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Canadian Journal of Remote Sensing
Journal canadien de télédétection

ISSN: 0703-8992 (Print) 1712-7971 (Online) Journal homepage: https://www.tandfonline.com/loi/ujrs20

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To cite this article: Joanne C. White, Nicholas C. Coops, Michael A. Wulder, Mikko Vastaranta, Thomas Hilker & Piotr Tompalski (2016) Remote Sensing Technologies for Enhancing Forest Inventories: A Review, Canadian Journal of Remote Sensing, 42:5, 619-641, DOI: 10.1080/07038992.2016.1207484

To link to this article: https://doi.org/10.1080/07038992.2016.1207484

Canadian Journal of Remote Sensing, 42:619–641, 2016
Published with license by Taylor & Francis
ISSN: 0703-8992 print / 1712-7971 online
DOI: 10.1080/07038992.2016.1207484

Remote Sensing Technologies for Enhancing Forest Inventories: A Review

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Abstract. Forest inventory and management requirements are changing rapidly in the context of an increasingly complex set of economic, environmental, and social policy objectives. Advanced remote sensing technologies provide data to assist in addressing these escalating information needs and to support the subsequent development and parameterization of models for an even broader range of information needs. This special issue contains papers that use a variety of remote sensing technologies to derive forest inventory or inventory-related information. Herein, we review the potential of 4 advanced remote sensing technologies, which we posit as having the greatest potential to influence forest inventories designed to characterize forest resource information for strategic, tactical, and operational planning: airborne laser scanning (ALS), terrestrial laser scanning (TLS), digital aerial photogrammetry (DAP), and high spatial resolution (HSR)/very high spatial resolution (VHSR) satellite optical imagery. ALS, in particular, has proven to be a transformative technology, offering forest inventories the required spatial detail and accuracy across large areas and a diverse range of forest types. The coupling of DAP with ALS technologies will likely have the greatest impact on forest inventory practices in the next decade, providing capacity for a broader suite of attributes, as well as for monitoring growth over time.

Résumé. Les exigences en matière d'inventaire forestier et de gestion évoluent rapidement dans le contexte d'un ensemble d'objectifs de politique économique, environnementale et sociale de plus en plus complexe. Les technologies de télédétection avancées fournissent des données pour aider à répondre à ces besoins croissants d'information et pour soutenir les futurs développements et le paramétrage de modèles pour une gamme encore plus large de besoins en information. Ce numéro spécial contient des articles qui utilisent une variété de technologies de télédétection pour obtenir des informations sur l'inventaire forestier ou liées à l'inventaire forestier. Ici, nous passons en revue le potentiel de 4 technologies de télédétection avancées que nous estimons comme ayant le plus grand potentiel d'influencer les inventaires forestiers conçus pour caractériser l'information des ressources forestières pour la planification stratégique, tactique et opérationnelle: le balayage laser aéroporté «airborne laser scanning (ALS)», le balayage laser terrestre (TLS), la photogrammétrie aérienne numérique (DAP), et l'imagerie optique satellite à haute résolution spatiale (HSR) ou à très haute résolution spatiale (VHSR). Le ALS, en particulier, s'est révélé être une technologie transformatrice, offrant aux inventaires forestiers des détails spatiaux ainsi que la précision nécessaires sur de grandes surfaces et un large éventail de types de forêts. Le couplage de la DAP avec les technologies du ALS aura probablement le plus grand impact sur les pratiques d'inventaire forestier dans la prochaine décennie en fournissant la capacité d'obtenir un ensemble plus large d'attributs, ainsi que la surveillance de la croissance au fil du temps.

INTRODUCTION

Sustainable forest management is a balancing act between the demands of an ever increasing human population and maintenance of the ecological functions of healthy forest ecosystems (MacDicken et al. 2015). Implicit in the term "sustainable" is a multi-faceted approach to forest management that considers a broad range of factors, including biodiversity, forest health, and resilience against disease and fire (Lindenmayer et al. 2000; Siry et al. 2005; Gauthier et al. 2014). Concurrent with an increasing demand for forest resources, there is also a desire for increased protection of forested ecosystems from harvest and other disturbances, especially those that imply a permanent land use change from forest. In this context of competing demands on the forest resource and increasing global competition among

Received 2 December 2015. Accepted 8 March 2016.
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fiber suppliers, value chain optimization has become a key driver of the contemporary forest industry (Shabani et al. 2013; Shahi and Pulkki 2015). Information needs for forest management are increasingly complex and wide ranging, posing new challenges for forest inventory programs. As such, forest information must be accurate, spatially detailed, up to date, and must characterize forest composition, structure, and, ultimately, wood supply attributes (Wulder, Bater, et al. 2008; Groot et al. 2015). The aforementioned information needs exceed the scope and design of many existing forest inventories, providing an opportunity for new information sources (Alam et al. 2014).

Forests are inventoried for multiple purposes. For example, forest resource information is gathered for strategic, tactical, and operational planning and forest management. National forest inventories (NFIs) are examples of inventories undertaken to acquire information about nationwide forest resources and enable national-level strategic planning and policy development. In this case, information of interest might include forest cover, growing stock volume, biomass, carbon balance, and large-scale wood procurement potential. In many countries, NFIs are based on field samples (Tomppo et al. 2010). Forest attribute maps can be produced, but the accuracy of the maps is generally inadequate for tactical forest management planning. For the latter, wood procurement potential is of primary interest, and forest management proposals involve detailed maps and information gathered by using stand cruising methods (i.e., stand-wise field inventories) or using detailed remote sensing methodologies (traditionally, aerial photography). In addition to stand attributes of interest, site types are classified to map forest growth potential, thinning regime, and biodiversity. The wood procurement chain from forest to user starts with knowledge of the stands available for harvest, because the mapping of potential harvesting sites is one of the key decisions for forest managers (Laamanen and Kangas 2011).

In the context of this review, we explicitly refer to forest inventories that involve the collection of forest resource information for strategic, tactical, or operational planning. In this context, forest inventories are spatial and involve some form of mapping. These inventories can extend across a range of spatial scales, from small community forests of ∼1,000 ha to large forest management areas in excess of 1 million ha. Traditionally, forest inventories have been designed to serve information needs associated with timber harvesting. In many nations, these inventories are based on ground sample plots or, in some cases, on the manual interpretation of aerial photography for stand delineation and attributes such as species composition, stand height, diameter at breast height (DBH), and basal area, which are then augmented with ground plot data sampled at relatively few locations to represent the forest landscape (Leckie and Gillis 1995; Tomppo et al. 2010). Although approaches vary by jurisdiction, common challenges to all traditional inventory approaches are the accuracy and consistency for subjective interpretations and measurements (Thompson et al. 2007), as well as costs. Although ground sampling is largely based on fixed costs, remote sensing technologies offer economies of scale, with data often becoming less expensive as the area of interest increases (Franklin et al. 2002). Although traditional inventory approaches have proven useful for ensuring that the area of harvested forest land does not exceed the area anticipated to regrow over a given period of time (often an 80 year–100 year cycle), they were not designed to provide direct measures of ecological values or timber quality. Enhanced information is required in order to characterize both the quality and quantity of the forest resources, including stand structure, composition, and productivity. In turn, this enhanced information can be used to support the development of improved management strategies for forest health, biodiversity, and endangered species, while at the same time improving wood utilization and production efficiencies by allowing forest managers and mill owners to match harvested logs with market forces and related processing requirements (Pitt and Pineau 2009; Alam et al. 2014; Listopad et al. 2015).

As demands on forest inventories continue to increase within a context of diminishing financial resources, remote sensing technologies will have an increasingly important and varied role in the forest inventory process. Some of the required information can be measured directly with advanced remote sensing technologies, whereas other required information can be derived indirectly via modeling (Brosofske et al. 2014). In this article, we offer context to this *Special Issue on Remote Sensing for Advanced Forest Inventory* and provide an update on the current capacity of 4 remote sensing technologies that—in our view—have the greatest potential to influence forest inventories focused on the collection of spatially explicit forest resource information with high spatial accuracy for strategic, tactical, and operational forest planning. These technologies include: airborne laser scanning (ALS), terrestrial laser scanning (TLS), digital aerial photogrammetry (DAP), and high spatial resolution (HSR) and very high spatial resolution (VHSR) satellite optical imagery. Previous reviews have typically focused on these technologies in isolation, rather than collectively, as we do herein, and few have specifically focused on the potential of these technologies in a forest inventory context. This inventory perspective allows us to address synergies among these technologies, as well as the current trend toward multisource inventories. We present the current state of the art for each of these technologies, identify important research issues in a forest inventory context, and provide some perspectives on the operational readiness of these technologies to inform forest inventory practices.

