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Individual snag detection using neighborhood attribute filtered airborne lidar data

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ABSTRACT

The ability to estimate and monitor standing dead trees (snags) has been difficult due to their irregular and sparse distribution, often requiring intensive sampling methods to obtain statistically significant estimates. This study presents a new method for estimating and monitoring snags using neighborhood attribute filtered airborne discrete-return lidar data. The method first develops and then applies an automated filtering algorithm that utilizes three dimensional neighborhood lidar point-based intensity and density statistics to remove lidar points associated with live trees and retain lidar points associated with snags. A traditional airborne lidar individual-tree detection procedure is then applied to the snag-filtered lidar point cloud, resulting in stem map of identified snags with height estimates. The filtering algorithm was developed using training datasets comprised of four different forest types in wide range of stand conditions, and then applied to independent data to determine successful snag detection rates. Detection rates ranged from 43 to 100%, increasing as the size of snags increased. The overall detection rate for snags with DBH $\geq$ 25 cm was 56% ($\pm$2.9%) with low commission error rates. The method provides the ability to estimate snag density and stem map a large proportion of snags across the landscape. The resulting information can be used to analyze the spatial distribution of snags, provide a better understanding of wildlife snag use dynamics, assess achievement of stocking standard requirements, and bring more clarity to snag stocking standards.

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1. Introduction

In recent years, recognition of the essential roles standing dead trees (snags) play in forest ecosystems has increased. For wildlife, snags provide critical nest, roost, and den habitat for a myriad of vertebrate species while also providing excellent foraging resources (Bate, 1995; Harmon, 2002; Laudenslayer, 2002; Mellen et al., 2006; Rose et al., 2001). For these reasons snags have been classified as key habitat components for many threatened and forest health indicator species (Harmon, 2002). Snags are also important for nutrient cycling, long-term carbon storage, and many fungal and invertebrate life cycles are dependent on snags (Boddy, Frankland, & van West, 2008; Harmon, 2002; Jonsson, Kruys, & Ranius, 2005). Due to all these attributes, snags are often considered to be key indicators of biodiversity and forest health.

As the recognition of the importance of snags has become more apparent, numerous certification programs and forest management regulatory bodies have developed minimum snag stocking requirements to help ensure that biodiversity is maintained or restored (Pasher & King, 2009). These most often require a certain density or volume of snags to be maintained over time in order to provide continuous habitat support and ecosystem sustainability (Franklin, Berg, Thornburgh, & Tappeiner, 1997; Holloway, Caspersen, Vanderwel, & Naylor, 2007). The standards and regulations are often based on results from snag sampling studies, which estimate the size and quantity of snags from field sampling methods. One limitation associated with this method is that the distribution of snags across forest stands is often highly variable, even within stands that are similar in many other respects (Fan, Shifley, Thompson, & Larsen, 2004). Most standard sampling designs are not efficient for rare events, such as snags (Yoccoz, Nichols, & Boulinier, 2001). Thus, the ability to estimate and monitor snags has proven to be inherently difficult; requiring complex, intensive, and often expensive sampling procedures to produce estimates of sufficient precision (Bate, Garton, & Wisdom, 1999; Bull, Holthausen, & Marx, 1990; Ducey, Jordan, Gove, & Valentine, 2002; Gray, 2003; Harmon & Sexton, 1996; Kenning, Ducey, Brisette, & Gove, 2005; Krebs, 1989; Lämas & Stahl, 1998; Rose et al., 2001). This has led to the exploration of utilizing remote sensing technologies to better estimate snag densities and distributions across the landscape (Bater, Coops, Gergel, LeMay, & Collins, 2009; Bütler & Schlaepfer, 2004; Croft, Heller, & Hamilton, 1982; Martinuzzi et al., 2009).

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Using remote sensing techniques to estimate the density and distribution of snags can provide a more practical, cost-effective, and reliable method (Bater et al., 2009). However, there have been few studies testing the capabilities of remote sensing to estimate snags. While some have used Landsat (Frescino, Edwards, & Moisen, 2001), most have utilized airborne multispectral imagery and have focused on stand-level disturbance events, such as insect outbreaks, disease or windfall (Guo, Kelly, Gong, & Liu, 2007; Hamilton, Megown, Ellenwood, Lachowski, & Maus, 2010; Kelly, Shaari, Guo, & Liu, 2004). Others have focused on the assessment of individual snags in a variety of forest types and conditions (Bütler & Schlaepfer, 2004; Croft et al., 1982; Haara & Nevalainen, 2002; Leckie, Jays, Gougeon, Sturrock, & Paradine, 2004; Pasher & King, 2009). Bütler and Schlaepfer (2004) achieved good results by developing a manual four-step individual-snag detection method that coupled airborne CIR photos (1:10,000) with a geographic information system (GIS). Their method produced an overall detection rate of 67% for snags ≥25 cm diameter at breast height (DBH), but also had many noted limitations; 1) most smaller snags were not detected, 2) high-levels of technology were required, including special software, and 3) accuracies were affected by factors such as aspect, surface slope, weather, and hour of flight. Their manual method, like most methods utilizing aerial imagery, also suffers from time and cost issues and is prone to operator interpretation bias and subjectivity errors (Bater et al., 2009). As a result, there has been an increased interest in augmenting techniques to estimate and detect snags using newer remote sensing technologies, such as airborne light detection and ranging (lidar), that have displayed potential in the identification of individual trees and the ability to predict live- and dead-tree attributes (Kim et al., 2009; Martinuzzi et al., 2009).

