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Review Article

AN EVALUATION OF EXISTING METHODS FOR ASSESSMENT OF ABOVE-GROUND BIOMASS IN FORESTS

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Forest ecosystems are one of the most important carbon sinks of the terrestrial ecosystem. Accurate estimation and mapping the distribution of forest biomass is prerequisite in answering a long-standing debate on the role of forest vegetation in the regional and global carbon cycle. Above Ground Biomass (AGB) is the most important and visible carbon pool of terrestrial forest ecosystem. A variety of approaches and data sources have been used to estimate forest's AGB: (i) field measurement; (ii) remotely sensed data; or (iii) ancillary data used in GIS-based modelling. Depending on the aim of the study, different compromises concerning the used methods appeared to be inevitable. Each method has been proven to be useful and has shown its advantages and disadvantages. Our objective in this paper is to review and summarize a range of approaches that could be adapted to estimate above ground biomass in Natural forests along with advantages and constraints associated therewith.

Keywords: Above-Ground Biomass, Forest Biomass, Carbon Stocks, Biomass Estimation, Remote Sensing

INTRODUCTION

Nature has provided us with natural carbon "sinks" or "sponges" such as the terrestrial ecosystem and the oceans. Forest ecosystems are one of the most important carbon sinks of the terrestrial ecosystem. Deforestation and forest degradation can result in carbon emission to the atmosphere, thus affecting global climate and environmental change (Houghton, 2005; Frolking *et al.*, 2009; Hansen *et al.*, 2013; Lu *et al*, 2014). Changes in the cover, use, and management of forests produce sources and sinks of carbon dioxide requires reliable estimates of the biomass density of forests (Brown, 2002). Estimating and monitoring of the forest carbon stock in different components and annual biomass or carbon increments in a live tree are important to understand the carbon balance of forested ecosystems. This is also important for national development planning as well as for scientific studies of ecosystem productivity, carbon budgets, etc. The subject of biomass assessment

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has received considerable attention for quite some time, especially after pulpwood demand in 1960s and oil crises in 1970s (de Gier, 2003). Forest ecosystems store nearly two third of terrestrial Carbon and have a larger C density (C mass per hectare) than any other land uses (Zhou *et al*., 2008). Forest biomass constitutes the largest terrestrial C-sink and accounts for 90% of all living terrestrial biomass (Tan *et al*., 2007; Zhao and Zhou, 2005; Singh, 2010). This important role of forest in the global carbon cycle was pointed out in several articles of Kyoto Protocol (Brown, 2002). Recently, United Nations Framework Convention on Climate Change (UNFCCC) has considered the need of reducing carbon emissions from deforestation and forest degradation in developing countries (REDD+); whose primary objective is to minimize the carbon emissions and enhance their carbon storage capacities through sustainable management programme (Gibbs *et al*., 2007; Sharma and Chaudhry, 2013).

The natural succession, anthropogenic actions such as deforestation, harvesting, plantation, silviculture, and natural disturbances such as pests, fire and climate change cause forest degradation and reduction in the productivity which inevitably reduced the potential for C-sequestration (IPCC, 2006; Singh, 2010). Thus Estimation of the accumulated biomass in the forest ecosystem is important for assessing the productivity and sustainability of the forest. Our objective in this paper is to review and summarize a range of approaches that could be adapted to estimate above ground biomass in Natural forests along with advantages and constraints associated therewith.

