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Remote sensing of aboveground forest biomass: A review

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Abstract: Forests are central to global carbon cycle, therefore, accurate inventorying and monitoring of forest aboveground biomass in local to regional scales is critical in understanding their role as atmospheric carbon sinks or sources. This article provides a review of various remote sensing applications in forest aboveground biomass inventorying and monitoring as well as highlights the associated challenges and opportunities. The review concluded that the use of remote sensing in large-scale forest aboveground biomass quantification provides plausible alternatives, when compared to the use of conventional approaches, which are labour-, cost-, and time-intensive and sometimes inapplicable due to poor accessibility. It was noted that although remote sensing provides reasonably accurate forest aboveground biomass estimates, active sensors, such as LiDAR and radar are not fully operational as yet due to complex pre-processing and high cost of data acquisition.

Key words: Aboveground biomass, allometric equations, biomass expansion factor, forest, LiDAR, multispectral remote sensing.

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Introduction

Considering the natural and fundamental role in the basic functioning of the biosphere by regulating global carbon cycle, forests unequivocally reduce atmospheric carbon content considerably. Despite the ravaging impacts of global climate change, forests are capable of stabilizing atmospheric carbon dioxide concentrations thereby mitigating the global warming and the climate change. It is estimated that 2-4 Gt C of atmospheric carbon can be sequestered by forests annually (Lu *et al.* 2010; Qureshi *et al.* 2012). Hence, understanding of the global climate change necessarily involves the quantification of forest parameters such as volume, aboveground biomass (AGB), and forest carbon stocks (Hyyppä *et al.* 2000; Ketterings *et al.* 2001; Steininger 2000). Repeated monitoring of AGB is an important task for sustainable and effective management of forests (Joshi *et al.* 2014). This involves data on various forest parameters such as height, basal area, diameter-at-breast height (dbh), etc. (Field *et al.* 1998). It is also important to have up-to-date knowledge on available low-cost forest AGB estimation methods (Mutanga *et al.* 2012; Muukkonen & Heiskanen 2007).

Conventionally, the AGB monitoring requires intensive field inventory, including taxonomical information, collateral and ancillary data analysis and mapping of the forest cover using remote sensing or other means. The conventional moni-

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toring of AGB is labour-, cost-, and time-intensive and sometimes inapplicable due to poor accessibility, making it practical only in relatively smaller areas (Mutanga *et al.* 2012). Remote sensing, on the other hand, offers an efficient and economical means for AGB monitoring by facilitating forest type and canopy density stratification, which greatly helps in field inventory. Its repeated coverage offers historical data required for change detection, while its digital data format can be easily integrated in a geographic information system (GIS) for further analysis. Many researchers have used remote sensing data to monitor forest AGB in different parts of the world (e.g., Cryus & Tanja 2004; Min *et al.* 2009; Mitchard *et al.* 2009; Patenaude *et al.* 2005; Straub *et al.* 2009; Zheng *et al.* 2004).

The underlying goal of this article is to: (i) review and synthesize different forest AGB estimation methods, using remotely-sensed data and (ii) highlight the limitations and successes in the application of the remote sensing-based methods. In order to address these aims, we firstly present an overview of different conventional methods available for accurate estimation of forest AGB and secondly provide different AGB remote sensing variables as well as highlight the effects of bioclimatic factors (i.e. age, species/forest type, rainfall and topography). Finally, the strengths and weaknesses of different remote sensing data used for AGB monitoring with specific emphasis on those applicable to South Africa are discussed.

Conventional AGB estimation techniques

The Intergovernmental Panel on Climate Change (IPCC) has aggregated AGB estimation methods into three different groups i.e., Tier-1, -2 and -3. Each of these tiers represent the level of methodological complexity in AGB estimation (Henry *et al.* 2011). Following the above grouping, literature shows that forest AGB and changes can be estimated directly or indirectly from forest inventory data by either using allometric equations, biomass expansion factors (BEF) or conversion factors such as wood density (Chave *et al.* 2008; Dovey 2009; Muukkonen & Heiskanen 2007). Although Henry *et al.* (2011), reported that conventional techniques generally provide accurate estimates of forest AGB, it is still regarded as environmentally unfriendly, time-consuming method, largely applicable to small sample sizes. Segura & Kanninen (2005) argued that the use of generic equations in conventional methods and stratification by ecological zones for forest AGB estimation does not accurately reflect the actual tree AGB in a specific area or region. Remote sensing methods have provided better alternative for forest AGB monitoring in terms of accessibility and the cost, most importantly in the developing world. While the use of conventional methods for the monitoring of AGB is not totally rejected by the authors of this review, integrating them with modern remote sensing data would considerably help in quantifying, monitoring, and understanding forest AGB at various scales (e.g., Chinembiri *et al.* 2013; Cryus & Tanja 2004; Min *et al.* 2009; Mitchard *et al.* 2009; Patenaude *et al.* 2005; Straub *et al.* 2009; Zheng *et al.* 2004).

