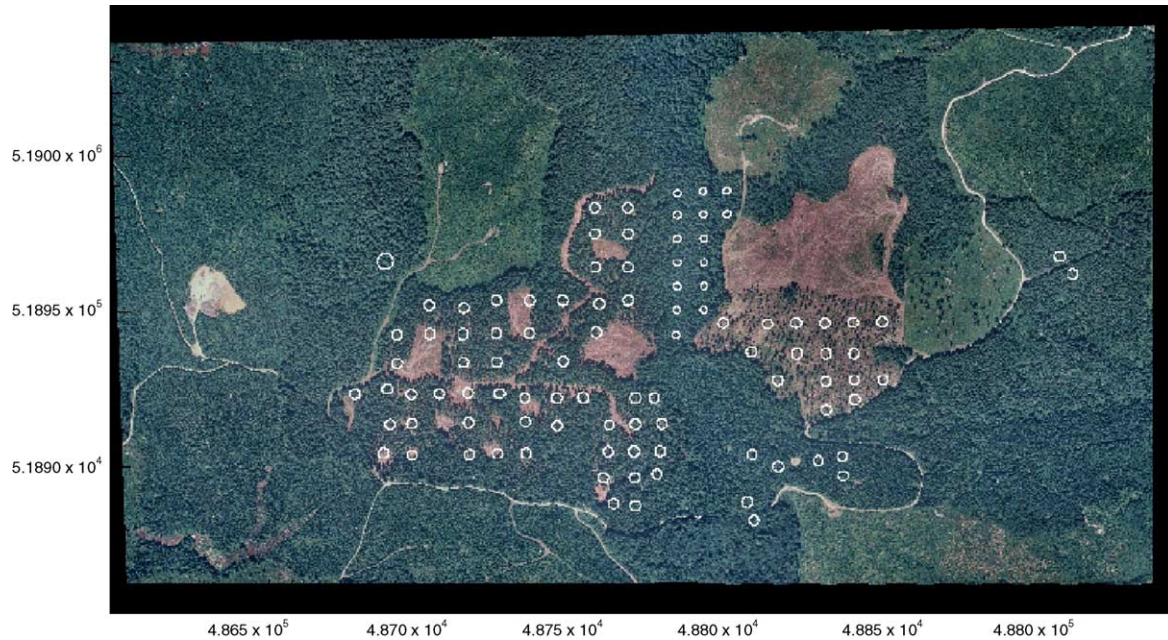


Fig. 1. Orthophoto of Capitol State Forest study area in Washington State (UTM coordinate system). Location and size of field plots are shown in white (courtesy of Washington State Department of Natural Resources, Resource Mapping Section).

density (Naesset, 1997a, 1997b; Means et al., 2000). A study in Norway developed an approach to estimate Lorey's height, crown lengths, and heights to crown base for plots in spruce-pine forest using height quantile estimators (Naesset & Okland, 2002). A recent study carried out in Switzerland used a K-means clustering algorithm to measure individual tree crown dimensions for forest fire risk assessment (Morsdorf et al., 2004). A recent study presented a methodology for estimating crown fuel parameters at individual tree and plot levels in an intensively managed, homogeneous Scots pine forest with little understory due to thinning (Riano et al., 2004). However, it is unclear how well this procedure works in stands with a more complex structure. While preliminary results from a study investigating the use of airborne LIDAR for estimation of canopy fuel parameters in stands with complex structure have been previously reported, there was no model validation carried out to assess the reliability of the models (Andersen et al., 2004). In this paper, we present and evaluate an approach to estimating several critical canopy fuel metrics, including canopy fuel weight, canopy bulk density, canopy base height, and canopy height, using high-density, multiple-return LIDAR data collected over a Pacific Northwest conifer forest.

2. Study area

The study area for this investigation was a 5.2 km² area within Capitol State Forest, Washington State, USA. This forest is primarily composed of coniferous Douglas-fir (*Pseudotsuga menziesii*) and western hemlock (*Tsuga heterophylla*), and, to a lesser degree, hardwoods such as red alder (*Alnus rubra*) and maple (*Acer* spp.). The extent of the study

area is shown in Fig. 1. This site is the location of an ongoing experimental silvicultural trial, and contains coniferous commercial forest stands of varying age and density (Curtis et al., 2004). An extensive, high-accuracy topographic survey was conducted throughout the area to enable rigorous evaluation of a variety of technologies relevant to precision forest management, including high-resolution remote sensing and terrestrial geopositioning systems.

A total of 101 fixed area field inventory plots were established over a range of stand conditions in 1999 and 2003 (see Fig. 1). Plot sizes ranged from 0.02 to 0.2 ha. Measurements acquired at each plot included species and diameter at breast height (DBH) for all trees greater than 14.2 cm in diameter. In addition, total height and height-to-base-of-live-crown were measured on a representative selection of trees over the range of diameters using a hand-held laser range-finder. A detailed description of the plot measurement protocol can be found in a previous report (Chapter 3, Curtis et al., 2004). The data from this selection were used to build regression models for estimating height and crown ratio for all trees within the inventory plots.

