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Above Ground Biomass Estimation Methods and Challenges: A Review

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Abstract
Forest ecosystems play an important role in global change on the earth. However, continued forest degradation and deforestation will results in the loss of forest biomass or carbon stock. Hence, current concerns for global change and ecosystem functioning require accurate biomass estimation and examination of its dynamics. In this end we reviewed the present scenarios of above ground biomass estimation, focusing predominantly on field measurement (destructive and non-destructive) and remote sensing (optical remote sensing, radar and light detection and ranging (LiDAR)) biomass estimation methods and identifying some important point or research findings in detail. In addition, we discuss the critical uncertainties or the source of errors in all methods. In the field methods the source of error encountered mainly from sampling error, measurement error and statistical or model error. In the remote sensing methods; optical sensor data is not suitable for estimation of vertical vegetation structures such as canopy height, Radar have the following uncertainty: costly data, no time-composite data as the case for optical data, limited area coverage and LiDAR also faces the following challenges spatially limited, data intensive, and expensive, can't applied extensively to larger areas, limited usage in harsh weather. Finally, we suggest that using both field measurement and remote sensing methods will increase the accuracy of biomass estimation.
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1. Introduction

Woody biomass is the accumulated mass, above and below ground, of the roots, wood, bark, and leaves of living and dead woody shrubs and trees. Biomass generally includes all live and dead material in all forms of vegetation (trees, shrubs, vines, etc.),or the trees and woody plants, including limbs, tops, needles, leaves, and other woody parts, grown in a forest, woodland, or rangeland environment (MacDicken 2015). Biomass of forests is very relevant for issues related to global change. For example, the role of tropical forests in global biogeochemical cycles, especially the carbon cycle and its relation to the greenhouse effect, has increasing interest in estimating the biomass density of tropical forests (Houghton 2005).

Forest ecosystem constitute large amount of biomass and thus it play a major role in carbon sequestration and global climate regulation (Houghton 2005;Lü et al. 2010). It can stabilizing atmospheric carbon dioxide concentrations through sequestration of 2-4 Gt of atmospheric carbon annually (Houghton 2005;Lü et al. 2010; Qureshi et al. 2012;Hansen et al. 2013). However, continued forest degradation and deforestation will results in the loss of forest biomass or carbon stock magnifying the negative effects of global climate change (Frolking et al. 2009; Hansen et al. 2013). Hence, Current concerns for global change and ecosystem functioning require accurate biomass estimation and examination of its dynamics (Shepardson et al. 2011) and which is important for quantifying carbon stock and sequestration rates, assessing potential impacts due to climate changes (Houghton 2007).

Different approaches have been applied to forest biomass estimation. Field measurements method is the most accurate to estimate forest biomass but it is time-consuming and labor-intensive, and it is impossible to cover large areas (Mutanga et al. 2012; Seidel et al. 2011). Remote sensing enables the estimation of forest biomass at multiple scales with large spatial and temporal coverage. It offers an efficient and economical means for monitoring AGB by facilitating forest type and canopy density stratification, which greatly helps in field inventory (Bortolot and Wynne 2005). Recently, with the ability to detect the structures of forest, RADAR and LiDAR remote sensing are also used to estimate forest biomass. However, there remain limitations in typical study areas and they have not been applied extensively to large scale studies because of cost constraints, saturation problem and environmental factors (Ji et al. 2012; Rauste 2005).

A major sources of error in the field measurement methods comes from; sampling selection, measurement and statistics or model (Temesgen et al. 2015). And also the source of error in remote sensing methods emanate from: knowledge and skill on image processing software and models (Lu et al. 2014; Skowronski et al. 2014). Given this, the main purposes of this paper is to review different forest AGB estimation methods (field measurement and remote sensing) and their challenges or uncertainty during implementation

1.1. Methods

To do this specific review, we try to read and review different articles and books that related to each individual biomass estimation methods and their limitation or uncertainty.

