A Review of Remote Sensing of Forest Biomass and Biofuel: Options for Small-Area Applications

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Abstract: Forests have served as a primary reservoir of terrestrial carbon and have long been investigated in the global climate change context. In addition, increased exposure in the public domain of climate change issues has caused greater interest in the role of forests in the global energy balance. Researchers have been investigating the use of forests as carbon sequestration systems, as well as using forest products for conversion into biofuels. Remote sensing has been widely utilized as a cost-effective tool to provide forest baseline data (e.g., biomass) for effective and efficient forest management. Forest biomass is one of the forest parameters that is widely investigated using remote sensing because biomass is directly related to the productivity of forests and provides valuable information that is necessary for understanding ecosystem functions and carbon cycling. In this paper, we review remote sensing of forest biomass, focusing on recent advances and applications (published after 2000). We also explore the challenges of using forest biomass as biofuel, a topic that is often neglected in remote sensing papers.

INTRODUCTION

Forest characterization and monitoring have long been research endeavors in remote sensing. In particular, forest biomass has been widely investigated using a range of remote sensing data and techniques because biomass is directly related to the productivity of forests and provides valuable information that is necessary for understanding ecosystem functions and carbon cycling (Dixon et al., 1994; Im and Jensen, 2008). Forest biomass is traditionally calculated allometrically by skilled foresters making field measurements of diameter at breast height (DBH). This process is made difficult by field conditions and the scale of the forest being measured, and the time required to obtain a reliable full forest inventory is often impractical. Remote sensing offers a viable alternative to this field inventory, requiring only small plots of inventoried forestry data evenly distributed throughout the forest for calculation. Remote sensing of forest biomass involves many different sensor types and processing algorithms, and can provide accurate results with greatly reduced cost and time from full forest inventories.

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Previous reviews on remote sensing of vegetation (forest) biomass, such as Lim et al. (2003), Hyyppa et al. (2008), and Van Leeuwen and Nieuwenhuis (2010), have focused exclusively on the methods and challenges of forest inventory using airborne Light Detection And Ranging (LiDAR) systems. These papers provide robust reviews of LiDAR processing methods as they are applied to specific forest situations. However, they do not review any other sensors as they apply to forest biomass estimation, a consideration we will address in this paper. Reviews similar to ours were published by Lu (2006) and Koch (2010), but each differs significantly from our review. While Lu (2006) has a similar structure and similar sensor type reviews as this paper, more than half of the papers we review here were published after Lu's paper was written. Koch (2010) reviews papers that are contemporary with the papers reviewed in this work, but it includes a very different set of references, and also does not review methods using spectral sensors such as Landsat and SPOT. In addition, this review focuses on the use of forest biomass for biofuel and explores the associated challenges, which were not included in the previous reviews.

This review focuses on recent research papers (published after 2000) that quantify forest biomass using various remote sensor data and methods. It is always important to keep the end use of any analysis in the forefront of consideration. Therefore, we also review key papers discussing the challenges of using forest biomass as biofuel (in Section 2 of the paper), something often neglected in remote sensing papers. This is followed by brief overviews of the papers selected for review in a third section of the paper, followed by detailed reviews of these papers in Sections 4 and 5. A concluding section discusses current issues and trends in the remote sensing of forest biomass.

FOREST BIOMASS AS BIOFUEL

In the public domain, increased exposure to climate change issues has caused greater interest in the role of forests in the global energy balance. Researchers have been investigating the use of forests as carbon sequestration systems, as well as the use of forest products for conversion into biofuels. Kirschbaum (2003) characterized the differences between these two processes and concluded that the best mitigation strategy for long-term climate change would be to maintain forests in perpetuity as carbon sinks. Kirschbaum (2003) also notes that forests have a large impact on overall global carbon cycles, yet management of any particular land area has a fixed (and decidedly small) effect on the overall carbon cycle. Because of this, a landowner who wishes to impact the global carbon cycle must manage his/her forest properties in perpetuity, deriving capital value from this process only during thinning operations. It is more likely that such land owners might wish to use their forested land in biofuels production, given the major release of carbon into the atmosphere caused by the burning of fossil fuels (ibid.).

Biofuels, combustibles derived from plants, are an alternative to fossil fuels. Duff and Murray (1996) showed that biofuels were already a mature technology a decade ago, and the understanding of the production and uses for biofuels has grown since then. Naik et al. (2010) provide a review of the major processes employed to convert biomass to biofuel, and discuss the concept of a "biorefinery." According to these authors, a biorefinery is a second-generation biofuel technology that requires purposefully managed energy crops harvested on strict time scales to ensure that the flow of forest biomass produces steady amounts of biofuel. Naik et al. (2010) are not specific on the types of biomass suitable for this biorefinery concept, but state that efficiency can be improved by combining several conversion processes and using multiple biomass inputs. This concept lends itself to landowners seeking to influence the global carbon cycle. By managing forest stands according to harvest times, steady flows of biofuels can be created, thus increasing capital gains and generating useful biofuels.

Raison (2006) and Olsson and Kjallstrand (2004) discuss more thoroughly the concepts of using forest residues and harvested timber products for bioenergy production. Olsson and Kjallstrand (2004) conclude that using forest residues for biofuels (i.e., stems and other products left behind in the forest) causes soil nutrient loss and increases the nitrogen content in the biofuels, and argue that sawdust and shavings make a more ideal biomass source. Raison (2006) notes that only 40% of a log is converted into sawn product, thus leaving a large quantity of biomass available for biofuel production, and would undoubtedly agree that sawmill residue would form an ideal biomass source. These concepts are certainly valid from a forestry perspective, but the energy community provides a more robust analysis of forest systems. In a brief review of research concerned with the sustainability and applicability of biofuel systems (Reijnders and Huijbregts, 2003; Gnansounou et al., 2009; Havlik et al., 2010; Helmmann and Verburg, 2010), a theme arises: the definition of the system boundary is crucial to the long-term implications of the project, with emphasis placed on indirect effects. For example, the energy balances of a biomass/biofuel operation are well known, but converting food crops to energy crops will have consequences far beyond the energy return for the specific crop. Choices in land use may lead to shifts in markets for food and other biomass products, which in turn may impact the profitability/sustainability of a biofuel operation. Backeus et al. (2005) investigate this specifically for a forest timber harvest/carbon sequestration scenario, and conclude that economics and policy are major drivers of such systems, and cannot be overlooked in any sustainability analysis.

Any plant biomass can be converted into biofuel, but certain species are well suited for this purpose (Naik et al., 2010). Fast-growing riparian species can achieve levels of biomass that are greater than those of slower-growing hardwoods, and are considered to be the most viable option for long-term fossil fuel reduction solutions (Sassner et al., 2008). These authors compared the cost effectiveness and biofuel yield from three different biomass types—*Salix* (willow), corn stover (leftover corn pieces after the cobs have been harvested), and *Picea* (spruce)—and found the energy efficiency of all three of these inputs to be nearly identical using two different conversion processes. The study also found that spruce had the lowest monetary cost of any of the inputs. These analyses are promising for showing that larger trees are competitive with woody plants in biofuel production, but the results are far from conclusive. In any study that calculates an energy efficiency or energy unit cost, questions must be asked of the boundaries of the system in which these figures are calculated, as discussed previously. At a biorefinery level, costs and energy balances are simpler to calculate: drawing the system boundary around the plant affords easy control over inputs and outputs. However, to a landowner, time, capital investment, equipment, and other inputs will affect the energy balance.

