

Review Article

The potential and challenge of remote sensing-based biomass estimation

DENGSHENG LU*

Center for the Study of Institutions, Population, and Environmental Change (CIPEC),
Indiana University, 408 N. Indiana Avenue, Bloomington, Indiana 47408, USA

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Remotely sensed data have become the primary source for biomass estimation. A summary of previous research on remote sensing-based biomass estimation approaches and a discussion of existing issues influencing biomass estimation are valuable for further improving biomass estimation performance. The literature review has demonstrated that biomass estimation remains a challenging task, especially in those study areas with complex forest stand structures and environmental conditions. Either optical sensor data or radar data are more suitable for forest sites with relatively simple forest stand structure than the sites with complex biophysical environments. A combination of spectral responses and image textures improves biomass estimation performance. More research is needed to focus on the integration of optical and radar data, the use of multi-source data, and the selection of suitable variables and algorithms for biomass estimation at different scales. Understanding and identifying major uncertainties caused by different stages of the biomass estimation procedure and devoting efforts to reduce these uncertainties are critical.

1. Introduction

The future of carbon emissions may be the largest source of uncertainty in climate scenarios. While fossil-fuel emissions may account for a significant part of global carbon emissions, the deforestation and fires associated with them make up a considerable proportion of total emissions, and make estimating even current emissions difficult. Estimates of the carbon sink have a high degree of uncertainty (Houghton *et al.* 2001, Myneni *et al.* 2001, DeFries *et al.* 2002, House *et al.* 2003, Hese *et al.* 2005, Houghton 2005), and what proportion comes from secondary forest regrowth is largely unknown, except for some small areas that have been carefully studied. One useful way to proceed is to develop approaches for estimating biomass changes in land cover using remotely sensed data. A number of studies have provided useful approaches for estimating biomass, and thus carbon, related to loss from deforestation and subsequent use of fire to remove the vegetation for agropastoral activities (Houghton *et al.* 1999, Achard *et al.* 2004, Hese *et al.* 2005, Houghton 2005).

Previous research has indicated that large-area deforestation resulted in effects on climate change, biological diversity, hydrological cycle, soil erosion and degradation (Shukla *et al.* 1990, Houghton 1991, Skole and Tucker 1993). After deforestation, regeneration of vegetation is common and the resulting landscape often consists of patches of successional forests and agricultural lands. For example, in the Amazon

*Corresponding author. Email: dlu@indiana.edu

basin, about 20–50% of the deforested area is in different stages of succession (Moran *et al.* 1994, Skole *et al.* 1994, Lucas *et al.* 2000, Roberts *et al.* 2002). Because of their rapid growth and increasing areal extent, successional forests play an important role in the global carbon budget and in ecological functions (Moran *et al.* 2000). Biomass governs the potential carbon emission that could be released to the atmosphere due to deforestation, and regional biomass changes have been associated with important outcomes in ecosystem functional characteristics and climate change. The roles and impacts of biomass on carbon cycles, soil nutrient allocations, fuel accumulation, and habitat environments in terrestrial ecosystems have long been recognized. Accurate delineation of biomass distribution at scales from local and regional to global becomes significant in reducing the uncertainty of carbon emission and sequestration, understanding their roles in influencing soil fertility and land degradation or restoration, and understanding the roles in environmental processes and sustainability (Foody 2003).

Biomass, in general, includes the above-ground and below-ground living mass, such as trees, shrubs, vines, roots, and the dead mass of fine and coarse litter associated with the soil. Due to the difficulty in collecting field data of below-ground biomass, most previous research on biomass estimation focused on above-ground biomass (AGB). In recent years remote sensing techniques have become prevalent in estimating AGB (Nelson *et al.* 1988, Franklin and Hiernaux 1991, Leblon *et al.* 1993, Nelson *et al.* 2000a, Steininger 2000, Zheng *et al.* 2004, Lu 2005). Most previous research on AGB estimation is for coniferous forests (Ardo 1992, Wu and Strahler 1994, Trotter *et al.* 1997, Zheng *et al.* 2004) because of its relatively simple forest stand structure and tree species composition. In moist tropical forests, the study of AGB estimation becomes problematic because of its complex stand structure and abundant variety in species composition (Lucas *et al.* 1998, Nelson *et al.* 2000a, Steininger 2000, Foody *et al.* 2001, 2003, Lu *et al.* 2005). The complexity of vegetation structures results in highly variable standing stocks of AGB and an even more variable rate of AGB accumulation following a deforestation event.

Different approaches, based on (1) field measurement (Brown *et al.* 1989, Brown and Iverson 1992, Honzák *et al.* 1996, Schroeder *et al.* 1997, Houghton *et al.* 2001, Brown 2002), (2) remote sensing (Tiwari 1994, Roy and Ravan 1996, Nelson *et al.* 2000a,b, Tomppo *et al.* 2002, Foody *et al.* 2003, Santos *et al.* 2003, Zheng *et al.* 2004, Lu 2005), and (3) GIS (Brown and Gaston 1995) have been applied for AGB estimation. Table 1 summarizes the major techniques. Traditional techniques based on field measurement are the most accurate ways for collecting biomass data. A sufficient number of field measurements is a prerequisite for developing AGB estimation models and for evaluating the AGB estimation results. However, these approaches are often time consuming, labour intensive, and difficult to implement, especially in remote areas; also, they cannot provide the spatial distribution of biomass in large areas. GIS-based methods using ancillary data are also difficult because of problems in obtaining good quality ancillary data, indirect relationships between AGB and ancillary data, and the comprehensive impacts of environmental conditions on AGB accumulation. Hence, GIS-based approaches have not applied extensively for AGB estimation. The advantages of remotely sensed data, such as in repetitiveness of data collection, a synoptic view, a digital format that allows fast processing of large quantities of data, and the high correlations between spectral bands and vegetation parameters, make it the primary source for large area AGB

Table 1. Summary of techniques for above-ground biomass estimation.

