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Remote Characterization of Biomass Measurements: Case Study of Mangrove Forests

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1. Introduction

Accurately quantifying forest biomass is of crucial importance for climate change studies and forest conservation. By quantifying the amount of above and belowground biomass and consequently carbon stored in forest ecosystems, we are able to derive estimates of carbon sequestration, emission and storage and help close the carbon budget.

Mangrove forests, in addition to providing habitat and nursery grounds for over 1300 animal species, are also an important sink of biomass. Although they only constitute about 3% of the total forested area globally, their carbon storage capacity-in forested biomass and soil carbon- is greater than that of tropical forests (Alongi, 2002; Lucas et al, 2007). In addition, the amount of mangrove carbon- in the form of litter and leaves- exported into offshore areas is immense, resulting in over 10% of the ocean's dissolved organic carbon originating from mangroves (Dittmar et al, 2006).

The measurement of forest aboveground biomass is carried out on two major scales: on the plot scale, biomass is measured from field measurements, allometric equation derivation and measurements of forest plots. On the larger scale, the field data are used to calibrate remotely sensed data to obtain stand-wide or even regional estimates of biomass. Currently, biomass can be calculated using average stand biomass values and optical data, such as aerial photography or satellite images (Landsat, MODIS, IKONOS, etc.). More recent studies have concentrated on deriving forest biomass values using radar (JERS, SIR-C, SRTM, Airsar) and/or Lidar (ICEsat/GLAS, LVIS) active remote sensing to retrieve more accurate and detailed measurements of forest biomass. The implementation of a generation of new active sensors, such as UAVSAR and ALOS/PALSAR has prompted the development of new techniques of biomass estimation that use the combination of multiple sensors and datasets, to quantify past, current and future biomass stocks.

Focusing on mangrove forest biomass estimation, this book chapter has 3 main objectives:

1. To describe in detail the field methodologies used to derive accurate estimates of biomass in mangrove forests.
2. To explain how mangrove forest biomass can be measured using several remote sensing techniques and datasets.
3. To describe the measurement challenges and errors that arise in estimates of forest biomass.

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2. Methodology

2.1 Measurement of biomass in the field

a. Deriving allometric equations of mangrove trees

To calculate the biomass of an entire forest stand, the biomass (or weight) of individual trees in the must be calculated and summed. There are three main methods used to calculate stand biomass:

The harvest method is a technique where all of the trees in are felled, cut into sections and components (such as trunk, bark, leaves, branches), dried and subsequently weighed. This method is very labor intensive when dealing with trees that weigh several tons (Brown, 1997; Komiyama et al., 2005, 2008) and cannot be reproduced on a large scale because all of the trees within a set area have to be felled.

The 'mean tree method' consists in the weighing of one (or several) trees considered to be average, and extrapolating the biomass to that of the entire stand. This method can only be used in plantations or other stands with trees of a homogeneous size.

The most common method of stand biomass retrieval is using allometric equations. The allometric equations are derived from selective sampling of trees that are representative of the size-classes found in a forest. These equations then estimate the whole or partial weight of the trees relative to the tree metrics, such as diameter at breast height (DBH) and tree height. These equations have to be both site and species-specific, as even within-species biomass allocation can vary greatly depending on the location.

Allometry implies that the size and growth rate of one part of a living organism is proportional to the size and growth rate of another. In the case of trees, allometric equations correlate tree diameter with height, leaf biomass, root biomass, branch biomass, etc. Allometric equations to estimate biomass and growth of mangroves have been developed for several decades. These equations are available and applicable for all of the structural forms of mangroves including dwarf trees (Ross et al., 2001) single–stemmed, and multi-stemmed tree forms (Komiyama et al, 2008, Clough et al., 1997; Dahdouh-Guebas and Koedam, 2006). In their paper on mangrove allometry, Komiyama et al. (2008) describe the current state of knowledge on mangrove biomass and productivity equations based on 72 published studies in great detail. In their 1993 paper, Saenger and Snedaker also reviewed 43 aboveground biomass equations of mangroves worldwide, to derive a single, global height-biomass and height-productivity equation. Studies by Soares and Schaeffer-Novelli, Ong et al. (2004) and Comley and McGuiness (2005) describe the available species and site-specific equations extensively. As opposed to the site and species specific equations, Chave et al. (2005) and Komiyama et al. (2005) have proposed the use of common allometric equations that are not dependent on either site or species. These equations are dependend on wood density, the static model of plant form and the Shinozaki pipe model (Shinozaki et al., 1964; Oohata and Shinozaki, 1979). These common equations are of the form:

