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A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems

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Remote sensing-based methods of aboveground biomass (AGB) estimation in forest ecosystems have gained increased attention, and substantial research has been conducted in the past three decades. This paper provides a survey of current biomass estimation methods using remote sensing data and discusses four critical issues – collection of field-based biomass reference data, extraction and selection of suitable variables from remote sensing data, identification of proper algorithms to develop biomass estimation models, and uncertainty analysis to refine the estimation procedure. Additionally, we discuss the impacts of scales on biomass estimation performance and describe a general biomass estimation procedure. Although optical sensor and radar data have been primary sources for AGB estimation, data saturation is an important factor resulting in estimation uncertainty. LIght Detection and Ranging (lidar) can remove data saturation, but limited availability of lidar data prevents its extensive application. This literature survey has indicated the limitations of using single-sensor data for biomass estimation and the importance of integrating multi-sensor/scale remote sensing data to produce accurate estimates over large areas. More research is needed to extract a vertical vegetation structure (e.g. canopy height) from interferometry synthetic aperture radar (InSAR) or optical stereo images to incorporate it into horizontal structures (e.g. canopy cover) in biomass estimation modeling.

Keywords: aboveground biomass; forest ecosystems; parametric vs. nonparametric algorithms; remote sensing; uncertainty

1. Introduction

Forest ecosystems play an important role in global change on the earth. Deforestation and forest degradation can result in carbon emission to the atmosphere, thus affecting global climate and environmental change (Achard et al. 2004; Hese et al. 2005; Houghton 2005; Frolking et al. 2009; Hansen et al. 2013). Current concerns for global change and ecosystem functioning require accurate biomass estimation and examination of its dynamics (Le Toan et al. 2011). In the past three decades, substantial effort has been made to develop biomass estimation models, including empirical-based and process-based

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ecosystem models (Lu et al. 2012; Chen 2013). Previous studies have summarized a wide range of biomass estimation techniques. For example, Wang et al. (2009) divided estimation approaches into (1) process model-based, (2) empirical model-based, (3) biomass expansion/conversion factor or coefficient-based, and (4) integration of plot and remotely sensed data. Goetz et al. (2009) and Gleason and Im (2011) summarized the application of major remote sensing data such as optical multispectral and hyperspectral sensor, radar (RAdio Detection and Ranging, e.g. airborne L- or P-band data), and lidar (LIght Detection and Ranging, e.g. airborne lidar or space-borne ICEsat GLAS) to biomass estimation. However, no studies have summarized what variables from which sensor data are suitable for biomass estimation, and which algorithms/approaches are most effective to integrate various variables into biomass estimation models.

Total biomass includes both aboveground biomass (AGB; e.g. trees, shrubs, and vines) and belowground biomass (e.g. living roots, dead fine and coarse litter associated with the soil). Due to the difficulty of collecting field survey data of belowground biomass, the majority of previous biomass studies have focused on AGB. Consequently, in this work, if no additional information is provided, 'biomass' represents only aboveground forest biomass.

The most accurate method to estimate forest biomass is based on field measurements, but collection of field measurements is time-consuming and labor-intensive, and it is impossible to census large geographic areas (Segura and Kanninen 2005; Seidel et al. 2011; Wang et al. 2011a). Geographic Information System (GIS)-based biomass estimation models using environmental variables cannot provide accurate biomass estimates because forest biomass often has weak relationships with environmental variables (Lu 2006; Chen 2013). Process-based ecosystem models employ biogeochemical processes, including photosynthesis, absorption, and carbon allocation. The models generally couple biology, soil, climate, hydrology, and anthropogenic effects (Smyth et al. 2013). Constraints in data source (e.g. climate data, soil, and topography), spatial resolution, and inaccuracy of models often result in high uncertainties in biomass estimates (Rivington et al. 2006; Verbeeck et al. 2006; Larocque et al. 2008; Zhang et al. 2012). Moreover, process-based ecosystem models assume homogeneous stands and lack the ability to provide spatial variability in forest biomass. Remote sensing has the capability to consistently capture land surface features over large areas when airplanes or satellites pass over. Its unique characteristics for data acquisition, large coverage, digital format, etc. make it the primary data source for large-scale biomass estimation (Lu et al. 2012; Chen 2013). Techniques using empirical regression models and nonparametric algorithms based on different sensor data (e.g. Landsat, radar, and lidar) have been developed (Muukkonen and Heiskanen 2007; Blackard et al. 2008; García et al. 2010; Mitchard et al. 2011). Previous research has shown that remote sensing-based models provide more accurate biomass estimation than other models (e.g. process-based ecosystem models, GIS-based empirical models; e.g. McRoberts et al. 2013). Therefore, this paper focuses on remote sensing-based biomass estimation methods in forest ecosystems.

Although much research has explored biomass estimation using remote sensing technology in the past three decades, methods to select suitable variables from remote sensing data and develop estimation models suitable for specific studies are still poorly understood. It is crucial to summarize the current status of remote sensing-based biomass estimation techniques and discuss potential solutions to improve biomass estimation performance. Expanding on Lu's (2006) review paper, this work aims to improve our understanding of remote sensing-based biomass estimation methods at varying scales by summarizing the progress made during the last decade. Compared to previous literature reviews (e.g. Goetz et al. 2009; Gleason and Im 2011; Lu et al. 2012; Song 2013; Chen 2013), this paper makes the following new contributions: (1) reviews potential variables and algorithms for establishing biomass estimation models; (2) emphasizes the importance of conducting uncertainty analysis of estimation results; (3) discusses the impacts of scales on biomass estimation; and (4) summarizes a general procedure to develop remote sensing-based biomass estimation models.

Biomass estimation using remote sensing data is a complex procedure that requires careful design of many steps. A comprehensive review of all aspects involved in biomass estimation will be a challenge and is also beyond the scope of a journal paper. Therefore, this paper will mainly focus on the following topics and is organized as follows: Section 2 summarizes methods to collect biomass reference data from field measurements. Remote sensing variables and algorithms for biomass estimation modeling are summarized in Sections 3 and 4. Uncertainty analysis and impacts of scale on biomass modeling are discussed in Sections 5 and 6. A general design for a biomass estimation procedure is summarized in Section 7, and finally, conclusions are provided in Section 8.

2. Collection and calculation of biomass reference data based on field measurements

Detailed spatial biomass reference data are a prerequisite for biomass estimation (Avitabile et al. 2011). The roles of biomass reference data can be grouped into five aspects: (1) identifying suitable variables from remote sensing data by establishing relationships between biomass reference data and potential variables; (2) developing biomass estimation models by relating biomass reference data and selected variables; (3) evaluating model estimates or comparing estimates among different models; (4) conducting uncertainty analysis to identify factors influencing the accuracy of biomass estimation; and (5) providing not only a statistical population estimate but also the standard error. Therefore, collecting high-quality and representative biomass reference data is critical for a successful biomass estimation study. In general, biomass reference data can be obtained using destructive sampling, allometric models, and conversion from volume to biomass (Lu 2006). Table 1 summarizes the major characteristics of the three categories. However, forest biomass reference data do not describe the spatial distribution. To explore these spatial patterns, reference data must be integrated with remotely sensed data.

Direct collection of field measurements is the most accurate method to obtain biomass reference data and is generally used to develop species-specific allometric models based on measured attributes such as diameter at breast height (DBH), tree height, and/or wood density (Overman et al. 1994; Chave et al. 2014). This method involves destroying trees and is only used to collect sample data in small areas due to prohibitive time and labor required for fieldwork (Klinge et al. 1975). In general, AGB for a specific tree can be expressed as a function of DBH, tree height (H), and/or wood density (S): AGB = f (DBH, H, S). Once allometric models are available for tree species, they can be used quickly and nondestructively for stand biomass inventories. Many models have been developed based on various combinations of the aforementioned three parameters through linear or nonlinear regression models (Saldarriaga et al. 1988; Overman et al. 1994; Parresol 1999; Segura and Kanninen 2005; Seidel et al. 2011; McRoberts and Westfall 2014). When allometric models are used for obtaining biomass reference data, caution should be taken because soil conditions, tree densities, land-use history, and climate may

Table 1. A summary of major characteristics of biomass calculation from field measurements.

Methods	Major characteristics	Advantages	Disadvantages	References
Destructive sampling	A tree is cut and dried, and all masses are weighed.	The most accurate approach. An input for development of allometric models.	Destroying trees is time-consuming and labor-intensive and suitable only for small areas.	(e.g. Klinge et al. 1975)
Allometric models	Established for each tree species with linear or nonlinear regression models based on the relationships between biomass and diameter at breast height, tree height, and/or wood density.	Many previous field measurements can be used to calculate biomass.	Not all species have allometric models. Environmental and climatic conditions may affect their applications.	(e.g. Overman et al. 1994; Nelson et al. 1999; Henry et al. 2010; Chave et al. 2014)
Conversion from volume	Biomass can be converted from volume at individual tree level or at plot level using volume expansion factor, average wood density, and biomass expansion factor.	Many previous sample plots can be used to calculate biomass.	Species composition and environmental conditions may affect the biomass estimation.	(e.g. Brown and Lugo 1984; Brown et al. 1989; Lehtonen et al. 2004; Segura and Kanninen 2005)

influence the growth of DBH and tree height, thus affecting the accumulation of tree biomass. Improper use of allometric models may lead to large uncertainties in biomass estimates (Clark and Kellner 2012) and caution should be taken when extrapolating biomass from allometric models.

Regional or national forest inventories have large tree-volume datasets at plot level and forest stand volume datasets at compartment or subcompartment level (Fang et al. 1998). Therefore, the conversion of tree volume to biomass can greatly reduce time and costs if proper methods are used. In general, biomass can be estimated as:

$$\mathrm{AGB(kg/ha)} = \mathrm{volume}\ (\mathrm{m}^3/\mathrm{ha}) \times \mathrm{VEF} \times \mathrm{WD} \times \mathrm{BEF} + \varepsilon \tag{1}$$

where VEF, WD, and BEF represent volume expansion factor, average wood density, and biomass expansion factor, respectively (Brown et al. 1989; Lehtonen et al. 2004; Wang et al. 2011a). Again, it is important to evaluate the accuracy of the biomass conversion from volume before biomass estimation modeling and evaluation.