Category	Methods	Data used	Characteristics	References
Field measurement-based methods	Destructive sampling	Sample trees	Individual trees	Klinge <i>et al.</i> (1975)
	Allometric equations	Sample trees	Individual trees	Overman <i>et al.</i> (1994), Honzák <i>et al.</i> (1996), Nelson <i>et al.</i> (1999)
	Conversion from volume to biomass	Volume from sample trees or stands	Individual trees or vegetation stands	Brown and Lugo (1984), Brown <i>et al.</i> (1989), Brown and Lugo (1992), Gillespie <i>et al.</i> (1992), Segura and Kanninen (2005)
Remote sensing-based methods	Methods based on fine spatial-resolution data	Aerial photographs, IKONOS	Per-pixel level	Tiwari and Singh (1984), Thenkabail <i>et al.</i> (2004)
	Methods based on medium spatial-resolution data	Landsat TM/ETM+, SPOT	Per-pixel level	Roy and Ravan (1996), Nelson <i>et al.</i> (2000a), Steininger (2000), Foody <i>et al.</i> (2003), Zheng <i>et al.</i> (2004), Lu (2005)
	Methods based on coarse spatial-resolution data	IRS-1C WiFS, AVHRR	Per-pixel level	Barbosa <i>et al.</i> (1999), Wylie <i>et al.</i> (2002), Dong <i>et al.</i> (2003)
	Methods based on radar data	Radar, lidar	Per-pixel level	Harrell <i>et al.</i> (1997), Lefsky <i>et al.</i> (1999b), Santos <i>et al.</i> (2002, 2003)
GIS-based methods	Methods based on ancillary data	Elevation, slope, soil, precipitation, etc.	Per-pixel level or per-field level	Brown <i>et al.</i> (1994), Iverson <i>et al.</i> (1994), Brown and Gaston (1995)

estimation, especially in areas of difficult access. Therefore, remote sensing-based AGB estimation has increasingly attracted scientific interest (Nelson *et al.* 1988, Sader *et al.* 1989, Franklin and Hiernaux 1991, Steininger 2000, Foody *et al.* 2003, Santos *et al.* 2003, Zheng *et al.* 2004, Lu 2005), and thus is the focus of this review paper.

Previous literature has summarized some remote sensing-based methods for biophysical parameter studies (Kimes *et al.* 1998, Wulder 1998, Shoshany 2000, Laidler and Treitz 2003, Kasischke *et al.* 2004, Lucas *et al.* 2004, Turner *et al.* 2004, Boyd and Danson 2005). For example, Wulder (1998) summarized some potential image processing methods that may be useful for estimation of forest structural

parameters. Kimes *et al.* (1998) reviewed the neural network approach for extraction of continuous vegetation variables from optical and radar measurements. Treitz and Howarth (1999) reviewed hyperspectral remote sensing for biophysical parameter estimation in the forest ecosystem. Laidler and Treitz (2003) reviewed biophysical parameter estimation in the arctic environments, and Graham and Harris (2003) reviewed the water-cloud model for extraction of biophysical parameters from radar data. Asner *et al.* (2003) summarized per-pixel analysis of forest structure using vegetation indices, spectral mixture analysis, and canopy-reflectance modelling. Although research on AGB estimation using remotely sensed data has been commonly explored during the past decades, a comprehensive review of AGB estimation is not available yet. A summary of previous efforts on AGB estimation and a discussion of existing issues affecting AGB estimation are valuable for understanding the relationships between AGB and remotely sensed data and for developing suitable models for AGB estimation in different biophysical environments at various scales. Therefore, this article aims to summarize the approaches for AGB estimation at different scales of remotely sensed data, to discuss the issues influencing AGB estimation, and to propose potential solutions and future research.

This article is organized as follows: §1 gives an introduction to biomass estimation; §2 and §3 summarize biomass estimation with optical sensor data at different spatial resolutions and with radar data; §4 briefly summarizes vegetation canopy models; §5 and §6 discuss the assessment approaches for the biomass estimation results and model transferability; §7 discusses important issues influencing biomass estimation; and, finally, §8 provides a summary and perspective of biomass studies.

2. Above-ground biomass estimation with optical sensor data

In general, the AGB can be directly estimated using remotely sensed data with different approaches, such as multiple regression analysis, K nearest-neighbour, and neural network (Roy and Ravan 1996, Nelson *et al.* 2000a, Steininger 2000, Foody *et al.* 2003, Zheng *et al.* 2004), and indirectly estimated from canopy parameters, such as crown diameter, which are first derived from remotely sensed data using multiple regression analysis or different canopy reflectance models (Wu and Strahler 1994, Woodcock *et al.* 1997, Phua and Saito 2003, Popescu *et al.* 2003). This section summarizes the AGB estimation approaches based on different spatial resolutions (i.e. fine, medium and coarse) of optical sensor data.

2.1 Fine spatial-resolution data

Fine spatial-resolution data can be airborne, such as aerial photographs, or spaceborne, such as IKONOS and QuickBird images, with spatial resolutions of less than 5 m (e.g. the spatial resolutions of panchromatic images of IKONOS and QuickBird are 0.83 and 0.61 m). They are frequently used for modelling tree parameters or forest canopy structures (Lévesque and King 1999, 2003). Many approaches have been used to extract biophysical parameters using fine spatial-resolution data. Culvenor (2003) summarized the techniques for extraction of individual tree information using fine spatial-resolution images. The techniques include a bottom-up algorithm (valley-following and directional texture), a top-down algorithm (multiscale edge segments, threshold-based spatial clustering, a double-aspect method, and vision expert system), and template matching.

Interpretation of aerial photographs has become widespread in applications related to forest inventory since the late 1940s. This technique has proven useful, especially for stratification and timber volume estimation. Photo interpretation can measure various forest characteristics, such as tree height, crown diameter, crown closure, and stand area. Tiwari and Singh (1984) used aerial photographs and non-harvest field sampling for forest biomass mapping in India. De Jong *et al.* (2003) used digital airborne imaging spectrometer (DAIS) data to estimate biomass using stepwise linear regression analysis in southern France. Many techniques or approaches used for extraction of biophysical parameters from aerial photography can also be used in high spatial-resolution satellite images. Thenkabail *et al.* (2004) used IKONOS data to estimate AGB of oil palm plantations in Africa. The fine spatial resolution and associated multispectral characteristics may become an important data source for AGB estimation. One important application may be its use as reference data for validation or accuracy assessment for medium and coarse spatial-resolution data applications. The drawback is that the high spectral variation and shadows caused by canopy and topography may create difficulty in developing AGB estimation models. Another drawback is the lack of a shortwave infrared image, which is often important for AGB estimation. Also, the need for large data storage and the time required for image processing prohibit its application in large areas. Last but not least, high spatial resolution imagery is much more expensive, and requires much more time to implement data analysis than medium spatial resolution images. The time for image processing and the cost for image purchase may be important factors influencing the extensive application of high spatial resolution images for AGB estimation in a large area.

2.2 Medium spatial-resolution data

The medium spatial-resolution ranges from 10 to 100 m. The most frequently used medium spatial-resolution data may be the time-series Landsat data, which have become the primary source in many applications, including AGB estimation at local and regional scales (Sader *et al.* 1989, Roy and Ravan 1996, Fazakas *et al.* 1999, Nelson *et al.* 2000a, Steininger 2000, Mickler *et al.* 2002, Foody *et al.* 2003, Phua and Saito 2003, Calvão and Palmeirim 2004, Zheng *et al.* 2004, Lu 2005). Lefsky *et al.* (2001) evaluated the utility of several remotely sensed data for estimating stand structure attributes—age, basal area, biomass, and diameter at breast height (DBH). Cohen and Goward (2004) summarized the Landsat's role in ecological applications. Table 2 provides some examples using Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data for AGB estimation. The major approaches include linear or nonlinear regression models, K nearest-neighbour, and neural network.