2. Forest Biomass estimation methods

Logical estimation methods for aboveground biomass and carbon stocks on forest land are increasingly important given concerns of global climate change, carbon sequestration protocols for the voluntary and timber extraction (Zhou and Hemstrom 2009). For this specific review we will see each biomass estimation methods, and their uncertainty during application.

2.1. Field measurements

Field measurements is a measurements that measure directly tree biomass using tools and equipments. Based on the level of impacts on the tree field measurement divided in to two: Destructive methods and Non-destructive methods.

2.1.1. Destructive Methods

Destructive estimation method entails harvesting trees like tree trunk, leaves and branches. sometimes also known as the harvest method, drying them, and weighing the biomass. It comprises field (site preparation, measurement of felled trees, weighing of logs and take sampling for laboratory) and laboratory (dry biomass, density and volume) measurement Operations (Ravindranath and Ostwald 2008; Picard et al. 2012)(Photo 1-3). While this method is the most direct and accurate method for quantifying biomass within a small unit area, it can be time and resources consuming and not feasible at large scale. As a result, it is often used for specific research purposes and for developing biomass equations for estimating biomass on large scale (Navar 2009; Ravindranath and Ostwald 2008; Segura and Kanninen 2005).

Photo 1: Stands were cut at height of 40cm diagonally (source melese et al 2013)

Photo 2: Fresh biomass measuring of biomass components (source melese et al 2013)

a) Biomass compartments

b) Stem

c) Branch

d) Leaves

Photo 3: Biomass sampling and drying (source melese et al 2013)

Note: Biomass sampling, drying and laboratory measurement are; 10 bundle of leaves, 5 cm thick disks from stem, 5 cm length disks form each branch, air-dried for one week oven dried for 24 hours at 70 0c in lab and laboratory measurement