In summary, the collection of a large number of biomass reference data at the plot level is time-consuming and labor-intensive. It is only suitable for a small area and cannot provide the spatial distribution. However, this kind of data is a prerequisite for developing biomass estimation models. Allometric models are the most common approach to obtain biomass reference data when DBH and/or tree height data at the plot level are available. One critical step is to carefully select suitable allometric models for specific tree species for a study (Chave et al. 2004; Melson et al. 2011).

3. Extraction and selection of potential variables from remote sensing data

Since the first Landsat satellite was launched in the early 1970s, a large number of different sensor data (e.g. Landsat, SPOT, QuickBird, IKONOS, WorldView, ASTER, MODIS, AVHRR, Radarsat, and ALOS PALSAR) have become available, especially in the last two decades. Variables for biomass modeling can be obtained from optical multispectral or hyperspectral images, active sensor radar data, and lidar data. Due to the limited availability of hyperspectral data (e.g. hyperspectral data are mainly airborne and captured in small areas), this section will primarily focus on optical multispectral data, radar, and lidar. Table 2 summarizes variables from remote sensing data that can be used for biomass modeling. It is important to identify the variables that can accurately predict biomass for a specific study.

3.1. Identification of suitable variables from remote sensing data for biomass estimation modeling

3.1.1. Optical sensor data

Different types of optical sensor data, such as Landsat, SPOT, ASTER, CBERS, QuickBird, MODIS, and AVHRR can be used for biomass estimation (Lu 2006; Luther et al. 2006; Fuchs et al. 2009; Lu et al. 2012; Song 2013; Du et al. 2014). Optical sensor data have various spatial, spectral, radiometric, and temporal resolutions. It is important to effectively employ suitable techniques to extract variables for biomass estimation modeling. Many techniques, such as vegetation indices, image transform algorithms (e.g. principal component analysis, PCA; minimum noise fraction transform; and tasseled cap transform, TCT), texture measures, and spectral mixture analysis (SMA), have been used to produce new variables from optical multispectral data (Lu 2006). Because Landsat has a large archive of free available data, it has become the primary data source for biomass estimation (Powell et al. 2010; Zhou et al. 2011; Avitabile et al. 2012; Du et al. 2012). For example, the potential variables from Landsat Thematic Mapper (TM) images include individual spectral bands, vegetation indices, transformed images, textural images, and fractional images (Foody et al. 2003; Zheng et al. 2004; Lu and Batistella 2005; Avitabile et al. 2012; Du et al. 2012; Lu et al. 2012).

Although many vegetation indices have been proposed in previous research (Bannari et al. 1995; McDonald et al. 1998), depending on the complexity of forest stand structure, indices vary in their relationships with biomass (Lu et al. 2004; Lu 2005). Three study areas in the Brazilian Amazon with various biophysical conditions and soil fertilities were selected to examine relationships between biomass and vegetation responses (e.g. spectral bands, vegetation indices, transformed images using PCA and TCT; Lu 2005).

Table 2. Potential variables used in a biomass estimation procedure.

Category	Variables	Description	References
Optical sensor data	Spectral features	Spectral bands, vegetation indices, and transformed images	(e.g. Foody et al. 2003; Zheng et al. 2004)
	Spatial features	Textural images and segments from the spectral bands	(e.g. Lu and Batistella 2005)
	Subpixel features	Fractional features such as green vegetation and NPV by unmixing the multispectral image	(e.g. Lu et al. 2005)
	Combination of spectral and spatial features	Combination of images such as spectral bands, vegetation indices, and textural images as extra bands	(e.g. Lu 2005; Lu et al. 2012)
Active sensor data	Radar	Backscattering coefficients, textural images, interferometry SAR, and Polarimetric SAR interferometry can be used as variables	(e.g. Mitchard et al. 2011; Nafiseh et al. 2011; Saatchi et al. 2011b; Carreiras et al. 2012; Sarker et al. 2012)
	Lidar	Lidar metrics based on statistical measures of point clouds or estimated products (e.g. CHM or individual trees) can be used as variables	(e.g. Popescu et al. 2011; Nelson et al. 2012; Chen 2013; Skowronski et al. 2014)
	Combination of radar and lidar data	For mapping biomass over large areas where field plots are scarce, lidar samples (e.g. strips) can be taken. Lidar-derived biomass calibrated by field data is then used as dependent variable, and radar data are used as independent variables for developing biomass estimation models. Lidar-derived biomass serves as "virtual" field data to create a spatially representative biomass "truth" dataset for mapping biomass wall-to-wall using radar data.	(e.g. Sun et al. 2011; Tsui et al. 2013)
Integration of optical and/ or active sensor data	Fusion of different sensor data e.g. optical and radar data	Fusion of Landsat and radar data to generate an enhanced multispectral image using different techniques such as wavelet-merging.	(e.g. Chen 2013; Montesano et al. 2013)
	Combination of optical and radar or lidar as extra variables	Lidar and/or radar data are combined with optical-sensor multispectral bands as extra variables	(e.g. Nelson et al. 2009; Chen et al. 2012; Selkowitz et al. 2012; Pflugmacher et al. 2014; Vaglio Laurin et al. 2014)

This research found that vegetation indices including near-infrared wavelength have weaker relationships with biomass than those including shortwave infrared wavelength, especially for forest sites with complex stand structures. The results of image transformations such as the first principal component from the PCA showed stronger relationships with biomass than individual spectral bands, somehow independent of different biophysical conditions. However, in a study area with poor soil conditions and relatively simple forest stand structure, near-infrared band or relevant vegetation indices had a strong relationship with biomass.

Many methods are available for extracting textures from remote sensing images, and the gray level co-occurrence matrix (GLCM)-based texture measures may be the most commonly used (Lu and Batistella 2005; Kuplich et al. 2005; Kayitakire et al. 2006; DeGrandi et al. 2009; Sarker et al. 2012). Lu and Batistella (2005) used the GLCM-based texture measures (i.e. mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation) with moving window sizes (e.g. 5 × 5, 7 × 7, 9 × 9, 11 × 11, 15 × 15, 19 × 19, and 25 × 25) and spectral bands (e.g. Landsat TM spectral bands 2, 3, 4, 5, and 7) to examine the relationships between biomass and textural images for secondary forest and mature forest in Rondônia State, Brazil. They found that textural images have stronger relationships with biomass than original spectral bands in mature forest due to complex forest stand structure, but the relationships exist inversely in secondary forest due to its relatively simple stand structure. The combination of spectral response (spectral bands or vegetation indices) and textural images improved biomass estimation performance compared to the use of individual spectral responses or textural images alone (Lu 2005). Spectral responses (e.g. vegetation indices, spectral bands, and the first principal component from image transform) play more important roles in biomass estimation than textural images when the forest stand structure is relatively simple, but textural images are more important than spectral responses in complex forest stand structures (Lu 2005).

In addition to per-pixel-based spectral responses and textural images, sub-pixel-based variables can be used as input variables for biomass estimation. Vegetation spectra can be regarded as a combination of green vegetation, nonphotosynthetic vegetation (NPV), shade, and soil (Roberts et al. 1998). In multispectral images such as Landsat TM, these fractional images can be developed using SMA (Lu et al. 2003, 2005). In practice, NPV is difficult to identify on multispectral images and its spectral signature is confused with soil. Lu et al. (2005) used SMA to extract green vegetation, shade, and soil fraction images from a Landsat TM image to examine the relationships between biomass and fractional images (e.g. green vegetation, shade, and soil fractions) for secondary forest and mature forest in Rondônia State. They found that the use of fractional variables provides better biomass estimation results than individual spectral bands (Lu et al. 2005).

Although optical sensor data have been the major data source for biomass estimation, previous research has indicated that data saturation in optical sensor data, especially in the forest sites with high biomass density, is one of the major problems resulting in poor biomass estimation performance (Lu et al. 2012). In Landsat TM imagery, data saturation may occur when biomass density reaches 100–150 t/ha in moist tropical forest, depending on the complexity of forest stand structures caused by biophysical environments (Foody et al. 2003; Lu et al. 2012). The complex biophysical environments and vegetation characteristics, e.g. phenology, species composition, growth phase, and health – will affect vegetation spectral signatures; thus, biomass estimation models based on optical spectral features cannot be directly transferred to different study areas for biomass mapping (Foody et al. 2003; Lu 2005). Another problem is the impacts of cloud cover on image collection, especially in moist tropical regions (Asner 2001), constraining its application to these regions.

In summary, optical sensors are primary data sources for biomass estimation, and selection of suitable variables is important for developing biomass estimation models, but previous research has not solved the following problems: (1) optical sensor data suffer the saturation problem for forest sites with high biomass density; (2) spectral-based variables are unstable and influenced by external factors such as atmosphere, soil moisture, vegetation phenology, and growth vigor. High-quality optical sensor data are dependent on the weather conditions when satellites pass over; and (3) lack of suitable methods to identify the variables that are most appropriate for biomass estimation modeling. Overall, optical sensor data are suitable for the retrieval of horizontal vegetation structures such as vegetation types and canopy cover, but it is not suitable for estimation of vertical vegetation structures such as canopy height, which is one of critical parameters for biomass estimation. Some optical sensor data such as ALOS/PRISM, Terra ASTER, and SPOT provide a stereo-viewing capability that can be used to develop vegetation canopy height, thus improving biomass estimation performance (St-Onge et al. 2008; Ni et al. 2014).

