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REVIEW

A review of radar remote sensing for biomass estimation

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Abstract Forest plays a vital role in regulating climate through carbon sequestration in its biomass. Biomass reflects the health and environmental conditions of a forest ecosystem. In context to the climate change mitigation mechanisms like REDD (reducing emissions from deforestation and forest degradation), an extensive forest monitoring campaign is especially important. Remote sensing of forest structure and biomass with synthetic aperture radar (SAR) bears significant potential for mapping and understanding forest ecological processes. Limitations of the conventional forest inventory procedures, like the extensive cost, labor and time, can be overcome through integrated geospatial techniques. Optical sensor or SAR data are suitable for extracting information about simple and homogeneous forest stand sites. However, optical sensors face serious limitations, specifically in tropical regions, like the cloud cover that SAR can overcome along with targeting saturation and penetration aspects. Simultaneous use of spectral information and image texture parameters improves the biomass assessment over undulating terrain and in radical conditions. Also, synergic use of multi-sensor optical and SAR has better potential than single sensor. Interferometric (InSAR) and polarimetric (PolSAR) SAR or a combination of the both (PolInSAR) serves as effective alternatives. These techniques could serve as valuable methods for biomass assessment of heterogeneous complex biophysical environments. However, SAR data have its own limitations and complexities. Identifying, understanding and solving major uncertainties in different stages of the biomass estimation procedure are critical. In this regard, the current study provides a review of radar remote sensing-based studies in forest biomass estimation.

Keywords Biomass · Interferometry · Polarimetry · SAR · Uncertainty

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Introduction

Forest is defined as an ecosystem dominated by trees and other woody vegetation with land area >0.5 ha, with >10 % canopy cover and not being utilized for agriculture or any non-forest land use (FAO 2001). Essentially important to mankind, the forest ecosystems have a control over climate, streams, soil, oxygen–carbon dioxide balance, wood supply, aesthetic diversity, biodiversity and provide various ecosystem services (Nabuurs et al. 2007). Forests inherit key information about climate change and are dynamic in terms of phenology, productivity and flammability changes. In tropical forests, increase in respiration with warming and drying shows a positive feedback as predicted by coupled climate–carbon models (Field et al. 2007), while for boreal and temperate forests, significant range shifts and forest expansion can be potentially caused due to climate change (Loehle 2000). Coordinated temporal continuous forests monitoring can put forward an evidence of the effect of climate change on natural systems and can act as a warning indicator of sudden shifts, for instance, changes in leaf water content before forest fires.

Deforestation affects the proper functioning of ecosystem services and has serious impacts on the meteorology and climate change scenario. Anthropogenic activities like fossil fuel burning and land use changes including deforestation and fires have resulted in teeming release of CO_2 into the atmosphere (Malhi 2002; Lu 2006). Hence, there is a growing need for forest monitoring and management especially for forest stand biomass, forest structure and biodiversity. Biomass is the living plant and animal material both aboveground and belowground usually expressed as dry weight. Aboveground biomass includes all living biomass above the soil including stem, stump, branches, bark, seeds and foliage. Forest biomass act as an indicator of climate change and forest health (Nabuurs et al. 2007; Kumar et al. 2013). Numerous studies on biomass assessment have focused on boreal and temperate forests as mentioned below in Table 2; however, studies on tropical forests are limited. This is due to the fact that tropical forests are complex and dynamic with complex species composition and structure, and environmental conditions which is difficult to assess and model. Optical remote sensing have been successful in forest biomass studies but over limited geographical regions. But in the tropical region, where cloud cover problem is predominant, it could not be really used. In these conditions, radar remote sensing provides the best solution as it has several advantages over optical remote sensing as all weather, day and night; penetrates clouds, vegetation, dry soil, sand, dry snow; sensitive to surface roughness, dielectric properties and moisture content; sensitive to polarization and frequency; imaging possibility from different types of polarized energy (HH, VV, HV and VH); and volumetric analysis.

However, radar remote sensing also has limitations like uncertainties in estimation, saturation, expensive datasets, difficulties in data processing and complex interaction with forests. This study attempts to provide a review of historic developments associated with radar remote sensing especially related to synthetic aperture radar (SAR)-based remote sensing applications for the forested environment with a focus toward biomass extraction.

Changing carbon scenario and global initiatives

Terrestrial ecosystems have a significant role in absorbing and emitting CO_2 through vegetation growth and metabolism, and respiration. While functioning as a carbon sink, the ecosystems imbibe for almost a third of anthropogenic fossil fuel emissions (Malhi 2002). Forests absorb nearly one-twelfth of the total earth's atmospheric CO_2 stock, most of which is stored as woody biomass or cycled into the soil and accounts for about 72 % of the earth's terrestrial carbon storage (Malhi 2002). Deforestation of tropical forests destroys carbon sinks and hence posses threat to future climate stabilization (Stephens et al. 2007). The United Nations Framework Convention on Climate Change (UNFCCC) agreed to provide financial incentives to promote emission reduction from deforestation below a baseline in developing countries, the concept referred to as reduced emissions from deforestation and forest degradation (REDD) (Gibbs et al. 2007). The concept of REDD evolved from reduced emissions from deforestation (RED), while further concepts of REDD+ and REDD++/REALU (reducing emissions from all land uses) have developed from REDD revealing the importance and severity of the concept on a global scale (Gibbs et al. 2007; Plugge et al. 2010; Sharma et al. 2013). REDD+ involves forest conservation and sustainable management and forest carbon stock enrichment, in addition to the objectives of REDD while REALU deals with the emissions from all the land uses and not just restricted to forests. REDD regime includes the following steps: assessment of forest carbon stocks and change over time, quantifying the amount of CO_2 reduction, qualifying for accounting, identifying and ranking of the relevant causes for human impact on forests (Sharma et al. 2013), developing a reference baseline for accounting changes of carbon stocks in forests and lastly executing a framework for the transfer of benefits at ground level (Plugge et al. 2010; Sharma et al. 2013). Townshend et al. (2012) have shown the utility of global Landsat optical datasets to account for cost-effective monitoring of the earth's land cover, forest cover and cover change along with specific data inputs from MODIS that can serve as important breakthrough in the field of REDD and climate-related studies in a global aspect. However, due to high uncertainty in carbon sink and emissions estimates, the exact size and cause of the sink remain a matter of unsure.

