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Estimation of forest structural parameters using 5 and 10 meter SPOT-5 satellite data

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ABSTRACT

Large areas of forest in the US and Canada are affected by insects and disease each year. Over the past century, outbreaks of the Eastern spruce budworm have become more frequent and severe. The notion of designing a more pest resistant landscape through prescriptive management practices hinges on our ability to effectively model forest–insect dynamics at regional scales. Increasingly, more detailed pixel-wise estimates of forest biophysical parameters are needed for such endeavors. Lidar technology, although promising, is not yet viable for repeated regional accounting, necessitating the development of methods which take advantage of existing spaceborne assets. Our objective is to use one of these assets (SPOT-5) to estimate a large set of forest structural attributes at a finer spatial grain size (5 m and 10 m) over a broader area than is currently available for the purpose of supplying needed input data for disturbance simulation modeling. We employ neighborhood statistics (standard deviation, variance, sill variance, and ratios of these metrics at 5 and 10 m) calculated from SPOT-5 sensor data and derivatives to estimate and map tree canopy diameter (CDIA), bole diameter at breast height (DBH), tree height (HT), crown closure (CC), vertical length of live crown (LC), and basal area (BA). A partial least squares (PLS) regression approach was used with these local statistics and field data to produce models for pixel-wise estimation and mapping of mean values, respectively, for hardwood and coniferous forest CDIA ($R^2=0.82$ and 0.93, RMSE 0.62 and 0.47 m), DBH ($R^2=0.82$ and 0.90, RMSE 2.92 and 3.75 cm), HT ($R^2=0.69$ and 0.92, RMSE 1.27 and 1.59 m), CC ($R^2=0.52$ and 0.68, RMSE 5.49 and 6.02%), LC ($R^2=0.58$ and 0.81, RMSE 0.96 and 1.25 m), and BA ($R^2=0.71$ and 0.74, RMSE 2.47 and 4.58 m^2 ha^{-1}) for a 3600 km^2 area in northeast Minnesota. This approach for quantifying forest structure is robust in the sense that a detailed forest cover type map is not required to stratify analysis at any step in the process. Hence, we show that multi-resolution SPOT-5 data are a practical alternative to lidar for regional characterization of forest biophysical parameters. However, lidar data may potentially be used to calibrate these SPOT-based structure models in the future.

1. Introduction

Large areas of forest in the US and Canada are affected by insects and disease each year. Over the past century, outbreaks of the Eastern spruce budworm (*Choristoneura fumiferana*) have become more frequent and severe as a result of past forest management practices, fire suppression, and pesticide application that favored expansion of host species (Blais, 1983). Because observed changes in insect disturbance history are largely human induced, it may also be possible to undo or at least mitigate these effects through prescriptive forest management (Blais, 1983). Forest ecologists have identified several forest stand characteristics such as tree species composition and basal area (Ghent, 1958; Batzer 1969; Crook et al., 1979; Bergeron et al., 1995; Alfaro et al., 2001; Sturtevant et al., 2004; Hennigar et al., 2008), host needle biomass and terrain position (Magnussen et al., 2004), forest age and crown closure (Alfaro et al., 2001), canopy position (Zhang & Alfaro, 2001), bole diameter (Bergeron et al., 1995), and other structural parameters that are indicative of the relative vulnerability of a stand to a spruce budworm outbreak should one occur. However, the notion of using this information to design a more pest resistant landscape is highly complex and hinges on our ability to effectively model multiple biological disturbance interactions at regional scales (Blais, 1983; Sturtevant et al., 2004). Ideally, spatially explicit landscape succession and disturbance models tailored for these efforts, such as LANDIS and LANDIS II (Mladenoff & He, 1999; Scheller & Mladenoff, 2004; Schumacher et al., 2004; Sturtevant et al., 2004; Scheller et al., 2007), make use of pixel-level information to parameterize the land surface to the extent that these data are available. While rudimentary pixel-level information describing the abundance and distribution of spruce budworm host species on a regional scale is available for some areas (e.g. Wolter et al., 2008), the need for more detailed forest structure information for these purposes and many others is increasingly coveted.