FOREST CARBON STOCK

FAO (2005) has defined biomass as “the organic material both above and below the ground, and both living and dead, e.g., trees, crops, grasses, tree litter, roots, etc.” Above-ground biomass, below-ground biomass, dead mass, litter, and soil organic matter are the main carbon pools in any forest ecosystem (FAO, 2005; IPCC, 2003; IPCC, 2006). The carbon dioxide fixed by plants during photosynthesis is transferred across the different carbon pools. AGB includes all living biomass above the soil including stem, stump, branches, bark, seeds, and foliage, while below ground biomass (BGB) includes all biomass of live roots excluding fine roots (<2 mm diameter), Dead mass includes all non-living woody biomass not contained in the litter, either standing, lying on the ground, or in the soil whereas litter includes all non-living biomass with a diameter less than a minimum diameter chosen by a given country, lying dead, in various states of decomposition above the mineral or organic soil (Houghton, 2005). The AGB of a tree constitutes the most important, visible and major portion of the carbon pool of the terrestrial forest ecosystem (Lu, 2006; Vashum and Jayakumar, 2012). Thus, estimating AGB carbon is the most critical step in quantifying forest’s carbon stocks and fluxes (Gibbs *et al*., 2007). The amount of carbon sequestered by a forest can be inferred from the biomass accumulation since approximately 50% of forest dry biomass is carbon (de Gier, 2003). Jana *et al.* (2009) estimated 47.45 and 47.12% of carbon content (except root) in the Above Ground Biomass (AGB) of *Shorea robusta* and *Albizzia lebbek*, respectively. Chaturvedi (1994) suggested using a factor of 0.48 to convert dry biomass to carbon. In many cases widely used values from look-up tables and correlations with AGB will be adequate to estimate carbon stocks in other pools. For example, root biomass is typically estimated to be 20% of the aboveground forest carbon stocks (e.g., Houghton *et al.,* 2001; Achard *et al.,* 2002; Ramankutty *et al.,* 2007). Similarly, dead wood or litter carbon stocks (down trees, standing dead, broken branches, leaves, etc.) are generally assumed to be equivalent to <H10–20% of the aboveground forest carbon estimate in mature forests (Delaney *et al.,* 1998; Houghton *et al.,* 2001; Achard *et al.,* 2002; Gibbs *et al*., 2007). Accurate estimation and mapping the distribution of forest biomass is prerequisite in answering a long-standing debate on the role of forest vegetation in the regional and global carbon cycle (Lu, 2006). Selection of appropriate biomass estimation method and use of reliable forest inventory data are two key factors for this purpose (Zhao and Zhou, 2005).

METHODS FOR ASSESSMENT OF FOREST BIOMASS

Owing to the dynamism of nature, the land use land cover features changes with time (Sharma *et al*., 2013). Reasonable methods for estimating tree biomass and carbon stocks on forest land are increasingly important given concerns of global climate change and carbon sequestration protocols for the voluntary and regulated markets (Zhou and Hemstrom, 2009). Estimation of the accumulated biomass in the forest ecosystem gives an idea of the potential amount of carbon that can be emitted in the form of carbon dioxide when forests are being cleared or burned, also enables us to estimate the amount of carbon dioxide that can be sequestered from the atmosphere by the forest, and hence important for many applications like timber extraction, tracking changes in the carbon stocks of forest and global carbon cycle (Vashum and Jayakumar, 2012). Among all the land-use systems involving trees, the most significant carbon pool preserved as AGB (Ravindranath and Ostwald, 2008), is susceptible to frequent changes which require recurrent monitoring (Sharma *et al*., 2013). A variety of approaches and data sources have been used to estimate forest's AGB: (i) field measurement; (ii) remotely sensed data; or (iii) ancillary data used in GIS-based modelling.

Field Measurement

Two methods of field measurement are available. The existing methods of sample tree biomass measurement can be categorized into (a) destructive sampling which entails direct measurement or (b) non-destructive which involves the application of allometric equations.

Destructive Method of Tree Biomass Estimation

Among all the available biomass estimation method, the destructive method, also known as the harvest method, is the most direct method for estimation of AGB and the carbon stocks stored in the forest ecosystems in which all plant material is weighed and samples are oven-dried (to remove all water remaining in living tissues) to obtain water content correction coefficients (Drake, 2001). Biomass measurements can be undertaken on a single-tree basis or on plot area basis. In the first case the biomass of each individual is measured, whereas in the second case the total biomass of a specific area or sample plot is measured (FAO, 2009). Although ground based techniques have enabled estimates in many areas, these approaches do have limitations. The first is that they are often imprecise due to the small portion of the trees that are sampled. The second limitation is that timely data are difficult to collect due to the cost and data collection times associated with ground inventories. A third limitation of ground based studies is cost (Ghasemi *et al*., 2011). This method may also not yield representative area estimates when the results have to be spatially extrapolated. As a result, it is often used for specific research purposes and for developing biomass equations to be applied for estimating biomass on large scale (FAO, 2009).

