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Scale considerations for integrating forest inventory plot data and satellite image data for regional forest mapping

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ABSTRACT

The integration of satellite image data with forest inventory plot data is a popular approach for mapping forest vegetation over large regions. Several methodological choices regarding spatial scale, mostly related to spatial resolution or grain, can profoundly influence forest maps developed from plot and imagery data. Yet often the consequences of scaling choices are not explicitly addressed. Our objective was to quantify the effects of several scale-related methods on map accuracy for multiple forest attributes, using a variety of diagnostics that address different map characteristics, to help guide map developers and users. We conducted nearest-neighbor imputation over a large region in the Pacific Northwest, USA, to investigate effects of imputation grain (single pixel or kernel); inclusion of heterogeneous plots; accuracy assessment grain and extent; and value of k ($k = 1$ and $k = 5$), where k is the number of nearest-neighbor plots. Spatial predictors were from rasters describing climate and topography and a time-series of Landsat imagery. Reference data were from regional forest inventory plots measured over two decades. All analyses were conducted at a spatial resolution of 30 m × 30 m. Effects of imputation grain and heterogeneous plots on map accuracy were small. Excluding heterogeneous plots slightly improved map accuracy and did not lessen the systematic agreement (AC_{SYS}) between our maps and observed plot data. Accuracy assessment grain strongly influenced map accuracy: maps assessed with a multi-pixel block were much more accurate than when assessed with a single pixel for almost all map diagnostics, but this was an artifact of methods rather than reflecting real differences among maps. Unsystematic agreement (AC_{UNS}) between our maps and plots, or random error, improved notably with increasing accuracy assessment extent for all scaling methods, indicating that reliability of most map applications can be improved through coarsening the map grain. Value of k strongly influenced map diagnostics. The $k = 5$ maps were better than $k = 1$ maps for local-scale accuracy, but at the cost of reduced AC_{SYS}, and loss of variability and poor areal representation of forest conditions over the study region. The $k = 1$ maps produced notably better predictions of the least abundant forest conditions (early-successional, late-successional, and broadleaf). None of the scaling methods were optimal for all map diagnostics. Nevertheless, given a variety of diagnostics associated with a range of scaling options, map developers and map users can make informed choices about methods and resulting maps that best meet their particular objectives, and we present some general guidelines in this regard. Most of our findings are applicable to mapping with Landsat data in other forested regions with similar forest inventory data, and to other methods for spatial prediction.

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1. Introduction

Applications of remote sensing to problems in ecology and in land and environmental management have grown exponentially in recent years. In particular, remotely sensed data acquired by the Landsat sensors have played a key role in ecological applications (Cohen & Goward, 2004), vegetation mapping (Xie, Sha, & Yu, 2008), and broad-scale forest inventory (McRoberts, Tomppo, & Næsset, 2010; Tomppo et al., 2008). Landsat imagery offers moderate spatial resolution, a long history, and a data archive that is accessible at no cost (Woodcock et al., 2008). These factors provide unique opportunities to extend applications of Landsat time-series to monitoring of forest change (Kennedy, Yang, & Cohen, 2010; Kennedy et al., 2012; Ohmann et al., 2012).

Despite its acknowledged utility, remotely sensed data cannot completely replace ground sample data for many applications. The information needs for broad-scale land cover data have expanded to include biodiversity, dead wood, species composition, and other attributes that cannot yet be reliably sensed remotely. Consequently, the integration of satellite imagery with regional or national forest inventory plot data has become a popular approach for estimation and spatial prediction of forest attributes over large geographic regions (McRoberts et al., 2010; Tomppo et al., 2008). Many countries in the world now use sample-based approaches for national forest inventories, and remote sensing is

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often used to enhance sampling and estimation through stratified, model-assisted, or model-based estimation (McRoberts et al., 2010). Many applications in ecology and ecosystem science also have combined remotely sensed and plot data for model-based spatial prediction over large landscapes.

With any spatial modeling, mapping, or estimation approach, the use of field plot data as training data or for model validation requires geographical co-registration of plot locations within imagery, so that paired values can be obtained from the two datasets. This co-registration raises a host of methodological issues having to do with scale, particularly spatial resolution (grain). Yet often the consequences of scaling choices, which interact with the spatial heterogeneity of the vegetation being mapped, are not addressed explicitly by the investigators (but see Arponen, Lehtomaki, Leppanen, Tomppo, & Moilanen, 2012; Fassnacht, Cohen, & Spies, 2006; McRoberts, 2010; Stehman & Wickham, 2011). A review by Lechner, Langford, Bekessy, and Jones (2012) reports that sources of uncertainty in mapping analyses – including several scale-dependent factors – were rarely addressed in landscape ecology studies that used spatial data.