All ecosystem process models require parameterization of the land surface in one form or another. At medium to large spatial scales the

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most realistic possibility for accurate estimation and periodic update of these parameters is satellite remote sensing (Hall et al., 1995; Widlowski et al., 2004). The need to easily extract forest biophysical parameters over large areas at a relatively fine grain size is significant, as it provides a means for the inclusion of previously missing forest parameter data into regional ecosystem models to directly estimate linkages between forest structure and ecosystem functioning (Song, 2007). As such, one of the most persistent objectives of satellite remote sensing has been classification and quantification of forest biophysical properties such as tree species composition (Wolter et al., 1995; Reese et al., 2002), canopy diameter (Li & Strahler, 1985; Woodcock et al., 1997; Cohen & Spies, 1990; Song & Woodcock, 2003; Song, 2007), stem density (Cohen & Spies, 1992; Hudak et al., 2006; McRoberts, 2008), basal area (Franklin, 1986; Franco-Lopez et al., 2001; Hudak et al., 2006; McRoberts et al., 2007; McRoberts, 2008; Wolter et al., 2008), above ground biomass or volume (Franco-Lopez et al., 2001; Santoro et al., 2002; Pulliainen et al., 2003; Zheng et al., 2004; Muukkonen & Heiskanen, 2005; Rauste, 2005; Hall et al., 2006; McRoberts et al., 2007), bole diameter (Greenberg et al., 2005), tree height (Maltamo et al., 2006; Walker et al., 2007), live crown height (Maltamo et al., 2006), crown closure (Li & Strahler, 1985; Cohen et al., 1990; Cohen et al., 1995; Woodcock et al., 1997), stand age (Cohen & Spies, 1992; Cohen et al., 1995; Franklin et al., 2001), disturbance (Vogelmann & Rock, 1989; Healey et al., 2005), health (Vogelmann & Rock, 1988), and other characteristic forest attributes that are commonly sought after to understand forest functional complexity (Mc Elhinny et al., 2005). While many satellite-based efforts have consistently achieved moderate to high levels of success measuring subsets of these parameters, more comprehensive parameter sets describing forest structural complexity beyond small study sites has not yet been achieved (Anderson et al., 2008). Although lidar technology, used by itself or in combination with other sensor data, is considered optimal for estimating many of these forest parameters (Hyyppä & Inkinen, 1999; Anderson et al., 2008; Hudak et al., 2008), automation and extrapolation to larger, regional scales remains a challenge.

Forests of the northern Great Lakes States (Minnesota, Wisconsin, and Michigan) consist largely of second and third growth stands with less than 9% of old growth (>120 years) remaining (Frelich & Reich, 1995). The diversity and smaller stature of these forests effectively precludes application of most Landsat-based techniques for estimating structure that have shown promise for western coniferous forests (Woodcock & Strahler, 1987; Cohen & Spies, 1992; Cohen et al., 1995; Hansen et al., 2001). Alternatively, nearest neighbor techniques, such as the popular *k*-Nearest Neighbor (*k*-NN) method described by McRoberts et al. (2007), have shown promise when used with Landsat data for estimating stand-level forest structure information in the Great Lakes region (McRoberts et al., 2007; McRoberts, 2008, 2009) and northern Europe (Katila & Tomppo, 2001; Tomppo et al., 2009). With *k*-NN, forest parameter predictions, for pixels without ground reference data, are calculated as linear combinations of reference pixel values that are nearest in feature space according to some distance metric (Tomppo et al., 2009). However, arbitrary selection of *k* neighbors, distance metrics, distance cutoff criteria, and neighbor weights are cited as potential limitations of the technique, as well as computation intensity when applied over large areas (Finley et al., 2006; McRoberts et al., 2007; Meng et al., 2009). While data reduction techniques (e.g., principal components analysis) applied to sensor data prior to analysis is a common prescription for increasing the efficiency of the *k*-NN algorithm (Meng et al., 2009; McRoberts et al., 2007), such data reduction may be undesirable if goals include identifying specific spectral regions or indices that best explain variance among dependent forest variables (see Wolter et al., 2008).