Uncertainties in the assessment of biomass or carbon stock are a major problem to cope up. The exact proportion of carbon sink from secondary forest regrowth is unknown apart from detailed studies for small areas; hence, the estimation suffers a high degree of uncertainty (House et al. 2003; Houghton 2005). Therefore, a better understanding of global carbon cycle can be made possible through accurate and reliable methods for assessing forest biophysical parameters including biomass, which in turn reveal the carbon sink that would ultimately end up in sustainable forest and natural resource management. Biomass is quantified as a mass of living plant material per unit area and includes above- and belowground living mass and the dead mass of soil litter. Estimation of aboveground biomass (AGB) is rather easy as compared to belowground biomass due to the intricacy involved in field data collection. Biomass has long-term impacts on carbon cycles, soil nutrient allocations, wildlife habitats, etc. To reduce the uncertainty in the measurements, precise estimations at local to global scales are necessary which explains its roles in environmental sustainability.

Remote sensing in biomass assessment

Maturing observation technologies and intense public interest in protecting and managing forests provides a necessity and opportunity to explore and better understand the global forests. The remote sensing technology (capture and analysis of satellite and aerial images) meets the steep logistical challenge of measuring the global forests at local to global levels in an accurate, precise, repeatable and economical manner. Remote sensing techniques to estimate biomass can account for the limitations of sample size, timeliness, expense and access at a range of scales (Patenaude et al. 2005). Remote sensing data can effectively provide a synoptic view over the large areas and greatly increase efficiency and usefulness of limited conventional methods (Patenaude et al. 2005). Roy et al. (1994) have used merged optical and airborne X-band SAR data for forest stratification and canopy characterization. Lucas et al. (2008) have hypothesized the synergic use of hyperspectral and LiDAR data for retrieving forest biomass. The technology offers temporal analysis with synoptic coverage that accounts for change detection of the global forests and its biophysical parameters over varied scales and levels. So, it can be used as a tool in AGB estimation. Therefore, remote sensing using optical, microwave, hyperspectral and LiDAR techniques for AGB estimation has increasingly attracted scientific interest.

Herold et al. (2007) classified the techniques involved in biomass estimation into primarily following four categories: (a) harvest mapping or destructive sampling-based, (b) non-destructive sampling-based, (c) airborne/spaceborne remote sensing-based, (d) model-based (empirical and semiempirical) techniques. The conventional method includes the harvest or destructive sampling approach that deals with the total removal of vegetation of pre-defined sample unit of the forest area (Husch et al. 2003). The non-destructive sampling approach which does not involve tree harvesting has been the most widely used technique for biomass estimation through in situ measurements. It includes regression equations with parameters like tree height, stem volume and basal area to estimate biomass. The most common regression equations used for biomass estimation are linear, quadratic, exponential and logarithmic (Husch et al. 2003). Apparently, remote sensing and model-based techniques can be included within the non-destructive methods. Alternatively, it would be better to classify the methods under three broad groups of (a) field-dependent, (b) partial field-dependent and (c) field-independent approaches. Destructive sampling technique can be included in field-dependent approach, while the non-destructive, remote sensing and model-based techniques can be categorized within the partial field-dependent approach. No method is purely field independent; however, the semiempirical model-based technique relies mainly on the theoretical basis along with experimental or observational data, whereas empirical models are developed using experimental or observational data only (Kumar 2009). On the other hand, remote sensing could be field independent, if the kind of biomass variation in a particular forest type is known, which can then be extended for biomass assessment of similar areas.

The unique characteristics of remote sensing data obtained with synoptic view, high spatiotemporal resolution and digital format that allow the handling of fast processing of huge amount of data in addition to the availability of data for inaccessible forest areas unavailable for field survey. Optical remote sensing data, SAR (microwave) data and LiDAR data are the main three types of remotely sensed data that are used to extract information for biomass and stand parameters. The use of remote sensing technology in the assessment of biomass has proved to be a better alternative to the conventional methods of biomass estimation (Lu 2005, 2006). Biomass estimation using optical remote sensing data is usually realized by revealing the correlation between biomass and spectral responses and/or vegetation indices derived from multispectral images. Lu (2006) classified the techniques used for estimation of AGB into following three main categories as: (1) field measurement-based methods, (2) remote sensing-based methods and (3) GIS-based methods. Optical remote sensing uses the technique of modeling based on biomass–vegetation index relations to estimate the aboveground biomass, as it uses the interactions between the electromagnetic waves with the leaf chemistry or structure to measure the vegetation indices like normalized difference vegetation index (NDVI), leaf area index (LAI), etc. (Kumar et al. 2013). On the basis of spatial resolution of satellite data, Lu (2006) categorized the optical sensor data for AGB estimation as fine, medium and coarse spatial resolution.