Komiyama et al., 2005:

$$\text{AGB} = 0.251\rho\text{DBH } 2.46 \; r2 = 0.98, \text{ with } n = 104, \text{ Dmax} = 49 \text{ cm, Relative error between } 3.99\ \% \text{ and } 30.1\ \% \quad (1)$$

Chave et al., 2005:

$$AGB = \rho \times \exp\left[-1.39 + 1.980\ln(DBH) + 0.207(\ln(DBH))^2 - 0.02081(\ln(DBH))^3\right]; \text{ standard error of } 19.5\ \% \quad (2)$$

or

$$AGB = \exp(-2.977 + \ln(\rho DBH^2 H)) = 0.0509 \times \rho DBH^2 H; \text{ standard error of 12.5 \% with } n = 84, D_{max} = 50 \text{ cm} \quad (3)$$

Where *AGB* is Aboveground biomass, ρ is wood density, (available at http://www.worldagroforestry.org/sea/Products/AFDbases/WD/index.htm), *DBH* is diameter at breast height and *H* is height of the tree. Figure 1 shows the allometric equations developed by Chave et al. (2005) and Komiyama et al (2008) for *Avicennia marina* mangrove trees.

When comparing the common equations to site and species specific equations, Komiyama et al. (2008) found that the average error was within 10%, thereby showing that wood density may be a more important factor in the determination of biomass than site or species.

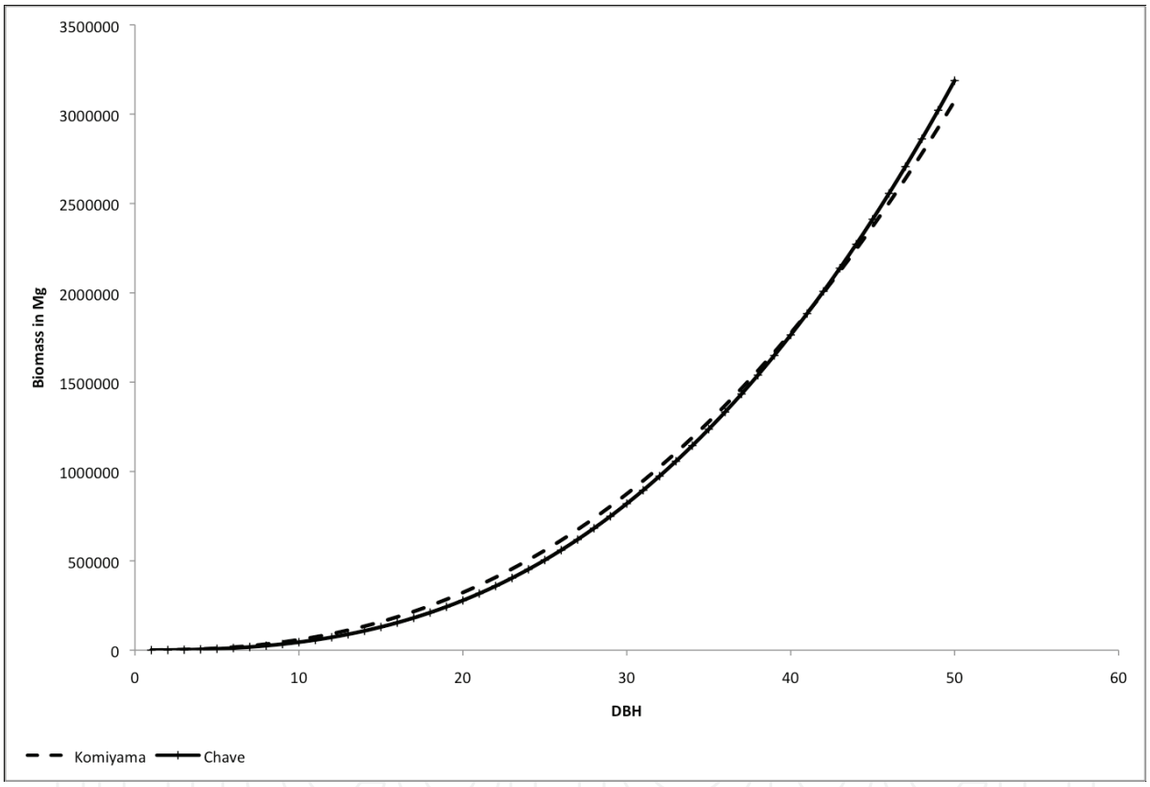

Fig. 1. Allometric equations developed by Chave et al (2005) and Komiyama (2008) for *Avicennia marina* trees. This plot shows the strong correlation between the two equations that are based on wood density.