ADVANCED REMOTE SENSING TECHNOLOGIES AND THEIR CURRENT USE IN FOREST INVENTORIES

Airborne Laser Scanning

ALS is an active remote sensing technology that measures the 3-dimensional distribution of vegetation within forest canopies and is, therefore, well suited for describing vertical forest structure (Lefsky et al. 1999; Wehr and Lohr 1999). LiDAR

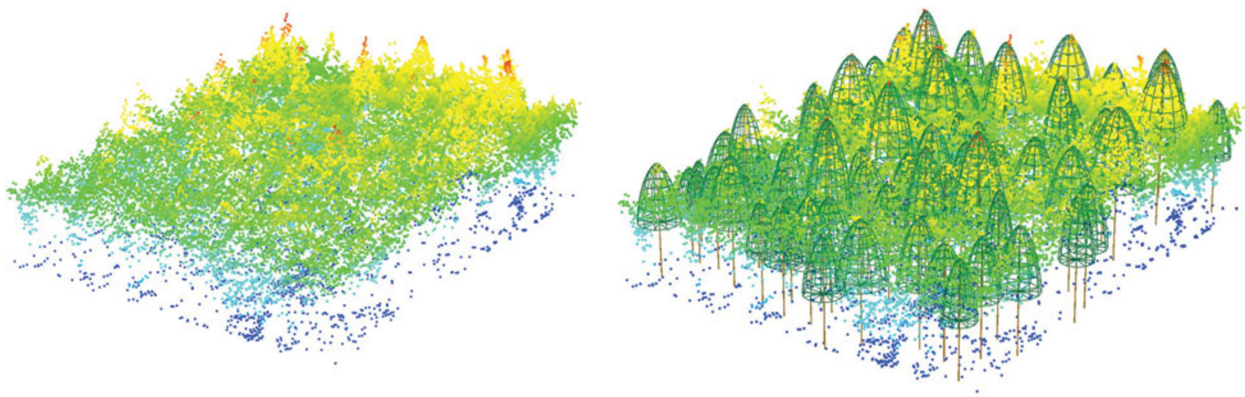

FIG. 1. An ALS point cloud (3.1 points/m^2) and subsequently fitted tree crowns of a forested site near Vancouver, Canada (images generated with FUSION/LDA software, USDA Forest Service).

systems are categorized by the mode with which they record the energy returning to the sensor. For each emitted laser pulse, discrete return systems will record single or multiple returns, with the maximum number of possible discrete returns recorded per emitted pulse having increased with advances in sensor technology (Lim et al. 2003). Conversely, a full-waveform system will record the returning energy as one continuous return or waveform (Lefsky et al. 2002). LiDAR utilizes a near-infrared light source and detector to measure the 3-dimensional locations of targets such as trees (Lim et al. 2003). The measured laser returns, combined with precise location information provided by the Global Navigation Satellite Systems (GNSS) and complemented by an Inertial Measurement Unit (IMU) to measure aircraft pointing, allow the generation of 3-dimensional point clouds representing the spatial distribution of canopy elements. For forest inventory, ALS data are typically acquired at altitudes between 500 m and 3000 m (Næsset 2005; Goodwin et al. 2006) and have been widely used for generation of bare-earth digital terrain models (DTM), as well as the estimation of forest inventory attributes (Hyyppä et al. 2008). Typically, these ALS systems emit laser pulses having footprints ranging from 0.1 m to 2 m (Lim et al. 2003; Wulder, Bater, et al. 2008), and can achieve submeter measurement accuracy of terrain surface heights (Reutebuch et al. 2003; Næsset 2015a). Operationally, LiDAR systems used in forest inventory applications have primarily been discrete return, small footprint, ALS systems (Hyyppä et al. 2008).

Determination of single-tree attributes typically requires ALS data with a higher pulse density than that used for the area-based approach. The required pulse density can be expected to vary by forest type, with detection capacity linked to crown size, crown form, and stand complexity (Vauhkonen et al. 2012). In an international benchmarking study, Kaartinen et al. (2012) found that increasing point density (from 2 points/m^2 to 8 points/m^2) had less impact on the accuracy of individual tree crown (ITC) outcomes than the method used to extract individual trees. LiDAR instruments have developed rapidly, with pulse repetition frequencies (PRF) increasing by more than 3 orders of magnitude from that of the first pulsed-laser system (Nelson 2013). This increase in PRF effectively means aircraft can fly higher and faster to cover a larger area than previously possible; however, there is an upper limit to this that results from speed-of-light limitations (i.e., energy from the emitted pulse must first return to the sensor before the next pulse is emitted in order to prevent range ambiguities). With higher PRF, sensors can operate in a *multiple-pulses-in-the-air* configuration, and there are now solutions to avoid range ambiguities (Nelson 2013). Higher PRF, however, can also mean that each pulse carries less energy and, thereby, has reduced capacity to penetrate the canopy. Figure 1 provides an example of ITCs derived from a high-density ALS point cloud. When planning a survey, users must typically disentangle their needs for pulse density and area coverage (Jakubowski et al. 2013), although in some cases, both criteria might be met; information needs will often dictate pulse-density requirements. For example, applications to determine species from crown level morphology (Dalponte et al. 2014) or the emergence of small trees (Næsset and Nelson 2007; Thieme et al. 2011), would require higher pulse densities (e.g., greater than 5 pulses per square meter). Conversely, lower pulse densities (e.g., ~0.2 to 1.2 pulses per square meter; Jakubowski et al. 2013; Næsset and Gobakken 2008) have proven robust in support of the area-based approach (ABA; Næsset 2002).

ALS estimation of tree heights at the plot and stand levels are becoming the standard by which to assess other height measures, with accuracy varying with canopy and terrain conditions (e.g., Gatziolis et al. 2010). Andersen et al. (2006) found that although ALS data provided less accurate estimates of individual tree heights (-0.73 m $\pm$ 0.43 m) when compared to rigorous field measurement methods (-0.27 m $\pm$ 0.27 m), the loss in accuracy was offset by the large-area coverage and efficiencies afforded by the ALS data. Bias for plot height estimation with ALS data is typically less than 0.5 m (e.g., Næsset 1997; Magnussen and Boudewyn 1998; Næsset and Økland 2002; Næsset

2007) and is known to be a function of the nature of the laser sampling and difficulties in consistently intersecting the actual apex of a given tree (Magnussen et al. 1999). Næsset (1997) demonstrated that ALS estimates of stand mean height have a bias of −0.4 m to 1.9 m. Additionally, as indicated in Magnussen et al. (2012), ALS-based plot-level predictions for dominant height, basal area, total stem volume, and aboveground biomass typically meet or exceed required specifications for accuracy. As summarized in Table 1, numerous reviews of ALS data for forest applications detail the capacity and accuracy of ALS data.

Research into the use of ALS data for forest inventory has generally followed either an area-based (Næsset 2002) or ITC or individual tree detection (ITD) approach (Brandtberg 1999; Hyyppä and Inkinen 1999). The area-based approach is dependent on the statistical relationship between predictor variables derived from the vertical distribution of LiDAR returns in the ALS point cloud and ground-based measurements (Næsset 2002). Derived predictive models are then applied over the area corresponding to ALS coverage, providing wall-to-wall estimates of inventory attributes of interest (e.g., Woods et al. 2011). The ITC approach is conceptually aligned with approaches developed using high spatial resolution imagery (Gougeon 1995) and involves isolation of individual trees from the canopy height model (CHM) or the point cloud, and derivation of tree height, crown dimensions, and other attributes using ground-based measurements for calibration. Information for individual trees can then be aggregated to provide estimates at the plot or stand level (Breidenbach and Astrup 2015).

In recent years, there has been increased focus on the integration of ALS data into enhanced forest inventory systems. From a research perspective, the robustness and repeatability of ALS data for forest inventory attribute estimation has been well demonstrated (e.g., Næsset et al. 2004; Bater et al. 2011; Holopainen et al. 2011). Operationally, the ABA has become a standard procedure for processing ALS point cloud data to spatial metrics that can then be used to generate predictive equations for forest inventory attributes (White, Wulder, Varhola, et al. 2013). Indeed, ABA has been at the operational stage for several years and can be considered a proven concept (Wulder et al. 2013; Næsset 2015b). The foremost advantages of the ABA are precise prediction of a suite of basic forest inventory variables such as stem volume, basal area, and height. ALS data and the ABA are increasingly being used operationally to inform forest inventories in a broad range of forest environments and management contexts (Næsset 2007; Woods et al. 2011; White, Wulder, Varhola, et al. 2013; Bouvier et al. 2015). Examples of ALS metrics and area-based estimates of merchantable volumes are provided in Figure 2.

