

Figure 4. LiDAR height distribution and example height metrics (A), and example topographic variables (B and C). In figure 4A the black line is the probability density function of LiDAR heights at an inventory plot. The green, red, and purple lines represent the modal height, mean height, and the standard deviation of heights, respectively. The blue tic marks on the Y axis represent individual LiDAR returns. Figure 4 B is solar insolation (W / m²) calculated from the LiDAR DEM. Figure 4 C is a table listing topographic and height metrics utilized in this study.

Imputation Model Development

Imputation Model Evaluation

Atwo-step process was employed to predict tree structural information at each of the validation inventory plots.

First, imputation models were developed to predict plot-level forest structure and species information (e.g., forest type and basal area) from plot-level LiDAR height metrics and LiDAR derived DEM variables.

¹ ¹ ² ² Michael J. Falkowski , Paul E. Gessler , Andrew T. Hudak , and Nicholas L. Crookston ¹ University of Idaho College of Natural Resources GLED, ² USDA Forest Service Rocky Mountain Research Station

Each Imputation model was evaluated based upon prediction accuracy and parsimony. For the second step, we calculated multivariate distance between each of the original inventory plots and each of the validation plots.

Tree-level data from the original forest inventory were then assigned to the closest (in multivariate space) validation inventory plot (Figure 1).

The accuracy of the imputed tree-level forest structure data was determined by comparing it to tree-level forest structure data measured during the validation inventory. FVS was parameterized with both the imputed and validation inventory data. Forest growth was then projected in 10-year increments for 100 years via FVS. To further evaluate the accuracy of the imputed tree-level forest structure data, the growth projections for six randomly selected stands were compared. Any multivariate distance could be used. However, for this study multivariate distance was based upon the randomForest proximity matrix (see Breiman, 2001 for a description of the randomForest method, and Hudak et al., Accepted for a description of the randomForest based multivariate distance).

Predicting Tree-Level Forest Structure From LiDAR Data

Multivariate statistical technique that uses nearest neighbors (in multivariate space) to predict missing data values (Figure 2).

Abstract

The accuracy of k-NN predictions will be evaluated by comparing them to independent forest inventory data.

This research evaluates the efficacy of k-nearest neighbor (k-NN) imputation models incorporating LiDAR data to predict and map tree-level forest structure data (individual tree height, diameter at breast height, and species) across a 30,000 ha study area in Northern Idaho, USA. The primary objective is to provide spatially explicit data to parameterize the Forest Vegetation Simulator (FVS), a forest growth model that operates at the individual tree-level. Eventually forest growth will be modeled across the entire study area. In addition to FVS parameterization, the imputed forest structure data could be used for many purposes including forest commodity assessment, carbon accounting, wildlife habitat modeling, etc. The final k-NN imputation model utilizes LiDAR derived height measurements and LiDAR topographic variables to predict treelevel forest structure and species composition data. When compared to an independent forest Inventory dataset, the imputed forest structure data had a species composition accuracy of 50%. The accuracy of forest structural attributes calculated from the imputed dataset were quite high when compared to the independent forest inventory data; the root mean square error of imputed basal area and quadratic mean diameter estimates were 5.28 m^2 / ha and 0.81cm, respectively. Furthermore, FVS growth projections based upon the imputed tree-level forest structure data **follow similar trends as compared to FVS growth projections based upon the independent forest** Inventory data. These results indicate that the imputation methods presented herein could eventually be used to parameterize FVS across the entire study area, facilitating the modeling of forest dynamics across the entire region.

Eighty- three 405 m^2 fixed-radius forest inventory plot were surveyed during the summer of 2003.

The Forest Vegetation Simulator

Breiman, L., 2001. Random Forests, Machine Learning, 45, 532. Crookston, N.L., and Dixon G.E., 2005. The forest vegetation simulator: A review of its structure, content and applications. Computer and Electronics in Agriculture. 49, 60-80. Evans, J.S., and Hudak, A.T., 2007. A multiscale curvature algorithm for classifying discrete return lidar in forested environments. IEEE Transactions on Geoscience and Remote Sensing 45(4): 1029-1038. Hudak, A.T., Crookston, N.L., Evans, J.S., Hall, D.E., and Falkowski M.J., Accepted. Nearest-neighbor imputation of species-level, plot-scale forest structure attributes from LiDAR data., Remote Sensing Environment. LeMay, V., and Temesgen, H., 2005. Comparision of Nearest Neighbor Methods for Estimating Basal Area and Stems per Hectare Using Auxiliary Variables. Forest Science, 51, 109-119. Makela, H., and Pekkarinen, A., 2004. Estimation of forest stand volumes by Landsat TM imagery and stand-level field-inventory data. Forest Ecology and Management. 196, 245-255.