Satellite remote sensing of forest AGB

The fast developments in remote sensing technology have provided multispectral, hyperspectral, light detection and ranging (LiDAR), and radio detection and ranging (radar) data. The most commonly used ones are the multispectral sensors, which measure reflectence by ground features in the visible, near-, middle-, and far-infrared portions of the electromagnetic spectrum. These sensors can be used for many forest-related studies. A survey of the forest studies that used the remote sensing, shows that remote sensing can provide information critically required for forest AGB assessment.

Forest AGB estimation using optical remote sensing data

Optical remote sensing makes use of natural radiation from sun and provides a two-dimensional view of forests and other earth surface features. Due to easy accessibility and affordability, a number of studies have employed optical remote sensing for forest AGB estimation (Basuki *et al.* 2013; Kajisa *et al.* 2009; Lu 2006; Lu *et al.* 2012) (see also Table 1). One of the strengths of optical remote sensing data both is that it is operational at local to global scales with sensors, such as Landsat TM, AVHRR, and MODIS providing globally consistent spatial data. In contrast, a study by Lu (2006) demonstrated that the use of coarse spatial resolution sensors (i.e., Landsat, MODIS etc.) for AGB estimation resulted in poor prediction accuracy due to the presence of mixed pixels together with a mismatch between the size of compartments and the pixel. However, Basuki *et al.* (2013) observed that the application of advanced techniques, such

Table 1. A summary of the use of multispectral data in estimating biomass.

Sensor	Study area	Approach	Findings	Reference
LiDAR& SPOT-5 HRG imagery	Gansu province, western China	Stepwise multiple regressions were used.	Integration of LiDAR and SPOT-5 data can increase biomass estimation accuracy than use of only LiDAR data (R^2 of 0.736 and 18.64 ton ha^{-1})	Qisheng (2012)
Landsat PALSAR	East Kalimantan, Indonesia	Discrete wavelet transforms (DWT), Brovey transform were used.	Biomass estimates ranged between 0.70–0.75 r^2 values.	Basuki *et al.* (2013)
Landsat	Georgia forest land	Vegetation indices and multiple regression analyses were used to develop AGB estimation models.	Hardwoods biomass was estimated with R^2 of 0.52, 0.30 for softwoods and 0.66 for mixed forests.	Min *et al.* (2009b)
Landsat (ETM+).	Kampong Thom Province in central Cambodia	Object-based approach was used.	ABG estimates ranges between 0.67 and 0.76 R^2.	Kajisa *et al.* (2009)
SPOT-5 HRG imagery	Sun Yat-Sen, Nanjing, China	Gray Level Co-occurrence Matrix was applied.	The results showed that ABG was poorly correlated with most textures.	Li *et al.* (2008)
Landsat TM imagery	Western Newfoundland, Canada	Biomass from Cluster Labeling based on Structure and Type (BioCLUST), was used.	BioCLUST offered plausible results.	Luther *et al.* (2006)

as spectral mixture analysis to decompose a mixture of spectral components of Landsat ETM^+ into vegetation, soil, and shade fractions and the integration of these components with radar data, using the discrete wavelet transform (DWT), improves forest AGB estimation accuracy significantly when compared to previous studies. Kajisa *et al.* (2009), who applied an object-based and statistical methods together with textural attributes derived from coarse images, observed significant improvements in AGB estimation accuracies. More recent research has focused on the use of hyperspectral data for forest AGB estimation.