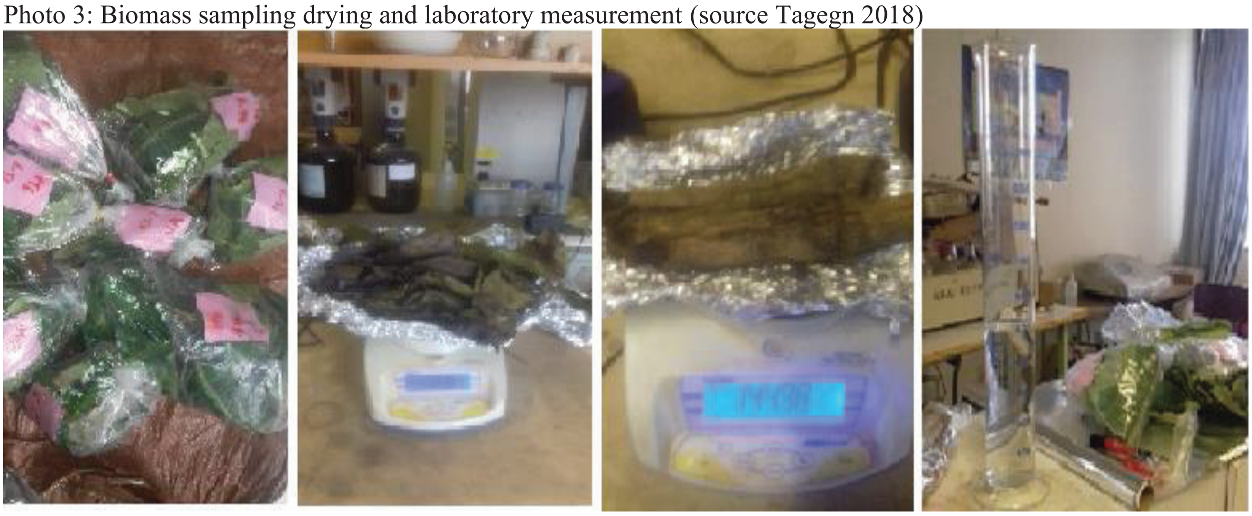
2.1.2. Non-destructive Methods

Non-destructive method is sampling measurements that do not require total felling of the trees, only the small branches are affected (Picard et al. 2012). It is applicable the ecosystems with rare or protected tree species where harvesting of such species is not practical or feasible (Montes et al. 2000). Estimating the above-ground forest biomass by non-destructive method is by climbing the tree to measure the various parts or by simply measuring the diameter at breast height, height of the tree, volume of the tree and wood density (Aboal et al. 2005; Liu and Westman 2009; Ravindranath and Ostwald 2007). According to Montes et al 2000 findings using non-destruction methods for biomass estimation can leads to 2.5-7.5 % per tree error. In Ethiopia defferent researcher used or using non destructive methods. However, these methods can also involve a lot of labor, time and climbing can be troublesome (abiye and teshome, 2017).

Photo 1: Measure DBH in all compartment (source: Tagegn 2018)

Photo 2: Fresh biomass measuring of biomass components (source Tagegn 2018; Damena 2016)

Photo 3: Biomass sampling drying and laboratory measurement (source Tagegn 2018)



By using destructive and non destructive method biomass equations (BE) or allometric equations can be developed for a single species or for a whole ecosystem type. Estimate biomass is using an appropriate Biomass Equation (BE) that can estimate tree biomass using easily measured parameters from forest inventories like DBH alone or including H together and others. Several researchers developed generalized and/or site specific multi-species or single species equations for different forest types. These equations are developed through creating relationships between different parameters of trees like DBH of the stem, total height of the tree, crown diameter etc. (Basuki et al. 2009; Brown 1997; Chave et al. 2014; Condit 2008; Djomo et al. 2010; Henry et al. 2013; Ngomanda et al. 2014; Rutishauser et al. 2013).

Whereas the applicability of the equation for single or mixed tree species and for specific or large-scale area depends on the employed data used to construct it (Somogyi et al. 2007). Consequently in order to achieve the maximum possible accuracy of these methods, applying the correct BE for the appropriate tree species and/or forest type is very crucial (Henry et al. 2011). Thus based on their agro ecological area of development origin and their recommended range of applicability both in forest type and input data requirement, the following published allometric equations are reviewed in the following tables.

Table 1: List of reviewed biomass equation and used methods

Researchers	Tropical forest	Equation	Methods they used
(Brown et al.)	Wet	$M=e(-2.409+0.952(\rho wD^2H)$	Destructive
(Brown 1997)	Dry	$M=34.47-8.0671D+0.6589D^2$	Destructive
	Moist	$M=e(2.134+2.53*\ln(D))$	Destructive
(Velazquez-Martinez et al. 1992)	Dry	M=10**(-0.5352+Lo g (BA)	Destructive
(Návar-Cháidez 2010)	Dry	$M=0.08479(pw^{0.55255} D^{2.2435} H^{0.4773})$	Destructive
	All	$M=(38.36*B^{-6.9045})D^{(B=d+hB*)}$	Non-Destructive
(Chave et al. 2005)	Dry	$M=0.112*(\rho wD^2 H)^{0.916}$	Destructive
	Moist	$M=0.0509*((\rho wD^2 H)$	Destructive
	Wet	$M=0.0776(\rho wD2H)^{0.94}$	Destructive
(Abiye and Teshome 2017)	For (Millettia ferruginea)	ln(TB)=ln(-2.588)+ 2.404 ln(DBH)	Non-Destructive

2.2. Remote sensing technique and its application in biomass estimation

Remote sensing technique developed rapidly in the late twentieth century, and remote sensing data with high spatiotemporal resolution, wide coverage, and timely updates has been widely used in the assessment of forest biomass and carbon stock on various scales (Lu 2006; TSITSI 2016). At this time, Remote sensing based methods of AGB estimation in forest ecosystems have gained attention, and substantial research has been conducted in the past three decades (Aricak et al. 2015; He et al. 2013; Liu et al. 2017; Sun et al. 2011; Urbazaev et al. 2018; Zheng et al. 2004).