Non-Destructive Method of Biomass Estimation

The non-destructive methods do not required tree felling. Tree measurements are made either by climbing the tree or taking photographs. These methods, however, can give only the volume of trees non-destructively. To estimate the tree biomass one has to rely on density values (which is already a product of destructive process) of tree components from literature (Deo, 2008). So in effect purely non-destructive biomass sampling does not exist. When destructive techniques are utilized they are typically done in a manner so that allometric equations can be developed to relate total oven-dry AGB to a particular tree (e.g., tree height or stem diameter at breast height) or forest stand structural attribute (e.g., basal area or volume over bark) (Drake, 2001). Biomass equations can be developed for a single species or for a whole ecosystem type. Many different model approaches both linear and nonlinear have been used (Satoo and Madgwick, 1982; FAO, 2009). Allometric relationships can often be developed because the growth of different tree components (e.g., stem diameter) is related to the increase in the overall aboveground mass of the tree throughout the growth cycle (Drake, 2001). For example, as trees grow there is typically a geometric increase in biomass per tree with increases in diameter (Brown, 1997). In field studies all stem diameters within a plot that are over a minimum size (e.g., 10 cm) are typically measured at breast height (1.37 m) or, in the case of large tropical trees, above any buttresses. The diameter measurements can then be related to tree biomass using an allometric equation that has been developed for that tree species or for trees belonging to a general structural type (e.g., the tropical wet forest equation). The estimated AGB values are then summed for all measured trees within a plot (Drake, 2001). 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) (Lu *et al.*, 2014). Tropical forests often contain 300 or more species, but research has shown that species-specific allometric relationships are not needed to generate reliable estimates of forest carbon stocks (Gibbs *et al*., 2007). Many models have been developed based on various combinations of the aforementioned three parameters through linear or nonlinear regression models (Segura and Kanninen 2005; Seidel *et al.,* 2011; McRoberts and Westfall, 2014; Lu *et al*., 2014). Moreover, incorporating more variable in the equation does not necessarily improve the accuracy of the estimate significantly. de Gier (1989)) and Wang (2006) found that incorporating the height did not significantly improve the models based on dbh alone. Further measurements of some of the variable (e.g., total tree height) in the field are more difficult, time consuming and less accurate than measuring dbh. Hence, dbh is the most common predictor in biomass equations (Jenkins *et al*., 2003; Wang, 2006; Zheng *et al*., 2004; Zianis and Mencuccini, 2004). 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 (Lu *et al*., 2014). Chave *et al*. (2004) pointed out that there are four types of uncertainties to be considered, that are (i) due to tree measurements, (ii) choice of allometric equations, (iii) sampling usually related to plot size, and (iv) representative of small measurement plot networks across large forest landscape (Singh, 2010). Published allometric equations for specific vegetation types and tree species are often used. Since the allometric coefficients vary between sites and species, and based on a certain range of tree diameters, the use of standard allometric equations can lead to significant errors in vegetation biomass estimations (Chave *et al*., 2005; Heiskanen, 2006). This problem occurs when allometric equations are applied to vegetation types that are outside the area where they were originally produced. As a consequence there has been efforts in developing generalized regional and national tree biomass equations that could be applied to a larger geographic footprint than most existing allometric equations (Lambert *et al*., 2005; Case and Hall, 2008; FAO, 2009; Brown, 1997; Chave *et al.,* 2005; Gibbs *et al*., 2007). The method of least squares regression is quite common in the development of biomass equations (Parresol, 1999). When biomass regressions are calculated by statistical least squares methods, the random part of sub-sampling error is automatically taken into account (Cunia, 1986). Unweighted least squares estimates are fully efficient only when the standard error of the residuals is constant for all classes of the dependent variables (Furnival, 1961). In reality the standard error of the residuals tend to vary with the size of trees. So, weighting of the regression coefficients is important (Parresol, 1999). Theoretically weights should be employed that are inversely proportional to the variance of the residuals (Furnival, 1961). The effort required to develop species- or location-specific relationships will not typically improve accuracy (Chambers *et al.,* 2001; Keller *et al.,* 2001; Chave *et al.,* 2005) but occasionally a localized relationship is warranted, as generalized equations may not adequately represent all forest types in all areas. Destructive sampling of 2–3 large trees should be used to check the validity of an allometric equation for specific locations (Brown, 2002; Gibbs *et al*., 2007). The 'Good Practice Guidance' IPCC, 2003 has also given priority for the selection and use of species specific or similar species allometric equations in the priority order of local to national to global scale in biomass calculation (Singh, 2010).