SAR vis-à-vis optical remote sensing

In addition to the benefits provided by remote sensing already mentioned, SAR offers certain unique capabilities that have advantages over optical sensors which are as follows:

(a) All weather capability (penetration capability through clouds), i.e., 24-h data
(b) Day and night capability (independent of intensity and sun illumination angle)
(c) Penetration through vegetation, soil sand and dry snow to a certain extent
(d) Sensitivity to surface roughness, dielectric properties and moisture (in liquid or vapor forms)
(e) Sensitive to wave polarization and frequency
(f) Volumetric analysis
(g) Better analysis from inaccessible areas

Forest biomass assessment involves the volumetric analysis of the vegetation, and this exploits the intrinsic capability of penetration of SAR through the tree canopies which is completely absent in optical remote sensing. The estimation is also sensitive to wave polarization and frequency, as higher wavelengths have greater penetration capacity and cross-polarization waves are more sensitive to biomass. The analysis also varies according to the moisture content of the vegetation. These unique qualities of SAR provide better estimation of biomass with reduced uncertainties in the assessment, as microwaves saturates at higher levels of biomass in comparison to optical electromagnetic waves.

In spite of such high potentials, there are some drawbacks of using SAR that needs to be overcome. Compared to optical data, the x- and y-resolutions are not same as range resolution varies with local incident angle. Interpretation requires good understanding of microwave frequency interaction with various targets, as data interpretation is affected by occurrence speckles and image distortions (overlay, foreshortening and shadows) due to undulating terrains. Speckle refers to a noise-like characteristic produced by coherent systems such as SAR caused by the constructive and destructive interference of radar return scattered from surfaces or objects on ground which makes image interpretation difficult. The speckle texture depends on SAR wavelength and target spacing. Layover occurs when the radar beam reaches the top of a tall object before it reaches the base. The top of the object is displaced toward the radar from its true position on the ground and lay over the base of the feature. Foreshortening starts with the gradual cease of layover at small depression angles. Under moderate slope conditions, though the radar return from foot reaches first followed by the top, the ground range will be less than the actual ground distance causing compression in the image called foreshortening. Shadows occur toward the far range, behind vertical features or slopes with steep sides. Since the radar beam does not illuminate the surface, shadowed regions will appear dark on an image as no energy is available to be backscattered. These are some of the general image distortions associated with the SAR images.

Unlike the optical data, the cost of SAR data is a serious constraint in the development of commercial technology for AGB estimation. Mission cost of ERS-2 was about 650 million US dollars (USD) and the data prices, varying with the product type, processing level and mode of delivery, ranged from 250 euro for a medium-resolution SAR scene, to more than 2,000 euro for a terrain-corrected, geo-coded SAR product covering an area of 100 km × 100 km for ERS datasets. Radarsat-1 also had a mission cost of 650 million dollars, however, without launching expenditures, and the data cost is 3,600 Canadian dollars (CAD) per SLC scene of 100 km × 100 km for newly acquired standard products and 1,500 CAD for archive products. Similarly, data charges of Radarsat-2 are 3,600 CAD per SLC scene of single polarized data and 3,800 for dual polarized data for standard products. The rate varies between 3,600 and 8,400 CAD per scene depending on the data acquisition mode. ALOS PALSAR archive standard products are priced at 600 euro per scene. The rate of COSMO-SkyMed standard products of new acquisition varies between 1,650 and 9,450 euro per scene depending on the acquisition mode, while for archive, it ranges between 825 and 4,725 euro per scene. A scene of RISAT-1 is worth at 12,000 INR (Indian Rupees) for Indian nationals. The huge cost incurred in SAR data acquisition and initial processing have created hurdles in the SAR-based researches, and developing technology of low-cost SAR missions are a burning issue that needs attention.

Several parameters are involved in SAR, like surface roughness, dielectric property, azimuth and range resolution, image geometry, distortions, multi-looking, incidence angle, polarization, etc. that adds to the complexity of the data, and hence, data interpretation becomes more difficult and complicated. Therefore, SAR data requires intricate, accurate and specific processing so as to extract maximum information from them. Processing of SAR comprises of certain complex steps that can be performed in specific software. Hence, SAR data acquisition and processing incurs huge cost and occupies huge space. SAR techniques are still in experimental mode, and the techniques need to be developed commercially.

SAR for biomass estimation

Spectral responses recorded in optical images are mainly due to the interaction between the solar radiance and forest stand canopies that serve as a limitation in the ability to predict forest biomass through optical remote sensing technologies. This results in weak correlation between biomass and spectral responses (or vegetation indices), specifically for mature heterogenous forests where the spectral responses start to saturate resulting in low sensitivities to branch and trunk biomass, i.e., the bole biomass. These limitations can be overcome by the use of SAR remote sensing, which has the additional capability to penetrate the cloud cover unlike the optical sensors. The unique qualities of the SAR data for forest biomass estimation make SAR a remarkable technology for forest investigations, particularly in the areas with frequent cloud cover. Simultaneously, unlike optical, SAR has specific characteristics like polarization, sensitivity toward moisture (dielectric constant), surface roughness, different incident angles, higher penetration capabilities, etc. that adds to its potentialities.

Carl A. Wiley, a mathematician in Goodyear Aircraft Company, Arizona, invented SAR in 1951 (Wiley 1985). SEASAT is the first radar satellite for civilian applications launched in June 27, 1978, by the National Aeronautics and Space Administration/Jet Propulsion Laboratory (NASA/JPL). SAR works on the principle of Doppler effect. Doppler shift is the frequency shift in electromagnetic waves due to the motion of scatterers toward or away from the observer. Frequency decreases when the source moves away from the receiver and vice versa. Doppler radar determines the frequency shift through measurement of the phase change in electromagnetic waves during a series of pulses. Table 1 gives the list of some selected SAR sensors till date (Ouchi 2013), along with their spatial resolution. There is a unique relation between the spatial and temporal (revisit) resolution, where revisit time for the wide-swath mode can be reduced at the expense of spatial resolution. Cosmo-SkyMed and SAR-Lupe with higher spatial resolution have their revisit time of 7 and <10 h, respectively, as compared to the nominal revisit times of 24, 25, 35 and 46 days of RADARSAT-2, RISAT-1, ENVISAT ASAR and ALOS PALSAR, respectively (Ouchi 2013).