3.1.2. Radar data

Synthetic aperture radar (SAR) is a promising approach for studying forest biomass because of its ability to penetrate forest canopy to a certain depth, its sensitivity to water content in vegetation, and weather independency (Le Toan et al. 1992, 2011; Dobson et al. 1995; Kasischke et al. 1997; Huang and Chen 2013). The regression technique based on backscattering amplitudes (Santos et al. 2002; Sandberg et al. 2011; Rahman and Sumantyo 2013) and the interferometry technique based on backscattering amplitudes and phases (Balzter et al. 2007) are commonly used in biomass estimation. The wavelength (e.g. X, C, L, P), polarization (e.g. HH, VV, HV, VH), incidence angle, land cover, and terrain properties (e.g. roughness and dielectric constant) are important factors influencing the backscattering coefficient of land cover surfaces. In general, longer wavelength radar has a stronger capability to penetrate forest canopy capturing more vertical structure information. Previous studies have demonstrated that L- and P-band data are more sensitive to biomass estimation than C-band data (Saatchi and Moghaddam 2000; Sun et al. 2002; Nafiseh et al. 2011). This is because short-wavelength X- or C-band interacts primarily with canopy elements and is appropriate for low biomass. In contrast, long-wavelength L- or P-band can interact with branch, trunk, and ground elements under the forest canopy, and is suitable for relatively high biomass density (Patenaude et al. 2005). Most radar-based biomass estimation studies use L-band SAR data, especially the ALOS PALSAR L-band data (Mitchard et al. 2011; Carreiras et al. 2012; Rahman and Sumantyo 2013). The SAR C-band data have not been extensively used because of the C-band's inability to capture forest biomass features (Le Toan et al. 1992; Lu 2006).

In a study area with complex forest stand structure, such as mature forest, data saturation in radar data is also a problem when backscattering values are used for biomass estimation (Lucas et al. 2007; Solberg et al. 2010). Alternatively, interferometry SAR (InSAR) can reduce this problem. InSAR, a technique in which the coherence of data is collected over a short time increment by two identical instruments (Balzter 2001;

Kellndorfer et al. 2004; Nafiseh et al. 2011), can increase the saturation range to a certain degree and thus improve the height-based biomass estimation (Saatchi et al. 2011a). A representative example is the interferometric water cloud model (Attema and Ulaby 1978; Askne and Santoro 2005), in which the total coherence of a forest is separated into the coherence sum of ground and canopy. The forest transmissivity is caused by radiation moving back and forth and penetrating gaps in the canopy (Askne and Santoro 2005). Previous studies have shown that the combination of InSAR and backscattering values is feasible for biomass or volume estimation, and the L-band saturation point increases to 200 t/ha (e.g. Saatchi et al. 2011a). Because of the high correlation between vegetation canopy height and biomass, InSAR capability in providing vegetation height feature provides promising tool for large-scale biomass estimation, this is especially important for tropical and subtropical regions because of cloud-cover problem (Kellndorfer et al. 2004; Solberg et al. 2014). However, the InSAR estimation accuracy is highly related to site conditions such as wind speed, moisture, and temperature (Pulliainen et al. 2003).

The Polarimetric SAR interferometry (Pol-InSAR), a combined polarization and interferometry, is a recently developed radar remote sensing technology. Pol-InSAR produces more sensitive characteristics in spatiality as well as shape and direction than interferometry or polarimetry for forest diffusions. A common biomass estimation procedure is primarily to estimate forest height using coherence information (Cloude and Papathanassiou 2003) and then convert it to biomass through correlation analysis (Garestier and Le Toan 2010). Polarization coherence tomography (PCT) provides a stereo stand scene and has increasingly generated attention in biomass estimation (Cloude 2006). Examination in the effects of choice of polarization channels and tree height estimation error on biomass estimation indicated that the characteristic parameters extracted from the relative reflectance functions based on PCT technology are sensitive to the biomass density (Luo et al. 2011). The use of relative reflectivity function results can improve biomass estimation accuracy. In addition to the above-mentioned techniques, the use of backscatter ratios (Foody et al. 1997) and radar image texture measures (Kuplich et al. 2005; DeGrandi et al. 2009) has the potential to improve biomass estimation performance.

In summary, it is difficult to use radar data for distinguishing vegetation types (Li et al. 2012b) because radar data reflect the roughness of land cover surfaces instead of the difference between the vegetation types, thus resulting in difficulty of biomass estimation. The speckle in radar data is another problem affecting its applications. Properly employing filtering methods to reduce noise and outliers in InSAR data is needed to improve the vegetation height estimation performance (Kellndorfer et al. 2004). Because of the stereo-viewing capability of InSAR data, biomass estimation using InSAR has attracted increased interests (Solberg et al. 2014). The planned European Space Agency P-band SAR data may provide a new opportunity for biomass estimation at regional and even global scales (Hélière et al. 2013). In addition, if the new satellite mission, similar to the canceled DESDynl mission that would have provided L-band Pol-SAR and multibeam lidar data, can be launched in the future, these data may improve biomass estimation at regional and global scales (Hall et al. 2011).

3.1.3. Lidar Data

A wide range of lidar metrics has been used for biomass estimation in the literature (Chen 2013; Maltamo et al. 2014). Extraction of lidar metrics depends on the laser return signal (discrete-return vs. waveform), scanning pattern (scanning or profiling), and footprint size (small vs. large). Since airborne discrete-return small-footprint lidar systems are most widely used for biomass estimation, we will first discuss the metrics from these systems before discussing the metrics from satellite lidar and application to large-scale biomass mapping.

In airborne lidar data, metrics can be extracted on the basis of either individual trees or areas (Chen 2013). The individual tree-based approach requires identifying tree features such as treetop (e.g. Popescu et al. 2002; Chen et al. 2006), crown radius (e.g. Popescu et al. 2003), or crown boundary (e.g. Chen et al. 2006; Zhen et al. 2014). Mapping individual trees requires high lidar data point density (generally 10 points per m^2 or higher) and is challenging in closed and multilayer canopies such as tropical rainforests. The area-based approach, which generates statistical metrics from laser returns or canopy height model (CHM) constructed from the returns, has been widely used (e.g. Lim et al. 2003; Chen et al. 2012; Lu et al. 2012). The area-based lidar metrics can be distinguished based on whether they are characterizing horizontal, vertical, or both horizontal and vertical canopy structures.

A horizontal lidar metric characterizes canopy structure in the horizontal dimension. The primary variable for horizontal canopy structure is canopy cover or crown cover, the proportion of ground space covered by the vertical projection of tree crowns. Different definitions of canopy cover exist depending on whether or not the gaps within a crown are considered part of the canopy. Lidar can be used to generate both types of canopy cover. Gaps are not considered canopy if cover is calculated as the proportion of canopy returns among all laser returns. However, if the CHM is generated first, canopy cover can be calculated as the proportion of CHM cells above a height threshold (e.g. 1 m). In the latter case, the crown surface is considered to be continuous, regardless of the possible vertical gaps between leaves, branches, and stems.

A vertical lidar metric characterizes canopy structure only in the vertical dimension. Vertical lidar metrics are generated either from canopy returns (resulting from point cloud) or canopy cells (from CHM), defined as laser returns or CHM cells of a certain height (e.g. 1 m) above the terrain in forests. Using canopy returns or cells, height statistics can be generated. Typically, the following statistics are calculated: mean, standard deviation, percentile heights, and relative frequencies of points at predefined height intervals.

The area-based lidar metrics that integrate canopy structure information in the horizontal and vertical dimensions are called three-dimensional (3D) lidar metrics in this study. The 3D lidar metrics are commonly generated using all returns and CHM cells within an area (including open ground). Similar statistics are generated for the 3D and vertical lidar metrics. On an area basis, the use of 3D lidar metrics for biomass prediction is well justified because they incorporate canopy cover and tree height information. To illustrate this difference in a hypothetical example: say two forest plots of identical size (e.g. circular plots with a 20-m radius). Plot A has one tree and plot B has two trees. All trees are in identical size and shape. Lidar data for the two plots are then acquired with the same sensor and configuration (flight speed, flight height, point density, etc.). This will result in identical point cloud distribution from each tree. Next, when generating a mean height statistic from laser returns for each plot to predict biomass density, if the statistic is generated from canopy returns only, the mean heights from the two plots are identical; in contrast, if the statistic is generated from all returns, the mean height from plot A will be half the mean height from plot B. Figure 1 shows a real example of two

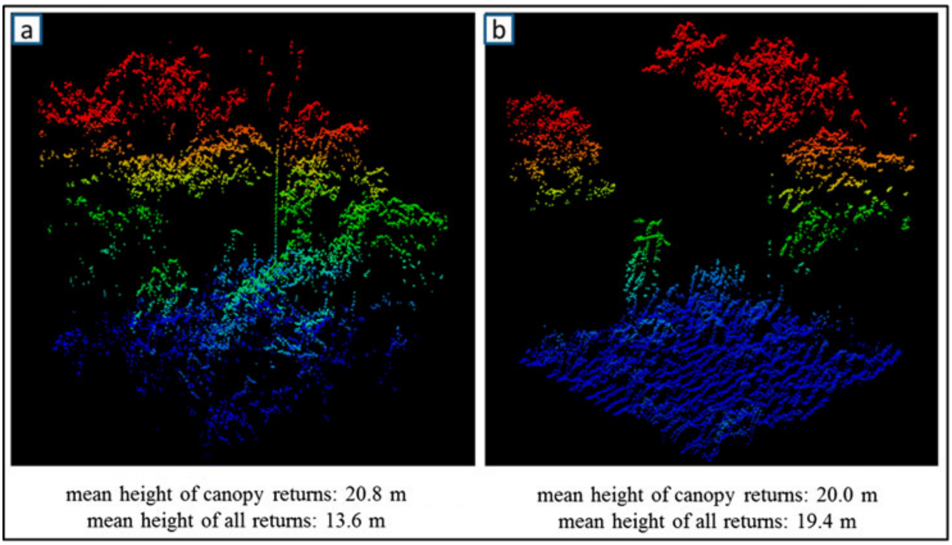

Figure 1. Importance of using 3D area-based lidar metrics that characterize both canopy cover and height information for biomass prediction.

40 × 40 m plots from tropical forests. The plot in Figure 1a has denser canopy and thus more biomass. An ordinal relationship is reflected in the mean height of all laser returns. However, if the mean height of canopy returns is calculated, the plot in Figure 1b has a slightly higher value than the plot in Figure 1a. This is because the mean height of canopy returns does not include horizontal information and thus cannot accurately predict biomass.