Different degrees of success for AGB estimation have been obtained in previous research. Foody *et al.* (2001) found that neural networks were useful for the AGB estimation using Landsat TM data in a Bornean tropical rain forest. In Finland and Sweden, Landsat TM data were used to estimate tree volume and AGB using the K nearest-neighbour estimation method (Halme and Tomppo 2001, Franco-Lopez *et al.* 2001, Tomppo *et al.* 2002). Nelson *et al.* (2000a) analysed secondary forest age and AGB estimation using Landsat TM data and found that AGB cannot be reliably estimated without the inclusion of secondary forest age. Steininger (2000) explored the ability to estimate AGB of tropical secondary forests using Landsat TM data and found that data saturation was a problem for AGB estimation in

Table 2. Selected examples of biomass estimation using Landsat TM data.

Datasets	Study area	Techniques	References
Landsat 5	Mauaus, Brazil	Liner and exponential regressions	Steininger (2000)
Landsat 5	Pará state (Altamira, Bragantina, and Ponta de Pedras) and Rondônia state (Machadinho d'Oeste)	Multiple regression analysis	Lu (2005)
Landsat 5	Sabah, Malaysia	Estimated crown diameter using an exponent model, then calculated biomass using crown diameter	Phua and Saito (2003)
Landsat 4 and 5	Manaus, Brazil; Danum Valley, Malaysia; Khun Kong, Thailand	Multiple regression model, neural network	Foody <i>et al.</i> (2003)
Landsat 5	Central Sweden	<i>K</i> nearest-neighbour method	Fazakas <i>et al.</i> (1999)
Landsat 5	Madhav National Park, India	Multiple regression analysis	Roy and Ravan (1996)
Landsat 7	Northern Wisconsin, USA	Multiple regression analysis	Zheng <i>et al.</i> (2004)
Landsat TM derived land cover data, forest inventory data, climate and soil data	South-eastern USA	A productivity model (PnET)	Mickler <i>et al.</i> (2002)

advanced successional forests. The canopy reflectance saturated when AGB approached about 15 kg m^{-2} or vegetation age reached over 15 years in the tropical secondary successional forests in Manaus, Brazil. A similar situation was found in Altamira, eastern Amazon, and in Rondônia, western Amazon, Brazil (Lu 2005). The complex forest stand structure, the impact of shadows caused by canopy and topography, and the complex environments influence AGB estimation performance (Steininger 2000, Lu 2005).

Spectral signatures or vegetation indices are often used for AGB estimation. Many vegetation indices have been developed and applied to biophysical parameter studies (Anderson and Hanson 1992, Anderson *et al.* 1993, Eastwood *et al.* 1997, Lu *et al.* 2004, Mutanga and Skidmore 2004). Vegetation indices have been recommended to remove variability caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when measuring biophysical properties (Elvidge and Chen 1995, Blackburn and Steele 1999). However, not all vegetation indices are significantly correlated with AGB. In general, vegetation indices can partially reduce the impacts on reflectance caused by environmental conditions and shadows, thus improve correlation between AGB and vegetation indices, especially in those sites with complex vegetation stand structures (Lu *et al.* 2004).

Image texture also has shown its importance in AGB estimation (Lu 2005, Lu and Batistella 2005). Individually, pure image textures or spectral responses are not

sufficient to establish highly accurate AGB estimation models. A combination of spectral and spatial information extraction techniques shows promise for improving estimation performance of forest stand parameters (Wulder 1998, Lu 2005). Research in the moist tropical forest in the Brazilian Amazon has indicated that image textures are more important than spectral responses for AGB estimation in the forest sites with complex vegetation stand structures (Lu 2005, Lu and Batistella 2005). However, in the forest sites with relatively simple vegetation stand structure, spectral signatures play a more important role than image textures. The roles of spectral responses and image textures in AGB estimation depend on the characteristics of the study area, i.e. the complexity of forest stand structure (Lu 2005). One critical step is to identify suitable image textures that are strongly correlated with AGB but are weakly correlated with each other. Identifying suitable image textures involves the determination of appropriate texture measures, moving window sizes, image bands, and so on (Franklin *et al.* 1996, Chen *et al.* 2004). Not all texture measures can effectively extract biomass information because image textures vary with the characteristics of the landscape under investigation and images used. Even for the same texture measure, selecting an appropriate window size and an image band is crucial. A small window size, such as 3×3 , often exaggerates the difference within the moving windows, increasing the noise content on the texture image. Conversely, a window size that is too large, such as 31×31 or larger, cannot effectively extract texture information due to too much smoothing of the textural variation (Lu 2005, Lu and Batistella 2005). Also, a large window size implies more processing time. In practice, it is still difficult to identify which texture measures, window sizes, and image bands are suitable for a specific research topic, and the lack of a guideline on how to select an appropriate texture further complicates the process. More research is needed to develop techniques for identification of suitable image textures for biomass estimation.

2.3 Coarse spatial-resolution data

The coarse spatial resolution is often greater than 100 m. Common coarse spatial-resolution data include NOAA Advanced Very High Resolution Radiometer (AVHRR), SPOT VEGETATION, and Moderate Resolution Imaging Spectroradiometer (MODIS). They are often used at national, continental, and global scales. The AVHRR data have long been the primary source in large-area surveys because they offer a good trade-off between spatial resolution, image coverage, and frequency in data acquisition. It is likely that AVHRR data are the most extensively used datasets for studies of vegetation dynamics on a continental scale. The close relationship between middle infrared (MIR) reflectance and AGB implies that MIR reflectance may be more sensitive to change in forest properties than the reflectance in visible and near-infrared wavelengths (Boyd *et al.* 1999). The AVHRR NDVI data were used to estimate biomass density and assess burned areas, burned biomass, and atmospheric emissions in Africa (Barbosa *et al.* 1999), and to estimate boreal and temperate forest woody biomass in six countries (Canada, Finland, Norway, Russia, USA, and Sweden) (Dong *et al.* 2003). Potter (1999) used the National Aeronautics and Space Administration–Carnegie Ames Stanford Approach model to estimate AGB on country-by-country changes in global forest cover for the years 1990–1995. The SPOT VEGETATION data with $1 \text{ km} \times 1 \text{ km}$ spatial resolution has also been used to estimate AGB in Canada (Fraser and Li 2002). As MODIS data are readily available, the large number of spectral bands

Table 3. Selected examples of biomass estimation using coarse spatial-resolution data.