3. Lidar data

High-density LIDAR data were acquired over the study area with a SAAB TopEye¹ system mounted on a helicopter platform in March, 1999. The system settings and flight parameters are shown in Table 1. The vendor provided raw

¹ The use of commercial names is for the convenience of the reader and does not imply any endorsement by the USDA Forest Service or the University of Washington.

Table 1
LIDAR data specifications

Flying height	200 m
Flying speed	25 m/s
Swath width	70 m
Forward tilt	8°
Laser pulse density	3.5 pulses/m ²
Laser pulse rate	7000 Hz

lidar data consisting of XYZ coordinates, off-nadir angle, and intensity for all LIDAR returns within the area. In addition, the vendor provided a “filtered ground” data set consisting of points presumed to be measurements of the terrain surface, identified via a proprietary filtering algorithm. These filtered ground returns were used to generate a 1.52 m digital terrain model (DTM). Comparison with check points collected in a high-accuracy topographic survey showed that the DTM had a mean error of 0.22 with a standard deviation of 0.24 m (Reutebuch et al., 2003). The LIDAR system collected up to four returns from each laser pulse, and all returns were used in this paper. The elevations of the LIDAR measurements were converted to heights by subtracting off the elevation of the underlying terrain (given by the DTM).

4. Field-based fuel estimates

Field-based estimates of canopy fuels were generated using the methodology developed for the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) by Scott and Reinhardt (Beukema et al., 1997; Scott & Reinhardt, 2001). In this approach, the crown fuel weight for each tree is estimated using the equations developed by Brown and Johnson (1976), where stem diameter is the primary predictor variable. These equations generate estimates of the total dry weight of live and dead material for each individual tree crown, and provide a break-down of the proportion of the total crown weight that is associated with foliage and different size classes of branchwood. According to the methodology of Scott and Reinhardt, crown fuels are defined as foliage and fine branchwood (50% of the 0 to 6 mm diameter branchwood). These crown weight equations can then be used to generate total crown fuel weight estimates for each tree in a plot given a tree list with information including species, diameter at breast height (DBH), crown ratio, and crown class. It should be noted that since crown class was not collected for all plots used in this study, crown weight was not adjusted for relative position of the tree within the stand.

In the context of Scott and Reinhardt’s methodology, it is assumed that the crown material on each tree crown is evenly distributed vertically along a crown’s length. In order to generate an aggregate measure of canopy bulk density at the plot level, the fuel weight for all trees within the plot are summed at 0.3048-m increments from the ground to the top

of the tallest tree. The canopy bulk density is then defined as the maximum 4.6 m running mean of crown fuel density within the plot. Following Scott and Reinhardt (2001), *canopy base height* is calculated as the lowest height at which the canopy fuel density exceeds a critical threshold (0.011 kg/m³). Analogously, *canopy height* is defined as the highest height at which the canopy fuel density is greater than 0.011 kg/m³. Using this methodology, estimates of canopy fuel weight, canopy bulk density, canopy base height, and canopy height were generated for each plot within the study area. An example of the canopy bulk density distribution and fuel parameter estimates for an inventory plot in the dense, mature Douglas-fir canopy unit is shown in Fig. 2.

5. Lidar-based fuel estimates

In an earlier study, Naesset and Bjerknæs (2001) used a limited number of LIDAR-based predictor variables, including the maximum (h_{\max}), mean (h_{mean}), and coefficient of variation (CV) of the LIDAR heights, several quantile-based metrics describing the LIDAR height distribution [25th (h_{25}), 50th (h_{50}), 75th (h_{75}), and 90th (h_{90}) percentile heights], and a canopy density metric (D ; percentage of first returns within the canopy) to estimate tree heights and stem density within young stands in Norway. It was expected that this pool of potential independent variables will collectively provide a concise description of canopy structure within the plot area, and therefore could also be used to estimate other

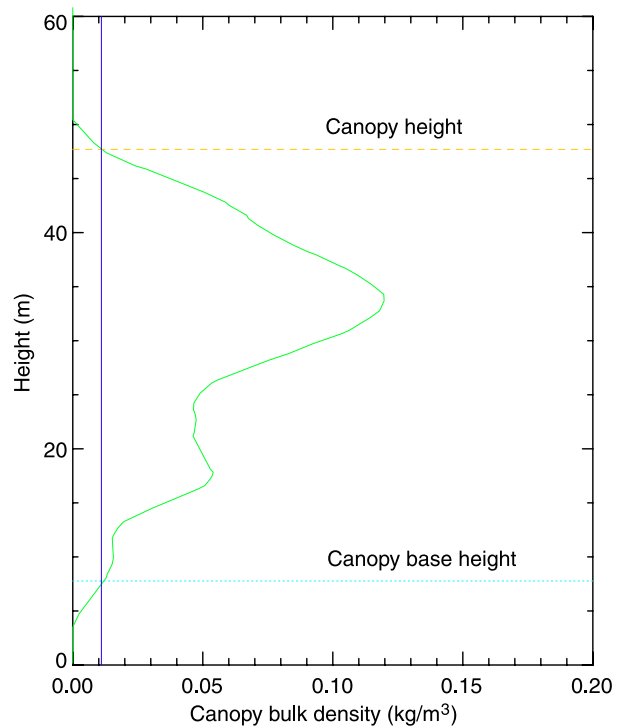


Fig. 2. Estimation of fuel parameters at inventory plot within dense, mature Douglas-fir canopy unit, Capitol Forest study area.