Eriksson (2006) further develops the idea of forests and their role in global carbon cycles, agreeing with the conclusions reached by Kirschbaum (2003). Eriksson

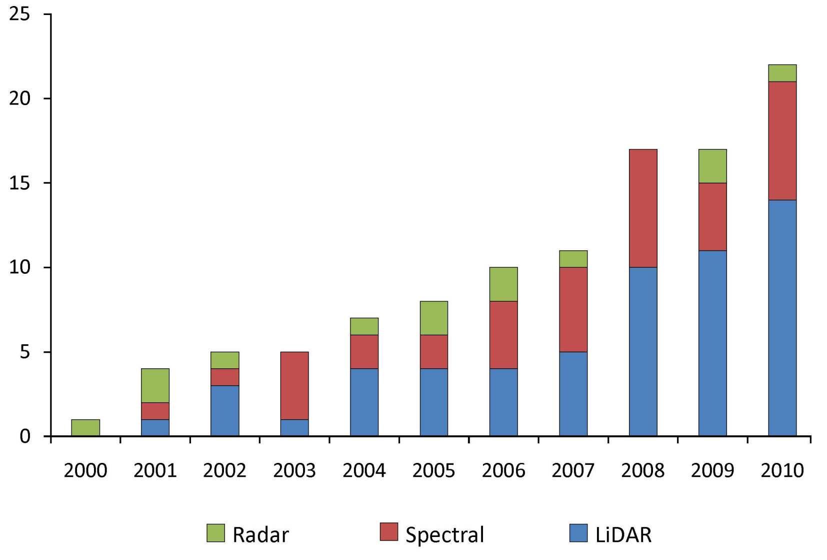

Fig. 1. Histogram of the selected papers by publication year by three sensor groups (radar, spectral, LiDAR). When multiple sensors were used, a primary sensor was counted. Biofuel-related papers are not included in this figure.

(2006), however, states that there is a fundamental conflict between managing forests for sustaining the carbon cycle or for producing biofuels, and that one alternative must be chosen in order to implement proper management techniques. The mean annual increment (MAI) of biomass in spruce and pine stands, Eriksson (2006) found, is greatest when low thinning regimes are implemented, and pine MAI can be further increased with fertilization. These results suggest that landowners who wish to affect global carbon cycles must choose the end use of their forest properties and that annual yield of biofuel is possible, supporting the systems described by Naik et al. (2010). In either application of forested land (for biofuel or for increases in the carbon pool), the most important forest metric for determining the potential of the forest is the amount of biomass contained therein.

Concerns about policy, forest residues, and system boundaries are real issues for any forest manager in deciding how best to utilize forested land. Remote sensing research that focuses on biomass estimation for bioenergy production often does not account for such contingencies when quantifying biomass. Adjusting remote sensing models to include such concerns may not be altogether feasible or necessary, but more care should be taken with assumptions of the applicability of biomass estimates and the implications that errors therein may have on the value and production of a proposed forest biofuel/carbon sequestering system.

BRIEF OVERVIEW

With the interest in estimating forest biomass established, a review of papers published after the year 2000 was conducted in this study. Figure 1 shows the distribution of the selected papers by publication year with three sensor groups (Radar, Spectral,

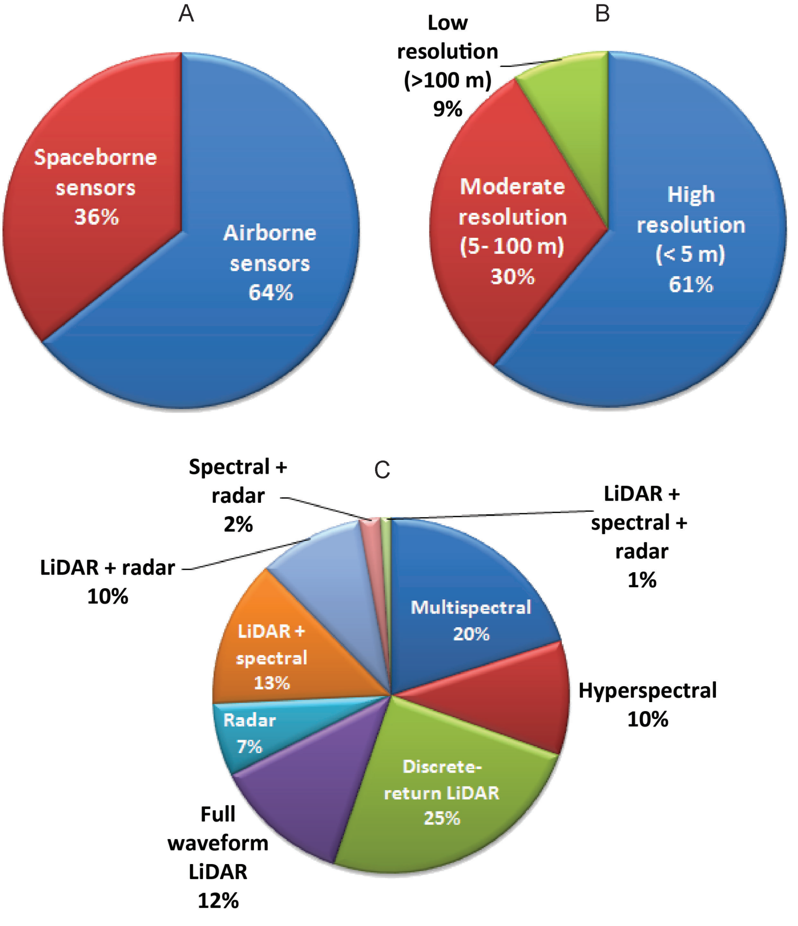

Fig. 2. Summary statistics of selected works by platform (A), spatial resolution (B), and sensor type (C). Plus symbol indicates multi-sensor data fusion.

and LiDAR), and it is noteworthy that the majority of the publications come from 2008 and later.

The papers included a wide range of remote sensors and methods for estimating forest biomass. A summary of this diverse group is presented in Figure 2. The methodologies of these papers increase in complexity as the size of the study area decreases, and therefore more discussion will be given to the sensors operated from airborne platforms. Further attention will be given to papers that implemented airborne LiDAR data, as these methods have gained widespread notoriety for their ability to accurately assess forest biomass. LiDAR methods fall into three broad categories: individual tree–based methods, plot-based methods, and stochastic methods; these categories will all be addressed, with attention given to full waveform decomposition of LiDAR signals and discrete return LiDAR. Also (and as discussed above) several key papers pertaining to the generation of biofuels from forests were reviewed to give context to this paper.

FOREST BIOMASS ESTIMATION USING SPACEBORNE REMOTE SENSOR DATA

This section summarizes the review of the forest biomass studies using spaceborne remote sensor data. Spaceborne sensors are classic instruments of image analysts and remote sensing scientists, and their data have been used successfully for a wide variety of applications since major space missions began launching several decades ago. Spaceborne systems offer unique advantages for a study that cannot be replicated with airborne or terrestrial systems. Spaceborne sensors are able to cover vast areas of the globe relatively frequently, offering sufficient data for applications in weather, disaster monitoring, and change detection. Furthermore, some spaceborne sensors operate continuously and can generate a huge volume of data that can provide robust support for researchers studying various physical phenomena.

Spaceborne sensors can be most broadly categorized by their sensor type: spectral, radar, and LiDAR. Spectral sensors are the most common and the longest operating, with the similar Landsat and SPOT series as classic examples. These spectral sensors are passive, meaning they capture energy reflected by the Earth, and there is a general trade-off between the wavelengths of energy that can be sensed and the spatial resolution at which they are sensed. Some sensors are hyperspectral, meaning they capture energy well beyond visible light up to 2500 nm in literally hundreds of narrow spectral bands. More commonly used are the multispectral sensors (Landsat, SPOT) which offer moderate spatial resolution and enough spectral information to perform analyses beyond those possible with a panchromatic sensor. While these spectral sensors offer expanded analysis capabilities beyond those of other sensor types, they are not always the ideal sensor type for forestry research. The moderate to coarse spatial resolution of the sensors is often not sufficient for the size of the forest tract that is analyzed, and cloud cover and other weather events make data collection unreliable. However, some of these sensor data (Landsat, Hyperion, MODIS) are available free of charge (provided existing coverage exists), thus encouraging their use and understanding by researchers. As a result, this class of sensors is the most understood and widely used by remote sensing researchers and image analysts who choose to study spaceborne imagery for forest biomass estimation.