Data from Remote Sensing satellites are available at various scales, from local to global, and from a number of different platforms and hence we are expected to provide information which can be related directly, and in different ways, to biomass information (Foody 2003; Rosenqvist et al. 2003). Although remote sensing technology cannot be used for underground biomass estimation, it has the ability to provide important information for aboveground biomass (AGB) (Lu 2006).

The advantages of remote sensing include the ability to obtain measurements from every location in the forest, the speedy in data collection and processed, the relatively low cost of many remote sensing data types, and the ability to collect data easily in areas complex to access on the ground (Bortolot and Wynne 2005). There are three different types of remote sensed methods such as optical remote sensing, radar and light detection and ranging (LiDAR) each methods have their own advantages and uncertainty in estimation of above ground biomass (Kumar et al. 2015; Sharma and Chaudhry 2015)

2.2.1. Optical Remote Sensing

The estimation of forest biomass by means of optical satellite data is very frequent used for biomass estimation. Most likely provides the best alternative to biomass estimation through field sampling due to its global coverage, repetitiveness and cost-effectiveness. The most common optical remote sensing data source for biomass estimation are: Land sat (TM, ETM+ OLI) IKONOS, Quick bird, Worldview, SPOT, and MODIS (Baccini et al. 2004; Lu et al. 2012; Thenkabail et al. 2004; Zheng et al. 2004). Optical remote sensing sensor categorized in to three based on their spatial resolution such as: fine spatial resolution data (< 5 m) IKONOS, Quick Bird, Worldview, medium-spatial resolution data (10-100 m) Land sat 4 5 7 TM/Enhanced TM+ and coarse-spatial resolution data (> 100m) MODIS, SPOT (Kumar et al. 2015).

In general, optical sensor data are suitable for examining horizontal vegetation structures such as vegetation types and canopy cover; but, it can't estimate vertical vegetation structures such as canopy height, which is one of the critical parameters for biomass estimation (St-Onge et al. 2008). Optical sensors technology are very importance in estimation of biomass and model development, however the following problems are still unsolved: (1) optical sensor data suffer the saturation problem such as high biomass density and (2) spectral-based variables are influenced by external factors such as atmosphere, soil moisture, vegetation penology, and growth vigor (Lu et al. 2016)

2.2.2. Radar

Over recent years, there has been increasing interest in synthetic aperture radar (SAR) data for aboveground biomass analyses, particularly in the areas of frequent cloud conditions where obtaining high quality optical data is difficult. The capability of radar (Radio Detection and Ranging) systems to collect data in bad weather and night overcomes this issue. Furthermore, the SAR sensor can penetrate vegetation to different degrees and provides information on the amount and three-dimensional (3-D) distribution of structures within the vegetation (Kumar et al. 2015). The most common optical remote sensing data source for biomass estimation are: JERS-1 (early 1990s), ALOS/PALSAR 1, ALOS/PALSAR 2 (2014); ERS 1-2, Envisat 1 -2 up to 2002; Radarsat 1- (1995) RadarSat-2 (2007) (Table 3).

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. Previous studies have demonstrated that Long wavelength such as L- and P-band data (interact with branch, trunk, and ground elements under the forest canopy) and HV polarization are suitable for biomass estimation (High Biomass Density) than short wavelength X- or C-band (interacts primarily with canopy elements) and is appropriate for low biomass (Patenaude et al. 2005; Sun et al. 2002; Ghasemi et al. 2011).