structural metrics such as canopy fuel weight, canopy bulk density, canopy base height, and canopy height. A program was written in IDL (Research Systems Inc. Interactive Data Language) for extraction of the LIDAR data within each plot area and calculation of these metrics from the distribution of LIDAR heights. This list of plot-level LIDAR metrics was then merged with the plot-level field-based canopy fuel estimates in a single text file and imported into *R* (<http://www.r-project.org/>), a statistical software package. Stepwise regression and all-subsets variable selection procedures were used within *R* to identify possible models for estimating each dependent variable, where an emphasis was placed upon developing parsimonious models containing a limited number of independent variables. A leave-one-out cross-validation procedure was used to assess the predictive value of each regression model, through a comparison of the root-mean-squared prediction error (or root-mean-square-error for cross-validation, denoted as $RMSE_{cv}$) and the standard error of the regression, denoted as RMSE (Michaelsen, 1987). In this context, $RMSE_{cv}$ is equivalent to the root-mean of the well-known PRESS statistic (sum of squares of predicted residuals; Neter et al., 1996). A close agreement between $RMSE_{cv}$ and RMSE indicates that the regression model is not overfitting the data and has good predictive value.

6. Results

6.1. Canopy fuel weight

Residual plots for canopy fuel weight prediction indicated that a square root transformation of canopy fuel weight was appropriate to meet the assumptions of linear

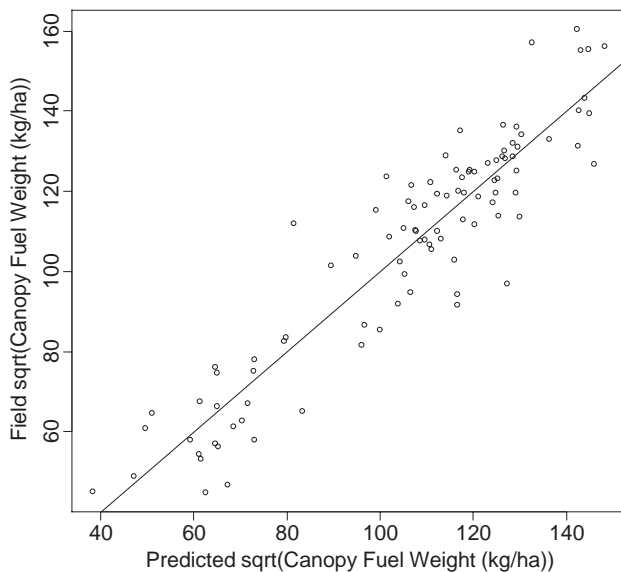


Fig. 3. Field-measured versus predicted (transformed) foliage weight ($R^2=0.86$; P -value <0.0001). Line shows 1:1 relationship.

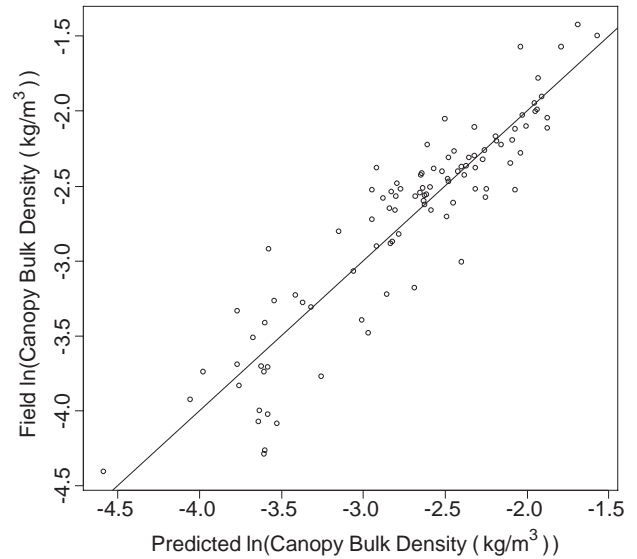


Fig. 4. Field-measured versus predicted (log-transformed) canopy bulk density ($R^2=0.84$; P -value <0.0001). Line shows 1:1 relationship.

regression. The model identified via regression analysis for estimating canopy fuel weight took the following form:

$$\sqrt{\text{canopy fuel weight}} = 22.7 + (2.9)h_{25} + (-1.7)h_{90} + (106.6)D$$

where D is the fraction of LIDAR first returns from the canopy (above 2 m in height).