Research into the ITC approach has also been extensive; however, the ITC approach is not as operationally advanced as the ABA, and the utility of the ITC approaches is still being explored (e.g., Duncanson et al. 2015), primarily as a result of challenges in individual tree detection (Holopainen et al. 2014). The success with which individual trees can be detected from the ALS data depends on stand density and configuration (Briedenbach et al. 2010; Vauhkonen et al. 2012), and challenges associated with both detection and allometry can impact ITC-based plot- and stand-level estimates, particularly in complex forests (Korpela et al. 2006; Vastaranta et al. 2011; Kaartinen et al. 2012). Synergies between area-based and individual tree approaches are currently an area of active research (e.g., Breidenbach et al. 2010; Lindberg et al. 2010; Vastaranta et al. 2012; Holopainen et al. 2014; Tompalski et al. 2015), as are improvements to the ITC approach via fusion of ALS and VHSR optical imagery (Paris and Bruzzon 2015).

In a forest inventory context, recent research has focused on species characterization (Ørka et al. 2013; Yu et al. 2014, Maltamo et al. 2015), tree size or diameter distributions (Magnussen et al. 2013; Saad et al. 2015; Kankare et al. 2015; Mehtätalo et al. 2015; Tompalski et al. 2015, Xu et al. 2014), and exploration of issues that directly impact the cost and efficiency of the ABA (Fekety et al. 2015; Junttila et al. 2015; Keränen et al. 2015; White, Arnett, et al. 2015; Packalén et al. 2015). Species composition information is required in order to inform a broad range of forest management information needs, including biodiversity, sustainable harvesting, and silvicultural prescriptions, to name but a few. In a forest inventory context, species-specific biomass and volume equations are used to calculate growing stock. Because different trees species will have different dimensions given the same age and site characteristics, models that incorporate DBH and height to derive individual tree volume are often designed to be species specific (e.g., Ung et al. 2008; Zianis et al. 2005).

To date, ALS data has proven to have limited capacity for species identification. Existing studies demonstrate that although there is potential for using ALS data for tree species classification, the methods are much more complex than methods used to estimate stand volume or basal area with ABA. Furthermore, these methods are usually limited to distinguishing only a small number of species or species in forest stands of relatively simple structure. Methods that utilize ALS point clouds to identify species are typically based on the distribution of ALS returns from the forest canopy, or on intensity of the ALS return (Donoghue et al. 2007). The first group of methods relies on the assumption that the spatial distribution of echoes is influenced by the differences in crown size, shape, density, and branching that exist among tree species (Brandtberg 2007). The usage of return intensity, however, is based on different spectral signatures of tree species in the near infrared part of the spectrum used in ALS (Holmgren and Persson 2004; Kim et al. 2009; Moffiet et al. 2005) and is often complicated by difficulties related to the lack of calibration of the raw intensity into physical units (Donoghue et al. 2007). Moreover, in order to accurately interpret the intensity values, factors such as the bidirectional reflectance distribution function (BRDF) and incidence angles of the targets must be known. Korpela et al. (2010) demonstrated that intensity features (metrics) were

TABLE 1
Reviews of ALS for forest applications

Author	Year	Title	Journal
Dubayah and Drake	2000	"LiDAR Remote Sensing for Forestry Applications"	*Journal of Forestry*
Lefsky et al.	2002	"LiDAR Remote for Ecosystem Studies"	*Bioscience*
Lim et al.	2003	"LiDAR Remote Sensing of Forest Structure"	*Progress in Physical Geography*
Næsset et al.	2004	"Laser Scanning of Forest Resources: The Nordic Experience"	*Scandinavian Journal of Forest Research*
Reutebuch et al.	2005	"Light Detection and Ranging (LIDAR): An Emerging Tool for Multiple Resource Inventory"	*Journal of Forestry*
Evans et al.	2006	"LiDAR–A New Tool for Forest Measurements?"	*The Forestry Chronicle*
Hyyppä et al.	2008	"Review of Methods of Small-Footprint Airborne Laser Scanning for Extracting Forest Inventory Data in Boreal Forests"	*International Journal of Remote Sensing*
Wulder, Bater, et al.	2008	"The Role of LiDAR in Sustainable Forest Management"	*The Forestry Chronicle*
Evans et al.	2009	"Discrete Return LiDAR in Natural Resources: Recommendations for Project Planning, Data Processing, and Deliverables"	*Remote Sensing*
Järnstedt et al.	2009	"LiDAR Utility for Natural Resource Managers"	*Remote Sensing*
van Leeuwen and Nieuwenhuis	2010	"Retrieval of Forest Structural Parameters Using LiDAR Remote Sensing"	*European Journal of Forest Research*
Pirotti	2011	"Analysis of Full-Waveform LiDAR Data for Forestry Applications: A Review of Investigations and Methods"	*iForest*
van Leeuwen et al.	2011	"Assessment of Standing Wood and Fiber Quality Using Ground and Airborne Laser Scanning: A Review"	*Forest Ecology and Management*
Hollaus and Wagner	2012	"Possibilities of Airborne Laser Scanning Data for Forestry Applications"	*Bodenkultur*
Wulder et al.	2012	"LiDAR Sampling for Large-Area Forest Characterization: A Review"	*Remote Sensing of Environment*
Montaghi et al.	2013	"Airborne Laser Scanning of Forest Resources: An Overview of Research in Italy as a Commentary Case Study"	*International Journal of Applied Earth Observation and Geoinformation*
Nelson	2013	"How Did We Get Here? An Early History of Forestry LiDAR"	*Canadian Journal of Remote Sensing*
Brosofske et al.	2014	"A Review of Methods for Mapping and Prediction of Inventory Attributes for Operational Forest Management"	*Forest Science*
Bouvier et al.	2015	"Generalizing Predictive Models of Forest Inventory Attributes Using an Area-Based Approach with Airborne LiDAR Data"	*Remote Sensing of Environment*
Kelly and Tommaso	2015	"Mapping Forests with LiDAR Provides Flexible, Accurate Data with Many Uses"	*California Agriculture*

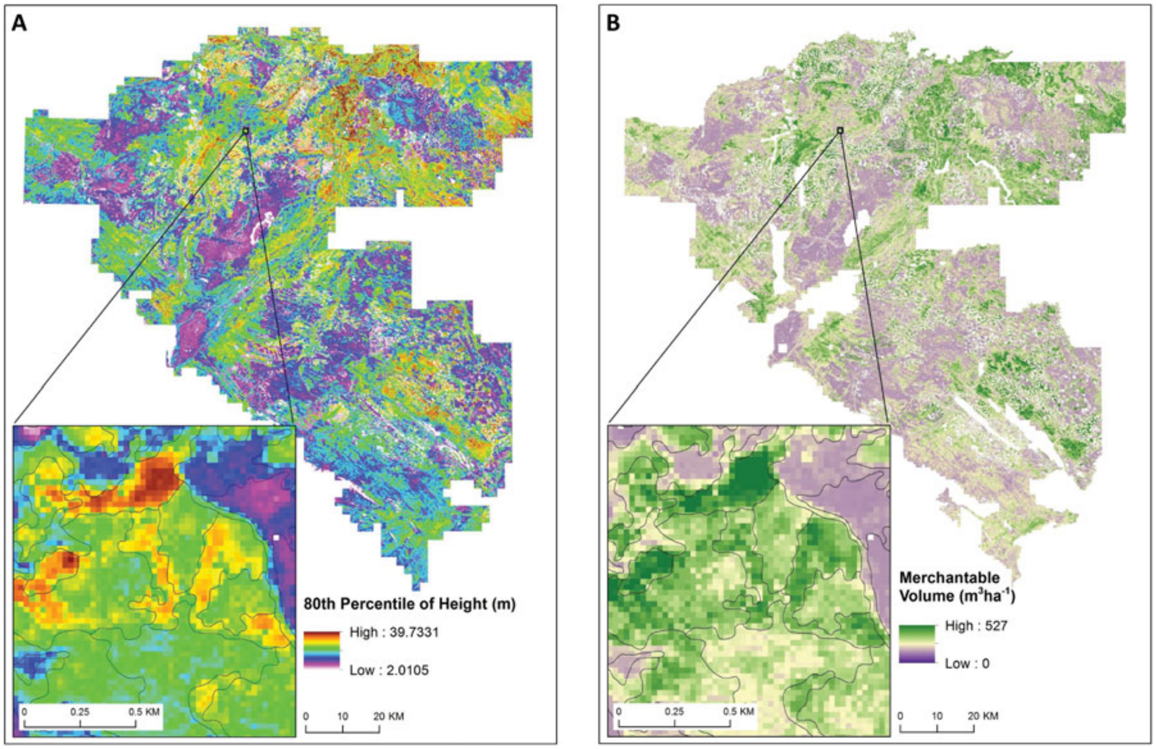

FIG. 2. ALS metrics and area-based model outcomes for a 1-million ha Forest Management (FMA) in Alberta, Canada. The 80th percentile of height (A) is calculated directly from the ALS point cloud, whereas the estimate of merchantable volume (B) is derived using the area-based approach and co-located ALS and ground-plot data. For details, see White et al. (2014).

dependent on absolute and relative tree sizes, and that intensity values were affected by foliage density and leaf size and orientation.