In summary, 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; Lu *et al*., 2014).

Remote Sensing-Based Biomass Estimation

Remote sensing–based methods of AGB estimation in forest ecosystems have gained increased attention, and substantial research has been conducted in the past three decades. As an alternative to traditional field methods, remote sensing techniques have been examined and a number of studies have been conducted (Sarker, 2010). Remote sensing is a process of acquiring data from a distance of an object, area or a phenomenon by analyzing the data through instruments without being in contact with the object or area which is/ are being examined. The advantages of biomass estimation using remote sensing can be described in terms of time (speedy processing), accessibility (to any location), cost (relatively low cost) and change detection (temporal data available) (Zachary and Randolph, 2005; Bortolot and Wynne, 2005; Sarker, 2010). Remotely sensed data with its synoptic view, high spatio-temporal resolution, and digital format allows fast processing of large quantity of data as well as the availability of data for that particular area of forest which is inaccessible by field survey (Sharma *et al*., 2013). Remote sensing measures the amount of microwave, optical or infrared radiation that is reflected or scattered by the imaged area in the direction of the sensor. This amount is related to biomass levels of the vegetation in the imaged resolution cell at certain electromagnetic wavelengths. Generally, biomass is either estimated via a direct relationship between spectral response and field estimates of biomass using multiple regression analysis, k-nearest neighbor, neural networks (Roy and Ravan, 1996; Nelson *et al*., 2000; Steininger, 2000; Foody *et al*., 2003; Zheng *et al*., 2004) or through indirect relationships, whereby attributes estimated from the remotely sensed data, such as Leaf Area Index (LAI), structure (crown closure and height) or image objects such as shadow fraction are used in equations to estimate biomass (Woodcock *et al*., 1997; Phua and Saito, 2003; Popescu *et al*., 2003; FAO, 2009).

However, remote sensing based AGB estimation is a complex procedure in which many factors such as atmospheric conditions, mixed pixel, data saturation complex biophysical environments, insufficient sample data, extracted remote sensing variables and selected algorithms may interactively affect AGB estimation (Luther *et al*., 2006; Singh, 2010). Successful estimation and modelling of AGB over large scales require (a) correct selection and application of remote sensing, (b) being coupled with field data for calibration and validation, and being integrated into (c) an appropriate modelling approach .

However, challenges exist to estimate biophysical data via available remote sensing technologies, such as optical, radar, and LiDAR data, which form the main tools capable of estimating forest AGB (Wang and Qi, 2008; Hall *et al.,* 2011). One issue is due to the varying spatial, temporal, radiometric, and spectral resolutions unique to each sensor system, resulting in different advantages and disadvantages to AGB estimation (Eisfeldar, 2012; Sarker, 2010). Attempts to use remote-sensing data to estimate carbon stocks have evolved along four major fronts:

Optical Remote Sensing Data

The estimation of forest biomass using optical satellite data is very common and many researchers have evaluated the capability of optical satellite data for biomass estimation using different types of data and image processing techniques. Optical remote sensing mainly responds to the leaf chemistry or structure to measure the vegetation indices like Normalized Difference Vegetation Index (NDVI) and uses the technique of modeling based on NDVI–biomass relations to estimate the AGB of the whole forest area (Dong *et al*., 2003; Sharma *et al.,* 2013). The most commonly used optical data for biomass estimation are Landsat TM (Foody *et al.,* 2003; Calvao and Palmeirim, 2004; Lu, 2005; Avitabile *et al.,* 2012; Du *et al.,* 2012; Lu *et al.,* 2012) Landsat ETM+ (Zheng *et al*., 2004; Rahman *et al*., 2005), IKONOS (Thenkabail *et al.,* 2004) Quickbird (Hyde *et al.,* 2006), SPOT-5 HGR (Li *et al.,* 2006), NOAA AVHRR (Hame *et al.,* 1997; Boyd *et al.,* 1999; Dong *et al.,* 2003), MODIS (Baccini *et al.,* 2004), and ASTER (Muukkonen and Heiskanen, 2005). In almost all cases different types of vegetation indices and band ratios were used to extract biomass from reflectance images, and different types of statistical modelling were applied to correlate vegetation index values or band ratio values with field estimations (Sarker, 2010).