Some of the spaceborne sensors collect data at very fine ground sampling distance and offer sub-meter spatial resolution in their images. These sensors are also passive, and generally contain a panchromatic band with very high spatial resolution (often sub-meter) and a multispectral band sensor that operates with lower spatial precision (usually between 1 and 5 m). These sensors are used in applications in which the subject matter is size-sensitive, and are not as common in forestry research as the spectral sensors due to the cost of acquisition. The two major sensors of this category that have been widely used are QuickBird and IKONOS.

Active spaceborne sensors include radar and LiDAR. These systems are able to detect relief characteristics of the Earth, as they operate by sending energy (in the form of radio waves, visible, or near-infrared light) toward the Earth and measuring the time it takes to return to the sensor. These sensors also require a fee for use, and require complex processing due to the nature of measuring signal return, thus presenting initial impediments to research efforts. Despite this, active sensors have the distinct advantage of being able to detect forest vertical structure beyond the canopy surface.

RADAR and LiDAR pulses can penetrate certain canopy substrates (depending on the energy/wavelength used for the collection) and can obtain much more detailed structural information than a passive sensor. These sub-canopy data make LiDAR and radar attractive as a sensor option to those with access to the data, as such information generally yields more accurate estimation of forest parameters.

Moderate-Resolution Multispectral Imagery

The Landsat series of satellites has proven to be a successful venture, providing decades of moderate-resolution multispectral imagery. In addition to these characteristics, Landsat data are free and open to the public, making it an ideal sensor for research. Not surprisingly, many remote sensing forestry researchers have chosen to use Landsat as a primary or significant imagery source (Tomppo et al., 2002; Cohen et al., 2003; Foody et al., 2003; Zheng et al., 2004; van Tuyl et al., 2005; Labrecque et al., 2006; Luther et al., 2006; Marynard et al., 2007; Zheng et al., 2007; Tangki and Chappell, 2008; Wijaya et al., 2010). To estimate forest biomass, many of the studies used band combinations of the Landsat data and vegetation indices in a regression with variety of standard field variables including mean height, Lorey's mean height (mean stand height weighted by basal area per tree), maximum height, crown width, and others. These efforts met with varying degrees of success, reporting acceptable correlations between the remote sensing models and field measures of biomass. Such models are often theoretically identical: they identify appropriate metrics from remotely sensed data and regress with field data. These applications are limited by the spatial resolution of the Landsat images and the confines of regression and remote sensing, a topic discussed at length by Cohen et al. (2003). As Landsat data contains only seven spectral bands, there is a theoretical limit to the amount of information that can be gleaned from such imagery. The studies mentioned above employed different combinations of Landsat bands, but all reported similar biomass estimation accuracies, suggesting that there is a limit to the usefulness of Landsat data and regression in forest inventory studies. Foody et al. (2003) employed a feed-forward neural network to model forest biomass, and was successful in extracting forest biomass with high levels of accuracy. While this method is not subject to some of the statistical assumptions faced by other studies using Landsat data, it still is limited by the moderate resolution of the imagery.

More recently, Li et al. (2010) used Landsat data to estimate secondary biomass (biomass below the canopy and from non-dominant trees) and found that the structural characteristics of vegetation greatly influence their spectral reflectance, thus showing promise for further development of Landsat biomass models. Gasparri et al. (2010) evaluated multi-temporal Landsat data to estimate biomass in a semiarid area. They found that different phenological responses of vegetation to environmental conditions resulted in unique regional and/or local patterns of biomass distribution and that these patterns were typically related to rain and land use. Forest Inventory and Analysis (FIA) field data have also been used to investigate biomass dynamics over the past 20 years in combination with multi-temporal Landsat data (Powell et al., 2010).

Landsat data offer researchers a cost effective method for quantifying biomass, and can provide very accurate results if the scale and robustness of the field data match the imagery well. Despite this, the scale of the forest unit of measurement still greatly determines the applicability of using Landsat data: forest plots that are too small are not represented well by image pixels larger than their spatial extent (Lu, 2006), and complex biophysical environments are not well represented at the scale of Landsat data.

SPOT is a satellite series launched and operated by the French government, providing quality imagery since 1986. Soenen et al. (2010) used the multispectral sensor from the SPOT satellite to perform their biomass calculations with 10 m spatial resolution. This research used forest structural parameters collected in the field and a multiple forward mode canopy reflectance model inversion to estimate biomass. The forest structural parameters that they used to inform their model would have been directly observable with LiDAR data, thus eliminating the need for the complex model inversion look-up table method they successfully implemented. However, because Soenen et al. (2010) used SPOT data, this complexity was required. Hyyppa and Hyyppa (2001) used SPOT in a regression model, similar to studies using Landsat data, and produced results that were similar to those studies using Landsat data. SPOT data are not free for consumption, and thus become cost prohibitive when considered against other sensor options, excluding it as a sensor possibility for small forest tracts in the U.S. for which Landsat data are available.

Foody et al. (2003) also note a key issue in remote sensing of biomass: the inability of models to transfer from study site to study site. Empirical models built from satellite imagery rarely transfer from one study area to another, even if the study sites are composed of similar forest species and climatic conditions (ibid.). This represents a classic problem in remote sensing, and one that we hope to address with the current research; however, the outlook is bleak, according to Foody et al., due to a large number of factors outlined in their paper. The ability to transfer biomass models may improve when leaving the spectral domain by employing LiDAR data, and provide a strong impetus for investigating biomass models using LiDAR over different study sites.

The ASTER satellite offers thermal reflectance at moderate spatial resolution (15 m), and was used by Muukkonen and Heiskanen (2007) as a method of improving the spatial resolution of MODIS data. Because ASTER offers near-infrared (NIR) and thermal imagery, it can be used effectively to detect vegetation. Identifying stand-wide biomass estimates using ASTER data enabled Muukkonen and Heiskanen (2007) to utilize a pre-existing land cover map (at 25 m spatial resolution) as field data for use with the coarse-resolution MODIS data. This fusion approach is not uncommon, and is an effective way of using coarse-resolution imagery to quantify forest parameters at a finer scale. Muukkonen and Heiskanen note, however, that while their approach was cost effective and produced accurate preliminary biomass estimates for large areas, the pixel estimates of biomass could have low accuracy. Furthermore, these authors observe that reliable forest data is required for generating relevant results, a common problem in estimating biomass (Lu, 2006). While forest biomass estimates will always depend heavily on the accuracy and completeness of field data, it can affect "scaling-up" cases even more, as seen with the ASTER satellite. Given these issues, and the fact that thermal sensing is not ideal for remote sensing of vegetation, ASTER is not found to be an ideal sensor for small-area forest biomass estimates. Chopping et al. (2008) investigated the usability of Multi-angle Imaging Spectro-Radiometer (MISR) on board the Terra satellite to measure woody biomass and other forest parameters for large parts of Arizona and New Mexico. The advantages of MISR over active or other passive sensors are: (1) timely and extensive estimates of forest biomass and other parameters at low cost; and (2) more accurate assessment of gaseous and particulate emissions from forest fires via estimates of biomass loss due to the consideration of the vertical dimension (ibid.).