Table 2: Characteristics of space born SAR

Satellite	Years	Agency	Frequency - polarization	Resolution-swath
ERS-1	1991-2000	ESA	C-VV	25 m-100km
JERS	1992- 1998	NASDA	L-HH	25 m-100 km
ERS-2	1995	ESA	C-VV	25 m-100 km
RADARSAT-1	1995	CSA	C-HH	10-100, 45-500km
ENVISAT-ASAR	2002	ESA	C-HH/VV/HV	25-1000m, 50-500km
ALOS-PALSAR-1	2006	JAXA	L-Polarimetric	10-100m, 100-350km
TerraSAR-X Cosmo-Skymed	2007	DLR Italy	X-Polarimetric	1m
RADARSAT 2	2007	CSA	C-Polarimetric	< 10 m
ALOS/PALSAR 2	2014	JAXA	L-in all Polarization	1-3 m, 25-490 km

Source: Le 2007; Sun 2018

A large number of recent studies have explored the use of radar data for above-ground biomass estimation (Ghasemi et al. 2011; Patenaude et al. 2005; Sun et al. 2002; Sun et al. 2011; Zheng et al. 2004). There are a number of advantages to radar remote sensing compared to optical remote sensing in terms of its utility in biomass estimation. The ability of radar to penetrate cloud, rain and haze makes it especially useful in the tropics. Furthermore, radar based sensors are active and have a controlled power outlet, which ensures consistent transmit and return rates (Collins et al. 2009). However there are a number of difficulties to estimate biomass; it can't distinguishing vegetation types, because radar data reflect the roughness of land-cover surfaces instead of the difference between the vegetation types, the accuracy affected during high wind speed, moisture, and temperature, thus resulting in difficulty of biomass estimation (Li et al. 2012).

2.2.3. LiDAR

The two-dimensional (2-D) nature of optical remote sensing data limits its use in direct quantification of some vegetation characteristics like tree height, canopy height, volume, etc. Light Detection and Ranging (LiDAR) is a relatively new and sophisticated technology that helps to overcome this limitation due to its ability to extend the spatial analysis to a third dimension. Its systems send out pulses of laser light and measure the signal return time to directly measure the height and vertical structures of forests (Vashum and Jayakumar 2012).

There are two types of LiDAR in function: i) small footprint (discrete return LiDAR) and ii) large footprint (full waveform LiDAR) (Todd et al. 2003). Both are generally operate in the 900- to 1064-nm wavelengths where vegetation reflectance is highest (Chen 2013; Dubayah and Drake 2000; Lefsky et al. 2002; Saatchi et al. 2011). Discrete return airborne LiDAR systems are more appropriate for fine-scale biomass mapping, while waveform space-borne LiDAR, has the appropriate for broad-scale biomass mapping (Chen 2013; Dubayah and Drake 2000; Lefsky et al. 2002; Saatchi et al. 2011). Common LiDAR remote sensing data source are: GLAS launched in 2003, ATLAS launched in 2018, GALA launched in 2020.

LiDAR technology have a potential to sample the vegetation types, penology, vertical distribution of canopy, canopy density and ground surfaces, providing detailed structural information about vegetation. This potential leads to more accurate estimations of basal area, crown size (Dubayah and Drake 2000; Lefsky et al. 2002). For instance, Zolkos et al. 2013 evaluated more than 70 studies for AGB estimation and concluded that LiDAR methods provide a higher accuracy compared to radar and optical data. More over Gonzalez et al 2010 did comparative analysis on three methods (LiDAR, Quick Bird and Field Measurement) and he stated that LiDAR has produced more accurate estimation of forest biomass than other methods.

Although LiDAR data have some advantages over radar and optical data, there are a few issues that restrict its use for field applications. For example, LiDAR data analyses are not simple and require more image processing knowledge and skill and specific software. The LiDAR data acquisition process is expensive and covers smaller areas, hence study areas are still limited to specific areas and have not been applied extensively to larger areas for biomass estimation (Kumar et al. 2015; Zolkos et al. 2013).