FVS is a forest growth model used to aid in forest management decision-making (Crookston and Dixon, 2005; Figure 1).

The modeled estimate of species composition prediction accuracy was only 37%, while the modeled estimate of basal area error (root mean square difference) was 13.04 m^2 / ha $(56.83 \text{ ft}^2 / \text{ ac})$.

K-Nearest Neighbors Imputation continuous predictions of tree level information at the landscape scale.

It is an empirically driven model that operates at the individual tree-level. Requires tree-level forest inventory data for parameterization (i.e., Measurements of diameter at breast height (DBH), species, height, etc. for each tree in a plot or stand). Obtaining broad-scale, spatially continuous inventory data is difficult. k-NN imputation models incorporating LiDAR data may provide a means to obtain spatially

> This study evaluated the efficacy of predicting tree-level forest structure data via k-NN imputation models incorporating LiDAR data. The imputed data were ultimately used to parameterize a treelevel forest growth model. When compared to independent forest inventory data, the imputation had an accuracy of 50% for predicting forest species composition. The accuracy of forest structure metrics (e.g, basal area and quadratic mean diameter were quite high). Furthermore, FVS growth the imputation model presented herein. projections based upon the imputed tree-level inventory data followed similar trends as compared to FVS growth projection based upon independent inventory data. This finding indicates that the methods presented herein could eventually be use to predict tree-level forest structure data across the entire study area, which could ultimately be use to project forest growth across the region. In addition to projecting forest growth, the imputed tree-level forest structure data could be used for a variety of applications including forest commodity assessment, carbon accounting, wildlife habitat assessment, etc. However, before this is accomplished we plan to further assess the accuracy of

Has been use extensively to predict stand-level forest inventory data (e.g., basal area, mean diameter, stand height, etc.) from remotely sensed data (Mäkelä and Pekkarinen, 2004; LeMay and Temesgen, 2005).

To date k-NN imputation has not been evaluated in the prediction of tree-level forest structure data.

Figure 2. Graphical Example of Imputation - Missing data in new plots are imputed from nearest sampl

Figure 1. Graphical and Tabular Examples of FVS Forest Growth Projections

Objectives

Evaluate the efficacy of k-NN imputation for predicting tree-level forest structure data in uninventoried areas.

Parameterize FVS with the imputed tree-level forest structure data as well as with the independent forest inventory data.

Compare FVS forest growth projections derived from each data set.

Study area and Forest Inventory Data Collection

LiDAR Acquisition and Processing

This study was conducted on Moscow Mountain, which lies at the extreme western extent of the Clearwater Mountains in Northern Idaho, USA (Figure 3). Moscow Mountain is topographically complex and primarily comprised of temperate mixedconifer forest.

The University of Idaho Experimental forest collected independent forest inventory data during the summer of 2006, which will be used as validation data in the current study.

Discrete return LiDAR data (1.95 m nominal post spacing) were acquired with an ALS40 system. Once acquired, the LiDAR data were separated into ground and non-ground returns using the Multiscale Curvature Classification algorithm (Evans and Hudak, 2007). Following classification, a digital elevation model was created, and the height above ground surface was calculated for all non-ground returns. Numerous LiDAR derived height metrics and topographic variables were calculated across the Moscow Mountain study area (Table 1, Figure 3).

METHODS

Literature Cited

Imputation Model Results

The final imputation model predicted forest type and basal area from three LiDAR derived topographic variables (heat load, elevation, and slope) and four LiDAR derived height metrics (mean height, median height, height of the 10th percentile, and height of the 75th

percentile).

When compared to the independent forest inventory data, the error rates for species composition and forest structure were much lower (Table 1).

Model Evaluation and FVS Parameterization

CONCLUSIONS

Table 1. Error Statistics for the Imputed Forest Inventory Data.