Datasets	Study area	Techniques	References
AVHRR NDVI	Canada, Finland, Norway, Russia, USA and Sweden	Regression models	Dong <i>et al.</i> (2003)
SPOT VEGETATION	Canada	Multiple regression and artificial neural network	Fraser and Li (2002)
Landsat TM and IRS-1C WiFS	Finland and Sweden	K nearest-neighbour method and nonlinear regression	Tomppo <i>et al.</i> (2002)
Landsat TM and AVHRR	Finland	Linear regression analysis	Häme <i>et al.</i> (1997)
MODIS, precipitation, temperature, and elevation	California, USA	Statistical models (generalized additive models, tree-based models, cross-validation analysis)	Baccini <i>et al.</i> (2004)

may be beneficial to the improvement of AGB estimation accuracy at the continental or global scale. Baccini *et al.* (2004) used MODIS data in combination with precipitation, temperature, and elevation for mapping AGB in national forest lands in California, USA. Table 3 provides some examples of AGB estimation using coarse spatial-resolution data.

Overall, the AGB estimation using coarse spatial-resolution data is still very limited because of the common occurrence of mixed pixels and the huge difference between the size of field-measurement data and pixel size in the image, resulting in difficulty in the integration of sample data and remote sensing-derived variables. A synthetic analysis of multiscale data with a combination of different modelling approaches may be needed for accurate AGB estimation in a large area. Häme *et al.* (1997) estimated coniferous forest biomass through a combination of Landsat TM and AVHRR data. Tomppo *et al.* (2002) combined TM and IRS-1C Wide Field Sensors (WiFS) data to estimate tree stem volume and AGB in Finland and Sweden. The Landsat TM data were used as an intermediate step between field data and WiFS data. The nonparametric K nearest-neighbour method was used to analyse relationships between Landsat TM and field data, and nonlinear regression analysis was used to develop models for predicting volume and biomass for WiFS pixels. Wylie *et al.* (2002) tested grass biomass estimation through scaling Landsat TM to coarse spatial-resolution satellite data (AVHRR) over the Great Plains of North America.

3. Above-ground biomass estimation with radar and lidar data

In many areas of the world, the frequent cloud conditions often restrain the acquisition of high-quality remotely sensed data by optical sensors. Thus, radar data become the only feasible way of acquiring remotely sensed data within a given time framework because the radar systems can collect Earth feature data irrespective of weather or light conditions. Due to this unique feature of radar data compared with optical sensor data, the radar data have been used extensively in many fields, including forest-cover identification and mapping, discrimination of forest

Table 4. Selected examples of biomass estimation using radar data.

Datasets	Study area	Techniques	References
SIR-C	South-eastern USA	Multiple regression analysis	Harrell <i>et al.</i> (1997)
SAR L band	Les Landes Forest, France	Adapted theoretical model	Beaudoin <i>et al.</i> (1994)
AIRSAR C, L, P bands	Freiburg, south-east Germany; Ruotsinkylä, Finland	Linear regression analysis	Rauste and Häme (1994)
JERS-1 SAR L band	Tápajos, Pará state and Manaus, Amazonas state, Brazil	Forest backscatter model	Luckman <i>et al.</i> (1998)
JERS-1 SAR L-band data	New South Wales, Australia	Linear regression analysis	Austin <i>et al.</i> (2003)
AeS-1 SAR P band	Tápajos River region, Pará state, Brazil	Regression models (logarithmic and polynomial functions)	Santos <i>et al.</i> (2003)
Airborne laser	Costa Rica	Linear regression, canopy height models	Nelson <i>et al.</i> (1997, 2000b)
Large-footprint lidar	North-east Costa Rica	Multiple regression analysis	Drake <i>et al.</i> (2002a,b)
Small-footprint lidar	Piedmont physiographic province of Virginia, south-eastern USA	Measure crown diameter using lidar, then estimate biomass using regression analysis	Popescu <i>et al.</i> (2003)
Small-footprint lidar	Turkey Lakes Watershed (TLW) near Sault Ste. Marie, Ontario, Canada	A multiplicative model	Lim <i>et al.</i> (2003b)

compartments and forest types, and estimation of forest stand parameters. Previous research has shown the potential of radar data in estimating AGB (Hussin *et al.* 1991, Ranson and Sun 1994, Dobson *et al.* 1995, Rignot *et al.* 1995, Saatchi and Moghaddam 1995, Foody *et al.* 1997, Harrell *et al.* 1997, Ranson *et al.* 1997, Luckman *et al.* 1997, 1998, Pairman *et al.* 1999, Imhoff *et al.* 2000, Kuplich *et al.* 2000, Castel *et al.* 2002, Sun *et al.* 2002, Santos *et al.* 2003, Treuhaft *et al.* 2004). Kasischke *et al.* (1997) reviewed radar data for ecological applications, including AGB estimation. Balzter (2001) reviewed Interferometric Synthetic Aperture Radar (InSAR) for forest mapping and monitoring. Lucas *et al.* (2004) and Kasischke *et al.* (2004) reviewed SAR data for AGB estimation in tropical forests and temperate and boreal forests, respectively. Table 4 provides some examples for AGB estimation using radar datasets.

Different radar data have their own characteristics in relating to forest stand parameters (Leckie 1998). For example, radar backscatter in the P and L bands is highly correlated with major forest parameters, such as tree age, tree height, DBH, basal area, and AGB. In particular, SAR L-band data have proven to be valuable for AGB estimation (Sader 1987, Luckman *et al.* 1997, Kurvonen *et al.* 1999, Sun *et al.* 2002). However, low or negligible correlations were found between SAR

C-band backscatter and AGB (Le Toan *et al.* 1992). Beaudoin *et al.* (1994) found that the HH return was related to both trunk and crown biomass, and the VV and HV returns were linked to crown biomass. Harrell *et al.* (1997) evaluated four techniques for AGB estimation in pine stands using SIR C- and L-band multi-polarization radar data and found that the L-band HH polarization data were the critical elements in AGB estimation. The addition of C-band HV or HH polarization data in the regression equations significantly improved AGB estimation performance. Kuplich *et al.* (2000) used JERS-1/SAR data for AGB estimation of regenerating forests and concluded that these data had the potential to estimate AGB for young, regenerating forests following block logging rather than selective logging. Sun *et al.* (2002) found that multi-polarization L-band SAR data were useful for AGB estimation of forest stands in mountainous areas. Castel *et al.* (2002) identified the significant relationships between the backscatter coefficient of JERS-1/SAR data and the stand biomass of a pine plantation. The JERS-1/SAR data improved AGB estimation results for young stands, compared to estimation for old stands. Santos *et al.* (2002) used JERS-1/SAR data to analyse the relationships between backscatter signals and biomass of forest and savanna formations. The forest structural-physiognomic characteristics and the radar's volume scattering and double bounce scattering are two important factors affecting these relationships.