This model had a coefficient of determination (R^2) of 0.86. It should be noted that in this context the coefficient of determination represents the percentage of variability explained by the regression relationship in the linearized space resulting from the transformation, not in the

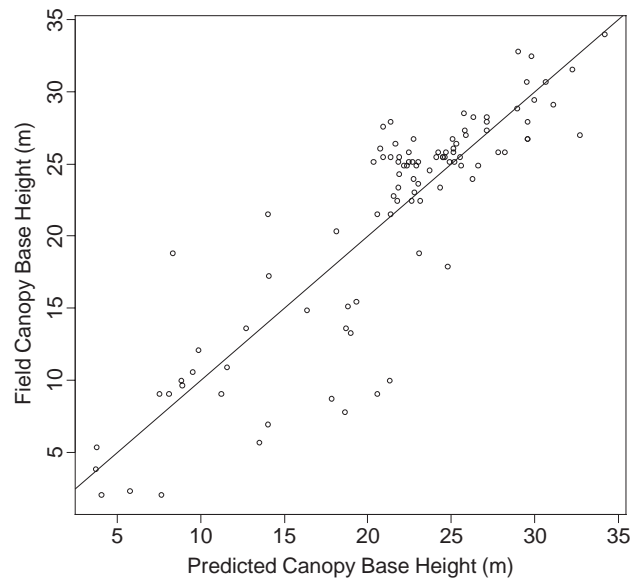


Fig. 5. Field-measured versus predicted canopy base height ($R^2=0.77$; P -value <0.0001). Line shows 1:1 relationship.

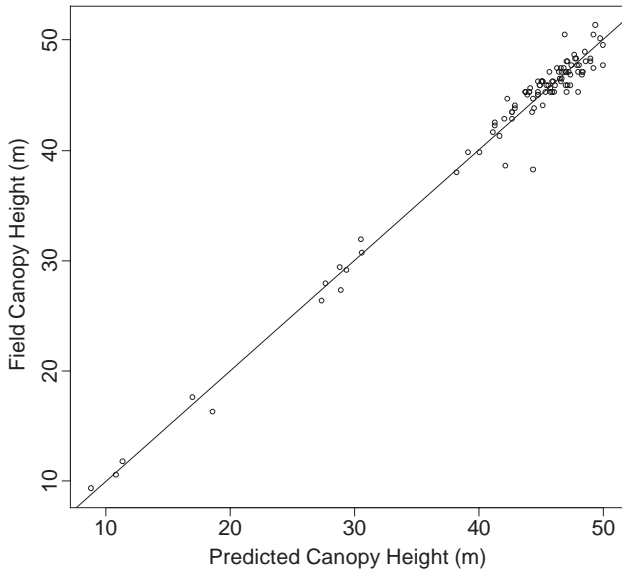


Fig. 6. Field-measured versus predicted canopy height ($R^2=0.98$; P -value <0.0001). Line shows 1:1 relationship.

original scale, so this measure should be interpreted with caution. A scatterplot of the field-based versus predicted LIDAR-based plot-level measures of (transformed) canopy fuel weight is shown in Fig. 3. The RMSE for this regression model was 11.1, and the $RMSE_{cv}$ was 11.5 (in transformed units).

6.2. Canopy bulk density

A logarithmic transform of canopy bulk density was used to stabilize the variance and account for the nonlinearity

evident in the residual plot. The model identified via regression analysis for estimating canopy bulk density took the following form:

$$\ln(\text{canopy bulk density}) = -4.3 + (3.2)h_{cv} + (0.02)h_{10} + (0.13)h_{25} + (-0.12)h_{90} + (2.4)D$$

This model had a coefficient of determination of 0.84. A scatterplot of the field-based versus predicted LIDAR-based plot-level measures of (log-transformed) canopy bulk density is shown in Fig. 4. The RMSE for this regression model was 0.27, and the $RMSE_{cv}$ from cross-validation was 0.29.

6.3. Canopy base height

The final model identified via regression analysis for estimating canopy base height took the following form:

$$\text{Canopy base height} = 3.2 + (19.3)h_{cv} + (0.7)h_{25} + (2.0)h_{50} + (-1.8)h_{75} + (-8.8)D$$

This model had a coefficient of determination of 0.77. A scatterplot of the field-based versus predicted (LIDAR-based) plot-level measures of canopy base height is shown in Fig. 5. The RMSE for this regression model was 3.9 m, and the $RMSE_{cv}$ from cross-validation was 4.1 m.