Hyperspectral Imagery

Spaceborne hyperspectral sensors commonly used for estimating forest biomass include AVHRR (1.1 km), MODIS (250 m–1 km), and Hyperion (30 m). AVHRR and MODIS have typically been used for identifying forest biomass at a regional or global scale, while Hyperion data provides useful information on local variation of forests at a moderate resolution. Dong et al. (2003) used the normalized difference vegetation index (NDVI) estimate provided by the AVHRR sensor to estimate forest biomass. This study investigated biomass at a global scale, and therefore their field data collection relied on estimates of wood volume published by the countries involved in the study. These estimates of wood volume were converted into above-stump biomass, and used to inform a regression model that used latitude and the inverse of the AVHRR NDVI as the significant regression variables. Their results were encouraging for a study at this scale, but were ultimately unreliable for small-area, high-accuracy forest inventories required by small property owners seeking to quantify their forests.

Large-area applications of forest biomass are often investigated using the MODIS sensor, a satellite that delivers frequent global coverage of hyperspectral imagery at coarse resolution (Muukkonen and Heiskanen, 2007; Saatchi et al., 2007; Anaya et al., 2009; Nelson et al., 2009; Randerson et al., 2009). Gallaun et al. (2010) produced European maps on above-ground biomass of forests for two species types (i.e., broadleaves and conifers) by combining MODIS data and national forest inventory data based on an automated up-scaling approach, which was not sensitive to scale mismatch between field and remote sensing measurements. These studies all employ the classic method for spectral sensors of classification and regression to estimate biomass (similar to those studies using Landsat and SPOT data), and do so with varying degrees of success for large areas. As MODIS is a hyperspectral sensor, there are a plethora of band combinations and indices available for regression modeling, and each of the studies mentioned above employs different band combinations based on their specific study areas. MODIS presents a viable sensor option for the applications of large-area biogeochemistry and forest inventory assessments, as well as carbon balance studies; it is, however, unsuitable for any forest quantification at the stand or plot level.

Thenkabail et al. (2004) compared biomass estimates derived from regression analysis from Hyperion to three other sensors: high-spatial-resolution IKONOS imagery, ALI imagery, and Landsat ETM+ imagery. At the scale of their analysis (30 m square plots), they found that Hyperion data was vastly superior to the other sensors at both quantifying biomass and classifying forests for land use/land cover applications. This finding is not surprising, given that the spatial resolution of Hyperion is competitive with both Landsat and ALI, and offers much more spectral information than either of these sensors. The IKONOS sensor offers sub-meter spatial resolution, but lacks the narrow spectral bands needed to differentiate between various forest types in complex stands such as the African rainforests used in Thenkabail et al. (2004).

Hyperion would seem an ideal sensor for any study attempting to quantify forest biomass: it offers hyperspectral resolution free of charge, like MODIS, but at a moderate spatial scale, allowing for implementation without the need for either large-area analysis (Schlerf et al., 2005; Le Maire et al., 2008; Anaya et al., 2009; Nelson et al., 2009; Randerson, 2009) or another data product to improve its spatial resolution (Muukkonen and Heiskanen, 2007). However, there are several practical limitations of using Hyperion data. First, the temporal coverage of the sensor is poor for multiple dates within the same study area. This can pose a major problem, as finding data covering the same time in the phenological cycle of a forest can be quite difficult. In addition, cloud cover becomes a more prevalent problem with longer lapses between coverage, meaning a study site may not be covered even if the data was collected at the appropriate time. Because of this hit-or-miss coverage characteristic, Hyperion does not make an ideal sensor for small-area forestry research as a general rule, but would work well if the coverage was available.

All of the spaceborne sensors reviewed (i.e., AVHRR, Landsat, ASTER, MODIS, Hyperion, SPOT) provided researchers with the data to successfully estimate forest biomass, although at varying scales and with varying degrees of success. All of these sensors operate with multispectral imagery and offer the best possibility for classification of forest types. However; the spectral sensors at moderate or coarse spatial resolution remain limited in their inability to capture any information about forest structure, which is strongly correlated to biomass (Popescu et al., 2002). A sensor fusion approach utilizing these spectral sensors is highly advantageous for automated biomass detection, as species classification coupled with forest structural data should provide very accurate biomass estimations. Multi-sensor data fusion will subsequently be discussed in detail. The coarse-resolution sensors are obviously of limited utility for small-area forest plot inventories, yet should not be discounted for all analyses, especially those operating at a regional or national level. The moderate-resolution sensors contain possibilities for small-area forest research, but their usefulness is highly dependent on the size and orientation of field inventory plots. Suganuma et al. (2006) examined three parameters—stand basal area, canopy coverage, and leaf area index (LAI)—to estimate biomass, and suggested that canopy coverage and LAI would be more appropriate in woodland biomass estimation from moderate-resolution remote sensing data, although stand basal area resulted in the highest correlation with woodland biomass. Li et al. (2010) have shown that further advances in using moderate-spatial-resolution data are possible, but different analytical frameworks than regression from spectral characteristics to biomass must be developed in order for these sensors to compete with airborne platforms in the accuracy of their assessment.

High-Spatial-Resolution Imagery

QuickBird is a high-spatial-resolution multispectral sensor that is privately owned and may be commissioned for a fee. The sensor has a spectral resolution that includes an NIR band, a key component of most vegetation remote sensing. Gonzalez et al. (2010) used QuickBird's panchromatic band to automatically detect tree crowns, and then used regression techniques to estimate biomass from the diameter of each tree crown. This study also derived biomass estimates from airborne LiDAR data, regressing various statistical measures of tree height against field biomass measures. They found that the QuickBird imagery resulted in higher error and lower total biomass estimates than the LiDAR data, suggesting that the height of the trees in the study area contributed to shadowing that interfered with the crown detection algorithm. Leboeuf et al. (2007) employed processing similar to QuickBird imagery to estimate biomass, using the *e*Cognition software to map tree shadows. These tree shadows were then converted to a "shadow fraction" that was then regressed with field data to model biomass. While this study produced accurate results, they were only interested in black spruce (*Picea mariana)* biomass, and noted in their conclusions that results were highly influenced by thresholds set during the shadow detection process. Broadbent et al. (2008) employed the tree crown detection algorithm proposed by Palace et al. (2008) to quantify biomass from QuickBird imagery and encountered similar difficulty in identifying forest structure at the individual-tree level due to shadowing, intrinsic crown characteristics by species, multiple sub-crowns within a single tree, and canopy gap disturbances.

IKONOS is another privately owned satellite sensor that provides similar spatial and spectral resolution to QuickBird imagery. Thenkabail et al. (2007) found that IKONOS data was inferior to Hyperion data for estimating biomass, for similar reasons to those of Gonzalez et al. (2010) in finding QuickBird to be inferior to LiDAR data. These high-spatial-resolution sensors do not readily lend themselves to forestry research: their ultrafine spatial resolution can be replicated with aerial photography, and it has been shown that spectral information is more important for detecting forest biomass (Thenkabail et al., 2007). In addition, the cost of acquiring the images from these sensors is prohibitive for most research purposes. While the spatial resolution offered by these sensors is excellent for crown delineation, care must be taken with shadowing and other effects of sun angle and tree height, further reducing the utility of these data for small-area forest quantification.