The saturation problem is also common in radar data. The saturation levels depend on the wavelengths (i.e. different bands, such as C, L, P), polarization (such as HV and VV), and the characteristics of vegetation stand structure and ground conditions. Luckman *et al.* (1997) found that the longer-wavelength (L-band) SAR image was more suitable to discriminate different levels of forest biomass up to a certain threshold. L-band backscatter shows no sensitivity to increased biomass density after the threshold, such as 40 tons per hectare, has been met, indicating that it is suitable for estimating biomass of regenerating forests in tropical regions. Ranson *et al.* (1997) used a combination of forest succession and radar backscatter models to infer forest biomass and found that reasonably good results were obtained when AGB was less than 15 kg m^{-2} . Austin *et al.* (2003) indicated that forest biomass estimation using radar data may be feasible when landscape characteristics are taken into account. More detailed reviews about the radar data saturation can be found in Balzter (2001), Lucas *et al.* (2004), and Kasischke *et al.* (2004).

Airborne laser and lidar systems are also used for forest parameter estimation (Nilsson 1996, Næsset 1997a,b, Lefsky *et al.* 2002, Zimble *et al.* 2003, Hyde *et al.* 2005, Næsset *et al.* 2005). Lim *et al.* (2003a) reviewed the application of lidar data to forest studies. In previous research, airborne laser data were used to estimate timber volume (Næsset 1997b), tropical forest biomass (Nelson *et al.* 1997), and stand height (Næsset 1997a, Næsset and Bjercknes 2001, Næsset *et al.* 2005). The lidar data were used to estimate Douglas fir western hemlock biomass (Lefsky *et al.* 1999a, Means *et al.* 1999), temperate mixed deciduous forest biomass (Lefsky *et al.* 1999b), tropical forest biomass (Drake *et al.* 2002a, 2003), tree height and stand volume (Nilsson 1996, Zimble *et al.* 2003), stand height (Wulder and Seemann 2003), tree crown diameter (Popescu *et al.* 2003), and canopy structure (Lovell *et al.* 2003). Because a lidar sensor can directly measure components of vegetation canopy structure, such as canopy height, previous research has indicated that use of lidar data is a promising approach for biophysical parameter estimation (Drake *et al.*

2002b, Lim *et al.* 2003a,b, Hyde *et al.* 2005). Lidar data alone, as well as in combination with other sensor or ancillary data, will provide an important data source for forest parameter estimation.

Previous research has indicated that long-wavelength radar data have the advantage in AGB estimation for complex forest stand structure and lidar data have the potential to provide vertical structure information (Lim *et al.* 2003a, Zimble *et al.* 2003). The radar or lidar data have important roles in AGB estimation, especially in study areas with frequent cloud conditions. However, the data analyses involved in pre-processing, removal of noise, and image processing require more skills, knowledge, and specific software. Also, most radar data were captured through airborne sensors, which may be much more expensive in data collection than space-borne images for a large area. Most previous research using radar or lidar data is still limited in the typical study areas, and has not been applied extensively to AGB estimation in regional and global scales because of the cost and labour constraints.

4. Vegetation canopy models

Multiple regression analysis has been frequently used for AGB estimation in previous research. However, identifying suitable variables for developing a multiple regression model is often difficult and time consuming because many potential variables may be used. Also, AGB is a comprehensive parameter that is related to many factors such as canopy structure, tree density, and tree species composition. Change in AGB is not directly shown in change of reflectance. The optical sensors mainly capture canopy information, thus the optical sensor data may be more suitable for estimation of canopy parameters such as crown density than AGB. Previous research has indicated that models of remotely sensed canopy reflectance may have the potential to estimate foliage and woody biomass (Franklin and Hiernaux 1991, Peddle *et al.* 1999). Many reflectance models have been developed for estimation of forest canopy structure parameters (Verhoef 1984, Li and Strahler 1985, Camillo 1987, Goel *et al.* 1991, Kuusk 1991, Jacquemoud *et al.* 2000, Gemmill *et al.* 2002, Gerard 2003). At least 32 models of vegetation canopy reflectance were reviewed by Goel (1988). They can be grouped into four main categories: geometrical models, turbid medium models, hybrid models, and computer-simulation models (Goel 1988). Qin and Goel (1995) found that almost all of these models were suitable for canopies with smaller leaves, high leaf area index (LAI), and high zenith angles. In particular, the mixed model, which quantitatively takes into account leaf size, shape, and orientation by adding a geometric optical mode, outperforms the other models. The neural-network model provides an additional technology for canopy models and has proven to be good for inversion of remotely sensed data (Abuelgasim *et al.* 1998). In geometric-optical models (Li and Strahler 1985, 1992, Hall *et al.* 1995, Peddle *et al.* 1999, 2001), the canopy is assumed to be an array of opaque or translucent sub-canopies of prescribed geometrical shapes (Goel 1988). This model was applied to semi-arid woodland vegetation structure (Franklin and Strahler 1988, Franklin and Turner 1992), moderately closed coniferous forest canopy (Li and Strahler 1985), and wood biomass estimation (Franklin and Hiernaux 1991). In turbid models, the canopy is treated as a horizontally uniform plane-parallel layer and canopy architecture as the LAI and the leaf angle distribution (Goel 1988). These models are suitable for the dense and horizontally uniform vegetated covers such as crops. The hybrid model presents a hybrid approach between two or more approaches such as radiative-transfer models and

geometric-optical models. Computer-simulation models simulate the arrangement and orientation of vegetation elements on a computer. Canopy architecture can be treated in more detail and more realistically than with other models, and this type of model often uses a Monte Carlo method (Qin and Goel 1995).

Because canopy parameters can be better estimated than AGB from remotely sensed data (Nelson *et al.* 2000b, Phua and Saito 2003, Popescu *et al.* 2003), the AGB may be indirectly inferred from the relationships between canopy structure and biomass. For example, Franklin and Hiernaux (1991) used the Li–Strahler canopy reflectance model to estimate the average crown area and tree density in Sahelian and Sudanian woodlands using Landsat TM data. Both vegetation parameters were then used to estimate above-ground woody biomass and green leaf biomass using allometric equations. This model was also used for estimation of crown size, stand density, and biomass, on an Oregon transect (Wu and Strahler 1994). Scientists have strived to model the vegetation canopies to predict the characteristics of specific types of structure within the canopy, such as tree height, density, and LAI through remotely sensed data. However, it remains a challenge to establish such models because of the complexity of canopy characteristics, atmospheric conditions, sun angle and viewing geometry, and terrain slope and aspect.

