



Tree-level forest inventory from high density point clouds

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- Background
- Objective
- Study Area
- Methods
- Results
- Conclusion







- Challenges
 - Limitations in human resources
 - Increase amount of work
 - "Classical" forestry
 - Contemporary forestry: marked dynamics, social dimensions
- Opportunities
 - Technology advancements
 - Material sciences: sensors
 - Computation: power and algorithms







- Remote sensing advancements
 - Price decrease
 - Lidar or imagery
- Computational advancement
 - Faster processors (CPU / GPU)
 - Multitude of procedures
 - Open or not
 - Geometric/algebraic or stochastic
 - Parametric or nonparametric







- Main: Forest inventory from remotely sensed data
 - Lidar and multispectral (RGBI)
- Focused: individual tree
 - Feed modern growth and yield models



Study area

- Elliott State Research Forest
 Approx. 83,000 ac
- 2021 flight
- High Resolution Imagery
 - 6 inches pixel
 - 4 bands: R, G, B, NIR
- High Density Lidar
 - Aerial
 - ≥ 7 points / ft² (>70 p/m²) - Colored
- 506 tiles of 1000 ' x 1000'











Coos County





Forest Inventory

- LIDAR: identify individual trees
 - Attributes
 - Number of trees
 - Total height of the trees
 - Location of the trees
 - DBH
 - Ground verified
- Imagery and lidar: species
 - Ground verified





Tree segmentation



- Based on DSM
 - Avoid inclusion of slope in the segmentation
- Optimal smoothing of DSM





DSM vs CHM











Tree segmentation: optimal smoothing

- Iterative filtering process with Gaussian kernels applied on progressive smooth DSM
- 2. Local maxima smoothing curve¹ refined using LOESS smoothing
- 3. Segmented regression² identified the shift in smoothing efficiency

D. A. Pouliot, D. J. King, and D. G. Pitt, "Development and evaluation of an automated tree detection-delineation algorithm for monitoring regenerating coniferous forests," Canadian Journal of Forest Research, vol. 35, pp. 2332–2345, 2005.

S. Fasola, V. M. R. Muggeo, and H. Küchenhoff, "A heuristic, iterative algorithm for change-point detection in abrupt change models," Computational Statistics, vol. 33, pp. 997–1015, 2018.





1.





Species identification and DBH and

HARS

- Three classes of species: Coniferous, Deciduous, Unknown
 - Regression: logistic regression
 - Machine learning techniques
- DBH: predicted from 2015 inventory:
 - 738 stands
 - ->30,000 trees
 - By classes of species

West, T.; Strimbu, B.M. 2025. Diameter and height modeling for accurate prediction of tree size in a Douglas-fir rainforest. Forestry: An International Journal of Forest Research, cpaf010, https://doi.org/10.1093/forestry/cpaf010

Field measurements

- Biodiversity plots
 - 208 plots in 2023
 - VRP with BAF 10
 - DBH
 - Used only DBH>4"
 - Attributes:
 - TPA
 - DBH
 - BA
 - 1/10 ac Inventory
 - 3 plots



Results: Tree segmentation

- 9.4 mil. trees
 - 9.04 mil. trees >4"
- Field: 13.5 mil. Trees >4"
- Paper Close to submission
 - 9 month of data prep.
 - Machine learning
 - 9.6 mil. trees





Species and DBH



- Species:
 - Binomial logistic regression using Lasso
 - Predictors: CHM, DSM, slope, aspect, flow, tree segmented
 - Lidar only
 - Accuracy: 82% coniferous, 74% deciduous, 65% unknown
 - No multispectral because no true orthophoto
- DBH:
 - Schumacher type equation
 - Accuracy: 92% coniferous, 88% deciduous and unknown
- Volume: >95% accuracy









Up to 5 feet off (double trees)







- Accurate (precision is given) forest inventory from lidar
- Multispectral imagery still an issue
- Improvements by Machine learning
 - Not significant yet
- Suppressed and dominated trees still an issue
- Data acquisition: focused on objective: ground vs inventory







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Oregon State College of Forestry