Approaches to species identification have also combined optical and ALS data, integrating ALS-derived geometrical properties of tree crowns with multispectral information obtained with airborne imagery, resulting in more comprehensive descriptions of tree species and increasing tree species classification accuracy (Holmgren et al. 2008; Puttonen et al. 2009). Moreover, the spectral properties can be more detailed if hyperspectral sensors are used (Puttonen et al. 2010; Vauhkonen et al. 2013; Matsuki et al. 2015). In such cases, it is possible to further increase the classification accuracy or increase the number of tree species that are distinguished (Jones et al. 2010; Alonzo et al. 2014; Ghosh et al. 2014). Methods for species identification have made use of high-density ALS point clouds (Ørka et al. 2013) and full-waveform information (Yu et al. 2014; Hovi et al. 2016; Vaughn et al. 2012). New multiwavelength ALS instruments such as the Optech Titan offer novel capabilities and promise for species identification, although research into multiwavelength ALS is nascent (e.g., St-Onge and Budei 2015). Based on the principles involved, successful approaches to species characterization are expected to be regionally specific, tailored to the species present, and use a series of rules to stratify stands by auxiliary information such as slope, aspect, and soil type and then use a combination of attributes derived from optical and ALS structural metrics to ultimately identify tree species (e.g., Cho et al. 2012; Zhang and Qiu 2012). The interest in obtaining species information, coupled with the rapidity of technological and algorithmic advances in the LiDAR remote sensing community, suggests that species identification with ALS data is poised for advancement. Also, as previously touched upon, forest inventories can require species information for a variety of reasons, with the most stringent being the correct allocation of species to guide harvesting and product selection at a mill. In cases where allometric equations to calculate biomass or volume are not species dependent, it is possible that the accuracy requirement on species classification may be relaxed (Tompalski et al. 2014).

Although classic ALS metrics, including tree height, percentiles, and cover have been used operationally in some regions, notably in the Nordic countries of Europe (Næsset et al. 2004), additional ALS structural metrics are providing novel opportunities for describing and investigating the vertical distribution of foliage within the canopy. These metrics allow the extraction of information that relates to stand density, successional status, stand developmental stage, and competition, all of which are expected to influence growth and wood fiber attributes (van Leeuwen et al. 2011; Auty et al. 2013; Kuprevicius et al. 2013; Luther et al. 2014; Mura et al. 2015). In addition, research is showing that ALS structural metrics can be linked to tree size and diameter distributions (e.g., Gobakken and Næsset 2004; Thomas et al. 2006; Packalén and Maltamo 2008; Magnussen et al. 2013; Ozdemir and Donoghue 2013; Tompalski et al. 2015), succession (van Ewijk et al. 2011), and age (Racine et al. 2014), as well as generation of metrics for refined biomass estimates (e.g., stem, branch, foliage), which has implications for bioenergy and carbon-cycling modeling (Vauhkonen et al. 2016; Kankare et al. 2015). Smaller laser footprints, greater pulse densities, and full-waveform systems may allow for increased capacity to estimate branch density, and crown volume and shape, especially in more open stands. Full-waveform ALS systems are actively being researched for the value-added information they could bring relative to discrete return systems for forest inventory applications (e.g., Pirotti 2011; Sumnall et al. 2016).

Finally, use of repeat ALS acquisitions representing different dates for estimation of stand growth is also a topic of interest. The use of multitemporal ALS data, or of ALS at an initial time step combined with a DAP point cloud (see Section 2.3) at subsequent time steps, are promising techniques for deriving tree growth information. Considerable research is required concerning the appropriate design of repeat LiDAR surveys to enable estimation of height growth increment (Yu, Hyyppä, Kukko, et al. 2006; Yu, Hyyppä, Kaartinen, et al. 2008; Næsset and Nelson 2007; Hopkinson et al. 2008); with potential for errors ranging from centimeters to a few meters (e.g., Wulder, Bater, et al. 2008). Bater et al. (2011) acquired ALS data repeatedly along the same flight lines in short succession and demonstrated the stability of ALS metrics. Critical issues include timing of ALS data acquisition to ensure that the growth increment exceeds the instrument noise and any expected measurement error or bias (Wulder, Bater, et al. 2008). The combination of LiDAR and simultaneous acquisition of DAP might be a cost-effective way to derive forest height change and is worthy of the current and additional research (Vastaranta et al. 2013). Some of the pioneering work on this topic demonstrated the potential of the concept (Korpela 2006; St-Onge et al. 2008), including the linkage to growth characterization over time (Véga and St-Onge 2008, 2009). The link of these growth estimates to traditional growth and yield curves remains an area requiring further research, as does the formulation of an error budget that quantifies sources of errors associated with estimates of growth, and the size of these errors relative to the actual growth increment measured (Wulder, Bater, et al. 2008).

Terrestrial Laser Scanning

Although airborne systems are able to cover large areas efficiently and relatively cost effectively (Næsset and Nelson 1997; Wulder, Bater, et al. 2008), difficulties persist in the observation of near-ground vegetation and the lower canopy characteristics, with foliage and branches obscured by elements of greater height (Hilker et al. 2010). In particular, the viewing geometry of ALS is not optimized for assessing the woody component of forests such as trunks, due to the vertical expression of growth, and is not directly visible to airborne systems (Lovell et al. 2003). As a complement to airborne measurements, a number of recent studies have used TLS systems, which observe canopy structure from below the canopy upwards (Hilker et al. 2010; Jupp et al. 2009). In a strategic or tactical forest inventory context, in which the aim is to produce forest attribute maps over relatively large areas, TLS can provide means for collecting field data that is required to build and validate models developed using remote sensing data that has the required spatial extent. Already, synergies between TLS and ALS have been shown to improve diameter distribution estimates (Vastaranta et al. 2014, Kankare et al. 2015) and estimates of biomass (Hauglin et al. 2014).

There are costs to using TLS in terms of equipment (field and lab) and time (for deployment and processing). If TLS is proposed to measure only attributes that can be easily measured by field crews, the justification is limited. As a result, Newnham et al. (2015) describe TLS as a transformational technology for plot-based forest surveys and make the point that TLS should not be viewed merely as a way to extend, or to automate, traditional plot data collection, but rather as a completely different approach to characterizing plot-level forest structure with an unprecedented level of detail. TLS systems typically have a LiDAR instrument mounted on a tripod, however, they can also be mobile on vehicles and acquire data across the whole, or parts, of the hemispherical field of view (mobile laser scanning or MLS; see Hyyppä et al. 2012, Liang, Hyyppä, et al. 2014). TLS systems, like ALS, can record one or a number of discrete returns per emitted laser pulse, or can be full waveform and, as a result, are capable of acquiring detailed information with regard to vegetation below the forest canopy (Figure 3). TLS systems can also collect data with one or more wavelengths of laser energy utilized (Danson et al. 2014). Links between TLS point clouds and forest inventory and forest structure parameters have focused principally on measurements of the trunk, such as DBH and taper, with errors in measuring stem diameters ranging between 1.5 cm and 3.3 cm (Hopkinson et al. 2004; Maas et al. 2008; Thies et al. 2004; Tansey et al. 2009). More recently, studies have moved on from DBH, describing more complex tree stem parameters and in some cases extracting the entire tree morphology itself (Moorthy et al. 2008; Béland et al. 2011; Raumonen et al. 2013; Liang, Kankare,et al. 2014). This information can then be used to reconstruct entire forest stands in a 3-dimensional fashion (Côté, Fournier, Egli 2011; Côté, Fournier, and Frazer 2012). Studies have also focused on gap fraction and leaf area index (LAI), such as Danson et al. (2007), who derived canopy gap fractions from TLS data, and work of Huang and Pretzsch (2010), who developed a method to predict LAI that incorporates nonuniformity of the foliage distribution. Vaccari et al (2013) also examined gap fraction from TLS and developed correction factors based on canopy perimeter to account for instrument bias when the laser footprint covers a mixture of canopy elements and gaps. Full-waveform TLS can