Studies that have used airborne waveform (Lefsky et al. 2002) or discrete-return (Asner et al. 2009, 2012; Asner and Mascaro 2014) lidar data to develop general biomass models across broad geographic extents suggested that mean height is a useful predictor for biomass. If the mean is generated from *all* CHM cells, the multiplication of mean height by the number of CHM cells is equivalent to the geometric volume of the total canopy (Chen et al. 2007). In such cases, mean height has a biological interpretation of characterizing 3D canopy volume over an area. Chen et al. (2007) found that a univariate model based on canopy geometric volume can outperform more complex models with lidar metrics selected by stepwise regression for estimating stem volume, a key variable related to stem biomass and total AGB. Current research indicates that volume-related 3D lidar metrics should be at the top of the list of lidar metrics to be tested for developing biomass estimation models, especially when such models are used to extrapolate biomass over large areas (model generality and thus parsimony is also critical).

Another useful lidar metric for biomass estimation is the quadratic mean height (QMH), which more heavily weights larger height values (Lefsky et al. 1999). Since most allometric models have a power relationship with DBH which is closely related to height, it is expected that tree biomass is nonlinearly related to tree height. In particular, taller trees have disproportionally a larger biomass (Brown et al. 2005). QMH incorporates these nonlinear relationships and was among the best biomass predictors in multiple studies (e.g. Lefsky et al. 1999; Chen et al. 2012; Lu et al. 2012).

Almost all lidar metrics can be generated from either point cloud or CHM. The 3D distribution of a tree's laser point cloud could vary depending on such parameters as point density, scan angle, and footprint size, which are related to specific sensor configuration and flight conditions (Næsset 2009). This can result in differences in the derived lidar metrics even for trees of the same type, size, and shape. If lidar metrics are derived from a CHM constructed from laser points, such a variation might be able to be reduced, even though it might introduce errors if inappropriate mathematical models (e.g. inverse distance weighting) are used for CHM construction. Additionally, CHM is produced using only the surface returns, ignoring laser returns from lower branches and stems of canopy. It is not completely clear how much impact it has on biomass estimation when the structural information inside canopy is lost. Lu et al. (2012) found that negligible differences exist in terms of biomass estimation performance when height metrics are generated from all returns, first returns only, last returns only, or CHM cells.

Previous lidar-based biomass estimation studies focused on small areas because of data availability constraints (e.g. Koch 2010; Leeuwen and Nieuwenhuis 2010; Gleason and Im 2011). For regional- to global-scale applications, spaceborne lidar – ICESat GLAS – was available between 2003 and 2009, and the use of GLAS data for biomass estimation has been shown valuable (Lefsky et al. 2005; Simard et al. 2008; Nelson 2010; Miller et al. 2011; Popescu et al. 2011; García et al. 2012). However, it is impossible to use GLAS for direct wall-to-wall biomass mapping due to the spatially discrete characteristics. On the other hand, given its global-scale sampling, GLAS has the potential for large-area biomass mapping when combined with satellite imagery (e.g. Saatchi et al. 2011b).

GLAS' most important metric for biomass estimation is likely the waveform extent – the distance between waveform signal start and signal end (Nelson et al. 2009, García et al. 2012) because the waveform extent is directly related to vegetation height in flat terrain. However, the waveform extent is broadened in sloped areas and exacerbated by its large footprint (approximately a 60-m diameter; Chen 2010a, 2010b). A simple remedy is to incorporate a terrain steepness index into a regression model (García et al. 2012). Another strategy is to directly estimate canopy height by extraction of ground elevation (Chen 2010a), and then use the vegetation height to estimate biomass or carbon (e.g. Saatchi et al. 2011b). Hopefully, the next generation of satellite lidar – ICESat-2 – will have a smaller footprint and thus will have fewer problems (Chen 2013).

Other GLAS waveform metrics used for biomass estimation include the slope of the leading extent (e.g. Boudreau et al. 2008; Hansen et al. 2013) and various waveform statistics such as maximum, variance, and skewness (e.g. Duncanson et al. 2010). When statistics are extracted from GLAS waveforms, they are not conceptually equivalent to statistics extracted from vertical profiles of airborne discrete-return point clouds. This is because the former has energy (or intensity) information in the vertical profile, and the latter usually does not. GLAS waveform metrics can also be extracted by conducting Gaussian decomposition of the waveforms (e.g. Liu and Chen 2013) and analyzing the relationships between Gaussian peaks, especially relative to the signal start and end (e.g. Ballhorn et al. 2011).

In summary, the most useful lidar predictors for biomass are those that can characterize 3D (in other words, both horizontal and vertical) canopy structure. If lidar metrics are generated on the basis of areas (e.g. plots or cells) from discrete-return lidar point cloud or CHM, users could start their biomass model fitting exercise by using either (1) two lidar metrics, one for vegetation height and the other for vegetation cover, or

(2) one 3D metric that relates to both horizontal and vertical canopy structures, such as the mean height of all laser points or CHM cells, including those from open space. Compared to the automatic selection of lidar metrics using procedures such as stepwise regression, such a strategy could lead to a more ecologically meaningful model that has better generality. This also suggests that, if a study area is fully covered by trees (such as close canopy in the tropics), whether the lidar metrics are generated by including points or CHM cells from open space is not a big issue because of the little variation of canopy cover. By the same token, for satellite lidar such as GLAS waveforms, simply using waveform extent is insufficient for predicting biomass because it only characterizes canopy height, the vertical dimensional information. Any innovation in deriving canopy cover from GLAS waveforms or developing lidar metrics that capture horizontal structure information will be expected to improve biomass prediction.

3.2. Integration of multisource data

Optical sensor, radar, and lidar have their own positive and negative characteristics and proper integration of them can improve biomass estimation accuracy (Walker et al. 2007; Kellndorfer et al. 2010). Topography and soil conditions also affect vegetation growth, thus influencing stand structure and biomass accumulation. Effective integration of multisource data is necessary to improve biomass estimation (Li et al. 2012a). In general, two techniques can be used to integrate different source data: (1) data fusion using certain techniques such as wavelet merging, PCA, and partial least squares (PLS) regression; and (2) combination of different source data as extra bands (Pohl and van Genderen 1998; Li 2010; Zhang 2010). A combination of different sensor data, such as GLAS and TM, ALOS PALSAR and lidar, GLAS and MODIS, and MODIS and MISR, has been explored for improving biomass estimation (Boudreau et al. 2008; St-Onge et al. 2008; Duncanson et al. 2010; Koch 2010; Chopping et al. 2011; Sun et al. 2011; Selkowitz et al. 2012; Montesano et al. 2013).

A large number of data fusion techniques have been developed, as reviewed by Pohl and van Genderen (1998), Li (2010), Zhang (2010), and Khaleghi et al. (2013). Most data fusion techniques such as sharpening-based approaches are based on enhancing spatial features through incorporating a high spatial resolution image into a multispectral image (Pohl and van Genderen 1998; Ehlers et al. 2010). The most common data source is from optical sensor data such as Landsat ETM+, SPOT, QuickBird, and IKONOS that have both multispectral bands and one panchromatic band in the same sensor data or between Landsat TM multispectral and SPOT panchromatic data. Although fusion of different resolution optical sensor data benefits visual interpretation through improved spatial resolution, limited new information is gained because the panchromatic band has similar spectral features with the visible bands in multispectral data. Improved spatial resolution is helpful for land covers such as urban landscapes with small patch sizes; however, this type of data fusion most likely does not enhance biomass estimation because forested areas have increased spectral signature heterogeneity (Lu et al. 2008).

Radar data characteristics differ from optical sensor data. Optical sensor data mainly represent land cover surface features, and radar data, especially with long wavelengths, can penetrate forest canopies to a certain depth capturing information about stems, branches, and understories, thus providing more vertical stand structure information for vegetation types. If both optical and radar data can be properly integrated into a new dataset, more new information on forest structure features can be included in the fused image (Lu et al. 2011). However, currently most data fusion techniques cannot effectively incorporate radar features into multispectral images to produce enhanced spectral features of vegetation, and thus cannot improve vegetation classification or biomass estimation (Lu et al. 2011). New fusion techniques to effectively integrate optical and radar data are needed.

Lidar data are powerful for estimating canopy structure but has limited spectral information because laser point intensity is from one wavelength. Optical sensors provide rich spectral information but the spectral reflectance does not have a strong relationship with canopy structure. Thus, lidar and optical sensor data are highly complementary. However, earlier studies that integrated lidar with optical data have reported mixed results. Some studies have shown that the addition of optical to lidar data had only slight or no improvements in biomass estimation (e.g. Hyde et al. 2006; Clark et al. 2011; Latifi et al. 2012). Conversely, Anderson et al. (2008) and Vaglio Laurin et al. (2014) found that integration of lidar and hyperspectral data improved biomass estimation significantly in a temperate mixed forest in eastern USA and a tropical forest in Africa. Further research is necessary to explain the discrepancies in these studies.

In addition to the direct use of continuous spectral values, another strategy to fuse optical data is by mapping vegetation types from optical data and incorporating these vegetation types as categorical variables in biomass modeling. The premise is that allometric models are species dependent at individual tree level and thus biomass models based on remote sensing data (usually developed at the plot level) should be dependent on vegetation types as well. Chen et al. (2012) adopted this strategy and used a mixed-effects model to combine aerial photography and lidar data for biomass mapping in California. The results indicated that the vegetation types can significantly improve biomass model performance. In addition to wall-to-wall data combination methods, an alternative is to use one sensor-derived result as a base map and another sensor-derived biomass data as a sample to extrapolate the results into a large area (Hese et al. 2005; Sun et al. 2011). The base map is usually developed from optical sensor data such as Landsat images, and site-level biomass data are generally derived from lidar.

In theory, different source data such as optical, radar/lidar, and ancillary can be used in a biomass estimation procedure. Most previous biomass estimation research is based on single remote sensing dataset such as Landsat TM, ALOS PALSAR, and lidar (Lu et al. 2012; Chen 2013). Because of the capability of lidar to provide tree or forest canopy height information, use of lidar data leads to better biomass estimation performance than individual optical or radar data (Clark et al. 2011). Bergen et al. (2009) provided an overview of a lidar and radar spaceborne mission for 3D vegetation structure mapping. Barbosa et al. (2014) examined the integration of Landsat and digital elevation model (DEM) data for biomass estimation in Brazil's Atlantic Forest and indicated an improvement in biomass estimation over steep slopes. In reality, combining different source data such as spectral bands, vegetation indices, textural images, lidar metrics, and DEM data have not been extensively used for biomass estimation modeling. The major reasons may be (1) the high correlation between input variables or weak relationships between input variables and biomass and (2) difficulty in using suitable algorithms to establish biomass estimation models that use multisource data.