Forest aboveground biomass estimation using hyperspectral remote sensing data

Sevral studies have used hyperspectral remote sensing to map forest AGB (Clark *et al.* 2011; Goodenough *et al.* 2008; Koch 2010; le Maire *et al.* 2008; Treuhaft *et al.* 2003). Goodenough *et al.* (2008) compared the use of hyperspectral AISA Eagle data to AVIRIS data and found that both images could be successfully employed in deriving plausible forest AGB estimates. The study showed a good correlation (r^2 = 0.87) between AGB estimates derived from the AISA Eagle and LiDAR data. Treuhaft *et al.* (2003) reported that forest AGB estimated from forest structure profiles using hyperspectral data may be more accurate when compared to estimates obtained from microwave power or optical radiance measurements. The importance of different wave-lengths in AGB estimation has been investigated by different several researchers with plausible results. Hongrui *et al.* (2011) estimated biomass of desert steppe in inner Mongolia based on red-edge reflectance curve area method. The results illustrated that the red-edge reflectance curve area (between normalized reflectance curve and wavelength in 680 - 780 nm region) performed better when compared with the use of conventional vegetation indices or the red-edge position alone. This method resulted in lower standard error of prediction (26.4 g m^{-2}) compared to that from optimal narrow-band ratio vegetation index (37.4 g m^{-2}).

Swatantran *et al.* (2011) observed that hyperspectral data is prone to saturation in dense forest canopies, such as in the tropical rain forest. Clark *et al.* (2011) estimated forest AGB using the 1.6 m spatial resolution hyperspectral imagery from the HYDICE (Hyperspectral Digital Imagery Collection Experiment) airborne sensor with 210 bands covering the full range of the electro-magnetic spectrum. The results yielded lower forest AGB estimates when compared to estimates derived using LiDAR metrics with an r^2 value of 0.90 and RMSE of 38.3 Mg ha^{-1}. Despite the lower estimates by the hyperspectral sensors, they concluded that airborne LiDAR and hyperspectral sensors can play an important role in the development of future sensors (Clark *et al.* 2011). A study by Anderson *et al.* (2008) demonstrated that integrating hyper-spectral and waveform LiDAR data provide improved AGB estimates when compared to the use of these data sets independently. In all forest conditions, 8 - 9 % more variation in basal area (BA), forest AGB and quadratic mean stem diameter (QMSD) was explained by the use of the multi-sensor data than either AVIRIS or LVIS alone, with the estimated error ranging from 5 to 8 % (Anderson *et al.* 2008).

Although hyperspectral data demonstrates some successes in AGB estimation, the data also suffers from band redundancy for specific applications. For example, neighbouring bands or even bands from different parts of the spectrum may be strongly correlated and contain highly similar information. Furthermore, the use of non-parametric techniques, such as spectral similarity measures, sub-pixel classification techniques, machine learning methods and decision tree classification techniques, make no assumption of data distribution, despite them being robust in reducing data dimensionality (Cho *et al.* 2010). In fact, these methods are computationally intensive, especially when applied on high spatial and spectral resolution data over large areas.

Forest aboveground biomass estimation using active remote sensing approaches

Forest aboveground biomass estimation using radar data involves the use of either backscatter values or interferometry technique (Ghasemi 2011). The backscatter values provide the most convenient and accurate method for biomass estimation as they can be compared to field biomass measurement using regression analysis especially in coniferous forests. Literature shows that the HH, VV, and HV backscatter are related to tree stuctural variables, such as trunk and crown biomass (Beaudoin *et al.* 1994; Ghasemi 2011; Santoro *et al.* 2006). Although this approach demonstrated accurate estimation of forest structural attributes, the most limiting factors in applying this method are: the (i) saturation level at various wavelengths (C, L and P bands) (ii) polarizations (e.g., HV and VV), and the (iii) vegetation stand characteristics including ground conditions. Due to these limitations, the backscatter technique can not be applied on any vegetation type without taking note of the stand characteristics and ground conditions. The other limitation of the radar remote sensing methods, based on the evaluation of backscattering amplitudes for the quantification of forest AGB, is that they saturate in forest areas characterized by biomass above 150 t ha^{-1} (Cutler *et al.* 2012). As a result, research has now shifted towards the use of synthetic aperture radar (SAR) interferometry, polarimetry alone or a combination of both. However, Pulliainen *et al.* (2003) observed that the accuracy of this approach is mostly dependant on the number of images used or site conditions viz., wind speed, moisture and whether the temperature was below freezing point.