Our study objective was to quantify the effects of several scale-related methods on estimates of map accuracy for multiple forest attributes. We define accuracy based on a variety of diagnostics that address different map characteristics. Although our method for vegetation mapping in this study was nearest-neighbor imputation (Eskelson et al., 2009), most of the scale issues we addressed apply more broadly to other methods for predictive vegetation mapping that rely on integrating plot and geospatial data. Our overall approach was to develop multiple versions of forest vegetation maps, using different combinations of scaling options, and then compare the results for a variety of map diagnostics. Implicit to our analysis is the concept that regional, multi-attribute forest maps serve a wide range of user needs, that there are trade-offs among different mapping approaches, and that no single spatial unit (e.g. pixels, blocks of pixels, polygons) is universally best for mapping or for accuracy assessment (Stehman & Wickham, 2011). We also recognize that relative model performance will vary to some degree among forest attributes, for different diagnostics, and among different ecosystems. Nevertheless, we draw some general conclusions from our findings that can inform both developers and users of regional forest maps developed from regional inventory plots and satellite imagery.

Nearest-neighbor techniques have emerged within the international forestry community as useful methods for predicting forest attributes as combinations of the k observations (i.e. field plots) that have similar characteristics in a space of ancillary variables (McRoberts, 2012; McRoberts et al., 2010; Tomppo et al., 2008). Nearest-neighbor methods are appealing because they are multivariate and nonparametric (require no assumptions about the distributions of response or predictor variables), and can be used to map multiple forest characteristics over large areas (Eskelson et al., 2009; McRoberts, 2012). Nearest-neighbor techniques based on forest inventory plots and satellite imagery were first implemented operationally in Finland in 1990, but have now been applied in locations spanning the globe (McRoberts et al., 2010).

Gradient nearest neighbor (GNN) is one variation of nearest-neighbor imputation that relies on constrained ordination (direct gradient analysis) for weighting distances in nearest-neighbor calculations (Ohmann & Gregory, 2002) (see Section 2.1). In past studies we have used GNN to map forest vegetation for a single point-in-time, for a variety of forest ecosystems and objectives (Ohmann, Gregory, Henderson, & Roberts, 2011; Ohmann, Gregory, & Spies, 2007; Pierce, Ohmann, Wimberly, Gregory, & Fried, 2009). We recently extended GNN to mapping multiple forest attributes at two dates based on two dates of Landsat imagery (Ohmann et al., 2012). For the current effort, conducted as part of a larger study to integrate data from Landsat time-series and regional inventory plots in an observation-based system for biomass and carbon monitoring in wooded ecosystems, we more fully utilized the Landsat time-series data to map a yearly time-series. Although we use multi-temporal plot and imagery data in our analyses, this is not a primary emphasis of this paper, and our methods and findings are equally applicable to single-date data. In addition, although we assessed the scaling effects empirically for the Oregon and California Cascades in the northwestern USA (Fig. 1), this region encompasses a wide range of physical environments and forest vegetation and our results should be generalizable to other locations.

We considered several aspects of spatial scale, which are described in more detail below: the imputation grain (the scale of the mapping unit used for nearest-neighbor distance calculations); the vegetation heterogeneity within plots used in modeling (which interacts with spatial grain); the accuracy assessment grain (single pixel or multi-pixel block); the spatial extent of accuracy assessment (from plot to larger hexagons); and the value of k, which refers to the number of nearest-neighbor plots used in calculating the forest attribute value that is imputed to a map unit. The effect of k is unique to nearest-neighbor imputation. Because we used Landsat satellite imagery, all analyses were conducted using raster data at a spatial resolution of 30 m × 30 m (referred to as 30-m).

2. Methods

2.1. GNN process for gradient modeling and spatial prediction

We developed a time-series of GNN maps for each combination of scaling options (imputation grain, within-plot heterogeneity, accuracy assessment grain and extent, and value of k). GNN was implemented as described in Ohmann and Gregory (2002) and Ohmann et al. (2011, 2012), but with the addition of kernel imputation, $k = 5$, and enhancements for multi-date (yearly) mapping. Neighbor selection in GNN is based on weighted Euclidean distance within multivariate gradient space as determined from canonical correspondence analysis (CCA) (ter Braak, 1986), a method of constrained ordination (direct gradient analysis).

Spatial predictors (explanatory variables, often referred to collectively as feature space) are listed in Table 1. Spectral variables were derived from Landsat imagery mosaics developed with the LandTrendr (Landsat Detection of Trends in Disturbance and Recovery) algorithms (Kennedy, Cohen, & Schroeder, 2007; Kennedy et al., 2010). LandTrendr is a trajectory-based change detection method that simultaneously examines a time-series of yearly Landsat TM satellite images. Using images

Fig. 1. The Oregon and California Cascades modeling region, shown in darker gray.