3.3. Identification of optimal variables for biomass estimation modeling

As discussed previously, many potential variables are available for use in biomass estimation modeling. However, not all variables are useful in modeling due to high inter-variable correlation or weak relationships with biomass (Lu 2006). Previous research mainly used spectral responses (e.g. spectral bands, vegetation indices) or textural images from optical sensor data, radar backscattering coefficients, and lidar metrics. Rarely has research examined methods to identify optimal variables based on remote sensing data. Although Landsat TM, ALOS PALSAR, and lidar are common data sources for biomass estimation, how to identify the optimal variables for biomass estimation in a specific study area is still poorly understood due to the different features of sensor data and the complex biophysical environments of study areas. In particular, how to select the optimal variables from multisource data such as Landsat TM and ALOS PALSAR and ancillary have not been explored. It is necessary to develop methods that can automatically identify optimal variables needed for biomass estimation modeling in a specific study area.

Different methods can be used to identify suitable variables for biomass modeling. The methods may include (1) identifying variables based on expert knowledge and experience in a specific study area; (2) selecting variables that have strong correlations with biomass and weak correlations to each other; (3) using stepwise regression analysis to automatically identify variables used in regression models; (4) stacking extracted images into one file and conducting PCA or PLS to extract new variables from the stacked image, then using a limited number of components as input variables for biomass estimation modeling; and (5) when the number of independent variables is larger than the number of sample plots, the random forest algorithm can be used to rank the importance of variables for biomass estimation in a given random forest model. Based on the analysis of ranked importance of variables, other algorithms can be used to create biomass estimation models. On the other hand, most biomass estimation models are only suitable for the specific study areas where the models are developed; and they are not transferable due to the effects of biophysical environments on remote sensing data. More research is needed to develop reliable and stable variables to create transferable biomass estimation models.

4. Identification of suitable algorithms for biomass estimation modeling

Many techniques have been developed for biomass estimation and they can be grouped into two broad categories: parametric and nonparametric algorithms. Parametric algorithms assume that the relationships between dependent (i.e. biomass) and independent (derived from remote sensing data) variables have explicit model structures that can be specified *a priori* by parameters. Examples are simple or multiple linear regression models. However, biomass is usually nonlinearly related to remote sensing variables, and therefore, nonlinear models such as power models (Næsset et al. 2011; Chen et al. 2012) and logistic regression model (McRoberts et al. 2013) were often used to estimate biomass with lidar-derived height. In practice, the relationships between biomass and remote sensing variables are often too complex to be captured by parametric algorithms. Conversely, nonparametric algorithms do not explicitly predefine the model structure, and instead, determine the model structure in a data-driven manner. Due to the flexibility of nonparametric algorithms, they are more adept in creating complicated nonlinear biomass models. Common nonparametric algorithms include K-nearest neighbor (K-NN), artificial neural network (ANN), random forest, support vector machine (SVM), and Maximum Entropy (MaxEnt). These methods are described in the previous literature (e.g. Moisen and Frescino 2002; Lu 2006; Powell et al. 2010; Saatchi et al. 2011b; Song 2013). The following subsections provide a brief introduction and comparison of the algorithms to better understand their strengths and restrictions.

4.1. Parametric-based algorithms

Regression-based models are the most common biomass estimation approach when using remote sensing data (Fuchs et al. 2009; Zhao et al. 2009; Tian et al. 2012; Lu et al. 2012; Kumar et al. 2013; Næsset et al. 2013b; Skowronski et al. 2014). In general, the independent variables can be spectral bands, vegetation indices, and textural images. Linear or nonlinear regression analysis may be used to establish biomass estimation models. The key is to identify suitable remote sensing variables that have strong relationships with biomass but weak relationships between the selected remote sensing variables themselves (Lu et al. 2012). Methods such as correlation coefficient analysis and stepwise regression analysis can be used to determine these variables (Lu 2005). Another group of parametric-based methods is spatial co-simulation algorithms where spatial interpolation of forest biomass/carbon is conducted based on sample plot data and remotely sensed images using conditional simulation such as sequential Gaussian simulation (Wang et al. 2009, 2011a; Zhang et al. 2013). These co-simulation algorithms are based on spatial autocorrelation of forest biomass/carbon and its spatial cross-correlation with spectral variables from remotely sensed images. It is assumed that forest biomass/carbon and spectral variables have a normal distribution. For interpolation at each location, a conditional distribution of forest biomass/carbon can be derived by calculating a conditional mean and variance. The conditional mean can be obtained using an unbiased cokriging estimator by weighting neighboring sample plot data, remotely sensed data, and neighboring estimates (if available). The weights vary depending on the spatial configuration of the data and spatial auto- and cross-correlation functions of the variables; generally, the closer the data location, the higher the weight. Moreover, the conditional variance can be calculated based on spatial configuration of the data and spatial auto- and cross-correlation functions of the variables. From the obtained conditional distribution, a realization of forest biomass/carbon can be generated by randomly drawing a value, essentially conducting a spatial interpolation. The above process can be repeated many times by randomly setting up different paths to determine the pixel estimation within a study area, resulting in more than one realization for each location. From the realizations, a sample mean and a sample variance are estimated and used as the estimate and measure of uncertainty of a location's forest biomass/carbon.

Fleming (2011) compared a spatial co-simulation with regression modeling for aboveground forest carbon mapping by combining Landsat TM images and national forest inventory sample plot data for southern Illinois dominated by natural deciduous forests and found that both methods produced similar results. However, the regression modeling resulted in a smoother spatial distribution of forest carbon stock with illogically negative values at some locations and the spatial co-simulation algorithm was computationally intensive.

4.2. Nonparametric-based algorithms

Although the regression-based model is commonly used for forest biomass estimation, the estimation accuracy may be poor if an insufficient number of sample plots are used or there is a weak linear relationship between variables and biomass (Lu 2006). An alternative approach is to use nonparametric-based modeling approaches. Many studies have explored the use of nonparametric-based models in estimation of forest attributes with remote sensing data (Saatchi et al. 2009; Breidenbach et al. 2012; McRoberts et al. 2012; Mutanga et al. 2012; Jung et al. 2013; Mitchard et al. 2013). Table 3 summarizes major nonparametric algorithms, including K-NN, ANN, regression tree, random forest, SVM, and MaxEnt. The subsequent text in this section provides a brief introduction of each algorithm.

The K-NN approach is a relatively simple algorithm and has been extensively used for land cover classification (McRoberts and Tomppo 2007; Latifi et al. 2010; Li et al. 2011) and estimation of forest stand parameters (Fazakas et al. 1999; Finley and McRoberts 2008; Fuchs et al. 2009; Breidenbach et al. 2010; Zhou et al. 2011; McRoberts et al. 2012). Each location's estimate is predicted as a weighted average value with k spectrally nearest neighbors using a weighting method (Tomppo et al. 2009). In this approach, the choice of the k value, type of distance measure including Euclidean distance and Mahalanobis distance, and weighed function are critical factors influencing the estimation accuracy (Chirici et al. 2008; Tomppo et al. 2008). An advantage of the K-NN method is that it avoids the unbalanced samples problem. Estimation bias can be generated from increasing the k value and a misregistration between plot and single pixel location. Detailed descriptions of the K-NN approach can be found in previous publications (Franco-Lopez et al. 2001; McRoberts et al. 2007; Tomppo et al. 2008; McRoberts 2012).

ANN has long been regarded as an important nonparametric algorithm for land cover classification and forest parameter estimation (Foody et al. 2001; Ingram et al. 2005; Xie et al. 2009; Lu et al. 2011). In contrast to conventional parametric approaches, ANN provides a more robust solution for complicated and nonlinear problems due to its universal approximation properties (Foody et al. 2001). The network commonly consists of one input layer, one or more hidden layers, and one output layer. ANN does not require the assumption that data have normal distribution and linear relationships between biomass and independent variables. Therefore, this algorithm can deal with different data through approximation using various complex mathematical functions, with independent variables from different data sources such as remote sensing and ancillary data. However, because ANN is a black-box model, the biomass estimation does not easily reveal the internal mechanism from the relationships between dependent variable and the selected independent variables. In ANN, a relatively large number of sample plots for iterating training and learning procedures are needed. If the parameters used in an ANN algorithm are not properly optimized, estimation accuracy may be poor. A detailed overview of ANN approach is provided in Mas and Flores (2008).

The regression tree model is another commonly used approach for biomass estimation (Moisen and Frescino 2002; Saatchi et al. 2007; Blackard et al. 2008). The tree is composed of a root node, a set of internal nodes, and a set of terminal nodes. Through a recursive partitioning algorithm for decreasing within-class entropy, input data are constantly stratified according to homogeneity. The value of the internal node depends on the predicted mean value of each terminal node belonging to a higher-level node. Low biomass values are generally overpredicted and high biomass values are underpredicted. Based on the regression tree theory, Carreiras et al. (2012) combined the strengths of bagging and boosting to produce the bagging stochastic gradient boosting (BagSGB) algorithm to estimate biomass using ALOS PALSAR data.

Table 3. A summary of major nonparametric algorithms for biomass estimation modeling.