3. Challenges of Biomass Estimation Methods

3.1. Challenges of Field Measurement Methods

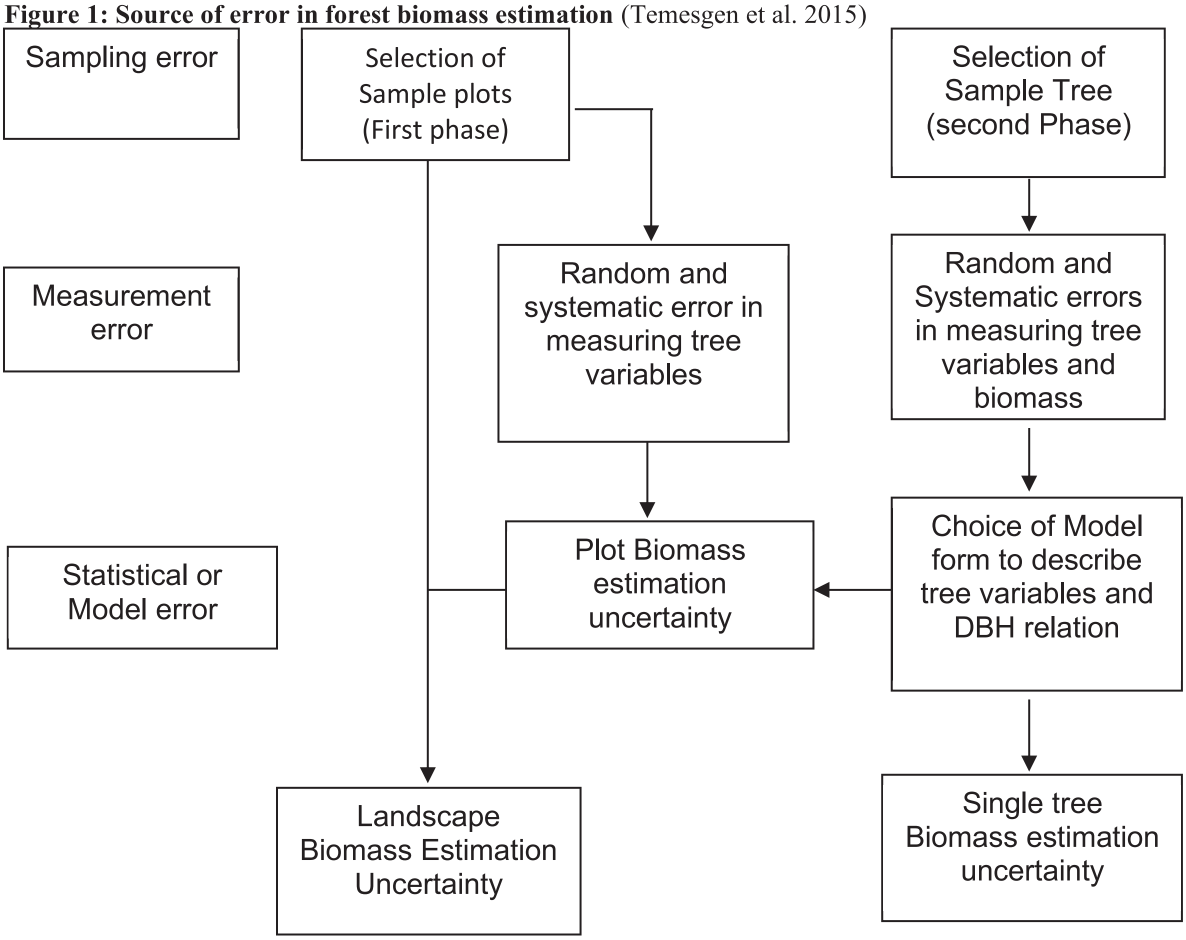
Many scholars indicated that the sources of error can emanate from sampling plot and tree because of variability in tree attributes such as wood density and crown architecture, thus affect the estimation of forest biomass. Generally, the source of errors categorized in two three such as: sampling error, measurement error and statistical or model error (Samalca 2007; Temesgen et al. 2015).

As indicated in the bellow figure 1, sampling errors have two set of phases; first-phase and second-phase . At the first phase, selection of sample plots from aerial photographs or satellite image introduces uncertainty on the biomass estimate. In the second phase, selection of sampled trees that are measured to develop biomass equation also leads to ambiguity of the biomass estimate. Sampling error is affected by sampling scheme, sample size, estimation procedure and inherent variability of the variable of interest (Avery and Burkhart 2015). In this regard, for instance, (ÖZÇELİK and Eraslan 2012) finding showed that the sampling error ranged from 2.51% to 22.63% per tree (and 2.65% of total biomass).