Radar Data

Spaceborne radar suffers from similar drawbacks that other spaceborne systems experience: potential lack of robust coverage of smaller area analysis units and poor spatial resolution. Two major advantages differentiate spaceborne radar from the spectral sensors reviewed above: the ability to detect forest structure, and the ability to penetrate cloud cover. Radar systems are active, sending radio waves from an aperture toward a target and measuring the time until the signal returns. Spaceborne radar systems employ synthetic aperture radar (SAR), a complex sensor configuration that greatly enhances the properties of the signal and allows spaceborne radar to act as a viable sensor alternative. A major drawback of radar sensors is the lack of data in "shadows." With a spectral sensor, the backside of a hill or shadow of a tree may appear black, but still contains spectral data about that space. Active sensors are unable to fill this data void, and if the orientation of the sensor is such that buildings, hills, or tall trees interfere with the study area, there may be a loss of data that might result in the need for a second data collection. Radar must also operate in a specific bandwidth of the electromagnetic spectrum, and each band has properties that may or may not make it suitable for biomass estimation, as detailed in Rauste (2005). In addition, spaceborne SAR data are highly complex, and require challenging processing methods to yield results.

Spaceborne radar estimates of forest biomass and height use the various available sensors, including SRTM (Kellndorfer et al., 2004; Simard et al., 2006), InSAR (Tighe et al., 2009; Huang et al., 2010) and SAR (Melon et al., 2001; Santoro, 2002; Rauste, 2005; Sun and Ranson, 2009). All of these radar instruments share similar characteristics (as discussed previously) and derive height information from direct processing of the radar backscattering. In order to accurately quantify biomass, spaceborne radar, like spaceborne LiDAR, remains a superior sensor option only for those researchers interested in global phenomena and global carbon cycles, given the scale at which the data are collected. It is also apparent (and is explicitly stated by Rauste, 2005) that spaceborne radar data may not provide robust estimates of biomass without additional sensor data. Studies that went one step beyond simply estimating height to quantify biomass needed either additional data in the form of full waveform LiDAR analysis (Simard et al., 2006; Sun and Ranson, 2009), spectral data (Rauste, 2005), or applied theoretical models (Melon et al., 2001) to achieve their results. Kellndorfer et al. (2004) also note that SRTM is very sensitive to the vertical structure of vegetation, which Melon et al. (2001) attempted to account for in their theoretical models of the forest, and Tighe et al. (2009) confirmed with their assertions that X-band SAR backscatters below the canopy, while C-band SAR will overestimate height. A further discussion of the errors associated with spaceborne radar can be found in Huang et al. (2010), who recommend that a minimum mapping unit of 18,000 m^2 be used for vegetation height estimates using InSAR. Solberg et al. (2010) used SRTM X-band InSAR to estimate boreal forest biomass in combination with airborne laser scanning (ALS) data. They found that a high-quality terrain model from the ALS data increased the accuracy of the biomass estimation from InSAR height. Airborne radar platforms have much greater potential for quantifying biomass in small-area, higher accuracy studies.

LiDAR Data

LiDAR data acquired via satellite offer another active sensor alternative for sensing biomass from space. LiDAR is not as robust at "seeing" through clouds as radar, and sometimes will not penetrate dense canopy as easily as X-band SAR, but spaceborne LiDAR remains a viable option for large-area estimation of biomass. LiDAR systems emit light (usually in a narrow wavelength in the infrared spectrum) and record the time it takes for each pulse of light to return to the sensor. Recently, LiDAR processing has featured waveform decomposition, which increases the information generated from a LiDAR pulse, and is ideal for use with spaceborne and other large-footprint LiDAR sensors. Nelson (2010) contends that the forestry community, having gained widespread understanding of airborne platforms, must now focus its attention on space, further advancing LiDAR science and forest quantification. While spaceborne LiDAR certainly is the next frontier for LiDAR analysis, it is currently unable to operate at the accuracies and resolutions of airborne studies, thus making it a poor choice for persons wishing to study smaller forest plots and stands.

One of the most commonly used spaceborne LiDAR systems for biomass quantification is GLAS, owned and operated by NASA. GLAS operates at the regional scale; it can provide results for large areas of the globe and can be used to estimate vegetation height (Rosette et al., 2008; Sun et al., 2008; Duncanson et al., 2010) and biomass

(Duong et al., 2008; Boudreau et al., 2008; Nelson et al., 2009; Nelson, 2010). These studies were all conducted for very large areas,[2] and all of these studies used estimates of height or biomass derived from airborne sensors as a surrogate for field work. This is a reasonable assumption for the scale of analysis employed by these papers, but obviously introduces error that can be eliminated via field sampling in smaller-area studies. Duncanson et al. (2010) and Sun et al. (2008) chose to analyze the full waveform of the GLAS data, thus providing more data than using the first and last return data used in other LiDAR studies, as well as increasing the processing complexity of the data. Boudreau et al. (2008) combined multiple data sources to estimate biomass, including GLAS, SRTM, Landsat ETM+, airborne LiDAR, ground inventory plots, and vegetation zone maps. Their study showed that spaceborne remote sensing measurements could be efficiently used for estimating biomass and carbon stocks over large areas. Nelson (2010) is critical of using GLAS to estimate biomass, and demonstrates the wide variability of results by changing the model used to estimate biomass. Nelson (2010) furthers this criticism by advocating standards for calibration of spaceborne biomass estimates, which currently are in different states of development for different sensors, and notes that biomass studies of the taiga, tundra, and low-biomass areas may be unsuitable for estimation using GLAS, due to the decreased functionality of GLAS in low-relief areas.

FOREST BIOMASS ESTIMATION USING AIRBORNE SENSOR DATA

Airborne sensor platforms offer some distinct advantages over spaceborne sensors for biomass estimation studies. Firstly, the flight altitude of the aircraft is obviously far lower than a satellite, and therefore the spatial resolution of airborne sensors is much finer than those operated from space, often surpassing the high-spatial resolution of sensors such as IKONOS and QuickBird. Secondly, the operation of the aircraft is conducted by skilled pilots who can assure that explicit, on-demand coverage of forest plots is executed successfully. In addition, issues of aircraft orientation have been largely addressed with the advent of more sophisticated internal measurement units (IMU) and differential processing of GPS data. The result of these improvements is that airborne platforms deliver data that have very high positional accuracy that can be collected relatively quickly over an area of interest. Airborne platforms do, however, suffer from impediments similar to those of spaceborne sensors. Cloud cover may be a problem for airborne platforms, and inclement weather may make flying dangerous and postpone collection; in areas of notoriously fierce weather, this may constitute a major problem. Also, most airborne sensors are privately owned, thus requiring a sometimes substantial fee for collection and availability that is at the discretion of the owner. In addition, airborne sensors are less competitive than satellite sensors for investigating biomass and carbon sequestration of forests at regional or national scales, which is necessary for understanding global energy balance and cycling. The sensor options available via satellite are also available from aircraft, including spectral sensors, radar, LiDAR, and aerial imagery. Traditionally, forest inventory studies were performed by skilled operators interpreting aerial imagery, but this process is time and labor intensive, leading researchers to strive for new means of assessing forest

[2]Sun et al. (2008) note that the positional error of GLAS is nearly 60 m.

structural information (Popescu et al., 2004). This section will first discuss airborne spectral sensors and airborne radar as they apply to forest biomass estimation, and then will ultimately discuss airborne LiDAR, which has been shown to be the most accurate and widely researched method of forest biomass estimation.