5. Accuracy assessment

Evaluation of the model performance and accuracy assessment of the estimated results are important aspects in the AGB estimation procedure. Two methods are often used to evaluate model performances. One is based on the coefficient of determination (R^2), if the models were developed using multiple regression analysis. Another way is to assess the root-mean-squared error (RMSE). In general, a high R^2 or a low RMSE value often indicates a good fit between the model developed and the sample plot data.

The majority of previous research on AGB estimation failed to provide accuracy assessments due to the difficulty in collecting ground reference data or the discrepancy between field measurements and AGB estimation results. In general, the assessment of AGB estimation results can be conducted based on different levels, such as per-pixel level, per-field level or polygon level, and the total amount for the study area. Fazakas *et al.* (1999) estimated AGB using Landsat TM data and assessed accuracy at a grid-cell level and an aggregation of cells. They found that the accuracy of estimated AGB at a grid-cell level was poor, but the accuracy increased when aggregations of cells were evaluated. The RMSE for an aggregation area of 510 ha of forest land was 8.7% for AGB and 4.6% for wood volume. Muinonen *et al.* (2001) analysed the RMSE of forest volume estimation based on forest-stand level. The RSME of estimated volume values ranged from 18% (or $28 \text{ m}^3 \text{ ha}^{-1}$) to 27% (or $41 \text{ m}^3 \text{ ha}^{-1}$).

Assessment of AGB estimation results at a per-pixel level is often difficult, and the accuracy may be misleading due to the registration errors between field collection data and the image. Also, the remotely sensed data in a single pixel usually consist of a mixture of information that is contained in an area of $30 \text{ m} \times 30 \text{ m}$ in Landsat TM data. However, measurements of physical parameters of a single pixel usually cannot be made due to the difficulty of precisely locating it in the field. Assessment based on the total AGB amount in a study area is also difficult because of the difficulty in collecting AGB data in a large area using traditional methods. The

suitable method may be based on the per-field or polygon level. At this level, the AGB reference data may be derived from different methods, such as allometric equations based on field-measured DBH and tree height, the conversion of stocking volume to AGB, and the estimated AGB results from fine spatial-resolution data, such as aerial photographs and IKONOS.

6. Model transferability

Model transferability is often a major point of interest in model development, but in reality it is difficult to directly transfer one model to different study areas because of the limitation of the model itself and the nature of remotely sensed data. Foody *et al.* (2003) discussed the problems encountered in model transfer. Each model has its limitation and optimal scale for implementation. For example, when using a regression model, attention should be given to understanding the applicable scale implemented in the original models. In general, models developed in one study area may be transferred to across-scene data if biophysical environments are similar and to multitemporal data of the same study area if the atmospheric calibration is accurately implemented. Accurate atmospheric correction between multi-temporal or multi-scene image data and similar biophysical environments in the study areas are critical for the model transfer. The remote sensing spectral signatures, vegetation indices, and image textures are often dependent on the image scale and environmental conditions. Caution must also be taken to assure the consistence between the images used in scale. Validation and calibration of the estimated results are necessary when transferred models are used for AGB estimation.

7. Discussion of important issues influencing biomass estimation

Many factors, such as economic conditions, limitation of remotely sensed data in spectral, spatial, and radiometric resolutions, complex forest stand structure, quality and quantity of sample plots, selection of suitable variables, and the modelling algorithms, often interplay and affect the success of AGB estimation. This section discusses important issues affecting AGB estimation and provides potential solutions.

7.1 Constraint of economic factors

Economic condition may be the most important factor affecting the implementation of field work, purchase of different sources of image data, and the time and number of professionals that can be devoted to the data analysis and development of AGB estimation models. For example, the economic factor directly influences the collection of sufficient number of biomass sample plots, which is often a constraint for developing robust AGB estimation models and for evaluating the estimation results, because of the time consuming, labour intensive, and difficult access to remote areas. The economic factor also affects the selection of remotely sensed data. High resolution images, such as IKONOS, are usually used in a typical site with limited areas. They are not suitable for a regional scale because of the storage capacity needed for a large volume of data, the expense to purchase the images, and the huge amount of time and labour needed to process the images. The Landsat TM data are often used in local and regional scales, but are difficult to use for national and global scales because of the constraint of economic conditions. The coarse spatial resolution data often make it difficult to accurately estimate AGB in a large

area due to the large number of mixed pixels. Selection of suitable variables from remotely sensed and ancillary data and selection of a suitable algorithm for the AGB estimation are complex procedures, requiring a good understanding of the relationships and interactions among tested variables and forest structure attributes and skills and knowledge in mathematics, modelling, computer programming, and remote sensing.

In order to achieve the best results with the constraint of economic factors, some remedial measures may be taken. For example, data sharing, including field measurements, ancillary data, and different sources of remotely sensed data, among different research teams can greatly reduce the cost in data collection. A good understanding of previous efforts in AGB estimation and designing an optimal image procedure suitable for the specific study area will greatly reduce the time to explore the suitable variables. A multiscale analysis combined with field samples, high, medium, and coarse spatial resolution data may improve the AGB estimation accuracy in national and global scales. A work team consisting of professionals from different disciplines, especially in remote sensing, GIS, forest study, modelling, and computer programming will benefit the AGB estimation. For remote sensing projects, there is often a trade-off between accuracy and cost. Higher accuracy often means higher investment in the research.

7.2 Limitation of remotely sensed data and potential solutions

Remote sensing systems provide different information features, such as in spectral, radiometric, spatial, and temporal resolutions, and in polarization and angularity (Barnsley 1999). Recognizing and understanding the strengths and weaknesses of different types of sensor data are essential for selecting suitable sensor data for AGB estimation in a specific study. Reviews of the characteristics of major types of remotely sensed data can be found in Barnsley (1999), Estes and Loveland (1999), Althausen (2002), and Lefsky and Cohen (2003).

In remotely sensed data, radiometric and atmospheric correction is an important but difficult task due to complex atmospheric conditions in time and space. Many methods, ranging from simple relative calibration and dark object subtraction to complex model-based calibration approaches (e.g. 6S), have been developed for radiometric and atmospheric normalization or correction (Markham and Barker 1987, Gilabert *et al.* 1994, Chavez 1996, Stefan and Itten 1997, Vermote *et al.* 1997, Tokola *et al.* 1999, Heo and FitzHugh 2000, Song *et al.* 2001, Du *et al.* 2002, Lu *et al.* 2002, McGovern *et al.* 2002, Canty *et al.* 2004, Hadjimitsis *et al.* 2004). Interested readers should check relevant references to identify the suitable approach for radiometric and atmospheric correction for a specific study, which is based on the availability of the software and related atmospheric data required in the selected approach.