b. Field Plots

The plot measurement method is the most common in situ approach to deriving stand level biomass. The philosophy behind this approach is that a representative sample of forest can intensively and non-destructively measured and then scaled up to derive forest-wide values. To begin with, an appropriate number of plots must be determined based upon the total size of the stand. Additionally, the plots must be located within the entire range of topography to capture as much local variation within the ecosystem as possible. One way to achieve a representative sampling of forest is to divide the forest into a grid and then

establish and measure the same number of plots per grid square. The size of the grid would be determined by the total number of hectares that the study forest occupies.

Once the method for establishing study plots is decided upon, the size and shape of the study plot can be determined. Plots can be small in diameter and circular in shape, or large and rectangular depending on the amount of field records needed. Within each plot, GPS location should be recorded along with qualitative boundary descriptions to indicate location, canopy gap effects, proximity to water and other geographical variation. These qualitative descriptions can be useful in re-locating plots for additional study, and they can provide insight into explaining any drastic variation in biomass from stand-out plots. It is not uncommon to remove the 5% outlying plots with respect to biomass before scaling up plot data to arrive a forest-wide value.

After location data has been recorded, measurement of the trees in the plot can begin. From plot center, basal area and percent canopy cover is recorded. For all trees greater than a certain threshold (often 5cm) in diameter at breast height (DBH) the following is recorded: species identification, DBH; distance and direction from plot center, height of the tree. Trees with buttresses, aerial roots or similar features that preclude the measurement at breast height are measured just above the obstacle. Split trunk trees are treated as two trees if the split is below breast height and one tree if the split is above breast height. All regeneration 5cm- at breast height and smaller present in the plot is counted and the species are listed.

c. Wood density measurements

One of the largest challenges posed to the scientific community in understanding rainforest dynamics worldwide is the ability to accurately measure and analyze tree growth in an evergreen hardwood ecosystem. Few datasets exist on life histories of mangrove trees, as the ability to utilize dendrochronology techniques common to temperate forests is diminished by the absence of temperature driven seasonality in the tropics. In response to the need to understand how tree species in tropical forests worldwide grow, forest ecologists have developed alternative tools such as wood density analysis and cambial pinning techniques to measure mangrove tree species growth rates. Wood density has been determined to be an important physical characteristic of wood and it is related to other wood properties, including: resistance, porosity, and the number, size, and chemical composition of the cells (Noguiera et al 2005). In the tropics, wood density has been shown to relate to a tree's resistance to physical impacts caused by wind or strong tides to relative growth rate and mortality (Muller-Landau, 2004).

Density is measured and reported in a number of ways. Most commonly, wood density is measured from the wet and dry weights of small wood samples taken with an increment borer. The density is typically reported as the unit-less ratio. For tree biomass estimate derivation from forest volume data the appropriate density measurement is called 'basic density' or 'basic specific gravity', and is calculated as oven-dry weight divided by wet volume (Fearnside, 1997). The wet volume is achieved through soaking to saturation in the laboratory after sampling. This is because trees in a forest vary in moisture content depending on water availability, seasonal variation, competition and other physiological stress factors.

In order to sample for wood density, 12 mm increment borers are used to extract a small cylindrical sample that does not harm the sampled tree. Two samples are taken perpendicular to each other at or around 140 cm above the ground. Care must be taken when using an increment borer to core straight into the tree toward the pith, though only a 4-5cm sample is needed for density measurement. If the ratio of sapwood to heartwood is

known for a given tree species, a further degree of accuracy can be achieved by coring to the pith and measuring sapwood and heartwood density separately. For most tropical tree species however, this ratio is unknown and therefore only one wood sample from each core (two per tree) need be obtained. Following extraction of wood samples, diameter and height of sampled trees will also need to be measured to calculate biomass. When in situ wood extraction has been completed, samples are soaked overnight in distilled water in a laboratory. Wet weights are measured to the nearest one thousandth milligram. Wood samples are then dried in an 80^{o}C oven for 24 hours and dry weights are measured on the same scale.