Algorithm	Description	Advantages	Disadvantage	References
K-nearest neighbor	The value of a target variable at a certain location is predicted as a weighted average with *k* neighbors by the inverse distance weighting method.	Various features can be used as predictor variables.	Selection of proper predictor variables is time-consuming.	(e.g. Chirici et al. 2008; Zhou et al. 2011; McRoberts 2012)
Artificial neural network	A black-box model in which output variables are connected with combinations of the input variables through network training.	Highly efficient and accurate approximation of complex nonlinear function and generalization.	Aptness of plunging into a local minimum and poor explainability to the model.	(e.g. Foody et al. 2001)
Regression tree	A tree-based model in which data are stratified into homogeneous subsets by decreasing the within-class entropy. The initial strata representatives can be identified without *a priori*.	Variable selection and interactively modeling, especially in providing easily understandable output.	High variance, implying that minor changes of data may result in a completely different split.	(e.g. Hese et al. 2005; Saatchi et al. 2007)
Random forest	A tree-based model in which a large number of regression trees are constructed by selecting random bootstrap samples from the discrete or continuous dataset. The output values are determined by averaging the outputs from all regression trees.	Less sensitive to noise in the training samples, thus more accurate models tend to be obtained.	Overfitting for a big noise dataset.	(e.g. Baccini et al. 2008; Avitabile et al. 2012; Mascaro et al. 2014; Tanase et al. 2014)
Support vector machine	Mapping the input data into a higher-dimensional kernel-induced feature	Generalization ability can be optimized using the principle of	Difficult to develop a favorable model when a large	(e.g. Marabel and Alvarez-Taboada 2013)

Table 3. (*Continued*)

Algorithm	Description	Advantages	Disadvantage	References
	space, turning the problem to a linear manner. A quadratic optimization problem can be solved.	structural risk minimization.	number of training samples are used.	
Maximum Entropy (MaxEnt)	A black-box method in which the target probability distribution can be estimated according to the probability distribution of maximum entropy with continuous or categorical environmental variables.	Effective despite small sample data.	Prior information is necessary.	(e.g. Saatchi et al. 2011b; Harris et al. 2012)

Random forest, a nonparametric ensemble modeling approach robust to overfitting, constructs numerous small regression trees contributing to predictions (Breiman 2001). These small regression trees are unpruned, based on another random sample subset from the training dataset each tree node is split as the trees grow. The distance between the target and reference units is calculated as one minus the proportion of terminal nodes from all regression trees where the target observation is in the same terminal node as the specific reference unit (Breiman 2001). In addition to the advantage of using discrete or continuous datasets, random forest can also deal with noise and large datasets (Ismail et al. 2010; Vincenzi et al. 2011). Because random forest is insensitive to noisy data in training datasets, the random forest approach provides better estimation performance than traditional regression tree approaches. The random forest algorithm is now widely used for biomass estimation (Baccini et al. 2008; Eskelson et al. 2009; Vauhkonen et al. 2010; Avitabile et al. 2012; Hudak et al. 2012; Pflugmacher et al. 2014; Tanase et al. 2014).

SVM is a statistical learning algorithm (Vapnik et al. 1997) which is an important method to estimate forest biophysical parameters using remote sensing data (Mountrakis et al. 2011; Marabel and Alvarez-Taboada 2013). An advantage of this approach is its ability to use small training sample data to produce relatively higher classification or estimation accuracy than other approaches. Mountrakis et al. (2011) provides a detailed overview of the SVM approach used in remote sensing fields. In SVM, the support vector regression (SVR) transforms the input data into a high-dimensional feature space using a nonlinear kernel function to minimize training error and the complexity of the model (Axelsson et al. 2013). The key to this approach is identifying suitable metaparameters: the kernel parameter, precision parameter, and penalty parameter (Cherkassky and Ma 2004). SVM employs the principle of structural risk minimization to simultaneously optimize performance and generalization to effectively alleviate the overfitting problem.

Compared to the regression tree, ANN and K-NN, SVM is better at solving small-sample, nonlinear, and high-dimensional problems.

The MaxEnt approach is a general-purpose machine-learning method for predicting or inferring target probability distribution from incomplete information (Phillips and Dudík 2008). Statistical features can be obtained without making any assumptions about the given input. Because of the complexity of biophysical environments and the cost of field surveys, the number of biomass sample plots is limited, and often insufficient for biomass estimation modeling. Therefore, it is important to have a modeling technique that does not require a large number of sample plots (Graham et al. 2004). The primary difference between MaxEnt and other algorithms such as boosted decision trees (Leathwick et al. 2006) and generalized linear models (GLM) (Ostendorf et al. 2004; Schwarz and Zimmermann 2005) is that MaxEnt can be used with the presence-only data. The MaxEnt approach requires two types of input variables: sample points data and feature variables such as original image, vegetation index, elevation, climate, soil, and other variables beneficial to biomass inversion. The target probability distribution can be obtained by finding the probability distribution of MaxEnt. An overfitting problem exists when the constraints are based on empirical averages of sample data, especially when a very large number of environmental variables are used (Phillips et al. 2006). The MaxEnt approach has recently been used for biomass estimation in large areas of tropical regions (Saatchi et al. 2011b; Harris et al. 2012).

Nonparametric data-driven algorithms (often called machine-learning algorithms) have become popular in biomass modeling. However, the model structure derived from these algorithms is often difficult to interpret (e.g. ANN). In other words, despite these algorithms possibly excel in 'mapping' biomass, they do not help the 'understanding' of biomass estimation. A lack of model structure will lower confidence when these models are applied to other areas and can affect model generality. Our recommendation is that if large representative field datasets exist for calibration, nonparametric models should be explored. However, such methods must be used with caution when field data are limited and the law of parsimony should always be followed.

4.3. Selection of suitable algorithms for biomass estimation modeling

As discussed in above subsections, each algorithm has its own strengths and requirements for data inputs. For example, traditional regression analysis requires an explicit model structure specified *a priori* by parameters. The input variables are mainly from remote sensing data; however, effective use of multisource data is necessary for improving biomass estimation performance. This requires that the selected algorithm be able to effectively handle the different characteristics of multisource data. Nonparametric algorithms such as random forest, K-NN, and ANN determine the model structure from the data in real time, and they are widely used for biomass estimation with multisource data. Because of the difficulty in identifying an optimal algorithm for biomass estimation, much research has been conducted for comparative analysis of different algorithms such as regression tree, random forest, and ANN to identify the most appropriate algorithm for establishing biomass estimation models (Moisen and Frescino 2002; Labrecque et al. 2006; Baccini et al. 2008; Goetz et al. 2009; Latifi et al. 2010). Previous research indicates that a nonparametric algorithm such as K-NN can provide better estimation results than multivariate regression (Tian et al. 2012). When the nonparametric algorithms are used for biomass estimation modeling, the key is to identify the optimal parameters.

Previous research had insufficient sample plots to develop robust biomass estimation models and evaluate the estimates. It is important to explore how different algorithms affect the biomass estimation performance.

5. Uncertainty analysis of biomass/carbon model predictions

The importance of implementing uncertainty analysis for remote sensing-derived forest biomass/carbon estimates has been recognized and much research has been conducted in the past decade (Gahegan and Ehlers 2000; Crosetto et al. 2001; Wang et al. 2009; Gonzalez et al. 2010; Olofsson et al. 2013; Rocchini et al. 2013; Montesano et al. 2014; Zhang et al. 2014). Accurately estimating and mapping forest biomass/carbon is critical to formulating national and global strategies to mitigate carbon concentration in the atmosphere and consequently global climate change (Chen et al. 2000). Unfortunately, forest biomass/carbon estimates are associated with various errors and uncertainties. Many studies have suggested that the relative errors of the estimates can vary from 5% to 30%, depending on the forest ecosystems, topographic characteristics, remotely sensed data and their spatial resolutions, methods used, *etc.* (Chen et al. 2000; Heath and Smith 2000; Keller et al. 2001; Chave et al. 2004; Saatchi et al. 2007; Nabuurs et al. 2008; Asner et al. 2009, 2011; Mascaro et al. 2011). For national and global strategies for forest management and planning scenarios, the level of required accuracy depends on the scales of the management decision. Generally, at regional scales an accuracy of higher than 90% is preferable while at national and global scales an accuracy of 80% may be appropriate.

Traditionally, the accuracy of forest biomass/carbon estimates is assessed by calculating the root mean square error (RMSE) and the Pearson's correlation coefficient of the estimated and observed values (Congalton 2001; Congalton and Green 2009; Wang and Gertner 2013). This method directly accounts for the quality of estimates. However, it lacks the ability to reveal spatial variability in estimation accuracy. Overall, the accuracy assessment and uncertainty analysis of remote sensing-derived forest biomass/carbon estimates have three challenges: (1) obtain field observations from sample plots, (2) find the major factors influencing biomass estimation performance, and (3) account for spatial variability in the estimation accuracy.

Currently, there are three widely used methods on how the quality of forest biomass/carbon estimates is assessed using field observations. In the first method, a set of sample plots is selected using the widely used sampling design strategies, including random sampling, systematic sampling, and stratified random sampling. The obtained sample plots are then divided into two subsets with random selection: one subset is used for model development and the other for model calibration. This method can reduce the cost of data collection; however, both subsets are produced from the same sampling design, which may lead to an overestimation of accuracy. The second widely used method is cross-validation. In this method, a set of sample plots is selected using one of the aforementioned sampling design methods and then one plot is removed while the remaining plots are used to develop a forest biomass/carbon estimation model. Compared with the first method, this method has similar advantage and at the same time improves the reliability of accuracy assessment. However, this method also ignores the independence requirement for accuracy assessment. The third method is the use of an independent dataset, a set of sample plots independently collected through a sampling design. Obviously, this method is theoretically reliable, but increases the costs.

Forest biomass/carbon estimates have many sources of uncertainty that can be accumulated and propagated through a modeling or mapping system. Quantifying and understanding uncertainties is crucial to improving quality of the estimates (Wang et al. 2009, 2011a; Lu et al. 2012). Many authors have investigated the uncertainties in estimating and mapping forest biomass/carbon (Heath and Smith 2000; Chen et al. 2000; Chave et al. 2004; Saatchi et al. 2007; Sierra et al. 2007; Larocque et al. 2008; Nabuurs et al. 2008; Asner et al. 2009; Wang et al. 2009). For example, Nabuurs et al. (2008) showed that uncertainty in forest carbon estimations was greater than the changes in carbon sequestration through forest management and planning. Saatchi et al. (2007) reported an uncertainty of 20% when regression models are used for total forest biomass mapping. In estimating forest biomass in the Tapajos National Forest, Brazil, Keller et al. (2001) investigated the uncertainties due to sampling, allometric models and ratios used to estimate biomass of roots, lianas, epiphytes, and necromass, and found that the primary source of uncertainty was the allometric models. This was also supported by Chave et al.'s (2004) study in which the errors from sampling, tree measurements, allometric models, and representativeness of small plots across a vast tropical forest landscape of Panama were analyzed. Using lidar data, Asner et al. (2009) quantified the impacts of environmental factors and invasive species on forest carbon sequestration for tropical forests. Moreover, Asner et al. (2011) and Mascaro et al. (2011) reported the errors of lidar-derived forest biomass estimates varied from 17 to 40 Mg C per ha (1Mg = 1000 kg) in the tropical forests. In addition, Montesano et al. (2014) assessed the uncertainty of aboveground live biomass estimates obtained using lidar and SAR data from both airborne and spaceborne platforms and regression modeling for boreal forest ecosystems across a low-biomass vegetation structure gradient in central Maine (USA), Aurskog (Norway), and across central Siberia (Russia). They found that the relative errors in biomass predictions changed across the forest gradient and showed a decreasing trend as biomass magnitudes increased. Their results also implied that it was difficult to obtain a relative error less than 50% when the differences in biomass at the site level and current spaceborne sensors were characterized.

