Visualizing the Process of Measuring Forest Conditions as a 3D Model

David Diaz
University of Washington

Abstract

The rapidly growing availability of high-resolution remotely-sensed datasets offers opportunities to observe and learn about the conditions and dynamics of natural environments with unprecedented scope. These datasets increasingly serve as the basis for estimating local environmental conditions or changes across entire landscape based on predictive models trained from field observations sampled from a comparatively much more limited area. The co-registration of remotely-sensed and ground-based datasets is a key determinant of the accuracy and precision of these predictive models, and confident co-registration remains a distinct hurdle in forest science and management limiting the full exploitation of the information contained in these complementary data sources. In this paper, I describe a reproducible system for generating 3D models of trees and forest inventory plots based on widely-collected field measurements. These 3D models will provide the basis for further work to minimize the misalignment between field and remotely-sensed forest data using a stochastic optimization approach. The focus of this paper is on the development of a visualization pipeline to inspect and refine this generative model.

1 Introduction

In the fields of ecology and natural resource management, high-resolution imagery and light detection and ranging (lidar) data are increasingly applied to identify and characterize the structure and composition of terrestrial ecosystems across entire landscapes. Modern remote sensing systems are often capable of generating dense three-dimensional point clouds that hold immense potential for understanding these ecosystems if the data can be successfully translated into meaningful attributes familiar to land owners and natural resource managers [Hudak et al. 2009].

Natural resource assessments, such as inventory or monitoring campaigns, typically involve sampling a relatively limited portion of the entire landscape of interest. Traditionally, these samples are statistically extrapolated across a landscape based on a simple random or stratified random sampling design. However, the emergence of remote sensing systems has fueled a growing interest in imputation models built to use remotely-sensed data using field plots as training examples. The models, which are increasingly applying machine learning algorithms for the task, can be applied to generate wall-to-wall maps that “fill in the gaps” between forest plots measured on the ground using remotely-sensed data [Ohmann and Gregory 2002; Hudak et al. 2008; Hudak et al. 2014; Riley et al. 2016].

Misalignment between field-based plots and remote sensing data introduces error into predictive models{Citation} trained to classify or quantify forest conditions. Efforts to more precisely and accurately co-register field plots with remotely sensed data can thus help reduce the error introduced into this predictive modeling approach and increase the precision with which a predictive model may be able to distinguish varying forest conditions across the landscape.

2 Related Work

A variety of geometric forms can be used to approximate the 3D shape of trees and forests. Parametric models including ellipsoids have a long history [Horn 1971; Koop 1989; Pollock 1996]. The "Pollock Model" represents the 3D rotation of Horn's 2D model [1971], developed particularly for integration of knowledge of the geometry of trees with image analysis. Similar approaches have emerged in various forms and to study different questions [Van Pelt and North 1996; Cescatti 1997; Sheng, Yongwei et al. 2001; Gong et al. 2002]. Non-parametric forms, such as convex hulls and alpha-hulls have also been employed [Vauhkonen et al. 2014; Vauhkonen 2015].

Research into the extraction or identification of individual trees has become increasingly common with the growth of lidar data, and stochastic optimization approaches in the Bayesian paradigm have also been demonstrated [Andersen et al. 2002; Lahivaara et al. 2014].

Relatively less attention, however, has been paid to the particular topic of reducing misalignment between ground-based forest plots with point cloud data. This theme has been treated using optimization approaches [Gatziolis 2009; Gatziolis 2012; Schrader-Patton et al. 2015], but these efforts have generally not utilized prior knowledge—in a probabilistic or Bayesian sense—about tree forms and likely ranges of measurement errors in the field or lidar observations.

Alternative approaches which do not directly try to reduce misalignment, but rather to incorporate spatial covariance in misaligned layers through a hierarchical modeling framework have also been demonstrated [Finley et al. 2014; Babcock et al. 2015].

3 Methods

Further down the road for this project, my interest ultimately lies in utilizing a Bayesian optimization approach [Gutmann and Corander 2016; Lintusaari et al. 2017] to leverage existing knowledge about the most likely shapes of trees and the expected sources and magnitudes of measurements errors to draw probabilistic inference including quantification of uncertainty about the most likely locations for forest inventory plots within a lidar scene.