Spectral/Radar Data

Most researchers who employ an airborne spectral sensor choose one with hyperspectral capabilities, like AISA, HyMap, CASI, AVIRIS, or DAIS (Hyyppa and Hyyppa, 2001; De Jong et al., 2003; Hill and Thomson, 2005; Bunting and Lucas, 2006; Goodenough et al., 2008; Lucas et al., 2008; Lu et al., 2009; Jones et al., 2010). These sensors are all functionally similar, collecting hyperspectral imagery within different bandwidths, and their spatial resolution is determined by their field of view and the flying altitude of the aircraft. The processing methods for these sensors are similar to those discussed previously using spaceborne hyperspectral imagery, but with more explanatory power because of their increased spatial resolution. A strength of hyperspectral imagery compared to active sensors is its ability to classify vegetation: this classification can be used to further estimate biomass, as shown by Jones et al. (2010), Bunting and Lucas (2006), and Hill and Thomson (2005). The accuracy of species classification has a major impact on the biomass assessment, and it can be undertaken in a variety of ways, including using the raw spectral data (Hill and Thomson, 2005; Bunting and Lucas, 2006), or with more sophisticated techniques, like support vector machines (SVM) (Jones et al., 2010). This species information can be combined with LiDAR data to robustly estimate biomass (Hill and Thomson, 2005; Goodenough et al., 2008; Lucas et al., 2008; Jones et al., 2010), or regressed directly using vegetation indices and field sampling (De Jong et al., 2003). Bunting and Lucas (2006) were interested in accurately identifying individual trees, which is a common issue among many airborne studies, and did so using solely CASI data and an object-based analysis.

Most of these spectral sensors were used for classification, and then LiDAR was used to perform biomass estimation of each classified species, which has been shown to be an accurate method of quantifying biomass with more power in mixed forests. The drawback of this approach is that it requires two sensors and possibly two data collections, which can be cost prohibitive for some users. The airborne spectral sensors provide adequate measures of forest biomass, but are better suited for other studies where species composition or plant chemistry is of interest. If a researcher has the funding available for an airborne mission, LiDAR is a better choice for estimating forest biomass. Hyyppa and Hyyppa (2001) investigated the effects of plot size on the biomass estimates from regression using AISA, SPOT, Landsat, and airborne SAR, and found that the accuracy of all sensor data models were significantly affected by plot size. They did not include LiDAR data in their study, and it is unclear whether plot-level LiDAR studies are affected similarly, or whether spectral methods that operate at the individual tree level (Bunting and Lucas, 2006) would also suffer from this loss of accuracy.

Active sensors should have an advantage when estimating forest biomass, due to their ability to garner forest structural information. As such, airborne radar would seem an ideal candidate for assessing forest biomass (Ranson et al., 2001), yet Fransson et al. (2000), Lucas et al. (2005), and Baltzer et al. (2007) all found significant challenges in using radar. Fransson et al. (2000) cite the need for high-spatial-resolution ground data as being very limited in radar studies from airborne platforms. Radar needs to be calibrated for each mission, and more specifically needs flat areas of low topographic relief that may be difficult to observe on a single radar flight if the area of interest is located in heavily forested or mountainous areas (Huang et al., 2010). Fransson et al. (2000) specifically mention that physical parameters surrounding the forest can influence the radar data, and are typically not accounted for in the calibration and modeling process. Balzter et al. (2007) conclude that LiDAR is better than radar at deriving individual tree heights, and state that for their study (and presumably many others), the accuracy of results achieved with active sensors might be inflated, owing to the homogeneity of the forest being studied. In the previously discussed spaceborne radar studies, LiDAR is frequently used as validation data, which renders comparisons between the two sensor choices moot. Lucas et al. (2005) conducted one of the few radar studies that employed field work for validation, which is a much more robust method of determining the accuracy of results. Lucas et al. (2006) investigated the relationships between AIRSAR backscatter and forest biomass calculated using field measurements and LiDAR-derived height information at the plot level. They found that L-band HV backscatter data resulted in the best performance in estimating biomass. Airborne spectral and radar sensors offer increased spatial resolution and on-demand coverage of forest plots, but still lack the explanatory power that airborne LiDAR generates. While airborne hyperspectral data is superior for purposes of classification, supplementing this data with LiDAR-derived height information can increase classification accuracy (Jones et al., 2010).

LiDAR Data

As discussed previously and noted by Nelson et al. (2007), airborne LiDAR has been shown to estimate biomass more accurately than any other sensor, even radar. Nelson et al. (2007) note that adding radar variables to their biomass regression equations only reduced the RMSE of their results by 0.3%. Because of this demonstrated superiority of LiDAR data, this review will focus more on the methods of biomass estimation for LiDAR studies than those previously reviewed. Airborne LiDAR sensors capture information contained within a specific footprint, and the size of this footprint may influence the choice of a processing unit. Nearly all small-footprint airborne LiDAR researchers implemented regression in some form when estimating biomass, and can be most broadly categorized into two groups: those that use the tree as the unit of measure and those that use multiple trees arranged into plots as the unit of measure. Each of these two analysis units yield successful results, and the choice of the specific analysis unit is often determined by either the point density of the LiDAR data, the robustness of field data collection, or whether another sensor is being used in conjunction with the LiDAR data. Individual-tree methods require some means of delineating trees, and this is often the source of the majority of the error for these studies. A further division of LiDAR data processing is discrete return vs. full waveform analysis. While conventional LiDAR sensors record multiple discrete returns from a pulse when it comes into contact with various forest strata, a full waveform LiDAR sensor records the signal of the entire backscattered laser pulses. Of those LiDAR with large footprint (i.e., LVIS), waveform processing is necessary to realize the full capabilities of the sensor. This section will discuss discrete return LiDAR processing at the individual-tree and plot levels, and then will discuss full waveform methods.

Individual-Tree Level. As stated previously, LiDAR-based methods that focus on the tree as the unit of measure require some means of delineating each tree. Næsset and Okland (2002) used field measures of tree positions and tree crowns, and matched LiDAR data to these locations, only using points that fell within a known tree to calculate tree height, their biophysical parameter of interest. Næsset and Okland (2002) acknowledge that their greatest source of error was in the positioning of the trees from field data, made especially important because these positions determined which laser points would be included in the study. This study used regression between seven laser height predictor variables and tree height, and reported good accuracy in comparing their laser-derived heights against field data. This is important to note, as tree height is often highly correlated with biomass, but this study is limited for applications where species are mixed and field data are not as robust. An adaptable model should be able to automatically delineate trees and then use laser height variables to calculate biophysical parameters, a concept employed by many studies (Popescu et al., 2004; Bortolot and Wynne, 2005; Popescu, 2007; Riggins et al., 2009; Gonzalez et al., 2010; Kwak et al., 2010).

Popescu et al. (2004) used both airborne LiDAR data and ATLAS image data to automatically identify trees and estimate their biomass. The ATLAS imagery was resampled to a much finer resolution so that it was spatially coincident with the LiDAR data, and this imagery was used to classify tree species. Individual trees were identified through a process of local maximum filtering, which produced a crown height map (CHM). The CHM was then matched with the ATLAS data and tree species identified, and field data validated the crowns that were detected and provided locations where spurious trees should be removed. Biomass was calculated using tree height and crown width, and very robust results were given for pines. The same process worked poorly on deciduous trees, owing to the greater variability of deciduous crown shape and greater potential for overlapping crowns, something that the algorithm could not account for. Popescu et al. (2004) identified that crown diameter is highly correlated with biomass, and strongly recommended that any study wishing to quantify biomass using regression should include crown width as a parameter. This study showed promising results and a good application of data fusion to quantify biomass, yet the poor results on deciduous trees indicate that the process is only suitable for softwoods, which tend to have more regular crown geometry than hardwoods. Similar to Popescu et al. (2004), Bortolot and Wynne (2005) identified individual trees by creating a CHM in the same manner, yet employed spatial filters to determine tree boundaries rather than using imagery to help determine their positions. Once this segmentation was complete, Bortolot and Wynne (2005) extracted laser height quantiles and regressed against field data to estimate biomass. To adapt their algorithm to different forest types, they used a Nelder-Mead simplex algorithm to optimize search parameters in each forest. This method shows promise in transferring from one forest type to another, and reported reasonable errors when estimating biomass. This method might have been greatly improved by the addition of spectral data to classify tree species, thus making the process more automated, although still requiring species- and area-specific allometric equations to calculate biomass.