2.2 Measurement of biomass from optical remote sensing

a. Using extent as a proxy for biomass

Optical or passive remote sensing uses visible and near-infrared reflectance from the earth to form images. This type of remote sensing data forms the basis for much of current global scale vegetation mapping due to the large number of sensors such as Landsat, MODIS, ASTER, IKONOS, etc., the greater ease of image interpretation and increasing numbers of freely available data archives. Google Earth ™ software for example, is based on a combination of optical remote sensing observations from MODIS, Landsat, Quickbird and in some instances aerial photography. Optical measurements have been widely used in studies that link AGB measurements from the field to satellite observations. The main challenge with optical data is the presence of persistent cloud cover, particularly in tropical regions, which make the use of optical data difficult.

The simplest approach to derive biomass from this type of data is to derive landcover or forest type using the optical data, then assign a value to each landcover type (in the case of mangroves these types could be determined by zonation, canopy shape, average density per pixel). To calculate biomass, the total area of each landcover type is then multiplied by the value. While this is the simplest method to estimate AGB, it does not take into account variations of structure and the error is great when looking at very large or very heterogeneous forests (Goetz et al, 2009).

b. Using NDVI as a proxy for biomass productivity

A variety of vegetation indices have been developed for retrieving vegetation structure from optical remote sensing. The most common way to estimate mangrove biomass is with the Normalized Difference Vegetation Index (NDVI) (Li et al 2007; Mather, 1999; Foody et al. 2001). The index is based on the characteristics that vegetation has noticeable absorption in the red and very strong reflectance in the near infrared (NIR). The formula used to calculate NDVI is (Mather, 1999):

$$NDVI = \frac{NIR - red}{NIR + red} \tag{4}$$

Different types of vegetation often show distinctive variability from one another due to such parameters as leaf shape, spacing of the plants, water content, and soil background. The use of NDVI has major drawbacks relating to biomass estimation - in addition to the problem arising from clouds, it has the problem of signal saturation at lower biomasses because of the shorter wavelengths that interact only with the canopy and do not take into account any effect of the trunk (Sader et al. 1989, Foody et al. 1996). Because the trunk is the main component of tree biomass, it is often underestimated. While the index has been shown to

be effective in retrieving biophysical variables of temperate, low biomass vegetation (Foody et al. 2001), it has proven difficult to use in tropical rainforests and mangroves. According Li et al (2007), the NDVI can measure coastal area biomass with R= 0.626 and RMSE = 0.99 kg m^{-2}. However they found that using the optical data only significantly underestimated the biomass of some woody mangrove forests (e.g. *Sonneratia apetala*) because the NDVI reflects canopy properties rather than the trunk properties that are crucial for accurate biomass retrieval.

2.3 Measurement of biomass using active remote sensing

a. Polarimetric SAR

Synthetic Aperture Radar (SAR) uses microwaves emitted by an instrument and reflected by the earth to form an image. Polarized microwave signals can be horizontally (H) or vertically (V) transmitted and received, resulting in co (HH and VV) and cross (HV or VH) polarized data. In Polarimetric systems, the backscatter coefficient σ^0 (sigma nought in decibels dB) and phase can be derived for each polarization.

The backscatter coefficient of a forest canopy depends upon the interaction of microwaves with leaves, branches, trunks, and in the case of mangroves – aboveground roots. More specifically, the polarization, frequency and incidence angle of the microwaves and the size, density, orientation and dielectric constant of the vegetation components affect this backscatter coefficient σ^0 (Lucas et al. 2007). Longer wavelenths (L- and P- band) are able to penetrate the canopy and are scattered by larger components, such as the trunk and the ground and thereby increase the returned signal. Shorter wavelengths interact with leaves and twigs resulting in a larger amount of signal absorbed and less signal return.

Scattering refers to the interaction of microwaves with different surfaces and can range from direct scattering (mirror-like, when only one reflection occurs) to diffuse scattering (multiple reflections at different angles). In mangroves, the radar signature or backscattering coefficient can vary greatly depending on mangrove type and structure. In particular, increases in backscatter can be the result of:

- high surface roughness resulting from aboveground roots and large amount of dead wood material during low tides and dry season.
- double bounce effect resulting from scattering from tree trunks to the ground/water and back or scattering from the ground/water to tree trunks and back (MacDonald, 1980; Krohn et al, 1983; Imhoff, 1995; Simard et al 2002). This increases the backscattering coefficient beyond the saturation level (Mougin et al 1999; Proisy et al, 2002).