The second source of error appeared from measurement of the tree variables, such as, *DBH*, height or weight measured by diameter tape or caliper, measuring tape, and weighing scale, respectively. Measurement error occurs due to various reasons, including instrument error, recording error, and error due to the nature of the object being measured (irregular girth shape) (Chave et al. 2004).

The third source of error is in the choice of model that describes the relation of biomass and tree variables (Chave et al. 2004; Jenkins et al. 2003; St-Onge et al. 2008). Several biomass equations of different model forms can be found from the literature. When different model forms are used for the same data set, one would expect to get different parameter estimates (Figure 1).

Figure 1: Source of error in forest biomass estimation (Temesgen et al. 2015)



3.2. Challenges of Remote Sensing Methods

Remote sensing techniques have many potential benefits in biomass estimation over field measurement methods at different scales ranging from local to regional, including cost, labor, and time. However, to select appropriate remote sensing data source we have to critically analyze; the scale of the study area, the data analysis procedure and costs. High spatial resolution data from both airborne and satellite platforms can provide accurate biomass estimates at local scales; however, for regional scales, a large volume of data is required, which is not only expensive but also difficult to process; this limits its application for larger areas **(**Kumar et al. 2015**)**. In general, in all remote sensing biomass estimation methods faces an error in related to selection of appropriate software, image acquisition and processing skill.

Optical sensor data are suitable for the retrieval of horizontal vegetation structures such as vegetation 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 (Ni et al. 2014; St-Onge et al. 2008). Proper integration of this vertical structure features and optical spectral response and textures in a biomass estimation model may be a new direction to improve biomass estimation accuracy, but has not been paid much attention yet (Ni et al. 2014; St-Onge et al. 2008). Moreover, previous research has not solved the challenge such as: (1) optical sensor data suffer the saturation problem for high biomass density; (2) influenced by bad weather condition (Lu et al. 2014).

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. Several other limitations of SAR are as follows: costly data, limited area coverage, it can't distinguishing vegetation types, non availability of global-level coherent datasets of SAR and the accuracy affected by bad weather. Refinements in handling and processing SAR data can improve the analyses which are promising prospects for future researches (Sinha et al. 2015).

Even if LiDAR data better than optical data and radar, there are a few issues that limit its use in the field applications. For instance, analyses of LiDAR data are not simple and require knowledge and skill on image processing in specific software. The LiDAR data acquisition process is expensive and covers smaller areas, hence have not been applied extensively to larger areas for biomass estimation **(**Kumar et al. 2015**)**. It is spatially limited, can't applied extensively to larger areas, limited usage in harsh weather and can be expensive ($350 - $450 / sq mile – 1 meter resolution) and technically demanding (Skowronski et al. 2014).

4. Summary of biomass estimation methods

We try to make a comparison the above stated remote sensing biomass estimation methods like optical remote sensed data source, radar detection and ranging (RADAR) and light detection and ranging (LiDAR). Clear advantage, limitation and source of data are discussed in the bellow table

Table 3: Summary of Biomass Estimation Methods

Methods and data source	Advantage	Limitation	References
Field measurement methods			
1. Destructive methods	• The most accurate approach. • An input for development of allometric models for assessing biomass on a larger-scale	• Destroying trees, time-consuming and labor-intensive suitable only for small areas. • It's not applicable for degraded forests containing threatened species	Picard et al. 2012 Montes et al 2000
2.Semi-destructive methods	• It's not destroying trees and save time and costs • Use to estimate endanger species biomass	• It's not measure the whole tree compartment which may affect the accuracy	Picard et al. 2012
Remote sensing methods			
1. Optical remote sensing (IKONOS, Quick bird, Worldview, SPOT, Land sat and MODIS)	• Satellite data regularly collected and freely available at global scale • Reduces time and cost of collecting forest inventory data	• Accuracy is low in closed forests with tree canopy overlap. • It is 2-D data so limited to vertical vegetation structures • It needs clear weather condition (absence of cloud)	Kumar et al 2015; (Gibbs et al. 2007) (Foody et al. 2003) (Zheng et al. 2004) (Steininger 2000)