Prior to implementing any optimization or stochastic modeling steps, however, I began by working step-by-step through the development of a generative model for producing 3D forms of trees and forest inventory plot data. I used the US Forest Service's Forest Inventory and Analysis (FIA) inventory and sampling design as template for this process. The FIA program offers one of the most intensively and repeatedly-measured forest inventory systems available, and includes thousands of plots in each region of the USA.

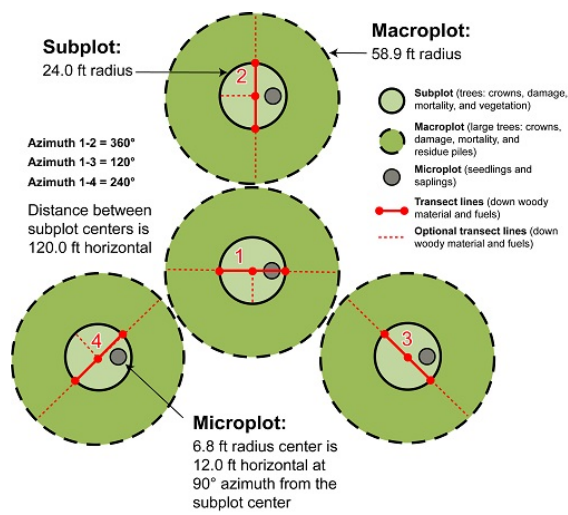

Figure 1: *Plot layout of the USFS National FIA Program. Four subplots are installed at each location to be sampled and a wide array of tree, vegetation, biophysical, and other attributes are measured.*

On each of the FIA subplots, the locations of individual trees have been mapped, along with typical measurements such as stem diameter, tree height, species, etc.

To visualize the process for generating 3D tree and crown surfaces, I developed a series of equations following the general process of establishing an FIA plot [USFS 2018]. These equations were coded in the Python programming language using the Anaconda distribution. A Jupyter Notebook [Thomas et al. 2016] was utilized to allow for integration of code, documentation, and interactive graphics in a reproducible browser-based environment. The code for this Notebook is published on GitHub[1] and can also be accessed and executed in the cloud without requiring local installation of any software using the Binder service[2].

4 Results

This notebook walks through a step-by-step process of establishing a plot on a landscape, and measuring the location, height, lean, and crown dimensions for a tree on that plot. I integrated widgets using the ipywidgets package to allow for user control of key parameters in each step. I utilized the plotly graphing library, which provides a Python wrapper for react.js and webGL for interactive visualizations. For example, the user is able to shift the X and Y coordinates of subplot 1 (the central plot in the FIA plot layout), as shown in Figure 2.

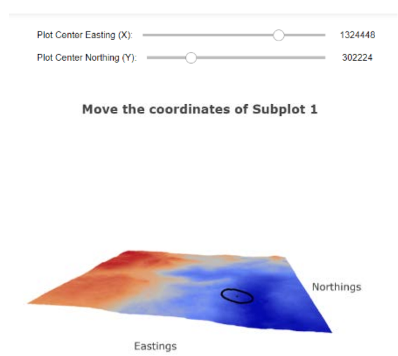

Figure 2: *Adjustable location of a plot on a 3D terrain surface.*

Similarly, the user can to control the location, height, direction of lean (angle from north), and amount of lean (angle from vertical) for the first tree on subplot 1 (Figure 3) and the shape and size of the tree's crown (Figure 4).