Table 2 summarizes the numerous works that have revealed the ability of SAR data in estimating forest biophysical parameters, particularly the AGB. The most frequently used methods in biomass estimation may be divided into two groups: (1) using backscatter values and (2) interferometry technique (Ghasemi et al. 2011). It has been proven that longer wavelengths (L and P band) with HV and VH polarizations yield better result than short wavelengths (X and C band) with HH or VV polarizations (Le Toan et al. 1992; Dobson et al. 1992). Hyperspectral remote sensing also has potential in retrieval of biomass (Treuhaft et al. 2003). Ghasemi et al. (2013) suggested the wavelet analysis to be even more effective in terms of biomass estimation.

SAR wavelength and polarization

SAR data can be acquired in K, X, C, L and P bands (different wavelengths) with different polarizations having variety of range and azimuth resolutions. Each of these bands has their own characteristics in relating to forest stand parameters. The X band interacts with the leaves and canopy cover surface, hence suitable for tree canopy surface layer information. The C band penetrates through leaves and are scattered by small branches and underlying features. L band has the higher penetrating capacity that penetrates through the surface layers and is scattered by the trunk and the main branches. With the greatest penetration capabilities, the P band penetrates into the canopy cover. Most part of P-band backscattering is due to the trunk and the trunk–ground interactions. Henceforth, the backscatters of the L and P band are most related to the biophysical parameters of the trees and are maximally used for forest biomass-related studies.

Polarization of the SAR signals are an important parameter of SAR data that interacts variably due to different orientations and structures of the features. Polarization of the electromagnetic waves refers to the direction of electric field and depends upon the interaction between signals and the reflectors. Microwave sensors emit signals in horizontal (H) or vertical (V) polarizations. The four combinations SAR data polarizations: (1) HH: The emitted and backscattered signals have horizontal polarization. (2) HV: The emitted signal has horizontal polarization, and the backscattered signal has vertical polarization. (3) VH: The emitted signal has vertical polarization, and the backscattered signal has horizontal polarization. (4) VV: Both emitted and reflected signals have vertical polarization (Ghasemi et al. 2011).

The C, L and P bands are frequently used in most of the biomass estimation studies. The longer wavelengths (L and P band) and the HV polarization are most sensitive to AGB (Luckman et al. 1997; Kurvonen et al. 1999; Sun et al. 2002). It was found that the co-polarized (HH and VV) data at the longer wavelengths, like P band, were sensitive to changing surface conditions (Ghasemi et al. 2011). Cross-polarized (HV and VH) backscattering mainly occurs from multiple scattering within the tree canopy and is less affected by the surface condition (Ranson and Sun 1994). Backscattering at longer wavelengths is lower than that from C band for low biomass sites, such as grassland, bogs, clear cuttings, areas of forest regeneration and young plantations, and hence, C band is preferred for lower vegetation biomass estimations (Ghasemi et al. 2011). P band gives very low backscattering for surfaces covered with grass or juvenile plant species since these act as small scattering elements as compared to P-band wavelength of 68 cm to give significant backscattering, while the same surfaces would be rough at C band, resulting to strong backscattering, where the leaves and small primary branches are the major scatterers for C band that saturates at nearly 10 kg/m^2 (Ranson and Sun 1994). The limitation of C band is the inability of much penetration into the canopy

Table 1 Selected SAR sensors for earth observation

Platform/sensor	Type	Agency/country	Band (polarizations)	Spatial resolution
AIRSAR	Airborne	NASA/USA	X/C/L (quad)	0.6, 3
ALMAZ-1	Spaceborne	USSR	S (HH)	8, 15
ALOS PALSAR	Spaceborne	JAXA/Japan	L (quad)	5, 10
C/X-SAR	Airborne	CCRS/Canada	X/C (quad)	0.9, 6
CALABAS	Airborne	FOA/Sweden	HF/VHF	3, 3
Cosmo-SkyMed (4)	Spaceborne	ASI/Italy	X (quad)	1, 1
CP-140 Spotlight SAR	Airborne	Lockheed Martin/Canada	X	<1, <1
DBSAR	Airborne	NASA/USA	L	10, 10
EMISAR	Airborne	DCRS/Denmark	C/L (quad)	2, 2
ENVISAT ASAR	Spaceborne	ESA	C (dual)	10, 30
ERS-1/2	Spaceborne	ESA	C (VV)	5, 25
E-SAR	Airborne	DLR/Germany	X/C/S/L/P (quad)	0.3, 1
F-SAR	Airborne	DLR/Germany	X/C/S/L/P (quad)	0.3, 0.2
Global Hawk	Airborne	Northrop Grumman/USA	X	1.8, 1.8
HJ-1-C	Spaceborne	China	S (VV)	5, 20
I-MASTER	Airborne	Thales-Astrium/UK	Ku	<1, <1
Ingara	Airborne	DSTO/Australia	X (quad)	0.15, 0.3
JERS-1 SAR	Spaceborne	NASDA/Japan	L (HH)	6, 18
JERS-1 SAR	Spaceborne	NASA/USA	C/L (quad)	7.5, 13
LiMIT	Airborne	MIT Lincoln Lab/USA	X	<1, <1
Lynx	Airborne	Sandia/USA	Ku (quad)	0.1, 0.1
MiniSAR	Airborne	Sandia/USA	Ka/Ku/X	0.1, 0.1
Mini-SAR	Airborne	TNO/Netherland	X	0.05. 0.05
PAMIR	Airborne	FHR-FGAN/Germany	X	0.1, 0.1
PHARUS	Airborne	TNO-FEL/Netherland	C (quad)	1, 3
Pi-SAR	Airborne	NICT, JAXA/Japan	X/L (quad)	0.37, 3
RADARSAT-1	Spaceborne	CSA/Canada	C (HH)	8, 8
RAMSES	Airborne	ONERA/France	W/Ka/Ku/X/C/S/L/P (quad)	0.12, 0.12
RARDASAT-2	Spaceborne	CSA/Canada	C (quad)	3, 3
RISAT-1	Spaceborne	ISRO/India	C (dual)	3, 3
SAR-Lupe (5)	Spaceborne	Germany	X (quad)	0.5, 0.5
SEASAT-SAR	Spaceborne	NASA/USA	L (HH)	6, 25
SIR-A	Shuttleborne	NASA/USA	L (HH)	7, 25
SIR-B	Shuttleborne	NASA/USA	L (HH)	7, 13
SIR-C/X-SAR	Shuttleborne	DLR/Germany, ASI/Italy	X (VV)	6, 10
SRTM	Shuttleborne	NASA/USA	C (dual)	15, 8
SRTM	Shuttleborne	DLR/Germany	X (VV)	8, 19
TanDEM-X	Spaceborne	DLR/Germany	X (quad)	1, 1
TerraSAR-X	Spaceborne	DLR/Germany	X (quad)	1, 1
UAVSAR	Airborne	NASA/USA	L (quad)	1, 1.8