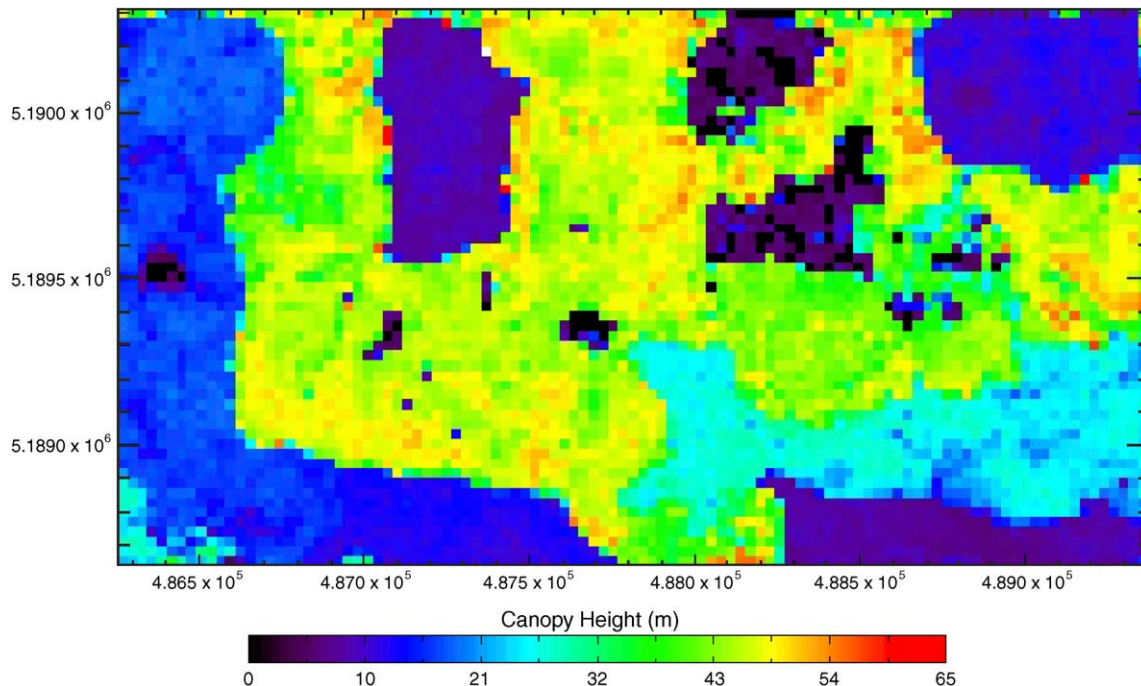


Fig. 7. Canopy height map (30-m resolution), Capitol Forest study area.

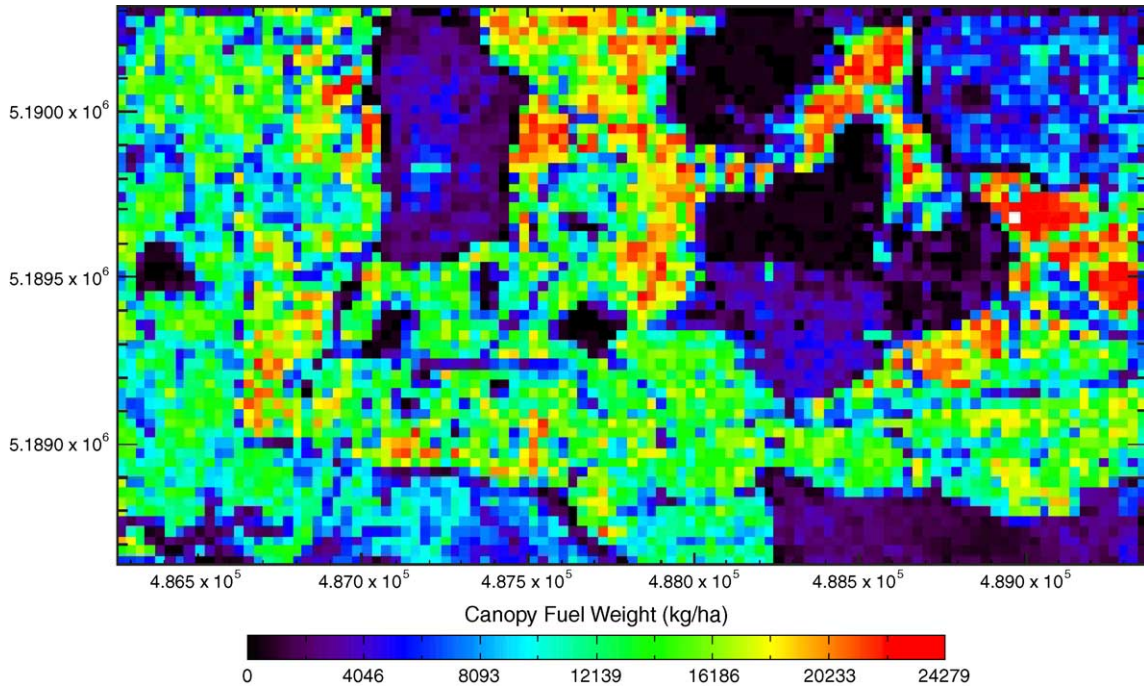


Fig. 8. Canopy fuel weight map (30-m resolution), Capitol Forest study area.