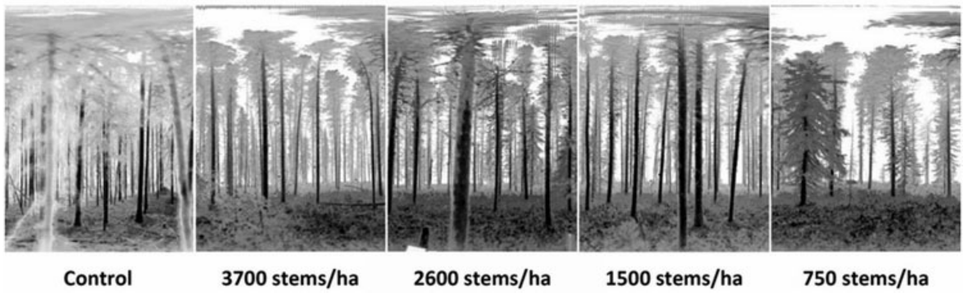

FIG. 3. TLS intensity images of plot thinning experiments in Alberta, Canada, observed from full-waveform TLS LiDAR. Distortion is due to the projection of the hemispherical data onto a 2-dimensional plane. LIDAR data acquired from the CSIRO ECHIDNA© Validation Instrument (EVI). For details, see Hilker et al. (2012).

potentially improve foliage and nonwood vegetation extraction in forest stands as the return pulse is fully digitized, enabling increased sensitivity to small return intensities and allowing for the modeling of secondary return obscuration (Strahler et al. 2008; Jupp and Lovell 2007). The use of full-waveform TLS therefore has a role to play in the extraction of tree structural parameters (Strahler et al. 2008) as well as to parameterize radiative transfer models (Ni-Meister et al. 2008). Van Leeuwen et al. (2013) utilized full-waveform TLS data to improve understanding of canopy radiation regimes within forest stands and developed models to estimate the vertical distribution of photosynthetically active radiation, which drives vegetation growth. To do so, geometrically explicit models of canopy structure derived from the full-waveform TLS were used to simulate the vertical distribution of light absorption with canopy depth.

Forest biomass is often difficult to quantify because it cannot be accurately measured without destructive sampling. In a boreal forest zone, 70%–80% of the tree biomass is located in the stem (Muukkonen 2006). By automatically reconstructing the tree stem from the TLS point clouds, Yu et al. (2013) demonstrated that the stem biomass, including both stem wood and bark, could be estimated with a high degree of accuracy when compared to trees subject to destructive sampling (that is, weighing of felled trees). Kankare et al. (2013) and Hauglin et al. (2013) improved upon branch biomass modeling using TLS-derived information from canopy shape and volume. With millions of 3-dimensional laser points characterizing a plot area, part of the challenge in using TLS data for forest inventory, and an area of active research, is how to make best use of the high level of detail afforded by TLS to improve and expand on plot-level measurements and estimates (Dassot et al. 2011; Newnham et al. 2015).

Although many TLS studies have investigated deriving individual tree structure, fewer have looked at complementarities and differences between TLS and ALS (Hilker et al. 2012; Kankare et al. 2014). Both terrestrial and airborne LiDAR describe stand structure by using point clouds, but terrestrial systems observe the canopy from a bottom– up perspective, whereas point clouds sampled from airborne systems are more regularly spaced and view the canopy from the top, down. Because objects closer to the instrument are more likely to produce a measureable return (Poisson distribution), point cloud distributions acquired from airborne observations are therefore skewed toward the top of the canopy, whereas those acquired from TLS are skewed toward the lower part of the tree crowns (Hilker et al. 2010). As a result, TLS is highly suited to investigate changes in the below-canopy structure, stand density, stem structure, branching, and understory.

Although ALS is sampled almost exclusively at close to near-nadir view, zenith angles thereby yielding a relatively homogeneous distribution of measurements per unit area, a ground-based system features a radial perspective with laser returns usually originating from a fixed location. Under the assumption of zero interceptions, the shot density is then inversely proportional to the square of the distance from the instrument. Another consideration is that terrestrial laser systems are able to describe vegetation structure over a number of different view angles (Côté et al. 2009; Jupp et al. 2009; Strahler et al. 2008). This may allow the analysis of some more complex structural parameters, such as canopy clumping effects or leaf angle distribution (Chen 1996; Chen and Cihlar 1995; Whitehead et al. 1990) and their impact on canopy metrics, although comprehensive studies on this subject are yet to be completed. Finally, the spatial resolution of TLS is typically much higher than that of ALS, especially in the vicinity of the plot center; the spatial range, however, is mostly limited to a few-hundred-meter radius, with ranges further reduced due to shading effects from tree trunks and other objects intercepting the LiDAR beams.

Ground-based data is less suitable for investigating stand structure over larger areas; the detail of the below-canopy structure obtainable from TLS, however, can be a valuable addition to large-area ALS observations, because they can help us understand the relationship between upper and lower canopy structure. These below-canopy measurements, when used in strategic sampling, can then help extrapolate this relationship over larger areas. For instance, a sampling grid may be laid out over an area of interest with detailed terrestrial measurements taken at each grid point, and airborne observations can be used to

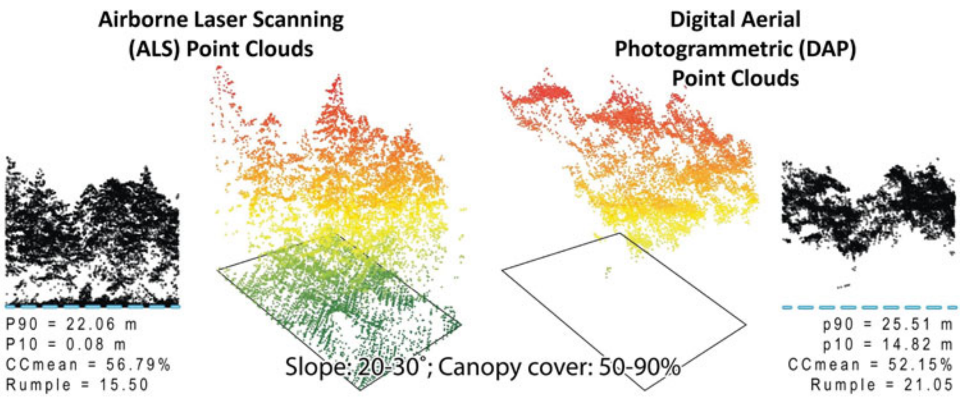

FIG. 4. Comparison of ALS and DAP point clouds in a coastal temperate forest in British Columbia, Canada. For details, see White, Stepper et al. (2015).

interpolate between these points. Relationships between TLS and ALS can then be used to model the below-canopy structure and upper-canopy light regime and might ultimately allow an indirect retrieval of the complete canopy structure from airborne LiDAR measurements across the landscape (Hilker et al. 2010; Holopainen et al. 2014). In addition, TLS could be used for supporting forest inventories by providing improved allometric equations for stem volume or biomass. The applicability of the current allometric equations is limited to particular climatic, geographic, and silvicultural conditions because equations have been developed using local or national ground-sample data. TLS brings flexibility to the modeling process; allometric equations can be still based on the easily measurable attributes, such as species, DBH, and height, but the data required for modeling can be collected using TLS. We assume that use of TLS to collect data in support of modeling from a limited number of plots or trees will be adapted to operational use in the near future.

Digital Aerial Photogrammetry

Digital aerial photogrammetry (DAP) is an emerging information source for 3D information that is considered similar to that of ALS (Leberl et al. 2010). Prior to more recent advances in digital cameras and imaging capacity, Baltsavias (1999) provided a comprehensive comparison of photogrammetry and laser scanning, highlighting advantages and disadvantages of both technologies with respect to acquisition, accuracy, maturity, and costs. Early work by Korpela (2006), Véga and St-Onge (2008, 2009), and St-Onge et al. (2008) established the potential of DAP for forest applications, and there is growing interest in the use of DAP for forest inventory applications (White, Wulder, Vastaranta, et al. 2013). New digital airborne camera systems, which permit greater acquisition overlap between images at no additional cost, coupled with state-of-the-art multi-image matching algorithms and advancements in computing hardware, have enabled the production of image-based point clouds (Leberl et al. 2010; Figure 4). Like ALS data, these image-based point clouds provide information on forest structure; however, unlike ALS data, image-based point clouds are limited in the amount of information they can convey on the vertical distribution of vegetation within the canopy (Vastaranta et al. 2013; White, Stepper, et al. 2015). Whereas laser pulses can penetrate through small openings in the forest canopy, DAP point clouds are limited to characterizing the outer canopy envelope (White, Wulder, Vastaranta, et al. 2013). DAP point clouds require an accurate DTM with a high spatial resolution in order to normalize point elevations to heights above ground. Algorithms intended for matching points to create ground-surface models are optimized for different physical considerations, that is, there is a low expectation for variance between ground points. Conversely, when characterizing the surface of a canopy, over-smoothing and reduction of local variance between points in surface development can obscure gaps and canopy detail. Specifically designed algorithms for canopy-surface generation show promise for improved portrayal of forest canopies from DAP point clouds (Baltsavias et al. 2008).