Spatial resolution expressed in meters in the azimuth (single-look) and range directions

and its saturation at around 60–70 tons/ha (Nizalapur et al. 2010). This limitation can be overcome using longer wavelength bands which have higher forest canopy penetration capability like the L band. The L and P band saturates usually at 100 t/ha for complex heterogenous tropical forest structures. The saturation level increases to about 250 t/ha for stands with simple structure and few dominant species. The best combination for biomass estimation in deciduous forests is the C and L band with the HH and HV polarization, while the same bands with just HV polarization is the best for coniferous forests (Ranson and Sun 1994). L band has the ability to estimate biomass

Table 2 SAR techniques and methods for AGB estimation

Study	Sensor/datasets	Study site	Models
Le Toan et al. (1992)	AirSAR	Landes forest, France	Regression analysis
Beaudoin et al. (1994)	SAR L band	Les Landes Forest, France	Adapted theoretical model
Ranson and Sun (1994)	AirSAR	Maine, USA	Regression analysis
Ranson et al. (1997)	AirSAR	Maine, USA	Gap-type forest succession model, Canopy backscatter models
Luckman et al. (1997)	ERS-1, JERS-1 and SIR-C	Tapajos, Brazil	Forest backscatter model
Kurvonen et al. (1999)	JERS-1 and ERS-1 SAR	Scandinavian forests, Finland	Backscattering model, Inversion algorithm
Kuplich et al. (2000)	JERS-1	Tapajos, Brazil; Southern Cameroon	Regression analysis
Fransson et al. (2001)	ERS-1/2, SPOT XS	Kattbole, Sweden	Regression analysis
Santos et al. (2002)	JERS-1	Amazonia, Brazil	Regression analysis
Sun et al. (2002)	SIR-C	Siberia	Regression analysis
Austin et al. (2003)	JERS-1 SAR	New South Wales, Australia	Regression analysis
Pulliainen et al. (2003)	ERS1/2	Finland	Interferometry, Empirical model
Santoro et al. (2003)	ERS-1/2	Kattbole, Sweden; Tuusula, Finland; Thüringer Wald, Germany; Bois de Boulogne, France	Interferometric water cloud model (IWCM)
Treuhaft et al. (2003)	C-band radar interferometry, hyperspectral	Central Oregon	Leaf area density (LAD) model
Santos et al. (2004)	Airborne SAR	Tápajos River region, Pará state, Brazil	Interferometric and polarimetric analysis, regression analysis
Rauste (2005)	SEASAT, JERS and airborne AIRSAR sensor	Selected sites in Sweden, Germany, Finland and Africa	Regression analysis
Jha et al. (2006)	ENVISAT ASAR	Western Ghats, Karnataka, India	Regression analysis
Hyde et al. (2006)	LiDAR, SAR/InSAR, ETM+, QB	Sierra Nevada, California, USA	Regression analysis
Lucas et al. (2006)	AirSAR, LiDAR	Queensland, Australia	Water cloud model (WCM)
Santoro et al. (2006)	JERS-1 SAR	Kattbole, Sweden; Tuusula, Finland; Bolshe-Murtinsky, Siberia	Radiative transfer model
Kumar (2007)	EnviSat ASAR, Landsat ETM	Dudhwa National Park, India	Regression analysis
Amini and Sumantyo (2009)	ALOS AVNIR-2, PRISM, JERS-1 SAR	Northern forests of Iran	Neural network
Neumann (2009)	PolInSAR data	Oberpfaffenhofen, Germany	PolInSAR–RVoG modeling, Inversion approaches, Model-based polarimetric decomposition
Kumar (2009)	Envisat ASAR	Dudhwa National Park, India	Interferometric water cloud model (IWCM)
Becek (2009)	SRTM	Nerang State Forest, Australia; Brunei Darussalam; Kalimantan, Indonesia; Washington State, USA; Bavaria, Germany	Canopy gap modeling, Interferometry