In forests, including mangroves, there is a positive relationship between measured backscattering coefficients σ^0 and the aboveground biomass. However this relationship only exists up to a threshold biomass value after which the backscattering coefficient saturates. The threshold is dependent on the polarization and wavelength of the radar signal. In mangroves, P-band frequency and HV polarization has been found to have the highest sensitivity to biomass, with a saturation level of 160 Mg ha -1, followed by L – HV (140 Mg/ha) and C-HV (70 Mg/ha) (Mougin, 1999; Proisy, 2002, Lucas, 2007).

The Japanese Aerospace Exploration Agency (JAXA) PALSAR (Phased Array L-Band Synthetic Aperture Radar) instrument on board the ALOS (ALOS (Advanced Land Observing Satellite)) platform is a fully polarimetric L-band SAR. The ALOS satellite was launched in 2006 and some preliminary studies have shown the use of L-band data to

estimate forest biomass and structure (Lucas, 2007). The Kyoto and Carbon (K&C) Initiative initiated by the Earth Observation Research and Applications Center (EORC) in 2000 (Rosenqvist et al. 2003) has developed and validated products derived from the PALSAR sensor to address land cover (forest) mapping, forest change mapping and biomass and structure estimations (Lowry et al, 2010). These products are freely available at http://www.eorc.jaxa.jp/ALOS/en/kc_mosaic/kc_mosaic.htm.

Because mangrove aboveground biomass often exceeds the threshold of 140 Mg/ha that is measurable using backscatter alone, other techniques, where tree height is measured instead of biomass directly, are often more appropriate. To derive tree height, two different types of active sensors- Radar and Lidar- can be used alone, or in combination, to increase the area of coverage.