In a forest inventory context, it has been proposed that, given an initial acquisition of ALS data to generate an accurate DTM, subsequent remeasurement or monitoring for forests might be accomplished with image-based point clouds (Vastaranta et al. 2013). Numerous studies have been undertaken across a range of forest environments to compare outcomes for an ABA to predicting forest inventory attributes such as height, DBH, and volume, using ALS and DAP. Studies have been conducted in even-aged, single-layer forests (e.g., Bohlin et al. 2012; Järnstedt et al. 2012; Nurminen et al. 2013; Vastaranta et al. 2013; Rahlf et al. 2014; Gobakken et al. 2015) and in more complex forest environments (Straub et al. 2013; Stepper et al. 2015a; Pitt et al. 2015; White, Stepper, et al. 2015). Generally, these studies have concluded that ALS data provides more accurate estimates of forest inventory attributes, but that the performance of DAP point clouds in an ABA is comparable, and depending on forest attributes of interest and related accuracy requirements, acceptable. Comparability in model performance using an ABA is driven by the accuracy with which canopy height can be derived from both ALS and DAP. For the majority of inventory attributes that have been modeled, height is a primary driver and, assuming canopy heights are being reasonably well characterized by the DAP, similarity in model outcomes between ALS and DAP is a reasonable expectation.

One reason for the forest inventory community's interest in DAP is cost, with DAP estimated to be one-third to one-half the cost of ALS data (White, Wulder, Vastaranta, 2013). Another reason stems from the long tradition of air photos and air photo interpretation in forest inventory, including the related need for species information, among other attributes, which can be obtained via expert interpretation. Related to this point, DAP provides spectral information, which can be combined with structural metrics to inform on species composition (Waser et al. 2011; St-Onge et al. 2015). One of the current issues associated with DAP is a lack of standards or best practices surrounding appropriate image inputs for point-cloud generation (White, Stepper, et al. 2015). Although optimal specifications have been suggested (Leberl et al. 2010), these likely vary by application and stand conditions, and, to date, there has been little benchmarking done for forest targets specifically (Haala et al. 2010, Remondino et al. 2014); however, more recent studies have begun to explore the impacts of acquisition parameters on information outcomes (e.g., Granholm et al. 2015; Ota et al. 2015). Because a variety of image parameters, including ground-sampling distance (GSD) and image overlap are being used in research contexts, comparison of inventory outcomes is challenging. In Europe in particular, where many jurisdictions already have ALS-derived DTMs, suboptimal imagery (according to the specifications of Leberl et al. 2010) is opportunistically being used to inform inventory applications (Stepper et al. 2015b, Ginzler and Hobi 2015). Algorithms for image matching likewise vary and continue to evolve, with Semiglobal Matching (SGM; Hirschmüller 2008) and Next-Generation Automatic Terrain Extraction (NGATE; Zhang et al. 2007) as the 2 most commonly reported in the literature.

Some of the ongoing research questions related to DAP and forest inventory are that of change monitoring through time (e.g., Vastaranta et al. 2013; Windisch et al. 2014; Wang et al. 2015), characterization of forest growth over time (Korpela 2006; Véga and St-Onge 2008, 2009) and the capacity to derive a broader range of attributes to meet additional information needs, including the derivation of class-size distribution models (Penner et al. 2015) and the use of DAP point clouds in an ITC or semi-ITC approach (Rahlf et al. 2015).

High-Spatial- and Very-High-Spatial-Resolution Optical Satellite Imagery

There is a long-standing tradition of using airborne imagery to support forest inventories. With the launch of the first commercial high-spatial-resolution satellite in 1999 (IKONOS), a new era began for forest information. What is considered as high spatial resolution (HSR; <10 m) or very high spatial resolution (VHSR; <1 m) is often a matter of perspective. Strahler et al. (1986) presented a framework for image-understanding based on an ability to discern objects of interest. That is, are there many pixels per object (allowing for identification) or are there many objects per pixel (where the individual characteristics are subsumed). Such a framework is valuable to avoid overspecifying a given data need, such as submeter data if the information need is to characterize conditions at the forest stand level. To avoid confusion, statement of the actual spatial resolution used in an application is recommended (e.g., Table 2), because there is no consensus within the remote sensing community with regard to nomenclature for spatial resolution (Belward and Skøien 2015). The classification schema for optical satellite remotely sensed data presented in Table 2 is similar to that proposed and used by Belward and Skøien (2015), although their definition of VHSR (0.5 m–4.9 m) and HSR (5.0 m–9.9 m) does not necessarily correlate with the studies reviewed and cited herein. As a result, we have opted for the nomenclature presented in Table 2.

Following the distinctions made by Strahler et al. (1986), Wulder et al. (2004) offer a review of the capacity of HSR satellite imagery to inform ecosystem characterization, including forest inventory. Falkowski et al. (2009) subsequently reviewed the potential of satellite-borne VHSR (i.e., < 1 m) optical imagery to provide forest inventory attributes. To date, much of the satellite-based VHSR imagery has been panchromatic (e.g., Quickbird-2 (0.60 m); Figure 5) and WorldView-1 (0.5 m), WorldView-2 (0.46 m)). The wide spectral range of panchromatic wavelengths (e.g., 400 nm to 900 nm) allows for smaller pixels; over more narrow spectral-band passes, it can be diffi-

TABLE 2
Spatial resolution nomenclature for optical satellite data (adapted from Wulder et al. 2008)

Spatial Resolution Range	Nomenclature	Example Sensors
< 1m	Very High Spatial Resolution (VHSR)	QuickBird, WorldView
1 m–10 m	High Spatial Resolution (HSR)	IKONOS, SPOT
10 m–100 m	Medium Spatial Resolution	Landsat, ASTER, AWIFS
100 m–1000 m	Low Spatial Resolution	MODIS, MERIS
> 1,000 m	Very Low Spatial Resolution	AVHRR, GOES

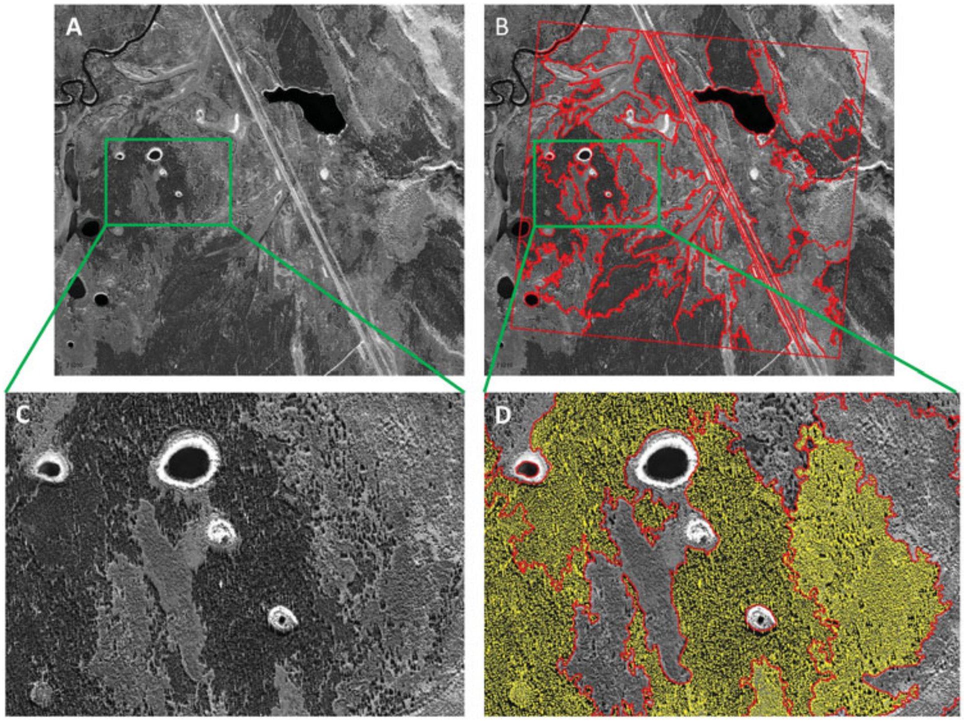

FIG. 5. Sample panchromatic QuickBird imagery (0.6 m resolution) acquired June 12, 2006, with an off-nadir view angle of 10.9 degrees (A and C) in the Yukon, Canada. Automated segmentation was used to delineate homogenous forest stands (B) and tree crowns were delineated (D) using the ITC algorithm of Gougeon (1995). For details, see Mora et al. (2010b).