Table 2 continued

Study	Sensor/datasets	Study site	Models
Nizalapur et al. (2010)	DLR ESAR	Rajpipla, Gujarat, India	Regression analysis
Yu et al. (2010)	SRTM, Landsat ETM, NED	Maine, USA	Biomass algorithms
Gama et al. (2010)	OrbiSAR-1	São Paulo State, Brazil	Regression analysis
Fatoyinbo and Armstrong (2010)	PolInSAR data	Mangrove forests, Nigeria	Regression analysis
Alappat et al. (2011)	E-SAR	Chandrapur Forest Division, Maharashtra, India	Regression analysis
Le Toan et al. (2011)	BIOMASS SAR	Mawas region, Indonesia; Les Landes, France	Regression analysis
Hamdan et al. (2011)	ALOS PALSAR	Forest Research Institute Malaysia, Malaysia	Regression analysis
Wollersheim et al. (2011)	POLSAR data	Petawawa Research Forest, Ontario, Canada	Polarimetric analysis
Englhart et al. (2012)	ALOS PALSAR, TerraSAR-X	Central Kalimantan, Borneo, Indonesia	Multiple linear regression (MLR), Artificial neural network (ANN), Support vector regression (SVR)
Sambatti et al. (2012)	Airborne X- and P-band interferometry data	Paragominas region, Pará, Brazil	Regression analysis
Antropov et al. (2013)	ALOS PALSAR	Central Finland	Semiempirical forest model, model inversion
Carreiras et al. (2013)	ALOS PALSAR	Mozambique, Africa	BagSGB model
Ghasemi et al. (2013)	ALOS PALSAR, ALOS AVNIR	Temperate deciduous forest	Wavelet analysis
Hame et al. (2013)	ALOS PALSAR, ALOS AVNIR	Lao PDR, Laos	Regression analysis, probability method
Peregon and Yamagata (2013)	ALOS PALSAR	Western Siberia	Regression analysis, Water cloud model (WCM)

from lower frequencies to 160 Mg/ha, whereas the capability range of P band is from 100 Mg/ha to 200 Mg/ha (Nizalapur et al. 2010). Depending on the forest type, specifically for the boreal forests, L band saturates at about 100–150 t/ha (Shugart et al. 2010), while P band is found to be sensitive to forest biomass up to a saturation level of 100–300 t/ha (GTOS 2009). The problem of saturation is dealt by Kasischke et al. (1997) where it is mentioned that the saturation point is higher for longer wavelengths and HV cross-polarization has the maximum sensitivity, while VV co-polarization is least sensitive. Based on the empirical relationships between AGB and SAR backscatter, Lucas et al. (2006) established that C, L and P band saturate at different levels with even stronger relationships at higher incidence angles and a larger dynamic range and consistency of relationships at HV polarizations. The most worthy band for biomass estimation is the L band as it interacts more with the trunk and branches with minimal sensitivities to the environmental conditions (Luckman et al. 1997; Kurvonen et al. 1999; Sun et al. 2002; Lucas et al. 2006). According to Hoekman and Quinones (1997), the combination of C and L bands has greater potential than using any one of the bands for biomass estimation.

Biomass estimation methods

The two most widely used approaches used for forest biomass estimations are (1) using backscatter values and (2) interferometry technique, along with polarimetric analyses. Detailed list of studies related to biomass estimation using these techniques is summarized in Table 2.

Biomass estimation using backscatter

Regression analysis is the most preferred method for biomass estimation relating backscatter values to field biomass measurement. This has been tested on various sites of coniferous forests of North Florida (USA) and Landes (France) with accurate results (Le Toan et al. 1992; Dobson et al. 1992). Beaudoin et al. (1994) observed relationship between VV and HV backscatter returns with crown biomass, while HH return was linked to both trunk and crown biomass. Using JERS-1 for assessing biomass of regenerating forests reveals the potential for AGB estimation for young forests as well (Kuplich et al. 2000). Longer wavelengths (L and P bands) with cross-polarizations (HV and VH) produced better result for biomass-related studies than short wavelengths (X and C bands) with co-polarizations (HH or VV) (Le Toan et al. 1992; Dobson et al. 1992; Lucas et al. 2006; Wollersheim et al. 2011; Hamdan et al. 2011).

The significant problem with this method is the saturation level of different wavelengths and polarizations relevant in several studies. The factors on which the saturation levels depend are the wavelengths (different for SAR bands), polarization (co- and cross-polarizations) and the vegetation stand structure and ground condition characteristics (Ghasemi et al. 2011). Santos et al. (2002) indicated the use of the ratio between C and L or P band to solve the saturation problem. Likewise, Hoekman and Quinones (1997) suggested the use of combined C and L bands in coniferous forest. Ranson et al. (1997) applied a synergic approach of forest succession and radar backscatter models to determine forest biomass and observed reasonably good results when biomass was <15 kg/m^2. Landscape properties like topography, surface water and forest structure are beneficial for estimating forest biomass using SAR showing more accurate results (Austin et al. 2003). Lucas et al. (2010) emphasized on the differences in surface moisture conditions and vegetation structure for developing AGB retrieval algorithms and concluded that PALSAR (L-band) data acquired during minimal surface moisture and rainfall showed better estimation of woody vegetation AGB over Queensland, Australia.

Biomass estimation using interferometry

Interferometry is a technique based on interference of waves. Interference, in physics, is a phenomenon where two waves superimpose resulting in a wave of greater or lower amplitude. It refers to the interaction of waves that are correlated with each other, either due to their same source of origin or due to same or nearly same frequency. Interference can either be constructive or destructive depending upon the phase difference between the waves. Interferometric synthetic aperture radar (InSAR or IfSAR) is a radar technique used in geodesy and remote sensing. This technique simultaneously uses two or more SAR images using differences in the phase of the waves returning to the sensor.

The approach involving interferometry has the potential to overcome the saturation problem demonstrated by Fransson et al. (2001) as it has a relatively high saturation point. The approach has the potential to yield more reliable results than the traditional single-image approach. In contrast, Pulliainen et al. (2003) proposed that the accuracy of this technique was highly dependent on certain factors which inherit dynamic variation including the site conditions (wind speed, moisture, temperature, etc.). It was observed that the estimation accuracy can enhance while using multi-temporal SAR images acquired under favorable conditions. This approach produced relative good results in several studies of boreal forests (Fransson et al. 2001; Pulliainen et al. 2003). Pulse coherent SAR operating between 80–120 MHz can be used to measure heavy forest biomass (Imhoff et al. 2000). Luckman et al. (1997) compared the accuracy for biomass estimation using this technique in boreal, temperate and tropical forests, where the best result was obtained in boreal forests using L-band images with 1-day interval. Tree heights were estimated using L band (Mette et al. 2004) and X and P band (Santos et al. 2004) interferometry with improved accuracy in comparison to the backscatter approach. InSAR technique can be combined with corresponding hyperspectral optical remote sensing and LiDAR that can augment the vertical-structure estimates following the biophysical parameters including the biomass (Treuhaft et al. 2004). Classification of biomass estimation methods can be grouped in four approaches depending upon the type of data (or sensors) and the techniques used (Fig. 1).