Airborne lidar is an active remote sensing technology employing an aircraft mounted laser capable of simultaneously mapping terrain and vegetation heights with sub-meter accuracy across large spatial extents (Lefsky, Cohen, Harding, & Parker, 2002). It has proven to be a very promising remote-sensing technology for increasing the accuracy and efficiency of large-scale forest inventories for a myriad of important forest inventory and wildlife habitat attributes (Maltamo, Malinen, Packalén, Suvanto, & Kangas, 2006; Martinuzzi et al., 2009; Næsset, 2002). Lidar data produce three-dimensional characterizations of objects in the form of point clouds that are defined by precise x, y and z coordinates. They also help characterize the reflectance and surface properties of intersected objects by providing intensity values, which are a measure of return-signal strength for each point. These attributes are useful for forest inventory and characterization because, in theory every object in a forest can be detected if adequate lidar point densities are collected within all vertical layers (e.g., understory & overstory) (Pesonen, Maltamo, Eerikäinen, & Packalén, 2008).

The use of airborne lidar in the estimation of snag attributes has received more attention recently. The methods for estimating snag attributes using airborne lidar can be separated into two assessment categories: plot-based and individual-tree (Reutebuch, Andersen, & McGaughey, 2005). Plot-based assessments seek to estimate plot-level attributes such as snag volume, biomass or abundance (Bater et al., 2009; Kim et al., 2009; Martinuzzi et al., 2009; Pesonen et al., 2008), while individual-tree based assessments seek to extract and measure individual trees using some type of segmentation method (Kaartinen & Hyyppä, 2008; Vauhkonen et al., 2011). Estimation of snag attributes using plot-based assessment methods have achieved mixed results. Pesonen et al. (2008) achieved relatively poor results predicting snag volume using plot-based canopy derived lidar-metrics (RMSE 79%), while Kim et al. (2009) achieved better results estimating snag biomass using similar plot-based metrics that were stratified based on intensity values. These studies both highlight the need for more research on the subject.

Individual-tree based snag assessment using airborne lidar has received less attention. All studies to date using individual-tree based assessment methods have focused on extracting both live and dead trees, with most attention on the former (Kaartinen & Hyyppä, 2008; Maltamo, Eerikäinen, Pitkänen, Hyyppä, & Vehmas, 2004; Mehtätalo, 2006; Morsdorf et al., 2010; Reitberger, Schörr, Krzystek, & Stilla, 2009; Vauhkonen et al., 2011; Wang, Weinacker, Koch, & Sterenczak, 2008). To the authors' knowledge, there have been no studies to date that have predominantly focused on identification of individual snags using an airborne lidar individual-tree assessment method. This study attempts to identify individual snags using airborne lidar data by applying an individual-tree assessment method to neighborhood attribute filtered lidar data focused on removing lidar points associated with live trees from the overstory (snag-filtered lidar data).

Neighborhood attribute point cloud filtering is a new airborne lidar analysis technique being introduced in this study. Its primary objective is to create an automated routine that accurately assigns the proper forest attribute to each lidar point. This information can then be used to filter the points and obtain a point cloud containing only points associated with the forest attribute(s) of interest, or to assign individual forest attribute probabilities or weights to each lidar point. In theory, this should provide an enhanced airborne lidar analysis framework for both plot-based and individual forest attribute assessments since lidar points not associated with the forest attribute(s) of interest are either removed from the analysis or have less influence on prediction models. Filtering is accomplished by using two inherent lidar point attributes: location and intensity. Each lidar point's attributes as well as its neighboring lidar points' attributes are used to create neighborhood statistics that are then used in a conditional framework to identify the forest attribute most likely to be associated with each lidar point. The location of each lidar point can be used to determine if a point intersected a forest attribute in the understory or overstory, and then neighborhood intensity and point density statistics can be used to help determine the unique forest attribute associated with each point. In this study, location and three dimensional (3D) neighborhood statistics are used in an attempt to identify individual lidar points associated with snags and live trees. Intensity is the primary lidar attribute used for the neighborhood point cloud filtering, therefore understanding the attribute's nuances are fundamental to successfully filtering the data.

Intensity values are an often underexploited feature of lidar data, due to variability and difficulty associated with acquisition settings and calibration (Wing et al., 2012). Intensity is a unitless measure of a laser pulse's discrete return energy stored as an integer value with a defined range (e.g., 0–255). Intensity data are primarily a measure of surface reflectance and are a function of the wavelength of the source energy, path distance, and the composition and orientation of the surface or object the laser pulse intersects (Boyd & Hill, 2007). Variability of the intensity data across similar targets is dependent upon adjustable lidar acquisition parameters. Laser beam divergence, type of source energy, path lengths and variable gain control settings all affect the variability of intensity. These acquisition parameters influence intensity at different rates and magnitudes, with path lengths and the variable gain control setting having the most influence. These attributes have limited the use of intensity data, due to variability associated with intensity values within and from different acquisitions. Even with these limitations intensity has already been used successfully in many forestry applications to differentiate between tree species, estimate live and dead biomass, and predict basal area (Donoghue, Watt, Cox, & Wilson, 2007; Holmgren & Persson, 2004; Hudak et al., 2006; Kim et al., 2009; Lim, Treitz, Baldwin, Morrison, & Green, 2003; Wing et al., 2012). Kim et al. (2009) used intensity value threshold stratification to estimate live and dead standing tree biomass. They stratified plot point clouds based on intensity values and found metrics created with the lower intensity plot point cloud better estimated standing dead biomass. More recently, Wing et al. (2012) utilized intensity information to help filter points in the understory (e.g., vegetation, stumps, coarse woody debris, tree boles). These studies point toward the potential of using intensity to help characterize many forest attributes. With the advent of post-calibration or normalization routines to reduce intensity variability and the standardization of