cult to receive sufficient levels of wavelength-specific energy at sensor for small pixels. As a result, spaceborne commercial multispectral data typically has a spatial resolution greater than 1 m. Although multispectral data might offer more powerful algorithm development for characterizing vegetation conditions (Xie et al. 2008) the higher spatial resolution possible from panchromatic imagery allows for both digital and manual interpretation approaches (Falkowski et al. 2009). VHSR panchromatic imagery has been used to identify dominant species (Mora et al. 2010a), stand height (Mora et al. 2010b; Mora, Wulder, White, Hobart, Gougeon, et al. 2013), and volume and biomass (Hirata 2008; Mora, Wulder, White, and Hobart 2013; Leboeuf et al. 2007). Leboeuf et al. (2012) estimated volume, basal area, height, and crown closure with VHSR imagery and a shadow fraction approach. Given the small spatial extents of VHSR images, their use over large areas comes with additional geometric and radiometric processing overhead, because multiple scenes must be used to cover an area of interest, necessitating image coregistration and normalization (Falkowski et al. 2009). Moreover, it has not been demonstrated unequivocally that this increased effort (e.g., the specialized tasking required to obtain the data, the increased image processing requirements) is justified by a significant gain in height estimation accuracy at the stand level. For instance, Mora, Wulder, White, and Hobart (2013) found that stand-level height estimates derived from VHSR data were similar to those generated using Landsat (Chen, Wulder, et al. 2012) with only a small increase in attribute accuracy associated with the VHSR. Whereas many VHSR satellites feature a directable sensor head to reduce revisit times, this also changes the angular conditions between the sun-surface-sensor for the same location on the ground. These different viewing conditions in a forest environment can mean that a tree visible from one angle is occluded from another (Wulder, Ortlepp, et al. 2008), not to mention BRDF effects (Pacifici et al. 2014).

One of the key capabilities offered by optical imagery in a forest inventory context is that of species determination (e.g., van Ewijk et al. 2014). Accurate tree species identification is a challenging and elusive goal in forest inventories even when undertaken via manual photo interpretation. Conventional approaches for estimating species composition, which use manual interpretation of aerial photography, are understood to have error rates of 30%–60% (Deegan and Befort 1990; Thompson et al. 2007) with accuracy depending on the complexity of the species mix and structural conditions present in a given region or location, as well as the scale of the photography (Penner 2008). Automated approaches to species identification using VHSR imagery have been demonstrated (Mora et al. 2010a; Immitzer et al. 2012; Li et al. 2015); however, a large-area implementation and validation has yet to be reported in the literature.

New opportunities for HSR/VHSR data from constellations of microsats (including cubesats) are emerging (Butler 2014). Microsats are simple, small satellites that are relatively low cost, operate in low orbits, and can be deployed in large numbers. At present, there are a number of commercial enterprises with a range of business models that are launching microsats (Hand 2015). Given the low cost and related difficulties that arise for producing data with high radiometric or geometric consistency (Butler 2014), the opportunities these microsats provide for forest inventory applications that require synoptic coverage and the capacity for automation would appear to be limited, at present. The large number of images poised to be available could provide opportunities for near-real-time detection of change and update; however, accurate georeferencing of the imagery would be required. Over some forest environments, change capture (such as for high-contrast stand-replacing disturbances) could be automated, taking advantage of the HSR and temporal frequency of the observations.

CHALLENGES TO IMPLEMENTATION AND UPTAKE OF NEW TECHNOLOGIES IN FOREST INVENTORY

There are a number of key challenges to the use of the aforementioned technologies and data sources in forest inventories, including data acquisition, cost, platform considerations, best-practice guidelines and technical capacity, and the availability of simulation and data processing tools. Different levels of data complexity and processing are required for different forest inventory outcomes. If general, broad synoptic trends suffice to inform strategic decision-making, or to indicate locations for further detailed investigation, lower cost and more generalized data might be sufficient. Alternatively, tree- and stand-level information is required to reduce engineering costs, inform stand selection and timing of harvest activities, and ensure that regulations are met. For these information needs, more detailed data will be required, either with a higher spatial or temporal resolution (or both), thereby justifying higher costs. Recently, there has been increased interest in the use of unmanned aerial vehicles (UAVs) or drone platforms to acquire both LiDAR and VHSR imagery (e.g., Wallace et al. 2014). Although drones can fill an operational niche (e.g., detailed data over small areas; Puliti et al. 2015), they are still considered experimental (Tang and Shao 2014) and currently cannot provide the stable platform necessary to efficiently acquire systematic, robust, calibrated data to support forest inventories over large areas (i.e., $> 1{,}000$ ha; e.g., Tuominen et al. 2015) with large area mapping and characterization being the context within which we focused our review.

Cost and complexity of data acquisition and subsequent processing is often raised as an impediment to the full integration of ALS data into enhanced forest inventory. The quality and appropriateness of ALS data for forest inventory depends on the sensor and the parameters chosen for the survey. Laser footprint size, scan angle, pulse density, returns per pulse, and swath overlap can impact the appropriateness of the data (e.g., Baltsavias 1999; Næsset 2009; Montaghi 2013; Wilkes et al. 2015) as well as data acquisition costs (Wulder, Bater, et al. 2008, Wulder et al. 2013). Costs are difficult to generalize and invariably involve trade-offs, particularly for large-area forest inventories (Jakubowski et al. 2013). Economies of scale prevail, with costs per hectare declining with increasing area, and cost-sharing consortia with multiple stakeholders, as a pragmatic mechanism for funding ALS data acquisition (Reutebuch et al. 2005). The use of ALS data as a sampling tool to supply calibration and validation is an additional option to reduce costs for large areas (Wulder et al. 2012). Although cost-benefit analyses are not common in the literature, they are important for understanding the value of the various data sources (Eid et al. 2004; Holopainen and Talvitie 2006; Holopainen et al. 2010; Holopainen et al. 2014; Bergseng et al. 2015).

There is already a wide understanding of the capabilities of the TLS for supporting forest inventories. Automatic algorithms have been developed for measuring tree and forest inventory attributes from the TLS data. However, before conventional field measurements can be replaced by TLS (or if, indeed, they should be), best practices of applying TLS in measuring sample plots needs to be developed. For example, due to occlusion by other trees and shrubs, automatic mapping of individual trees has proven to be a challenging task, especially in multilayered stands but also in dense managed stands. Detection of all trees in the plot is a prerequisite for unbiased forest inventory attributes to be compiled for sample plots. Although stem diameter from multiple heights can be measured and stem volume derived with high accuracy, there are a limited number of studies in which tree heights or species are automatically measured or determined from TLS data. These basic forest inventory attributes (tree number, species, DBH, and height) must be automatically derived for an operational implementation of TLS. From a static platform (e.g., tripod mount), the number of required scans and the georeferencing of the scans affect both the accuracy of the measurements and the time taken to complete the plot. Research is ongoing into the measurement of sample plots, using laser scanning data collected from moving platforms (varying from all-terrain vehicle to backpack, e.g., Liang, Kukko, et al. 2014) and thus avoiding occlusion. Despite significant research in the past decade on TLS, the full integration of this technology into enhanced forest inventories worldwide remains challenging, with a number of technological, methodological, and operational issues needing to be addressed (Newnham et al. 2015).

Costs for acquisition of digital airborne images might be lower relative to ALS data, but these data do not offer the full range of capabilities afforded by ALS data, particularly in the realm of forest operations, where a detailed DTM under canopy generated from ALS data can result in significant cost savings. Thus, acquisition costs must be considered in the context of the information's utility and accuracy to support decision-making (Gobakken et al. 2015). For DAP, the requirement for an accurate, high-spatial-resolution DTM in order to obtain accurate normalized canopy heights must also be considered. Moreover, an ABA requires ground-plot measurements, regardless of whether ALS or DAP data are used. Optimal parameters for image acquisition have not yet been determined, and the impact of varying acquisition parameters on model outcomes have yet to be fully explored and documented.

As the number of earth observation satellites collecting data at spatial resolutions appropriate for forest monitoring proliferates (Belward and Skøien 2015), the options for users also increase. Linking the information needs to data selection remains of primary importance. From a forest inventory and update perspective, satellite data offers a range of opportunities from single-tree isolation (Gougeon and Leckie 2006; Zhou et al. 2013) and select inventory attribute generation (Immitzer et al. 2016) through to the capture of change for update and audit purposes (Chen, Hay, et al. 2012). HSR spaceborne measures are likely the best solution for remote locations and regions where deployment of aircraft is problematic. The integration of HSR satellite imagery with measures of 3-dimensional structure from laser instruments has shown a capacity for increasing the breadth and quality of forest inventory attributes that can be measured (Hilker et al. 2008; Zhou and Qui 2015) and is expected to persist as an area of research and applications interest. Acquisition parameters that have a low tolerance for cloud cover and limited viewing geometry will result in a decreased opportunity for successful image collects (Wulder, Ortlepp, et al. 2008). The use of object-based approaches that utilize the HSR detail for attribution and generalization procedures to reduce the impact of radiometry and differential viewing geometry shows promise (Wulder, White, et al. 2008).