Limitations and uncertainties

Remote sensing systems provide variety of data acquisition modes, such as in spectral, radiometric, spatial and temporal resolutions and in polarization and angularity. 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 area. In rugged or mountainous regions, topographic factors such as slope and aspect can considerably affect vegetation reflectance, resulting in spurious relationships between AGB and backscattering values. Hence, removal of topographic effects is necessary. Approaches have been developed for topographic correction of SAR data (Soja et al. 2010). The limitation in spatial and radiometric resolutions inherent in the remotely sensed data is an important factor affecting the AGB estimation performance. The remote sensors with coarse spatial resolution mainly capture canopy information, instead of individual tree information. Different sensor data have their own characteristics in reflecting land surfaces, and thus, integration of different

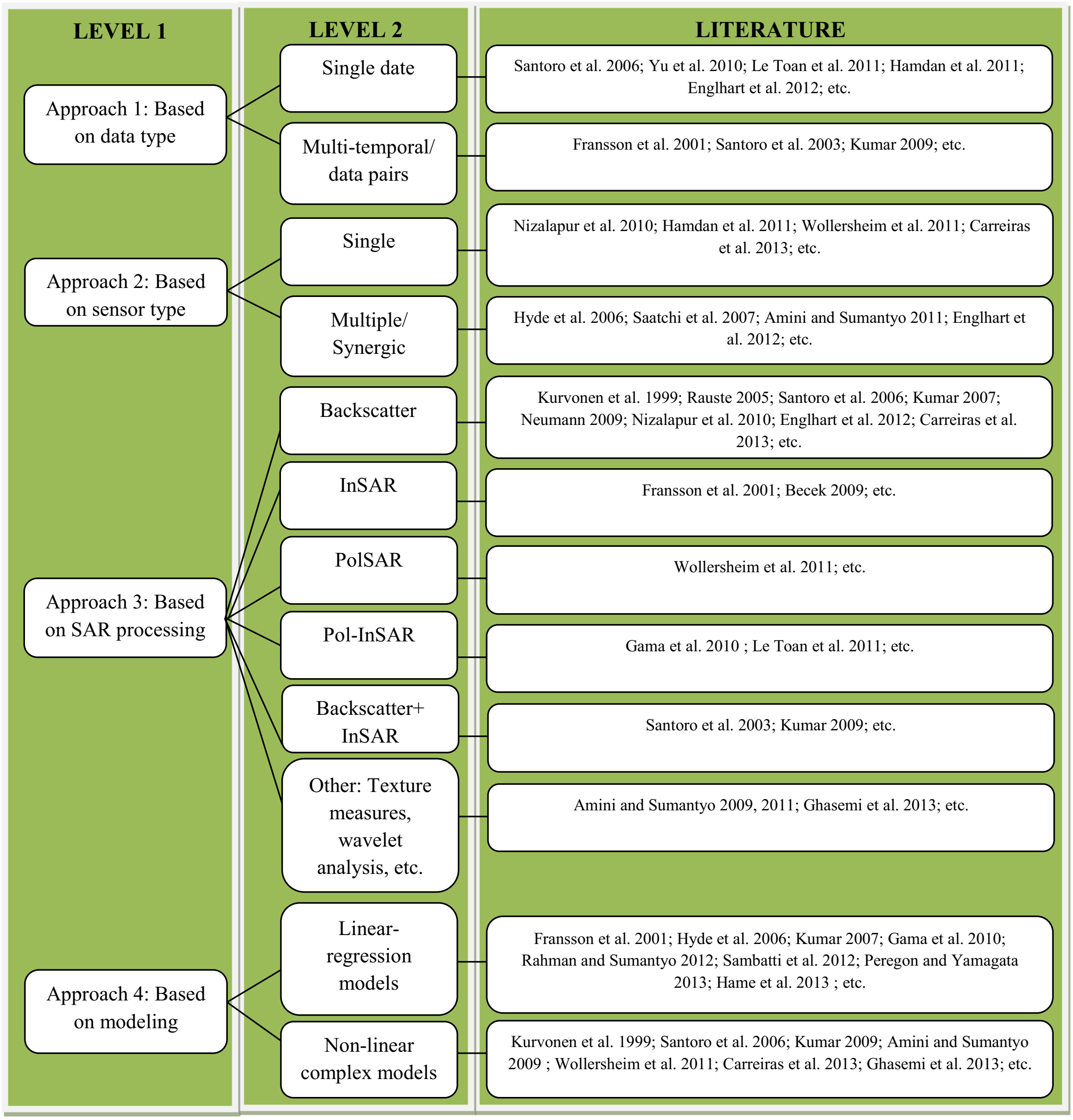

Fig. 1 Classification of biomass estimation methods

sources of remotely sensed data may enhance the information extraction process. 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 (Ban 2003).

The last decade witnessed some of the major milestone researches targeting the subject of uncertainty in remote sensing, GIS, spatial models and geographical sciences (Congalton 1991; Sinha et al. 2012; Liang et al. 2013; Shen et al. 2015). The three challenges identified by Dungan (2002) include (a) the unavailability of appropriate reference data due to expensive and time-consuming issues, (b) challenge to represent or visualize spatially varying intervals and (c) inadequacy of statistical models that assume errors to be independent and spatial units to be dependent.