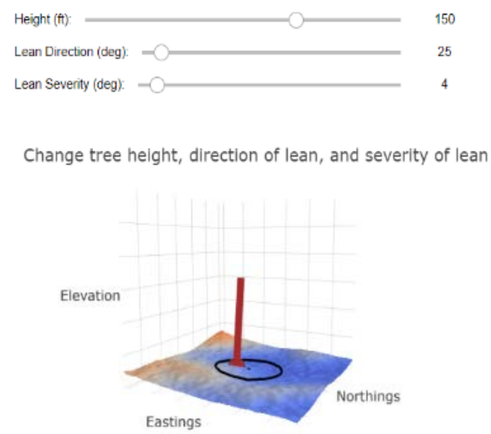

Figure 3: *Adjustable lean and height of a tree*

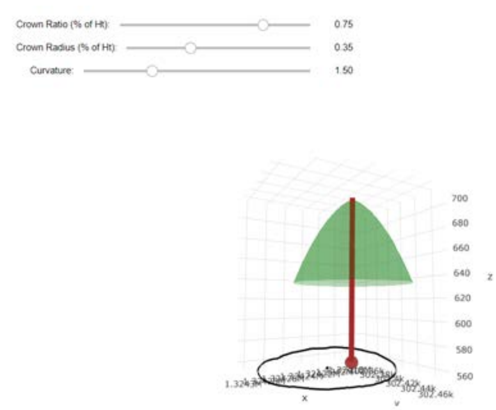

Figure 4: *Adjustable crown attributes for a tree.*

5 Discussion

The interactive graphics allowed for thorough inspection of the step-wise data-generating model, and illustrated the effects of each parameter in the model clearly. However, the interactivity of the graphics was constrained by the apparent need to reload an entire figure upon a change in the data rather than simply updating changed data. This is a shortcoming of the 'offline' mode as currently implemented for

[1] https://github.com/d-diaz/Lidar_Plot_Registration/blob/master/FIA%20Plot%20Simulation.ipynb

[2] Access the GitHub repo through Binder here https://mybinder.org/v2/gh/d-diaz/Lidar_Plot_Registration/master

plotly graphics, which can be remedied if the graphs are served from the plotly web service instead of locally within a notebook regardless of whether the user is connected to the internet. Nevertheless, although the lag time/flickering of the visualization would render it problematic for a general audience, for the intended use of a technical user focused on refining a series of equations, this issue did not present a major bottleneck.

The interactive plotting approach allowed for bugs in the code to be quickly identified, and helped translate complex mathematical equations into a more accessible form via intuitive widget-based controls.

The formatting effort required to style each visualization in the notebook involved significant redundancies and consumed a substantially larger amount of time than coding and debugging the underlying math equations did. Nevertheless, the ability to visually confirm that the model is behaving as intended was indispensable.

6 Future Work

I will continue the development of this notebook in coming weeks and months to flesh out the remainder of the generative model, including the visualization of additional trees on subplot 1 and other subplots. This framework has allowed for a transparent verification of the models form and function, and will facilitate the implementation of these equations using stochastic parameters which will ultimately be employed in a Bayesian optimization approach with real inventory data.

References

ANDERSEN, H.-E., REUTEBUCH, S.E., AND SCHREUDER, G.F. 2002. Bayesian object recognition for the analysis of complex forest scenes in airborne laser scanner data. *International archives of photogrammetry remote sensing and spatial information sciences 34,* 3/A, 35–41.

BABCOCK, C., FINLEY, A.O., BRADFORD, J.B., KOLKA, R., BIRDSEY, R., AND RYAN, M.G. 2015. LiDAR based prediction of forest biomass using hierarchical models with spatially varying coefficients. *Remote Sensing of Environment 169,* 113–127.

CESCATTI, A. 1997. Modelling the radiative transfer in discontinuous canopies of asymmetric crowns. I. Model structure and algorithms. *Ecological Modelling 101,* 2–3, 263–274.

FINLEY, A.O., BANERJEE, S., AND COOK, B.D. 2014. Bayesian hierarchical models for spatially misaligned data in R. *Methods in Ecology and Evolution 5,* 6, 514–523.

GATZIOLIS, D. 2009. Precise FIA plot registration using field and dense LIDAR data. *Proceedings of the eighth annual forest inventory and analysis symposium*, U.S. Department of Agriculture, Forest Service, 243–249.

GATZIOLIS, D. 2012. Advancements in LiDAR-based registration of FIA field plots. *Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012,* U.S. Department of Agriculture, Forest Service, Northern Research Station, 432–437.