Uncertainties such as complexity of atmosphere, course temporal and spatial resolutions, saturation problems in deriving forest AGB estimates associated with broad optical sensors and radar data has led to the introduction of LiDAR sensor to improve on these limitations. Thus, the advent of LiDAR imaging techniques coupled with advanced statistical techniques ranging from simple regression between LiDAR-derived height metrics and forest AGB to methods including automated tree crown delineation, stochastic simulation and machine learning approaches, have resulted in a number of different studies exploring their potential in deriving accurate biomass among other forests studies (Cho *et al.* 2012; Gleason & Im 2012; Lefsky *et al.* 2001a & 2005; Lima *et al.* 2003; Weishampel *et al.* 1996; Wulder 1998).

Gleason & Im (2012) studied the effectiveness of four modelling techniques, namely linear mixed-effects (LME) regression, random forest (RF), support vector regression (SVR), and Cubist in deriving forest AGB in moderately dense forest (40 - 60 % canopy closure) at both tree and plot levels using LiDAR. The results from the four methods were almost similar at individual tree level AGB estimates (RMSE 505, 506, 457, and 502 kg tree^{-1}). Furthermore, forest aboveground biomass estimation accuracy improved when modelled at the plot level, whereas support vector regression (SVR) produced the most accurate biomass model (RMSE

671 kg per 380 m^2 plot when forest plots were modelled as a collection of trees). Kaiguang *et al.* (2009) investigated the effectiveness of canopy height distributions (CHD) and canopy height quantile functions (CHQ) as LiDAR metrics for estimating AGB as well as the capability of LiDAR for mapping AGB at a range of scales. Their results demonstrated that the models can accurately predict forest AGB and yield consistent predictive performances across a variety of scales with an r-square ranging from 0.80 to 0.95 (RMSE ranging from 14.3 to 33.7 Mg ha^{-1}) among all the fitted models. A meta-analysis of more than 70 studies on terrestrial AGB estimation using LiDAR remote sensing by Zolkos *et al.* (2013) indicated that (i) biomass models developed from airborne LiDAR metrics are significantly more accurate than those using radar or passive optical data alone, (ii) biomass models developed from multi-sensor metrics were more variable than LiDAR-only models and they did not improve biomass estimates, (iii) model accuracies varied with forest type, and the underlying causes for the observed differences were multi-faceted, and (iv) relative to the magnitude of field biomass, model errors declined with increasing plot size.

Successes and limitations of forest AGB estimation in South Africa

Few attempts have been made in estimating AGB in South African forests especially on indigenous forests and partly on plantation forests using field inventory data (Christie & Scholes 1995; Dube *et al.* 2014a, 2014b, 2015, 2016; Dube & Mutanga 2015a, 2015b; Dovey 2009; Schönau & Boden 1982) with limited remote sensing applications. The limited number of studies on AGB estimation are as a result of inadequate number of allometric equations for tree species in Sub-Saharan Africa and South Africa in particular. For example, a close analysis of Chave *et al.* (2005) study clearly indicated that none of the trees from African forests were used to develop allometric equations. Zianis & Mencuccini (2004) reported ca. 279 allometric equations from all continents, except for Africa. Therefore, this clearly demonstrates that little has been done to understand AGB and carbon stocks in Sub-Saharan Africa in general and South Africa in particular. Available forest AGB studies in South Africa mostly utilized merchantable volume together with expansion factors and this has been identified as a critical source of uncertainties. According to Tsui *et al.* (2012) the proportion of most tree AGB components vary strongly with stand age, and this introduces errors especially when age dependent expansion factors are not available for the conversion. For example, Dovey (2009) constructed simple multipliers, and later used them together with merchantable plantation timber volumes to estimate AGB for different *Eucalyptus* spp.*, Pinus patula* and *Acacia mearnsii* components. These limitations, therefore, provide opportunities for studies that will estimate AGB in South Africa with the continuous availability of remote sensing data and advanced techniques for estimating AGB.

Conclusions

The present study has reviewed the various remote sensing applications in AGB monitoring, emphasizing the limitations and the prospects linked to these techniques. The review established that remote sensing applications provide a plausible AGB estimates when compared to labour-intensive, costly, and time consuming traditional techniques. We, therefore, conclude that more research is needed on the application of remote sensing for estimating the AGB, especially in developing world in order to meet the Kyoto Protocol objectives.

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