The quality of forest biomass/carbon estimates also depends on the spatial resolutions of remotely sensed data and size of sample plots. Keller et al. (2001) demonstrated that the accuracy of forest biomass estimates due to sampling error can increase by 10% when the size of sample plots is increased from 0.25 ha to 1 ha. Chave et al. (2004) studied the relationship between the accuracy of forest biomass estimates and the size of sample plots in a tropical region and indicated that the sample plots should be larger than 0.25 ha in size. Mascaro et al. (2011) also showed forest carbon stock errors declined by 38% as sample plots increased from 0.36 ha to 1 ha.

In addition, Wang et al. (2011a) and Zhang et al. (2013) investigated the effects of location errors of sample plots on the accuracy of forest biomass/carbon estimates by randomly perturbing the east and north coordinates of sample plots and found that the location errors did not lead to significant bias in population mean estimates. However, the perturbations significantly decreased correlation between forest carbon and Landsat TM spectral variables and changed the pixel level spatial distribution of forest carbon estimates. When the plot location errors were greater than 1600 m, the spatial distributions of the estimates became random. However, the impacts of the plot location errors were mitigated when the sample plot and remotely sensed data were combined and scaled up from a finer (such as 30 m × 30 m) to a coarser spatial resolution (such as 1 km × 1 km).

The uncertainties can be grouped into errors associated with: (1) tree variables, including sampling, measurement, recording and grouping errors when tree variables such as DBH and height are measured; (2) conversion coefficients and models including variation of conversion factors from volume to biomass and then to carbon, inappropriate selection and usage of allometric models for relationship of tree volume and DBH and height, and incorrect regression models relating forest biomass/carbon to spectral variables; (3) uncertainties of spectral values due to unbalanced platforms, scanner motions, poor atmospheric conditions, and slope; inappropriate spatial interpolation methods for geometrical and radiometric corrections, and incorrect methods for image enhancement and analysis; (4) sample plot locations, including global positing system (GPS) coordinates used to locate the sample plots, geometric correction and the uncertainties due to mismatch of sample plots with spatial resolutions of remotely sensed data; (5) differences in sizes of sample plots and image pixels, disagreement between remotely sensed data and plot observations when portions of trees on boundaries are outside plots although both sample plots and pixels have the same spatial resolutions; and (6) temporal differences between field plot measurements and remotely sensed data.

To quantify the spatial uncertainties, Wang et al. (2009) conducted a spatial uncertainty analysis of forest carbon in Wu-Yuan County of Jiangxi Province, China using a spatial error budget approach. In this method, input uncertainties were measured and their propagation to outputs was modeled using polynomial regression, linking input and output uncertainties. The contributions of the input uncertainties to the output uncertainties were then calculated. This method identifies the primary sources of uncertainty, allowing the reduction in uncertainties and increased forest biomass/carbon estimate accuracy. A similar method was applied in Lu et al. (2012) in spatial uncertainty analysis of remote sensing-derived natural resource map products (Gertner et al. 2002; Wang et al. 2005). In addition, other methods such as Fourier Amplitude Sensitivity Test, Taylor series, and response surface modeling can be used to model propagation of uncertainties (Iman and Helton 1988; Gertner et al. 1996; Helton and Davis 2003; Wang et al. 2005). When all factors impacting forest biomass/carbon estimate accuracy are considered, spatial uncertainty analysis and error budget methods can identify sources of uncertainty, model their accumulation and propagation, and quantify their contributions to output uncertainties, thus determining the main factors affecting estimate accuracy. This will provide the guidelines to make efforts to reduce the uncertainty by refining the biomass estimation procedure through analyzing major factors influencing biomass estimation performance.

In a word, it is clear that the accuracy of forest biomass/carbon model predictions increases as the size of sample plot data increases. Accurately locating sample plots can improve the quality of the estimates and their spatial distribution. However, forest biomass/carbon model predictions are associated with many sources of uncertainty and the impact of uncertainties on accuracy of the predictions is often greater than the change in carbon sequestration through forest management and planning. Moreover, the uncertainty varies spatially and temporally. A major factor that affects the accuracy of biomass/carbon estimation in one study area may become minor in another. Therefore, spatial uncertainty analysis and error budget should be conducted to identify the major factors and further to provide a mechanism of quality control for forest biomass/carbon model predictions

6. Impacts of scale issues on biomass estimation modeling

The extent of a study area directly affects biomass estimation procedure design. On a local scale, biomass estimation results are typically used as reference data for validation or evaluation of other estimates from relatively coarse spatial resolution images. Therefore, local biomass estimations must be highly accurate and spatially precise. Optical sensor data such as QuickBird and IKONOS are common sources for this purpose (Thenkabail et al. 2004; Leboeuf et al. 2007). However, complex forest stand structures, tall tree-induced shadow problems, and high spectral variation in the same vegetation types reduce estimation accuracy. Use of textural images or object-based methods has the potential to solve these problems (Kayitakire et al. 2006). However, use of the spectral and/or spatial information for biomass estimation modeling is often insufficient for obtaining accurate biomass estimates. Substantial research has indicated lidar-based biomass estimation (e.g. Zhao et al. 2009; Chen et al. 2012; Næsset et al. 2013b) can lead to better performance than optical sensor-based approaches (Tian et al. 2012). This is because lidar data provides tree height information which is critical for biomass estimation. Proper integration of high spatial resolution optical sensor and lidar data may improve biomass estimation performance.

Medium spatial resolution images such as Landsat are a common data source for biomass estimation at a regional scale. Previous research has indicated that spectral, spatial, and subpixel fractional features are important variables for biomass estimation. In particular, integration of spectral and textural images provides more accurate biomass estimates than either dataset alone (Lu 2005). Meanwhile, radar data with long wavelengths can reduce data saturation, and thus, integration of optical and radar data may improve biomass estimation. On the other hand, ancillary data such as DEM and soil types can be valuable input variables for biomass modeling, but they have not yet been used extensively, probably due to their formats and resolutions. It is challenging to integrate multisource data, such as remote sensing and ancillary data, in a biomass estimation procedure. The keys are identifying suitable variables from different source data and selecting an appropriate algorithm to develop biomass estimation models that will provide the best results. However, there is a lack of guidelines or methods to automatically select the optimal variables and algorithms for a study.

Biomass estimation at continental and global scales has gained increasing attention in the last decade due to the concerns of global climate change and daily availability of coarse spatial resolution images from MODIS and AVHRR (Hame et al. 1997; Baccini et al. 2008; Du et al. 2014). The major challenges at continental and global scales include mixed pixels due to coarse spatial resolutions and inconsistency in sizes between sample plots and image pixels (Wang et al. 2004, 2009; Wang and Zhang 2014). Mixed pixels lead to uncertainties in forest biomass/carbon estimates. The SMA approach is a potential solution to this land use and land cover classification, but it cannot be directly applied to the modeling and mapping of forest biomass/carbon. Novel methods are needed to solve this problem. Furthermore, global cover satellite images often have spatial resolution of 1 km × 1 km, sample plots are usually less than 50 m × 50 m. These inconsistencies in spatial resolutions result in a mismatch between sample plot and remotely sensed data. Wang et al. (2005, 2009) and Wang and Zhang (2014) developed a spatial block co-simulation algorithm. In this method, data from sample plots at both finer and coarser spatial resolutions are assumed to be normally distributed. The conditional distribution of forest biomass/carbon at a coarser spatial resolution can be derived using estimates of the finer spatial resolution and sample plot data. Using the obtained distribution, spatial co-simulation can be conducted at a block level based on the spatial co-simulation algorithm.

Study area scales require the selection of proper spatial-resolution (or cell size) remote sensing data and sizes of sample plots. In theory, high spatial resolution images at a local scale can be related to small sample plots, but in a forest ecosystem, plots that are too small will lose representativeness and generate high uncertainty in biomass calculation because of the forest stand complexity. The majority of sample plots are 400–1000 m^2 (Keller et al. 2001; Næsset et al. 2011; Lu et al. 2012). These plot sizes may be too large for high spatial resolution images such as QuickBird with 0.6 m/2.4 m, resulting in high spectral variation due to the heterogeneity in the forest stand site. These sample plot sizes are suitable for medium spatial resolution images such as Landsat TM, but may be not suitable for coarse spatial resolution (e.g. 1 km) images such as MODIS and AVHRR data. Collecting field data is very costly. The priority is to choose a sample plot size and number that can represent the entire study area with minimal costs, considering total survey area, travel distance, and accessibility. The second priority is minimal mapping unit requirement. To avoid edge problems, a minimal mapping unit must be at least 10 m × 10 m – the size needed to include large trees because the tree is usually the minimum sampling unit in the field for biomass studies even if very high spatial resolution (e.g. 1 m) satellite data are used.