GONG, P., SHENG, Y., AND BIGING, G.S. 2002. 3D model-based tree measurement from high-resolution aerial imagery. *Photogrammetric Engineering and Remote Sensing 68,* 11, 1203–1212.

GUTMANN, M.U. AND CORANDER, J. 2016. Bayesian Optimization for Likelihood-Free Inference of Simulator-Based Statistical Models. *17,* 125, 1–47.

HORN, H.S. 1971. *The adaptive geometry of trees*. Princeton University Press.

HUDAK, A.T., CROOKSTON, N.L., EVANS, J.S., HALL, D.E., AND FALKOWSKI, M.J. 2008. Nearest neighbor imputation of species-level, plot-scale forest structure attributes from LiDAR data. *Remote Sensing of Environment 112*, 5, 2232–2245.

Hudak, A.T., Evans, J.S., and Stuart Smith, A.M. 2009. LiDAR Utility for Natural Resource Managers. *Remote Sensing 1*, 4, 934–951.

Hudak, A.T., Haren, A.T., Crookston, N.L., Liebermann, R.J., and Ohmann, J.L. 2014. Imputing Forest Structure Attributes from Stand Inventory and Remotely Sensed Data in Western Oregon, USA. *Forest Science 60*, 2, 253–269.

Koop, H. 1989. *Forest dynamics: SILVI-STAR: a comprehensive monitoring system*. Springer, Berlin Heidelberg New York London Paris Tokyo Hong Kong.

Lahivaara, T., Seppanen, A., Kaipio, J.P., et al. 2014. Bayesian Approach to Tree Detection Based on Airborne Laser Scanning Data. *IEEE Transactions on Geoscience and Remote Sensing 52*, 5, 2690–2699.

Lintusaari, J., Vuollekoski, H., Kangasrääsiö, A., et al. 2017. ELFI: Engine for Likelihood Free Inference. *arXiv:1708.00707 [cs, stat]*.

Ohmann, J.L. and Gregory, M.J. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest- neighbor imputation in coastal Oregon, U.S.A. *Canadian Journal of Forest Research 32*, 725–741.

Pollock, R.J. 1996. The automatic recognition of individual trees in aerial images of forests based on a synthetic tree crown image model. https://open.library.ubc.ca/cIRcle/collections/ubctheses/831/items/1.0051597.

Riley, K.L., Grenfell, I.C., and Finney, M.A. 2016. Mapping forest vegetation for the western United States using modified random forests imputation of FIA forest plots. *Ecosphere 7*, 10, e01472.

Schrader-Patton, C., Liknes, Greg C., Gatziolis, D., et al. 2015. Refining FIA plot locations using LiDAR point clouds. *Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station*, 247–252.

Sheng, Yongwei, Gong, P., and Biging, G. S. 2001. Model-Based Conifer-Crown Surface Reconstruction from High-Resolution Aerial Images. *Photogrammetric Engineering & Remote Sensing 67*, 8, 957–965.

Thomas, K., Benjamin, R.-K., Fernando, P., et al. 2016. Jupyter Notebooks – a publishing format for reproducible computational workflows. *Stand Alone*, 87–90.

USFS. 2018. *Field Instructions for the Annual Inventory of California, Oregon, and Washington, 2018*. USDA Forest Service, Pacific Northwest Research Station, Resource Monitoring and Assessment Program, Portland, OR.

Van Pelt, R. and North, M.P. 1996. Analyzing canopy structure in Pacific Northwest old-growth forests with a stand-scale crown model. *Northwest Science 70*, special, 15–30.

Vauhkonen, J. 2015. Reconstructing forest canopy from the 3D triangulations of airborne laser scanning point data for the visualization and planning of forested landscapes. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences II-3/W4*, 255–261.

Vauhkonen, J., Næsset, E., and Gobakken, T. 2014. Deriving airborne laser scanning based computational canopy volume for forest biomass and allometry studies. *ISPRS Journal of Photogrammetry and Remote Sensing 96*, 57–66.