Technology transfer has an important role to play in the uptake of innovative technologies into operational practice. Best-practice guidelines for generating forest inventory attributes from ALS data using an ABA have recently been generated, synthesizing more than 3 decades of research on this topic (White, Wulder, Varhola, et al. 2013). Such guidelines incorporate sound scientific approaches into existing forest management contexts and offer technical staff access to proven methods for successful implementation. A lack of technical capacity has been identified as a barrier to the uptake of new technologies in forest inventory (Morgenroth and Visser 2013; Næsset 2015b).

Despite the large body of research associated with the use of ALS and TLS data for forest inventory, there is still much that could be better understood in the relationship between statistical attributes of LiDAR point clouds and forest structure. These include issues around variations resulting from hit density, incidence angle, penetration into the forest canopy, tree shape, the calibration and use of intensity in improving structural and species estimation, as well as sampling issues associated with spacing and footprint size and their impact on stand characterization and tree detection (Evans et al. 2006). The combination of TLS observations collected from different locations can be a useful technique for overcoming limitations inherent to the radial perspective of TLS and might result in more realistic estimates when characterizing the below-canopy biomass in a spatially explicit mode. To provide the best guidelines for data acquisition and analysis, a more comprehensive understanding of the relationships between ALS point clouds and vegetation characteristics is needed. For example, both individual-tree-based approaches and plot-level structural attributes derived from ALS need calibration and validation data for their development and application, and some degree of recalibration is typically necessary for new airborne surveys due to the variation in ALS point density and flight pattern (Næsset 2007). Simulation of ALS data acquisition within a controlled model environment provides a capacity to test the adequacy of the scan parameters and the accuracy of the analyzed methods. These models therefore allow users to create controlled experimental conditions in which forest-stand and tree conditions as well as the ALS acquisition and system parameters attributes are modeled. The data produced from these simulations provide point clouds, which can then be tested and assessed against calibration data to ensure that the configurations are appropriate for the local forest environment. A number of model environments already exist, ranging from the simplest, which uses plain geometric volumes without laser beam crown penetration (Lovell et al. 2005; Frazer et al. 2011) to more complex models, which simulate the interaction of each laser beam based on probability and vegetation clumping factors (Goodwin et al. 2007; Spriggs et al. 2015). These models relate a range of ongoing efforts to provide data users with a more comprehensive understanding of the impacts of decisions made when acquiring and processing LiDAR data (e.g., Kukko and Hyyppä 2009; Wang et al. 2013). LiDAR-based information on forest vertical structure can also be used to parameterize physically based radiative transfer models. These physical models, such as the Discrete Anisotropic Radiative Transfer (DART) are useful for upscaling leaf-level observations to the canopy (Schneider et al. 2014). In addition, physical models allow for exploration of assumptions made when using LiDAR to derive structural parameters such as LAI (Calders et al. 2013).

SUMMARY AND CONCLUSIONS

For forest managers charged with the sustainable management of the forest resource, forest inventories are critical tools. Historically in some jurisdictions, such as Canada where the majority of the forest resources are publicly owned and where forest stewardship responsibilities are vested with provincial and territorial governments, forest inventories were largely undertaken by provincial or territorial government agencies using in-house staff; however, today data collection, interpretation, and modeling are often outsourced and undertaken by specialty contractors, with government personnel providing audits and quality control of the derived products (Pitt and Pineau 2009). Although technological and application advancements have been made (e.g., Finland; Hyyppä et al. 2012; Holopainen et al. 2014), many forest inventory approaches worldwide remain based on manual interpretation of aerial photography (Kangas and Maltamo 2006) that facilitate stand delineation, with a suite of forest attributes derived for these stands, including tree species composition, height, stocking, site quality, health status, and stand age (Woods et al. 2011). Supported by limited ground sampling and empirical yield table estimates, stand-site productivity and growth are then inferred.

The application of remote sensing technologies, combined with additional auxiliary geospatial datasets for modeling forest inventory variables is not a new phenomenon (Leckie and Gillis 1995). Since the 1980s, digital remote sensing satellite imagery, such as from the Landsat series of satellites, have provided broad scale information about forest cover, health, condition, and land cover (Magnussen et al. 2000; Wulder, Bater, et al. 2008). The increasing availability and decreasing costs of ALS, TLS, DAP, and HSR/VHSR data are rapidly expanding the options available for forest inventory. As a result, a number of countries and jurisdictions are increasingly making use of these data to meet their forest inventory information needs. Herein we have demonstrated that operational readiness is a complicated concept, and that it varies with information need. For example, the use of ALS data in an ABA to estimate a limited suite of essential inventory attributes (e.g., height, basal area, volume) is operationally viable. In this case, the data (ALS) is employed in a specific approach (ABA) to satisfy a clearly articulated information need. Conversely, the use of ALS data to predict species is still very much in the realm of research. Thus, the operational readiness of these technologies is difficult to generalize, depending not only on information needs, but also on context and technical capacity. Moreover, the technologies presented are synergistic, and as demonstrated by the literature presented herein, can be used in concert to generate new and useful information products.

As in any field of inquiry, there is no end to the research questions that could be posed; however, some of these questions will need to be addressed before there is widespread operational adoption of these remote sensing technologies (Nelson et al. 2003), as exemplified by the long history of research into the use of ALS data (Nelson 2013) and the ABA to produce enhanced forest inventories (White, Wulder, Varhola, et al. 2013; Næsset 2015b). Tree species identification remains a critical component of forest inventory, with species informing a variety of stand-based calculations such as volume, mean annual growth, site index, as well as average wood attributes, potential end-uses, and habitat information. There are challenges to easily deriving species information from ALS (Ørka et al. 2009; Korpela et al. 2010), and these strongly limit the capacity of ALS to usurp conventional forest inventory approaches. In the absence of species information, it is difficult to make full use of the extracted structural information, or to apply estimates based on species-specific allometry. However, the challenge of species characterization is not limited to ALS data; despite a range of available HSR satellite and airborne optical and hyperspectral sensors, automatic species delineation remains challenging for these data sources, as well (Leckie et al. 2005).

Although the capacity of ALS to predict standing volume, biomass, and other forest inventory attributes at one point in time is well known, there are a limited number of studies that have examined the capacity of ALS to predict forest growth through time (e.g., Næsset and Gobakken 2005; Yu et al. 2008). The reasons for this are numerous and include the relatively new state of the technology and operational cost, which effectively limits the number of acquisitions from the same area, as well as a rapid evolution in instrument technology and a short service life that introduces a need for calibration across instruments and acquisitions. Despite these drawbacks, the measurement of forest growth over larger areas to inform and refine growth and yield models will be invaluable for forest inventory and management (van Leeuwen and Nieuwenhuis 2010; Wulder, Bater, et al. 2008). The integration of ALS and DAP data to inform on forest growth is a topic that merits further research, and there are further opportunities for synergies between ALS and DAP to be explored. The combination of structural and functional canopy attributes will be critical for remote assessment of species, vegetation health, habitat suitability, stress potentials, and climate effects. DAP may provide an opportunity to complement ALS-based estimates of structure by adding a spectral component, in addition to high-density point clouds derived from top-of-canopy data. From our evaluation of the literature, we posit that ALS and DAP are the remote sensing technologies presented herein that will likely have the greatest impact on forest inventories in the next decade.

Looking forward, sustainable forest management requires accurate and spatially detailed estimates of a broad suite of forest inventory attributes. Value chain optimization requires spatially explicit estimates of log product volumes, and some of the information needs associated with provisioning ecosystem goods and services are likely beyond the design specifications of most current forest inventories. To satisfy these information needs by using conventional inventory techniques would be prohibitively expensive due to the required ground-sampling density. The advanced remote sensing technologies presented herein offer the capacity to augment ground-sample data to provide enhanced forest inventory information over large areas. In order to use these technologies effectively, information needs must be clearly articulated and prioritized, and appropriate data sources must be identified. Many of these technologies complement one another, so their synergies must also be considered. Finally, the value of the information to support decision making should be a priority, ensuring that investments in new data sources for forest inventory support the broadest range of information needs possible.

ACKNOWLEDGEMENTS

We thank three anonymous reviewers and the Associate Editor for their helpful comments and suggestions.

FUNDING

This work was supported in part by an NSERC Discovery grant to Prof. Nicholas Coops. The Canadian Wood Fibre Centre, of the Canadian Forest Service, Natural Resources Canada, provided additional support.

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