Direct use of high spatial resolution optical sensor or radar data in biomass estimation is uncommon due to its relatively poor estimation accuracy. In contrast, lidar is a promising tool for biomass estimation at a local scale, but has not been extensively used for large-area biomass estimation as a result of its limitations in data availability, cost, and large data volumes. Therefore, one of recent research directions on biomass estimation is the integration of lidar and other sensor data (Sun et al. 2011; Nelson et al. 2012). For example, integration of lidar and QuickBird (Chen and Hay 2011), lidar and radar (Næsset et al. 2011; Montesano et al. 2013; Tsui et al. 2013), and lidar and MODIS (Wang et al. 2011b) has been explored to estimate biomass or other forest stand attributes such as canopy height. Another line of research is to infer the population parameters (e.g. mean and variance) of the biomass over a study area using lidar-estimated biomass as samples (Andersen et al. 2014; d'Oliveira et al. 2012; Gregoire et al. 2011; McRoberts et al. 2013; Næsset et al. 2011, 2013a, 2013b; Nelson et al. 2012; Strunk et al. 2012). For a detailed discussion of this topic, readers can refer to Wulder et al. (2012), which reviewed the use of lidar sampling for large forest ecosystems to map and monitor forest attributes, including biomass. Using lidar as a sampling tool and integrating lidar with other sensor data will in the future provide timely and accurate biomass estimation in a large area.

7. Design of a general procedure for remote sensing-based biomass estimation

Biomass estimation using remote sensing techniques requires a careful design of each step in the estimation procedure. The extent and complexity of a study area affect collection of sample plots, selection of remote sensing data and algorithms for establishing a biomass estimation model. Biomass estimation is a systematic chain that requires understanding the weak parts of the chain. Uncertainty analysis is an important tool to identify major factors affecting biomass estimation accuracy and thus improving estimation procedures. Figure 2 illustrates the major steps used in biomass estimation modeling.

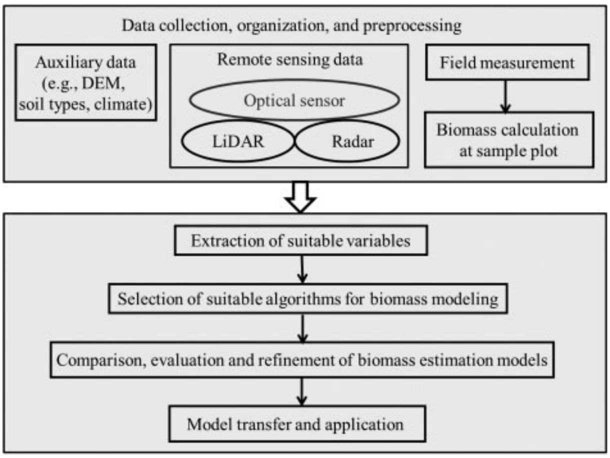

Figure 2. General strategy of biomass estimation modeling using remote sensing techniques.

7.1. Data collection and organization

Field survey, remote sensing (e.g. optical, radar, and/or lidar), and possibly auxiliary data (e.g. DEM, soil type) are needed for biomass estimation research. Collecting a sufficient number of sample plots is a prerequisite, and also most costly, time-consuming, and labor-intensive. A sample plot collection design involving determination of number, location, and size of sample plots, is crucial. The number of samples collected in a study depends on the availability of economic resources and labor; however, the sample size should fit the minimum statistical requirements. The location of sample plots should be determined through statistical sampling techniques (e.g. random, system, stratified random sampling) and thoughtful consideration of the study area extent, land covers, and accessibility.

When remote sensing and auxiliary data are used, geometric rectification or registration is required so that all datasets are in the same coordinate system. Furthermore, radiometric and atmospheric calibration of remote sensing data is needed for biomass estimation (Song et al. 2001). If lidar is used for predicting biomass, intensity needs to be calibrated (Höfle and Pfeifer 2007). Satellite lidar data are affected by clouds and need to be screened before use (Chen 2010b), however, airborne lidar data are usually collected below cloud level and in good weather. Lidar has the highest geometric accuracy among all sensors. When airborne lidar data are used for biomass estimation, little, if any, geometric and atmospheric calibration is necessary. Since many spaceborne and airborne sensor data are available, understanding of their strengths and weakness is important for selecting suitable datasets for specific purposes. Establishing a spatial database to manage multisource datasets is valuable to effectively using them to develop biomass estimation models and evaluate their estimates.

7.2. Selection of suitable variables from remote sensing data

As discussed in Section 3, many potential variables can be used, and selection of appropriate data is important considering the study area's scale, data availability, and landscape complexity. One critical step is to identify variables suitable for the specific study. Effective integration of different sensor data or different source data will be an important research topic for improving biomass estimation performance.

7.3. Selection of appropriate algorithms for biomass estimation modeling

As summarized in Section 4, biomass estimation studies have used different algorithms such as traditional regression analysis, PLS, spatial co-simulation, and nonparametric algorithms such as ANN and K-NN (Lu 2006; Luther et al. 2006; Wang et al. 2011a; Song 2013; Chen 2013; Vaglio Laurin et al. 2014). Because of the complex biophysical environments and many potential variables, it is often unclear which algorithm should be used for specific vegetation types or landscapes. In practice, a comparative analysis of different algorithms is used to identify a best one.

7.4. Evaluation of modeling results and refinement of the modeling procedure

Understanding the robustness and reliability of the models and accuracy of estimates requires an evaluation of estimation results. However, the difficulty in collecting a sufficient sample of plots is a major constraint for evaluating biomass estimates (Lu 2006). Uncertainty analysis (see Section 5), especially in large study areas is valuable to identify major factors influencing biomass estimation performance (Wang et al. 2009; Lu et al. 2012; Zhang et al. 2013). Based on uncertainty analysis, we can better understand how biophysical conditions, remote sensing data, and algorithms affect biomass estimation, and we can take measures to optimize the biomass modeling procedure.

7.5. Model transfer and applications

One important goal for developing a biomass estimation model is its application to a large area. Another goal is applying models to different time periods to generating time series of biomass estimates so biomass dynamic change can be examined (Lu 2006). However, previous research has indicated that a remote sensing-based biomass estimation model is not suitable for direct application to different study areas (Foody et al. 2003) due to the differences in vegetation structure, species composition, vegetation vigor, and impacts of atmospheric and soil moisture conditions on spectral signatures. Overall, limited research has been conducted on biomass estimation model transfer. This is most likely due to large variation in remote sensing signature and biomass relationships across space and time. However, in airborne lidar, Lefsky et al. (2002) and Asner et al. (2012) had some encouraging results when power models based on mean canopy height were used to predict biomass across large geographic extent. Lefsky et al. (2002) found that 84% of biomass variations across three sites in North America (a temperate conifer forest in Oregon, USA, a temperate deciduous forest in Maryland, USA, and a boreal conifer forest in Manitoba, Canada) can be explained using a model solely based on the mean canopy height squared. Asner et al. (2012) found that plot-scale biomass across four tropical forest sites in Panama, Peru, Madagascar, and Hawaii can be captured using lidar mean canopy height, after accounting for the relationship of wood density and basal area to mean canopy height at each site. In addition, it is needed to assess the quality of the population estimate and its uncertainty from model transfer and application. Otherwise, the uncertainty of the results is unknown.

8. Conclusions

Remote sensing is a major data source for biomass estimation on various scales. Although different sensor data have been used, the guidelines to support automated selection of optimal variables and modeling algorithms do not exist. Various parametric and nonparametric algorithms have been developed, but no universal algorithm is available and selection of an optimal algorithm for biomass modeling is poorly understood. In reality, biomass estimation using remote sensing technology is a comprehensive procedure with many steps: field survey data collection, biomass calculation at plot level, remote sensing data selection, variable extraction, proper algorithm selection, and error evaluation. It is important to identify major factors causing uncertainties, and put substantial effort into reducing these uncertainties to develop an optimal biomass estimation procedure. In summary, the major conclusions for biomass estimation using remote sensing techniques are as follows:

(1) Optical sensor data especially Landsat images are a common data source for biomass estimation. However, optical sensor data are suitable for developing horizontal vegetation structure, such as vegetation canopy cover, instead of vertical vegetation structure such as canopy height. The stereo-viewing capability in optical sensor data such as ALOS/PRISM, Terra ASTER, and SPOT can provide vertical vegetation structure. Proper integration of this vertical structure features and optical spectral response and textures in a biomass estimation model may be a new direction to improve biomass estimation accuracy, but has not been paid much attention yet.

(2) Long wavelength radar data are an important data source for biomass estimation, especially when optical sensor data are not available due to the cloud cover in tropical regions. Radar's ability to capture vertical forest structure features makes it suitable for biomass estimation, but its speckle problem and inability to distinguish vegetation types affect biomass estimation accuracy. More research is needed to effectively use InSAR for extraction of vegetation canopy height, thus improving biomass estimation accuracy.

(3) Data saturation in optical and radar data is an important factor influencing the accuracy of biomass estimation in forests with complex stand structures. More research is needed to reduce the data saturation problem through the use of advanced image processing technologies. New methods are also needed to identify suitable variables that will optimally represent the forest biomass features to reliably relate the selected variables and biomass.

(4) Compared to optical and radar data, lidar is the most promising technique for biomass estimation because canopy height information derived from lidar strongly relates to biomass even at high levels (>1000 mg/ha; e.g. Means et al. 1999). In the past, airborne lidar data were mainly used in small areas due to high costs and large volume. As technologies advance, the use of airborne lidar data for biomass mapping will expand from local to regional levels (e.g. Skowronski and Lister 2012). The combination of airborne lidar and satellite imagery is another promising approach for large-area biomass mapping.

(5) Traditional regression analysis is a commonly used method to develop biomass estimation models with remote sensing data. However, nonparametric algorithms such as random forest and SVM may provide more accurate estimates than linear

regression models especially when multisource data are used in large study areas. The challenge is to optimize the corresponding parameters used in the algorithms. More research is needed to automatically optimize the parameters used in corresponding nonparametric algorithms.

(6) The extent and complexity of a study area is important concerns in the selection of suitable remote sensing data and biomass estimation algorithms.
(7) Integration of multiscale data from high spatial resolution datasets, such as QuickBird and lidar, medium spatial resolution datasets, such as Landsat and radar, and coarse spatial resolution datasets, such as MODIS, will be a new direction for global biomass estimation, but it has not yet received much attention.
(8) Biomass estimation is a comprehensive procedure that requires a careful design at each step. Uncertainty analysis is an important tool to identify major factors influencing biomass estimation performance.

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