The five possible sources of uncertainty in remote sensing analysis are described by Dungan (2002) as: (1) variable uncertainty, (2) spatial support uncertainty, (3) positional uncertainty, (4) model uncertainty and (5) parametric uncertainty.

The geostatistical term 'support' refers to the spatial resolution. Moreover, these variables also have a temporal resolution. SAR remote sensing is no exception regarding the issue of uncertainty in the analysis in addition to other complexities and ambiguities that are specific to SAR techniques. Several other limitations of SAR are as follows: (1) costly data, (2) temporal repeativity, (3) few satellite constellation, (4) no time-composite data as the case for optical data, (5) limited area coverage and (6) non-availability of global-level coherent datasets of SAR. Refinements in handling and processing SAR data can improve the analyses which are promising prospects for future researches.

Finally, it is often difficult to transfer one model developed in a specific study area to other study areas because of the environmental characteristics apart from the limitation of the model itself and the nature of remotely sensed data. Foody et al. (2003) discussed the problems encountered in model transfer. Many factors, such as uncertainties in the remotely sensed data (image preprocessing and different stages of processing), AGB calculation based on the field measurements, the disparity between remote sensing acquisition date and field data collection and the size of sample plot compared with the spatial resolution of remotely sensed data, could affect the success of model transferability.

In addition to the sources of uncertainty in remote sensing analysis, there are several possible loopholes for uncertainties to slink in biomass assessment through remote sensing. The key prerequisite for developing AGB estimation models is the availability of a high-quality data source. Allometric equations for calculating AGB requires DBH (diameter at breast height) and/or height, which is a source of uncertainty (Keller et al. 2001; Ketterings et al. 2001). Mode of AGB sample collection is another source of ambiguity (Keller et al. 2001). Satellite, ancillary and sample data need to be co-registered accurately for AGB calculation (Lu 2006). The important sources of uncertainties in AGB enumeration can be summarized as:

1. Mode of AGB sample data collection
2. Selection of proper sample data collection sites
3. Atmospheric corrections
4. Registration errors between satellite data and AGB sample data
5. Incompetence between satellite image pixel size and sample plot dimensions
6. Selection of suitable remote sensing-derived variables to derive relationship with field inventorized AGB
7. Algorithms and equations for developing AGB estimation models

The level of uncertainty and the evaluation of the model performance can be accounted by the coefficient of determination (R^2) and root-mean-squared error (RMSE) (Deepika et al. 2014). A high R^2 or low RMSE value denotes good-fit between the sample data and the model developed. Most of the earlier AGB studies suffered from difficulties in collection of field data and resulting inconsistencies between field measurements and AGB estimation. However, the accuracy can enhance on improving certain parameters. For example, the canopy height can be calculated more accurately using laser or LiDAR technology. Zolkos et al. (2013) proved that airborne LiDAR-generated AGB models are more accurate than those developed from radar or passive optical data. This is attributed to the strong relationship of the LiDAR systems to the biomass level even beyond 1,000 t/ha that greatly exceeds the normal saturation level of passive optical or radar sensors (Yavasli 2012). Variables that are strongly correlated should be used for developing algorithms, and SAR backscatter coefficients often have shown better relationship than optical-derived parameters. However, this selection is a complex process that requires good understanding of the interactions among the tested variables and forest structural and biophysical attributes. Selection of satellite sensors is hence vital for AGB estimation. Integration of optical and radar data can reduce the data saturation in optical sensor images. Development of advanced models using multi-source data is important for reducing uncertainties. Methods of data integration, development of advanced models, better selection and quantification of variables are hotspots for future research to improve current technology for biomass estimation by use of radar data. Interferometry and polarimetry are the two radar-based techniques that need to be explored further in AGB studies. Improvements in SAR data resolution are also a matter of research. Using digital beam-forming techniques, wide-swath coverage can be obtained without degrading the spatial resolution. Hence, a new generation spaceborne SAR systems is planned using this technology, for example, TanDEM-L shall cover a swath width of 350 km with spatial resolution of 10 m, and the revisit time will be 8 days (Ouchi 2013). As already mentioned, interferometry gives information on height and research is required for further improvement in this. Combined polarimetric and interferometric SAR (PolInSAR) has a greater potential for calculating biomass at higher densities (Yavasli 2012). With the advent of different SAR missions in future like follow-up of ALOS and RISAT, NISAR, MAPSAR, etc., there are further possibilities of improvement in this technology for AGB estimation.

Conclusion

Estimation of AGB in tropical forests are difficult to carry out due to high dynamism of these forests as well as tedious accessibility conditions. Although use of multi-sensor or multi-resolution data has the potential to improve AGB estimation performance, the time and labor involvement in image processing will be significantly increased. The economic factor will be an important aspect in the use of multi-source remotely sensed data in a large area. In spite of these limitations, SAR provides an efficient means for assessment of AGB and it can overcome important limitations of optical remote sensing. High wavelength and cross-polarization in SAR are more sensitive to biomass. Texture analysis along with backscatter, interferometry and polarimetric analysis of SAR improves the estimation of biomass. Regression analysis remained the most common, effective and easy-to-use technique for biomass estimation. Model-based approaches using semiempirical models including radiative transfer models, WCM and IWCM are used for AGB estimations using SAR. Though LiDAR act as the most suitable single sensor for biomass estimation, the synergic use of optical and SAR would be the obvious choice due to their easy availability, cheaper cost and time of processing. Synergic use of multi-temporal optical, microwave (SAR/InSAR/PolInSAR) and LiDAR can potentially be the best combination in remote sensing integrated with the use of model-based approach (semi-empirical) for the estimation of biomass. Overall, it can be concluded that AGB can be estimated with reliable accuracy using backscatter intensity values, polarimetric and interferometric techniques.

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