Estimates of forest structure made using high spatial resolution (0.6 m–4.0 m) satellite data (Shugart et al., 2000; Song & Woodcock, 2003; Song, 2007; Lamonaca et al., 2008; Wulder et al., 2008), airborne or spaceborne lidar (Lefsky et al., 1999, 2005), or combinations of optical satellite data with airborne lidar (Donoghue & Watt, 2006; Wulder et al., 2007) are increasingly precise, but are limited for regional application due to high cost to coverage area ratios (Zheng et al., 2008) compared to more synoptic satellite sensors such as SPOT (60×60 km), Landsat (185×185 km), or MODIS (2330 km swath). Moreover, airborne lidar coverage represents only a fraction of the regional need for such data, and while it is ideal for measuring tree height, and subsequently, estimating forest biomass, it generally cannot provide direct information on canopy diameter (Song, 2007).

In this study we take advantage of the geospatial relationship between tree canopy size (i.e. diameter) and resulting representations of these canopies when imaged at two different pixel resolutions (Woodcock et al., 1997; Song & Woodcock, 2003; Song, 2007) to estimate mean canopy diameter (CDIA), tree height (HT), bole diameter at breast height (DBH), canopy closure (CC), basal area (BA), and height of live crown (LC) using 5 m and 10 m SPOT-5 (Systeme pour l'Observation de la Terre) satellite sensor data collected over northeast Minnesota. SPOT-5 sensor data is convenient as it represents a reasonable compromise between high and medium spatial resolution, while also having a large coverage area compared to IKONOS or Quickbird satellite data.

1.1. Study objective

The primary goal of this paper is to demonstrate a unique approach for modeling and mapping a set of forest structure parameters (Appendix A) using optical sensor data with a relatively fine spatial resolution (5 m and 10 m), but with large enough coverage area (60 km×60 km) to be practical for repeated, regional studies. We employ a broad suite of predictor variables (Table 1) derived from the SPOT-5 sensor data including panchromatic (PAN, 5 m) and multispectral (XS, 10 m) reflectance bands, XS indices, semivariogram sill parameters and sill ratios (Song & Woodcock, 2003; Song, 2007), and

Table 1
Local statistics calculated within Euclidean neighborhoods for SPOT-5 bands and derivatives.

Variables	Descriptions
GRN	Mean of 10 m visible green (July)
RED	Mean of 10 m visible red (July)
NIR	Mean of 10 m near-infrared (July)
SWIR	Mean of 20 m shortwave infrared (July)
P5	Mean of 5 m PANchromatic band (August)
P10P	Mean of simulated 10 m PAN: P5 regularized to10 m
P10X	Mean of simulated 10 m PAN: (GRN + RED)/2
SNIR	Standard deviation of NIR
S5	Standard deviation of P5
S10P	Standard deviation of P10P
S10X	Standard deviation of P10X
VNIR	Variance of NIR
V5	Variance of P5
V10P	Variance of P10P
V10X	Variance of P10X
C5	Semivariogram sill parameter for P5
C10P	Semivariogram sill parameter for P10P
C10X	Semivariogram sill parameter for P10X
NDVI	Normalized difference vegetation index: (NIR-RED) / (NIR+RED)
MSI	Moisture stress index: SWIR/NIR
SVR	Shortwave infrared to visible ratio: SWIR/[(RED+GRN)/2]
S510P	Ratio of standard deviations: S5/S10P
S510X	Ratio of standard deviations: S5/S10X
V510P	Ratio of variances: V5/V10P
V510X	Ratio of variances: V5/V10X
C510P	Ratio of semivariogram sill parameters: C5/C10P
C510X	Ratio of semivariogram sill parameters: C5/C10X

There are four multi-spectral bands (15 July 2006), one 5 m panchromatic (P5) band (31 August 2006), and two simulated 10 m panchromatic bands: one produced from the August panchromatic image (P10P) and the other from the multi-spectral July image (P10X). The remaining image variables were derived using these seven bands that are highlighted in bold. Prefixes *S*, *V*, and *C* (except SVR and SWIR) are used specifically to denote standard deviation, variance, and sill, respectively.