In rugged or mountainous regions, topographic factors such as slope and aspect can considerably affect vegetation reflectance, resulting in spurious relationships between AGB and reflectance. Hence, removal of topographic effects on vegetation reflectance is necessary. Many approaches have been developed to reduce the topographic effects, including band ratio (Holben and Justice 1981) and linear transformations such as principal component analysis or regression models (Conese *et al.* 1988, Pouch and Campagna 1990, Naugle and Lashlee 1992, Conese *et al.* 1993), topographic correction methods (Civco 1989, Colby 1991), integration of DEM and remotely sensed data (Walsh *et al.* 1990, Franklin *et al.* 1994), and slope/

aspect stratification (Ricketts *et al.* 1992). In particular, different topographic correction approaches, such as Minnaert, statistical–empirical, and atmospheric and topographic correction (ATCOR) models, are often used. More detailed information can be found in previous literature (Teillet *et al.* 1982, Civco 1989, Colby 1991, Meyer *et al.* 1993, Richter 1997, Gu and Gillespie 1998, Hale and Rock 2003).

The limitation in spatial, spectral, and radiometric resolutions inherent in the remotely sensed data is an important factor affecting the AGB estimation performance. For example, a Landsat TM image with 30-m spatial resolution often contains many mixed pixels, which may contain different tree species and vegetation ages in a single pixel. Under these conditions, the remote sensors mainly capture canopy information, instead of individual tree information. The coarse spectral resolution (e.g. Landsat TM data have six bands for visible, near-infrared, and short-wave infrared, plus one thermal infrared band) limits differentiation of subtle differences among forest sites. The relatively coarse radiometric resolution (e.g. 8-bit for Landsat TM data) encourages digital number (DN) value saturation due to similar stand structures, impacts of canopy shadowing, and topographic factors, even if the AGB varies in different sites. One possibility to reduce the data saturation problem is to use narrow-wavelength images (Mutanga and Skidmore 2004). The hyperspectral image may improve AGB estimation performance because of its large number of spectral bands with very narrow wavelengths. There is often a trade-off among spatial, spectral, and radiometric resolutions because of the constraint in data volume.

Different sensor data have their own characteristics in reflecting land surfaces, and thus integration of different sources of remotely sensed data may enhance the information extraction process. For example, the integration of radar and optical-sensor data has the potential to improve AGB estimation because it may reduce the mixed pixels and data saturation problems and incorporates radar information in the new dataset. Data fusion of multi-sensor or multi-resolution data takes advantage of the strengths of distinct image data for improvement of visual interpretation and quantitative analysis. Many methods have been developed to integrate different sensors or spectral and spatial information (Gong 1994, Solberg *et al.* 1996, Pohl and van Genderen 1998, Chen and Stow 2003). For AGB studies, it is important to preserve the spectral integrity of the input dataset when the data fusion approach is used to produce an output. Therefore, a principal component analysis based data fusion approach may be suitable. In recent years, wavelet-merging techniques have shown to be another effective approach to generate a better improvement of spectral and spatial information contents (Li *et al.* 2002, Simone *et al.* 2002, Ulfarsson *et al.* 2003). Townsend (2002) has shown that integration of Landsat TM and SAR data improved model performance for forest basal area estimation. Previous research indicated that integration of Landsat TM and radar (Haack *et al.* 2002, Ban 2003), SPOT HRV and Landsat TM (Welch and Ehlers 1987, Munehika *et al.* 1993, Yocky 1996), and SPOT multispectral and panchromatic bands (Garguet-Duport *et al.* 1996, Shaban and Dikshit 2002) can improve classification results. More research is needed to explore the improvement of AGB estimation through multi-sensor data fusion. Although use of multi-sensor or multi-resolution data has the potential to improve AGB estimation performance, the time and labour involved in image processing will be significantly increased. Again, the economic factor will be an important aspect in the use of multi-source remotely sensed data in a large area.

Mixed pixels in medium and coarse spatial-resolution data are common and have been recognized as a problem in applications of remotely sensed data (Fisher 1997). One frequently used method to reduce the mixed pixel problem is to implement data fusion through use of higher spatial-resolution data, such as the SPOT panchromatic band. An alternative is to apply the spectral mixture analysis (SMA) approach to unmix the multispectral image into fraction images, representing the areal proportion of each endmember in a pixel. Previous research has indicated that green vegetation and shade fractions derived from the SMA approach are closely related to the characteristics of vegetation stand structures, especially the vertical structure and canopy geometry of vegetation stands (Lu *et al.* 2005). This characteristic provides a potential to improve AGB estimation (Peddle *et al.* 1999). A detailed description of the SMA approach and its applications have been provided in previous literature (Smith *et al.* 1990, Settle and Drake 1993, Adams *et al.* 1995, Tompkins *et al.* 1997, Shimabukuro *et al.* 1998, Garcia-Haro *et al.* 1999, Dennison and Roberts 2003, Lu *et al.* 2003, Theseira *et al.* 2003). Another way to reduce the mixed pixel problem is to directly use fine spatial-resolution data, such as IKONOS (Thenkabail *et al.* 2004, Wulder *et al.* 2004). Wulder *et al.* (2004) reviewed and discussed the technical aspects of high spatial-resolution data for estimation of attributes used for forest ecosystems.

7.3 Data quality and uncertainty

A high-quality data source is a prerequisite for developing AGB estimation models. In general, AGB is calculated using allometric equations based on measured DBH and/or height (Overman *et al.* 1994, Nelson *et al.* 1999), or from the conversion of forest stocking volume (Brown *et al.* 1989, Gillespie *et al.* 1992). These methods may generate major uncertainty because of different purposes of field measurements, inconsistency of data collection dates, complex tree species composition, and different wood densities. Calibration or validation of the calculated AGB is necessary. Previous research has discussed the uncertainties of using allometric equations (Brown *et al.* 1995, Keller *et al.* 2001, Ketterings *et al.* 2001) and of conversion from stocking volume (Fearnside 1992). A detailed discussion about the collection of AGB samples and its quality is beyond the scope of this paper. Also, it is important to ensure that the remotely sensed data, ancillary data, and sample plots are accurately registered before implementing AGB estimation. The importance of geometric accuracies of field sample plots and remotely sensed data is obvious because poor geometric accuracy could result in spurious relationships between AGB and the remotely sensed data (Halme and Tomppo 2001).