6.4. Canopy height

The final model identified via regression analysis for estimating canopy height took the following form:

$$\text{Canopy height} = 2.8 + (0.25)h_{\text{max}} + (0.25)h_{25} + (-1.0)h_{50} + (1.5)h_{75} + (3.5)D$$

This model had a coefficient of determination of 0.98. A scatterplot of the field-based versus predicted LIDAR-based

plot-level measures of canopy height is shown in Fig. 6. The RMSE for this regression model was 1.3 m, and the RMSE_{cv} from cross-validation was 1.5 m.

6.5. Mapping canopy fuels

After regression models have been developed to establish a functional relationship between the LIDAR data and the canopy fuel measures, these equations can be used to

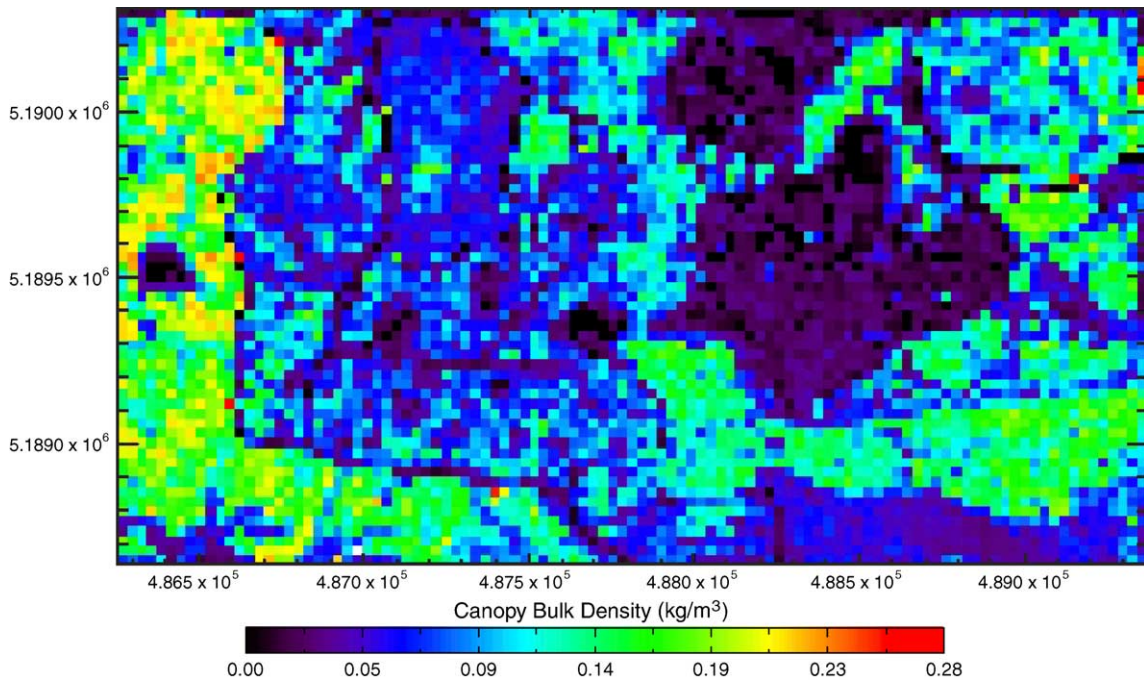


Fig. 9. Canopy bulk density map (30-m resolution), Capitol Forest study area.

