Influence of inventory plot and Landsat imagery positional accuracies on nearest-neighbor (NN) imputation maps of vegetation composition and structure.

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Introduction

Spatially explicit information regarding a wide range of forest attributes is often required for land management decisions—support, inventory and modeling, and policy formulation. Nearest neighbor (NN) imputation maps are widely used in the Pacific Northwest region of the US, when spatially explicit information regarding a wide range of forest attributes are required at regional and watershed scales. However, regional NN imputation maps have generally not been suitable for fine-scale (i.e., stand level) decision-making for activities such as fuel reduction and forest restoration treatments, which would benefit greatly from NN imputation maps developed for both regional and stand-level applications.

Objectives

NN imputation maps are predicated on relating forest attributes from field plots to spatial predictors such as climate, topography, satellite imagery, and LiDAR data. Potential sources of error in NN imputation maps include the incorrect extraction of remotely sensed spatial predictors for a given field plot, which can result from poor positional accuracy of field plots or poor geo-referring of spatial predictors such as satellite imagery. The extent to which positional accuracy of these two data sources (plots and satellite imagery) influences NN imputation map accuracy is poorly understood, but is increasingly important if NN imputation maps are developed for stand level applications. To address these questions we wanted to:

1. Quantify the positional error of federal inventory plots and Landsat TM imagery within a 500,000 ha area of Eastern Oregon Cascades, USA.
2. Quantify individual and combined influences of positional error from plot locations and Landsat TM imagery on NN imputation map accuracy for a variety of forest composition and structural attributes.
3. Determine if the influence of field plot and Landsat TM positional error on NN imputation accuracy is greater when NN imputation maps are developed using field data of smaller spatial grain.

Study Area

The study area encompasses 539,269 ha (1,312,561 ac) of the Eastern Oregon Cascades, covering most of the Deschutes National Forest (gray area in map).

Large-scale gradients of topography, climate, and parent material influence vegetation composition and productivity in the study area. Western proportions of the study area are characterized by high elevations, high precipitation, and moderated temperature ranges, resulting in montane and subalpine conifer forests. The eastern portion of the study area is lower in elevation, and has a more arid and continental climate; resulting in lower productivity drier conifer forests.

In contrast to large-scale composition gradients, variability in forest structure is more strongly influenced by small-scale disturbances such as wildfire, insect outbreaks, and timber harvests.

Data Sources

Plot and Subplot Footprints

- 232 plots from the USDA Forest Service Forest Inventory and Analysis Program (FIA) and The USDA Forest Service Region 6 Current Vegetation Survey (R6). Plots measured between 2004-2009.
- Vegetation attributes (% cover, DBH, TPL, Snags, CWD, etc.) calculated at plot-level and subplot.
- Official coordinates collected using recreational grade GPS at time of field measurement. Sub-meter coordinates collected using a Trimble WAAS enabled and post-processed DGPS during 2009-2010.

Spatial predictors are grids with 30m cell.

Climate data comes from PRISM ( Daly et al. 2008) at 40 year normals (1971-2010).

Topography and LiDAR vegetation structure from LiDAR data collected in 2009 and 2010.

Topographic spatial predictors calculated from LiDAR 30m bare earth model. Vegetation structure spatial predictors calculated from LiDAR point cloud using the grid metrics function in FUSION.

Choice of LiDAR-derived vegetation predictors based on prior work relating LiDAR vegetation to forest structure in the Pacific Northwest (Hudak et al. 2008, Palkowksi et al. 2010, Kane et al. 2010).

Plot & Imagery Positional Accuracy

- Sub-meter DGPS accuracy for the 232 plots was 0.018 m (95% CI 0.011-0.025 m).
- On average, accuracy of official plot coordinates was poor (RMSE ≥ 26.0 m).
- 50%, 12%, and 4% of official plot coordinates had positional error greater than 15.30, 10.00, and 6.00 respectively.

Results: Species Composition

- Accuracy of species predictions varied by species, spatial grain of field plots, positional accuracy of plots, and positional accuracy of Landsat TM imagery. Accuracy was especially poor for PIMO, which had the lowest prevalence of the selected species.
- In general, accuracy of species predictions was greater at larger spatial grain (i.e. field plots vs. subplots). Co-variance errors were greater for predictions based on field plots.

For many species, prediction accuracy either declines or is not significantly different with increased positional accuracy of plots or Landsat TM imagery, likely the result of fine-scale spatial predictors being over-weighted in gradient analysis when species composition is more strongly controlled by large-scale climatic and topographic gradients.

Results: Vegetation Structure

- Models with larger spatial grain (i.e. field plots) have smaller maximum distances between modeled and reference scale (lower KS values), and have higher unsymmetric agreement (AC25, colored triangles). There was little difference in systematic (AC25, colored squares) between models.

Conclusions

- Important to note only a limited number and type of accuracy diagnostics used. For example, Kappa statistic does not provide components of map error needed to assess potential limitations.
- For this data set, finer spatial grain field data and increased positional accuracy of spatial predictors did not improve accuracy of NN maps of species composition and structure.
- Despite plot (and to a lesser extent Landsat TM imagery) positional errors that were often ≥ ½ pixel width of spatial predictors, positional accuracy consistently did not influence NN prediction accuracy.
- Potential explanations for these findings include:
  - Poor sample size (323 plots)
  - Hybrid species-structure response matrix used in gradient analysis may confound relationships between field data and spatial predictors operating separately for composition and structure at large (climate, topography) and small (LiDAR, forest disturbance history) spatial scales.
  - Tuning separate models for composition and structure may be needed to maximize predictive accuracy.
  - Higher positional accuracy may not matter if within context of forest spatial heterogeneity operating at larger scales (i.e. larger gradients and patch sizes of species and structure).
  - Subplot may be too small of a sample unit, resulting in high measurement variability and inadequate species/structural representation for relating to spatial predictors.

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References

[Complete list of references provided here]