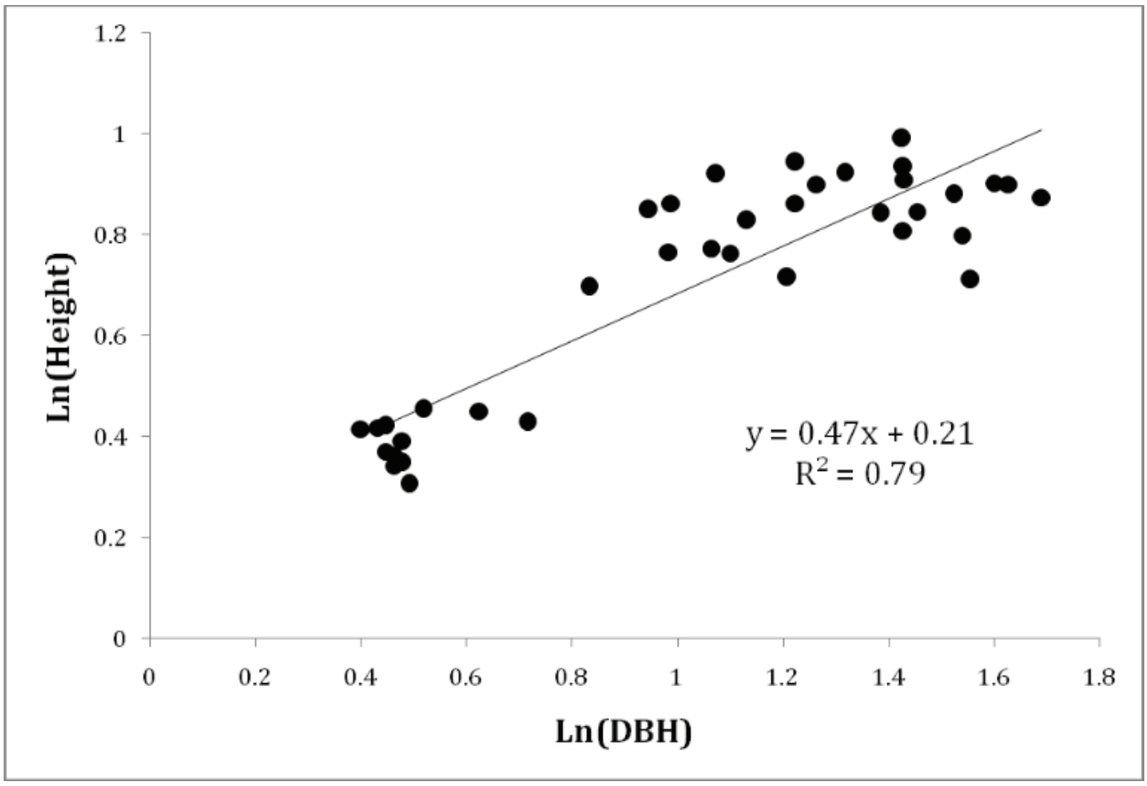

Fig. 2. Allometric equation relating the DBH to tree height in Avicennia marina trees. The equation relating DBH to height is ln(height) = 0.47*DBH +0.21, with an R^2 of 0.79.

b. Interferometric SAR

Forest structure (in terms of height and density) is a direct measurement that can be used to derive biomass, especially in high biomass systems, such as mangroves. To measure tree height using radar data, a technique known as interferometric Synthetic Aperture Radar (InSAR) is used (Graham, 1974). InSAR estimates the tree height by using interference patterns between two radar signals in order to derive terrain height. To derive biomass, the tree height is directly correlated to DBH (figure 2) and biomass through site-specific allometric equations or regional to global equations such as the one derived by Saenger and Snedaker (1993).

To quantify forest structure and make estimations of biomass in mangroves, the Digital Elevation Model (DEM) derived from the Shuttle Radar Topography Mission (SRTM) has proven most successful. In 2006 and 2008, Simard et al. used the SRTM DEM in combination with field validation data and Lidar to estimate mangrove forest 3-D structure and aboveground biomass. Fatoyinbo et al. (2008) used the combination of field data, Landsat and SRTM data to derive mangrove height, extent and aboveground biomass storage for Mozambique. The use of InSAR data, such as the SRTM DEM (or any other interferometric SAR dataset) to derive tree height is based on the principle that the radar signal measures the height at some depth in the tree canopy. In the case of C-band data, such as SRTM, the microwave signal penetrates the canopy and measures height at some depth within. X-band signals do not penetrate as deeply and measure height at a more shallow depth, whereas P- and L-band penetrate the canopy completely and measure deeper in the canopy than C band. Therefore, in order to measure the "true" height of the tree canopy, the DEM has to be calibrated by shifting the DEM height up to the "actual canopy height".

The height measurement that can be derived from InSAR data is the sum of the tree canopy height and the height of the ground. In forests where there is significant topography, the height of the ground has to be subtracted before calculating the height of the canopy. In mangroves however, the topography is negligible and the ground is considered flat, as these trees grow at sea level.

To calibrate the InSAR data, "real" canopy height measurements, from field measurements or Lidar data have to be used. Lidar (Light Detection and Ranging) measures vegetation height at very high accuracy (up to millimeters) and is considered the most accurate and consistent measurement of vegetation structure because of its systematic measurements and because field-based measurements are often limited in amount and spatial distribution. The ICESat/GLAS (Geoscience Laser Altimeter System) sensor is a spaceborne waveform Lidar system, which continuously records the amplitude of the lidar pulse returned through the different layers of the forest canopy. This provides a measurement of the vertical structure of the forest. The GLAS footprint has an ellipsoid form with a diameter of approximately 70m, and each footprint is separated by 172 m along track and 7.5 km between tracks (at the equator). Because the lidar only measures relatively few and small areas, it is generally used to calibrate other datasets. This data provides the best alternative for global canopy height calibration and is freely available from the National Snow and Ice Data Center (http://nsidc.org/data/icesat). An example of GLAS shots over the mangroves of the Niger Delta in Nigeria is presented in Figure 3 and in Figure 4 the mangrove height map of Nigeria and Cameroon derived from SRTM and GLAS is shown.