2. RADAR	• Provides information on surface roughness and moisture content. • May penetrate vegetation, sand, and surface layers of snow. • Enables resolution to be independent distance to the object of with the size of a resolution cell being as small as 1 x 1 m.	• High wind speed, rainfall, freezing, and temperature, affect the accuracy • Less accurate in complex canopies of mature forests because signal saturates • Can be expensive and technically demanding	(Gibbs et al. 2007) (Urbazaev et al. 2018) (Mitchard et al. 2011); (Ghasemi et al. 2011) (Sarker et al. 2012)
3. LiDAR	• *High spatial resolution (<5 cm)* • *It is not affected by extreme weather* • *Can be used to map inaccessible and featureless areas* • It is measures vertical forest structure such as: canopy heights, and aboveground biomass with high level of accuracy	• It is spatially limited • Can't applied extensively to larger areas • Limited usage in harsh weather • Can be expensive ($350 - $450 / sq mile – 1 meter resolution) and technically demanding	(Gibbs et al. 2007) (Nelson et al. 2012); (Dong and Chen 2017); (Skowronski et al. 2014) http:/code.google.com/creative/radiohead/

2. Conclusion

Forest ecosystems play an important role in global change on the earth. However, continued forest degradation and deforestation will results in the loss of forest biomass or carbon stock. Hence, current concerns for global change and ecosystem functioning require accurate biomass estimation and examination of its dynamics. In this end, we reviewed the present scenarios of above ground biomass estimation, focusing predominantly on field measurement (destructive and non-destructive) and remote sensing (optical remote sensing, radar and light detection and ranging (LiDAR)**.** Destructive estimation method entails harvesting trees like tree trunk, leaves and branches (or shrubs, herbs, etc.), drying them, and then weighing the biomass. Non-destructive method is sampling measurements that do not require total felling of the trees, only the small branches are affected and It is applicable in threatened forest ecosystems. The source of errors in both methods categorized in two three such as: sampling error, measurement error and statistical or model error.

In remote sensing, there are three different types of remote sensed methods, such as optical remote sensing, radar and light detection and ranging (LiDAR) each of remote sensing data type have their own advantages and uncertainty in estimation of above ground biomass. optical satellite data is very frequent used and different scholars were assessed the potential of optical remote sensing methods for biomass estimation using different types of data and image processing techniques. SAR sensor can penetrate vegetation to different degrees and provides information on the amount and three-dimensional (3-D) distribution of structures within the vegetation. Light Detection and Ranging (LiDAR) is a relatively new and sophisticated technology that helps to overcome this limitation due to its ability to extend the spatial analysis to a third dimension. Optical sensor data is not suitable for estimation of vertical vegetation structures such as canopy height, which is one of critical parameters for biomass estimation. Radar have the following uncertainty costly data, limited area coverage, it can't distinguishing vegetation types, non availability of global-level coherent datasets of SAR and the accuracy affected by bad weather. LiDAR also faces the following challenges spatially limited, data intensive, and expensive, can't applied extensively to larger areas, limited usage in harsh weather. Finally, we suggest that using both field measurement and remote sensing methods will increase the accuracy of biomass estimation.

List of Abbreviation

GTOS: Global Terrestrial Observing System, IPCC: Intergovernmental Panel on Climate Change, AGB: Aboveground Biomass, LiDAR: Light Detection and Ranging, DBH: Diameter at Brest Height, BE: Biomass Equation, RADAR: Radio Detection and Ranging, SAR: Synthetic Aperture Radar

Ethics approval and consent to participate

All authors eager for this review publication therefore it is not applicable.

Consent for publication

All authors consent to the publication of this review.

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