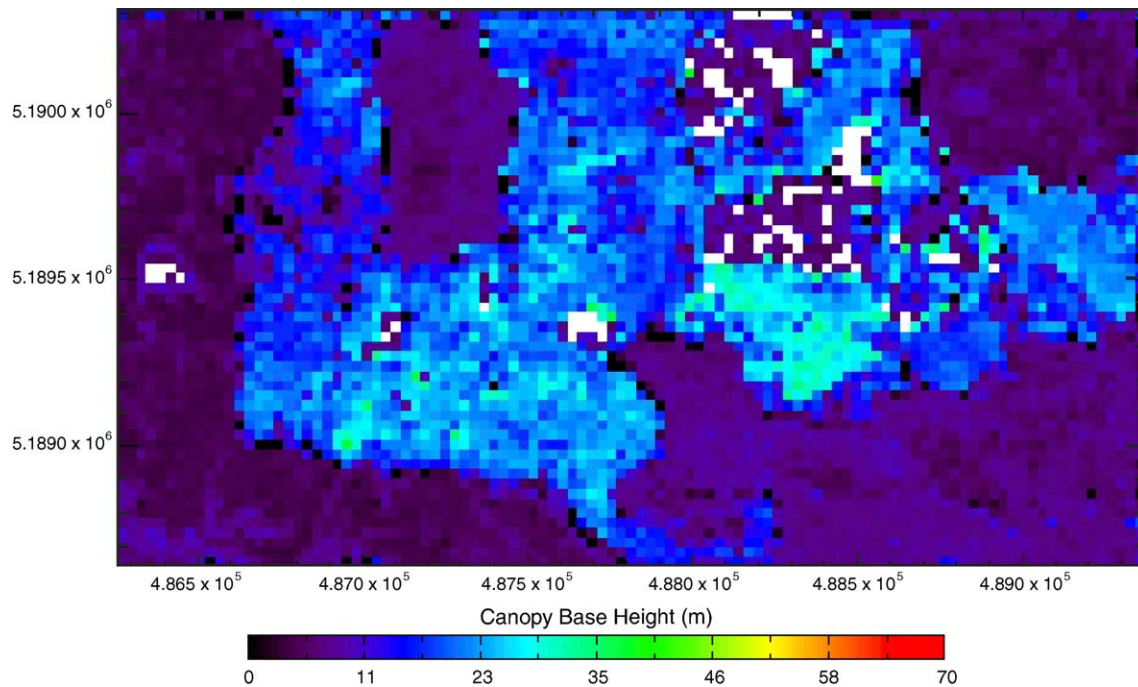


Fig. 10. Canopy base height map (30-m resolution), Capitol Forest study area. Areas with no canopy vegetation present are shown in white.

generate maps of canopy fuel distributions over the entire extent of the LIDAR data coverage. These maps represent spatially-explicit data layers that can be used as direct inputs into fire behavior models to support the analysis of fire risk and the implementation of fuel mitigation programs. Figs. 7–10 show maps of canopy height, canopy fuel weight, canopy bulk density, and canopy base height over the Capitol Forest study area, with measurements provided at a 30×30 m grid cell resolution.

7. Discussion

The results of this study indicate that LIDAR can be used to generate accurate estimates of critical canopy fuel metrics, including canopy fuel weight, canopy bulk density, canopy base height, and canopy height. It appears that the LIDAR-based forest metrics, based upon the height distribution of LIDAR measurements, capture structural information related to quantitative canopy fuel characteristics. Results of the cross-validation procedure, as well as qualitative assessment of the canopy fuel maps, indicate that the models have reasonable predictive value over the extent of the study area.

There are a number of possible sources for the discrepancy between the LIDAR-based metric within a plot area and the model-based estimate generated from a tree list. First, crown base heights and tree heights for many of the trees were not directly measured in the field but were estimated using regression models. This could possibly introduce a significant source of variability into the field-based canopy fuel estimates. Second, defining

canopy base height and stand height as a threshold value of crown bulk density makes this metric highly sensitive to the modeling assumptions related to how fuels are vertically distributed within a tree crown. Even small deviations from the assumed uniform distribution of fuels along the length of the crown for several trees in the plot could have a large effect on the estimate of canopy base height and canopy height. Edge effects could also lead to significant differences between the LIDAR- and field-based estimates. The field-based canopy fuel estimates do not account for the spatial position of tree crowns within the plot, and therefore the crown fuel estimates are calculated for the entire crown associated with each stem falling in the plot, even if a large proportion of the crown is located outside of the plot area. In contrast, the LIDAR data extracted for a given plot include only measurements of canopy materials that were located within the plot area. Edge effects are likely more pronounced in less dense stands and where plot sizes are smaller. Conversely, we would expect edge effects to be less important in stands with a more even and uniform closed canopy.

Another possible reason for a discrepancy between LIDAR and field-based estimates is the nature of laser scanner data. LIDAR data represent measurements of all canopy components, including foliage, branches, and stems. Furthermore, the relative frequency of stem and large branch measurements increases with a lower stem density, since more laser pulses are able to penetrate through canopy openings. However, in the context of canopy fuels analysis, stems and large branches are not considered fuel. This may lead to a negative bias in the LIDAR estimate of canopy

base height in less dense stands when compared to the field-based estimates.

When implementing the regression-based approach to mapping canopy fuel variables as described here, it is critical to acquire field data over the full range of stand types present in the area to be mapped. Estimates of fuel variables in areas with different stand structures from those sampled are extrapolations outside the domain of the field data and are unreliable. This is particularly evident in the case of estimating canopy bulk density (Fig. 9) and canopy base height (Fig. 10), where the estimates are reasonable within stands where field data were collected, but are dubious in areas outside of these sampled stand types (i.e., clearcuts, very young stands). It should also be noted that the variability in stand structures present within the Capitol Forest study area is not necessarily representative of natural structural variability within Pacific Northwest forests. For example, many of the plots used in this analysis were established in a heavily thinned unit, where many residual trees were taller than 45 m, yet the fuel loading was quite low due to the low residual stem density (40 trees per hectare). Therefore, the regression models developed in this paper are meant to demonstrate the potential of this methodology for canopy fuel estimation, and do not necessarily reflect fundamental physical relationships between lidar distributions and biophysical properties of natural stands.