Popescu (2007) used the method proposed in Popescu et al. (2004) of identifying a CHM and determining crown width. This research proved highly successful at estimating pine biomass once again, but this time the errors were reported at the tree level, not at the plot level as before. These results are coincident, and may suggest that plot-level measures based on individual trees are similar to aggregating individual tree measures to plot level. Persson et al. (2002) and Yu et al. (2004) performed similar analyses, and Yu et al. (2004) performed the analysis in a forest with frequent temporal coverage of forest inventory, and used their models to predict forest growth.

More recent papers identifying individual trees incorporate more advanced statistical methods (Salas et al., 2010; Vaukhonen et al., 2010) and methods that use more sophisticated filtering of CHMs (Kwak et al., 2010). Kwak et al. (2010) used a watershed segmentation algorithm given in previous literature to identify individual trees, and then calculated the crown geometric volume of each tree. This is a logical progression of the notion that crown width is strongly correlated with DBH, and it is expected that results of such a method would prove superior to previous methods that measured crown width. Kwak et al. (2010) did not show this to be the case, but not because their processing was substandard: some field conditions contributed to this poor accuracy. In their study area, tree allometry was not reported at the species level, but rather at the hardwood/softwood divide, thus introducing a vast source of potential error. Kwak et al. (2010) could have overcome this with destructive sampling, but as their study area was located within a nature preserve, this was not possible. Another source of error, as in all CHM applications, is the issue of overlapping crowns. It has become clear that using the tree segmentation approach will not yield more accurate results until the problem of crown overlap can be solved by some means, and using an individual-tree approach that relies on regression must overcome this issue to continue as a research topic.

Salas et al. (2010) proposed that statistical models used to describe laser-derived tree variables should account for spatial variation, and that much previous research was conducted outside of this assumption. While Popescu et al. (2004) and others mention that they investigated the spatial autocorrelation of their results, Salas et al. contend that such a check needs to be built into any models that predict biomass or any other biophysical variable, and found that using a linear mixed effects model produced the best results when estimating tree diameter, which is highly correlated to biomass. Vaukhonen et al. (2010) used the process of imputation to estimate individual tree variables, a process based on the k-most similar neighbor algorithm and the random forest model, both stochastic models that simulate forests. The results of these studies (Salas et al., 2010; Vaukhonen et al., 2010) suggest that any statistical estimates of forest properties estimated from LiDAR variables must move beyond traditional regression for non-spatial variables, and include robust metrics for error control.

Individual tree measures provide an intuitive means of assessing forest biomass. Trees can be measured directly in the field and easily checked against laser-derived output, providing valuable validation information. This process can be quite tedious, especially for large study areas, and often requires time-consuming and expensive field data collection to provide robust validation. Also, LiDAR returns may or may not record information on sub-dominant trees, and if such trees are recorded it is likely with a smaller number of returns than the dominant trees. As such, an aggregation of single trees within a plot will likely underestimate the biomass for the entire plot, a problem exacerbated by the inability of tree detection algorithms to deal with crown overlap. However, with individual tree methods, species-specific allometrics can be correctly applied to each tree provided either field data or image classification are available, something that plot-based methods can only match in pure stands without a classification step.

Offshoots of individual-tree methods are those that employ the concept of crown geometric volume (CGV), instead of a CHM. These methods operate on the assumption that a 3D geometric representation of a tree crown will provide valid measurements from which to estimate biomass. Chen et al. (2007) propose a simple model using tree geometry that works well for one species only, but would be limited in mixed stands. Kato et al. (2009) calculate CGV using a radial basis function to classify LiDAR points into individual trees. Validation of the CGV as implemented by Kato et al (2009) requires using a total station to collect multiple points of the tree crown, which in dense forest would be difficult and would be significantly affected by crown overlap. Despite this, Kato et al. (2009) represent a forward step in LiDAR/biomass studies, explicitly mentioning the problems with site-specific regression analyses. The need for regression to estimate biomass, constituting the vast majority of the studies reviewed, limits the applicability of these models outside of forestry and between different forests, and must be addressed in the future.

Plot Level. Plot-level LiDAR studies have reached operational status in forestry (Breidenbach et al., 2010), most often utilizing a regression approach based on height and canopy density metrics. Breidenbach et al. (2010) also note that in the Nordic countries, most new forest inventories are based on LiDAR data. The accuracy of stand-level estimates of forest biomass depends largely on the method and accuracy of field data collection. If field data collection accurately represents the entire biomass of the study plot, then stand-level metrics will prove accurate, yet this is often not the case for several reasons. First, LiDAR returns may not include sub-dominant trees or provide robust details about each tree in the plot, creating a fundamental mismatch between the LiDAR and field data. Second, while tree height has been shown to be accurately measured at the plot level (Popescu et al., 2002), any inaccuracy at this step will influence the accuracy of a biomass estimate due to errors in the allometric chain. Ioki et al. (2010) and Hawbaker et al. (2010) provided results that surpass individual tree measures of hardwood forests, suggesting that plot-level measurements are more appropriate for broadleaved forests than individual-tree measures. Garcia et al. (2010) estimated biomass fractions using the models based on LiDAR-derived height, intensity, or height combined with intensity data. They reported that the normalized intensity-based model improved the accuracy in biomass estimation. They also agreed that LiDAR models have a common problem of transferability to other areas as optical data, which was demonstrated by Foody et al. (2003). Kim et al. (2010) successfully distinguished between live and dead standing tree biomass using LiDAR data at the plot level. It is clear from plot-level studies that LiDAR is the most appropriate data source for estimating forest structural variables, and that adding additional sensor data will improve the accuracy of these measures (Hyde et al., 2006). Despite some of the shortcomings of plot-level methods for estimating forest biomass, they are still preferred in forestry operations, provided that field data is robust and accurate (Breidenbach et al., 2010). Many studies have combined LiDAR-derived measurements with spectral data to improve performance of forest parameter estimation (e.g., Lefsky et al., 2005; Lucas et al., 2008; Chen et al., 2010; Erdody and Moskal, 2010).

Plot-level studies have had success in quantifying forest properties other than biomass (Donoghue et al., 2007; Solberg et al., 2009). In these studies, the researchers attempted to quantify species mixtures and LAI, and met with success. These studies are encouraging, as both of these variables are important measures for quantifying biomass. Knowing the species of trees is essential for applying the correct allometric equation, and the ability to detect species using remotely sensed data is of keen interest in forestry research. Traditionally, species identification has been conducted using spectral sensors, but Donoghue et al. (2007), were able to successfully differentiate between several species using LiDAR intensity data; however, their study area contained only two species of trees: Sitka spruce and lodgepole pine. They report that using LiDAR intensity data for classification can be difficult, as there is no published standard for radiometric calibration of LiDAR data, an improvement that would surely further the usefulness of LiDAR in forest studies. If studies of LiDAR intensity can be advanced to the point of accurate species detection, it would eliminate much of the need for sensor fusion and eliminate the problems of scale and temporal mismatch often seen therein. Solberg et al. (2009) found that plot-level estimates of LAI were successfully identified by LiDAR penetration rate. Plot-level estimates of LAI are the only appropriate use of LiDAR in forests, as individual tree measures of LAI are strongly influenced by the surrounding canopy, making an individual tree measure of LAI within a forest stand invalid. However, plot-level LAI may be of use in informing biomass studies as an additional variable in regression techniques, and further studies may show this estimate to improve the accuracy of plot-level estimates of biomass.