Optical sensors are primary data sources for biomass estimation, and selection of suitable variables is important for developing biomass estimation models, but following problems are still unsolved: (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 is 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 modelling. Overall, optical sensor data is suitable for 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 (Lu *et al*., 2014). Although some researchers (Lu, 2005; Fuchs *et al*., 2009) used spatial processing such as texture measurements these were unable to obtain significant improvement probably because fine resolution data is required for better textural properties (Sarker, 2010).

Optical sensor data such as ALOS/PRISM, Terra ASTER and SPOT provide 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; Lu *et al*., 2014). Nonetheless, optical remote sensing systems are operational at the global scale and some satellite systems (Landsat and AVHRR) provide a globally consistent record for the last 30 years (Gibbs *et al*., 2007)

Very High-resolution Aerial Imagery

The spatial detail of optical images collected from airborne sensors (as fine as ~10 cm pixels) can be used to directly collect measurements of tree height and crown area or diameter. Allometric relationships between ground-based measurements of tree carbon stocks and its crown area with or without tree height can be applied to estimate forest carbon stocks with high certainty. These data are collected over relatively small areas (several thousands of ha), but could be used for inaccessible areas or in a sampling scheme. An airplane-mounted system, using dual cameras and collecting imagery that can be viewed in 3D, has been demonstrated to reduce costs of conducting forest inventories, particularly for highly variable, widely spaced or inaccessible sites (Brown *et al.,* 2005; Brown and Pearson, 2005) and for dense forests (Pearson *et al.,* 2005; Gibbs *et al*., 2007).

Microwave or 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.,* 2011; Huang and Chen 2013; Lu *et al*., 2014; Fransson and Israelsson, 1999; Tsolmon *et al.,* 2002; Sarker, 2010). The radar signals returned from the ground and tops of trees are used to estimate tree height, which are then converted to forest carbon stock estimates using allometry (Gibbs *et al.,* 2007). They have foliage penetration capabilities which allow SAR to re-code back-scattenng not only from the upper canopy structure but also from woody biomass components (Sarker, 2010). 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 (Lu *et al,* 2014).

Ulaby *et al.,* (1990) and McDonald *et al.,* (1991) found that radar backscatter at high frequencies (C-bands and X-bands) is dominated by scattering processes in the crown layer of branches and foliage and that it does not penetrate and scatter significantly from the bole, while backscatter at lower frequencies (P-bands and L-bands) is dominated by scattering processes involving the major woody biomass components (trunks and branches) Radar backscattering at longer wavelengths (L-bands and P-bands) is lower than that from the C-band for low biomass sites, such as grasslands, bogs, clear cuttings, areas of forest regeneration, and young plantations The opposite occurs when the woody biomass reaches a certain level and backscattering at longer wavelengths becomes greater than that from the C-band (Ranson and Sun, 1994; Sarker, 2010). However, in the past, only single polarization, single incident angle and lower resolution space borne SAR sensors (JERS-1, ERS-1/2) was available, thus the potential of SAR data for biomass estimation especially using dual polarization or quad polarization SAR with high resolution was not investigated except for limited studies with airborne SAR data With the establishment of PALSAR (L-band) and RADARSAT-2 (C-band) data are now available with different polarizations, different resolutions, and varying incident angles and these data now offer opportunity to scientific community to re-examine potential of SAR data for biomass estimation (Sarker, 2010).

It is difficult to use radar data for distinguishing vegetation types (Li *et al*., 2012), 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 (Lu *et al,* 2014).