8. Conclusions

The results of this study indicate that LIDAR can be used to estimate canopy fuel metrics efficiently and accurately over an extensive area within a Pacific Northwest conifer forest. Canopy fuel estimates based upon the distribution of LIDAR height measurements can be used to generate maps that provide a spatially-explicit description of the distribution of canopy fuels over the landscape. These maps (or GIS coverages) can serve as a direct input into a fire-behavior model such as FARSITE, potentially enabling a more realistic and accurate prediction of fire spread and intensity.

In the future, this methodology will be applied to LIDAR data collected in different stand types, including a fire-prone site in eastern Washington State. A more rigorous model validation procedure will be carried out to assess the general applicability of these models in different forest types and with LIDAR data acquired from different systems and at different densities. It is likely that a more extensive pool of explanatory variables will be developed to improve our understanding of the structural relationships between the distribution of LIDAR measurements and canopy fuel characteristics.

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References

- Andersen, H.-E., McGaughey, R. J., Reutebuch, S. E., Carson, W. W., & Schreuder, G. (2004). Estimating forest crown fuel variables using LIDAR data. *Proceedings of the ASPRS 2004 Annual Conference, Denver, May 23-27, 2004*. Bethesda, MD: American Society of Photogrammetry and Remote Sensing. CD-ROM.
- Beukema, S. J., Greenough, D. C., Robinson, C. E., Kurtz, W. A., Reinhardt, E. D., Crookston, N. L., Brown, J. K., Hardy, C. C., & Stage A. R. (1997). An introduction to the fire and fuels extension to FVS. In R. Teck, M. Mauer, & J. Adams (Eds.), *Proceedings of the Forest Vegetation Simulator Conference, February 3-7, 1997, Fort Collins, CO*. General Technical Report INT-GTR-373. Ogden, UT. U.S. Department of Agriculture, Forest Service, Intermountain Research Station. pp. 191–195.
- Brown, J. K., & Johnston, C. M. (1976). *Debris Prediction System*. Ogden, UT. US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Fuel Science RWU 2104, 28 pp.
- Curtis, R., Marshall, D., & DeBell, D. (Eds.) (2004). *Silvicultural Options for Young-Growth Douglas-Fir Forests: The Capitol Forest Study – Establishment and First Results*. General Technical Report PNW-GTR-598. Portland, OR. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 110 pp.
- Finney, M. A. (1998). *FARSITE: Fire Area Simulator-model development and evaluation*. Research Paper RMRS-RP-4. Ogden, UT. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 47 pp.
- Means, J., Acker, S., Fitt, B., Renslow, M., Emerson, L., & Hendrix, C. (2000). Predicting forest stand characteristics with airborne laser scanning lidar. *Photogrammetric Engineering and Remote Sensing*, 66(11), 1367–1371.
- Michaelsen, J. (1987). Cross-validation in statistical climate forecast models. *Journal of Climate and Applied Meteorology*, 26(11), 1589–1600.
- Morsdorf, F., Meier, E., Koetz, B., Itten, K.I., Dobbertin, M., & Allgower, B. (2004). LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management. *Remote Sensing of Environment*, 92(3), 353–362.
- Naesset, E. (1997a). Determination of mean tree height of forest stands using airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 52(2), 49–56.
- Naesset, E. (1997b). Estimating timber volume of forest stands using airborne laser scanner data. *Remote Sensing of Environment*, 61(2), 246–253.
- Naesset, E., & Bjerknes, K. -O. (2001). Estimating tree heights and number of stems in young forest stands using airborne laser scanner data. *Remote Sensing of Environment*, 78(3), 328–340.
- Naesset, E., & Okland, T. (2002). Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. *Remote Sensing of Environment*, 79(1), 105–115.
- Neter, J., Kutner, M., Nachtsheim, C., & Wasserman, W. (1996). *Applied linear regression models*. Chicago: McGraw-Hill.
- Reutebuch, S. E., McGaughey, R. J., Andersen, H. -E., & Carson, W. W. (2003). Accuracy of a high-resolution LIDAR terrain model under a conifer forest canopy. *Canadian Journal of Remote Sensing*, 29(5), 527–535.
- Riano, D., Chuvieco, E., Condis, S., Gonzalez-Matesanz, J., & Ustin, S. L. (2004). Generation of crown bulk density for *Pinus sylvestris* from LIDAR. *Remote Sensing of Environment*, 92(3), 345–352.
- Scott, J., & Reinhardt, E. (2001). *Assessing crown fire potential by linking models of surface and crown fire behavior*. Research Paper RMRS-RP-

29. Fort Collins, CO. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 59 pp.
- Teck, R. M., Moeur, M., & Eav, B. (1996). Forecasting ecosystems with the Forest Vegetation Simulator. *Journal of Forestry*, 94(12), 7–10.
- Wykoff, W. R., Crookston, N. L., & Stage, A. R. (1982). *User's guide to the Stand Prognosis Model*. General Technical Report INT-133. Ogden, UT. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, 112 pp.