Full Waveform. Full waveform analysis of LiDAR pulses constitutes another branch of LiDAR research. There are two general ways for processing backscattered waveform: (1) decomposing the waveform into a sum of components or returns, generating a denser 3D point cloud; and (2) applying a spatio-temporal analysis by preserving the entire 1D waveform. Papers that used full waveform analysis to estimate biomass (Ni-Miester et al., 2001; Anderson et al., 2006; Kimes et al., 2006; Koetz et al., 2006; Brandtberg, 2007; Anderson et al., 2008; Kirchhof et al., 2008; Reitberger et al., 2008; Wagner et al., 2008; Chauve et al., 2009) used the first approach to generate many more points in the canopy and applied similar methodologies to those LiDAR studies discussed previously. CHM creation is still a relevant issue for some methods, and Wagner et al. (2008) and Chauve et al. (2009) investigated how CHM creation from waveform decomposition performs. Chauve et al. (2009) found that DTM and CHM heights are not significantly improved by the additional points generated from full waveform decomposition, but the additional points could be used to characterize vegetation structure (i.e., crown properties and subdominant vegetation) more thoroughly. Individual tree detection also remains an issue after waveform analysis; Reitberger et al. (2008) used k-means clustering and an expectation maximization algorithm to partition the CHM into individual trees, and also noted that it is easier to classify deciduous trees in a leaf-off condition. Koetz et al. (2006) estimated biomass by using a look-up table approach based on inverting a waveform algorithm, a time-consuming process that is also site-specific. Ni-Miester et al. (2001) also suggest inversion for estimating parameters, but without a look-up table, based on their study of how waveforms behave in different canopies. A similar approach was tested by Morsdorf et al. (2009) using multi-spectral full waveform canopy LiDAR, but at much higher spatial resolution.

There is also the processing-unit divide of tree and plot level within waveform LiDAR studies, but more often the "plot" is the footprint of the laser sensor, which has been shown to be more accurate than arbitrary ground plots (Anderson et al., 2006; Brandtberg, 2007). Although full waveform LiDAR data contain abundant forest information, Anderson et al. (2006) point out that LiDAR-derived metrics are not always significantly correlated with the structural characteristics of forests at the tree level. Anderson et al. (2008) estimated biomass and noted that the estimates drastically improved with the integration of AVIRIS data. This is not indicative that large-footprint LiDAR is less effective than small-footprint, as Popescu et al. (2004), among others, also integrated imagery to improve their estimates of biomass. Kimes et al. (2006) show faith in the large-footprint LVIS LiDAR, as its estimates of biomass were used as their ground control for height prediction using the MISR sensor.

Whether an analysis uses the full LiDAR waveform or traditional multiple discrete returns, or whether it uses the individual tree or plot as a unit of study, the properties of the LiDAR collection will influence the results of the study, a topic discussed by Magnussen et al. (2010), van Aardt et al. (2008), Næsset (2004a, 2004b, 2005, 2009), and Gobakken and Næsset (2008). Næsset (2004a) reports that first return measurements of height and canopy density are relatively stable regardless of the flying altitude of the sensor, and also concludes that biophysical stand characteristics are relatively unaffected by flying height. Næsset (2009) then reported that the numbers of single and first echoes differ between flight altitudes, and that the stability of these measures decreases with flying height, which is intuitive. Næsset (2009) further contends that different sensors are equally well suited for regression-to-biomass studies, and that lower pulse repetition frequencies produce upward-shifted canopy height distributions. In addition to the height of the sensor, another major issue for LiDAR studies is the point density, or number of points per unit area that the sensor collects. Gobakken and Næsset (2008) concluded that estimates of maximum height are seriously affected by point density, but there is no clear pattern between other variables and point density. The data that support this study are the same source data, but thinned to represent different densities, which may have affected the results differently than flying two missions over the same area with different point densities. The issue of point density is also relevant to replication error, which can give false accuracy to a study. Magnussen et al. (2010) contend that replication effects are unimportant as long as the pulse density is greater than 1 pt/m^2.

Using regression between field estimates of biomass and airborne LiDAR-derived metrics has been thoroughly researched, and recent works have sought to develop new methods of analyzing LiDAR that are not subject to the issues represented by site-specific regression models. While field work will always be necessary for model calibration/validation of forest studies, it may be possible to develop models that are beholden only to field estimates of biomass that may be applicable to other sites, a problem not addressed in biomass models as discussed by Foody et al. (2003). As LiDAR becomes more understood, full waveform analysis and robust statistical measures are pushing the science of estimating biomass forward toward highly accurate forest inventories with more standardized collection configurations.

CONCLUSIONS

More recent methods of estimating biomass involve more sophisticated statistical measures and a closer examination of some of the basic principles of previous methods. Breidenbach et al. (2010) propose a method known as "semi-individual tree crown" delineation for estimation of forest parameters. This method is an extension of previous methods, and uses the same k-most similar neighbor and random forest methods used by Vaukhonen et al. (2010) while allowing for unbiased estimates of crowns. This unbiased measure comes from the predefinition of crowns by a segmentation algorithm, then later applying imputation methods to assign tree attributes. Breidenbach et al. (2010) and Vaukhonen et al. (2010) both implement the process of imputation, a stochastic method that accounts for uncertainty among the LiDAR variables and field validation data.

Zhao et al. (2009) proposed a different method of biomass estimation that is scale invariant. Their method focuses on the canopy height distribution and canopy quantile functions as functional predictor variables for biomass estimation and regression. The notion that this process is scale invariant is derived from the methodology: no explicit form for the allometry equation is assumed when forming the model, and as such, the model can be applied across species and forest types. Despite the scale invariance of the model, is it sensitive to plot size: RMSE decreased with increasing plot size. The authors explain that this process is due to edge effects on smaller plots. This is problematic, as any method that is transferable between forest types and plots should be equally functional on plots of any size, especially when the model is touted as scale invariant. However, the results obtained from this method provide a robust and relatively accurate method of accounting for forest biomass that eliminates some of the errors associated with strict individual-tree and plot-based methods.

Researchers attempting to quantify forest biomass have done so using a variety of remotely sensed data and estimation methods. Regression with field data is most commonly employed, regardless of sensor selection, and has proven to be most accurate in smaller-area applications when using small footprint LiDAR. Spaceborne sensors are most appropriate for those applications where the scale of analysis is regional or national, as small-footprint LiDAR data would prove to be too expensive both monetarily and computationally. In any study, the accuracy and dependability of the results must be weighed against the scale and cost of the remotely sensed data. Regression techniques, with increasing complexity, have improved to the point where forest operations outside of research are being conducted using airborne LiDAR data (Næsset, 2007; Breidenbach et al., 2010), and large-area mapping and monitoring can be successfully implemented using spaceborne sensor data.

Based on a review of numerous recent studies of forest biomass estimation, satellite/airborne LiDAR, with expectation of continued technological improvements, will continue to play an important role in this field in the future. Because different sensors (e.g., LiDAR and hyperspectral) on board a satellite or airplane are available that allow concurrent data collection from multiple sensors, multi-sensor data fusion is also expected to provide a set of robust tools for forest biomass estimation. A major challenge in the forthcoming decade is to advance modeling techniques to increase the accuracy of biomass estimation. Modeling techniques for biomass estimation have not fully utilized abundant information contained in individual and/or combined recent remote sensor data. Interactions and relationships among the biophysical and structural characteristics of forests and sensor signals should be further investigated. Improvements of individual models or combined analytic frameworks such as stochastic models, machine learning, and sophisticated tree crown detection and multi-sensor data fusion algorithms promise to increase the accuracy of forest biomass estimation.

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