LiDAR (Light Detection and Ranging)

Light Detection and Ranging (LiDAR) is a relatively new type of remote sensing technique that provides forest biomass estimation accuracies equal to or surpassing those obtained from other remote sensing techniques (Bortolot and Wynne, 2005; Hyde *et al*, 2007; Sarker, 2010; Chen 2013; Maltamo *et al.* 2014). LiDAR systems send out pulses of laser light and measure the signal return time to directly measure the height and vertical structures of forests. LiDAR remote sensing is designed to allow the signal to penetrate the canopy (Vashum and Jayakumar, 2012). The LiDAR method can estimate biomass levels of 1300 t/ha, which far exceeds the capabilities of radar (Drake *et al*, 2002; Sarker, 2010). However, the problem is that the LiDAR sensor is not available on space borne satellites and acquiring LiDAR data is very costly, as a result biomass estimation from LiDAR at regional and global scales is still not promising (Lu, 2006). LiDAR data is powerful for estimating canopy structure but has limited spectral information because laser point intensity is from one wavelength (Lu *et al,* 2014).

Optical sensor, radar, and LiDAR have their own positive and negative characteristics and proper integration of them can improve biomass estimation accuracy (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.,* 2012; Lu *et al.,* 2014).

Ancillary Data used in GIS Based Modeling

Models are used to extrapolate biomass estimates over time and/or space from a limited dataset. These are generally empirical models based on a network of repeatedly measured sample plots, which may have biomass estimations built in or may require allometric relationships to convert volume to biomass (FAO, 2009). The one of the most common procedure used for estimating individual tree biomass is mathematical models calculated by regression analysis (Parresol, 1999; Segura and Kanninen 2005). Because such models do not exist for most forested areas, process models that are based on multiple environmental variables and are calibrated to account for different vegetation types may be optimal (Australian Greenhouse Office, 1999; FAO, 2009). Large number of biomass models exists in literature; and it is really difficult to choose appropriate model for a particular set of data. However, the usual index of fit, the root mean square error (RMSE), can be used to compare models that have the same dependent variable (Furnival, 1961). Global Dynamic Vegetation Models are also being used to estimate biomass. However, because of model assumptions and simplifications the outcomes are not generally suitable to accurately represent the state of biomass distribution. These models are more suitable to run in conjunction with climate models (FAO, 2009). Special software has been developed to predict biomass parameters based on existing equations (e.g. BIOPAK, Means *et al.,* 1994; Seidel *et al.,* 2011). GIS-based biomass estimation models using environmental variables cannot provide accurate biomass estimates because forest biomass often has weak relationships with environmental variables (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, 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 (Lu *et al,* 2014). One simple, yet rather uncertain approach, is provided by the IPCC guidelines for Land Use, Land-Use Change and Forestry (LULUCF). The Tier 1 method to estimate biomass uses a standardized eco-climatic stratification and regional default values to generate approximate biomass estimates that may be used when no other information is available, i.e. in some developing countries (FAO, 2009).

During the last two decades, throughout world have put considerable effort into developing models for estimating tree biomass and carbon stock over large scale. However, applying those broad-scale models to regional or fine-scale analyses can be challenging. For example, broad-scale estimates of merchantable tree biomass based on lumping many species may differ considerably from estimates made with more regionally representative models, and the potential success of a AGB estimation project might hinge on these differences. Therefore, understanding the potential alternative approaches for estimating forest biomass is very important for local analyses of biomass supply and forest carbon accounting (Zhou and Hemstrom, 2009)

CONCLUSION

Biomass is a crucial ecological variable for understanding the evolution and potential future changes of the climate system. Biomass estimation is a comprehensive procedure that requires a careful design at each step. The integration of field, remote sensing data and models provides the most feasible approach by which biomass can be mapped at large spatial scales. Within this framework, methods are needed to assess the degree of uncertainty of these biomass estimates as they are fundamental when providing input to models that assess changes in carbon and carbon stocks over time as a result of deforestation, afforestation, natural disturbances and other factors that may result in changes to the forest. Although a lot of effort has been made in estimating biomass using both field-based and remote sensing techniques, no universal and transferable technique has been developed so far to quantify biomass carbon sources and sinks due to the complexity of the environmental, topographic and Biophysical characteristics of forest ecosystems. While there has been numerous studies carried out to estimate the forest biomass and the forest carbon stocks, there is still a further need to develop robust methods to quantify the estimates of biomass of all forest components and carbon stocks more accurately which is always connected with open research questions, new fields of investigation or new findings.

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