In the past decade, uncertainty research in GIS has made good progress, but in remote sensing it had not obtained sufficient attention until recent years (Mowrer and Congalton 2000, Hunsaker *et al.* 2001, Foody and Atkinson 2002). Dungan (2002) found that five types of uncertainties exist in remotely sensed data: positional, support, parametric, structural (model), and variables. Friedl *et al.* (2001) summarized three primary sources of errors: errors introduced through the image acquisition process, errors produced by the application of data processing techniques, and errors associated with interactions between instrument resolution and the scale of an ecological process on the ground. In AGB research, the important uncertainty sources may be from the collection of AGB sample data, the atmospheric correction, the registration errors between remotely sensed data and AGB sample data, selection of suitable remote sensing-derived variables, and

algorithms used to develop AGB estimation models. Understanding and identifying the sources of uncertainties and then devoting efforts to improving them are critical in improving AGB estimation performance. For example, stratification of the remotely sensed data based on ancillary data showed an effective way to improve estimation accuracy within each stratum (Katila and Tomppo 2001). Another way to reduce the uncertainty is to develop the allometric equations based on each forest type, which is first classified from remotely sensed data. However, this approach requires a larger number of samples than other approaches. Because of the difficulty in collecting AGB sample data, the AGB estimation approach based on forest type has not been extensively used. More research is needed in the future for reducing the uncertainties from different sources in the AGB estimation procedure.

7.4 Selection of suitable variables

Many remote sensing variables, including spectral signatures, vegetation indices, transformed images, and image textures, may become potential variables for AGB estimation. Selection of suitable variables is a critical step for developing an AGB estimation model, because some variables are weakly correlated with AGB or they have high correlation each other. If the variables are weakly related to AGB, incorporation of such variables may reduce the AGB estimation performance. Usually, the selected variables should be significantly correlated with AGB but weakly correlated each other. Some potential methods, such as stepwise regression analysis, correlation analysis, neural network, and feature extraction approaches, may be used to identify the suitable variables.

The selection of variables using stepwise regression analysis and correlation analysis is simply based on the relationships between AGB and tested variables. An advanced method is to use neural network, which may provide a new insight for AGB estimation. For example, a neural network may be used as a selection tool to determine suitable variables and used as an adaptable system to incorporate different kinds of data, such as spectral data and ancillary data, for extraction of vegetation variables (Kimes *et al.* 1998). Another potential approach for selecting suitable variables is based on feature extraction approaches, which are often used in image transformation to extract the major information and reduce the image dimension. Many feature extraction approaches have been developed, including principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, nonparametric weighted feature extraction, wavelet transform, and SMA (Okin *et al.* 2001, Asner and Heidebrecht 2002, Lobell *et al.* 2002, Landgrebe 2003, Neville *et al.* 2003).

7.5 Modelling

Different modelling algorithms have their own merits and requirements in input parameters. Many factors, such as the spatial resolution of remotely sensed data, the availability of biomass sample data and ancillary data, the scale of the study area, the availability of related software, and the analyst's skills and knowledge, affect the selection of modelling algorithms. Although different algorithms, such as multiple regression analysis, K nearest-neighbour, neural network, and vegetation canopy models, have been used for AGB estimation, there is lack of a comparative study of different modelling approaches, thus it is not clear which algorithm is suitable for a specific study area. Previous literature has indicated that multiple regression analysis

may be the most common approach for development of AGB estimation models, especially when the medium spatial-resolution data are used for AGB estimation. As ancillary data are readily available, the neural network may provide a potential approach for AGB estimation because neural network is a nonparametric technique, and it can incorporate different data sources. Also, GIS techniques can be useful in developing advanced models through the combination of remotely sensed and ancillary data. It may be difficult to develop a universal model for AGB estimation, but it is valuable to develop or identify models suitable for different biophysical environments. More research is needed to develop advanced models for AGB estimation using multi-source data.

8. Summary and perspectives

Remote sensing techniques have many advantages in AGB estimation over traditional field measurement methods and provide the potential to estimate AGB at different scales. The user's need, the characteristics of remotely sensed data, the scale of the study area, and the availability of economic support have important influences on the design of an AGB estimation procedure. Fine spatial-resolution data, such as airborne aerial photographs and spaceborne IKONOS images, may provide accurate AGB estimation at a local scale. However, the large volume of data and impacts of the shadow problem restrain its application for a large area. Medium spatial-resolution data, such as Landsat TM, provide the potential for AGB estimation at a regional level, but the mixed pixels and data saturation are found to be a problem in AGB estimation in those sites with complex biophysical environments. The coarse spatial-resolution data, such as AVHRR or MODIS, may provide AGB estimation at a national or global scale, but have not yet been used extensively because of the difficulty in linking coarse spatial-resolution data and field measurements. A combination of multi-scale remotely sensed data, from coarse, to medium, to fine spatial resolutions, may improve AGB estimation accuracy at the national or global scale.

The AGB may be directly estimated using linear or nonlinear regression models, neural network, and K nearest-neighbour, or indirectly estimated from other canopy parameters, which can be better derived from remotely sensed data. A combination of spectral responses and image textures has proven useful in improving AGB estimation performance. The incorporation of remote sensing and GIS will also be useful in improving AGB estimation results when multi-source data are available. Development of advanced models using spectral mixture techniques and neural network approaches may provide new insights for AGB estimation. In practice, the lack of sufficient and high-quality AGB sample plots is a major problem in developing AGB estimation models and in implementing validation and accuracy assessment of the AGB estimation results.

Remote sensing-based AGB estimation is a complex procedure in which many factors, such as atmospheric conditions, mixed pixels, data saturation, complex biophysical environments, insufficient sample data, extracted remote sensing variables, and the selected algorithms, may interactively affect AGB estimation performance. To identify the major uncertainties during the process of developing the AGB estimation models is critical for improving the AGB estimation performance. Some potential solutions include (1) accurate atmospheric calibration to reduce the impacts of uncertainty caused by the different atmospheric conditions; (2) selection of suitable vegetation indices and image textures to reduce the impacts

of environmental conditions and canopy shadows; (3) the integration of optical and radar data to reduce the data saturation in optical-sensor images; (4) the integration of multi-source data, and (5) the reduction of the mixed pixel problem by using SMA or data fusion. Therefore, future research may focus on the integration of multi-source data, which involves the effective integration of remote sensing (including optical and microwave data), GIS, and modelling techniques; a combination of multi-scale remotely sensed data, which involves the integration of field measurements with high (e.g. IKONOS), medium (e.g. Landsat TM/ETM+ and Terra ASTER), and coarse (e.g. MODIS and AVHRR) spatial-resolution data; and the development of a suitable procedure for AGB estimation, which involves identification of the major uncertainties and development of approaches to reduce these uncertainties.

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