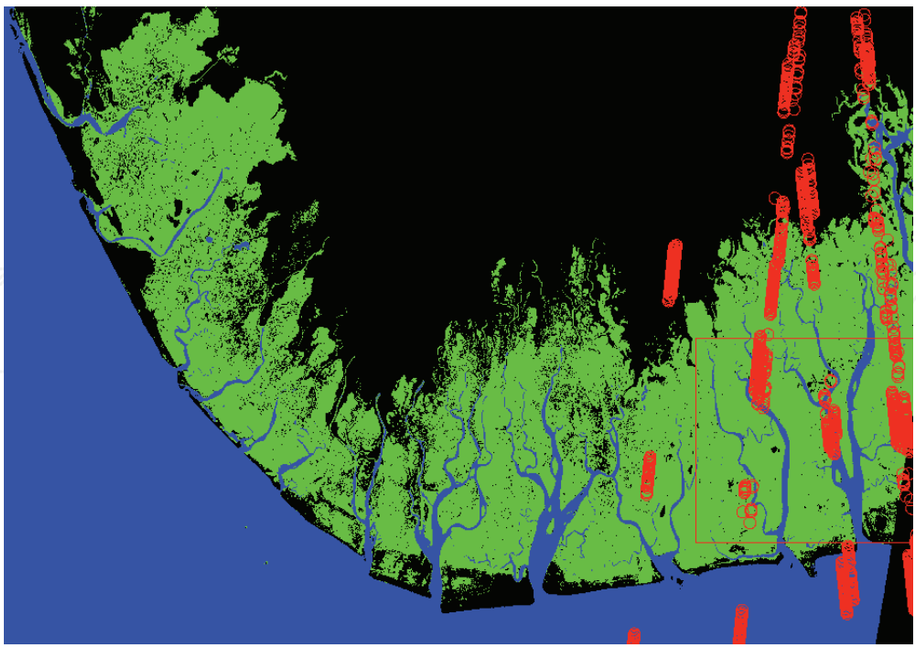

Fig. 3. Example of the available GLAS footprints available over the mangrove forests in the Niger Delta. The GLAS footprints are shown in red, mangrove forests in bright green, the ocean in blue and other landcover in black.

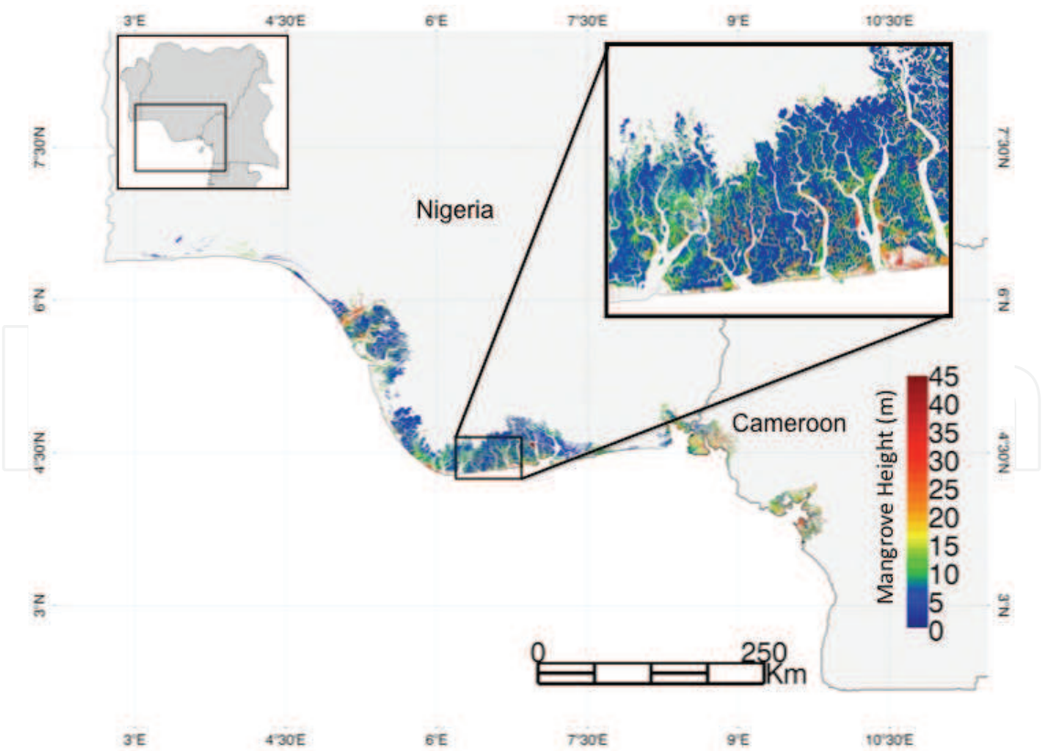

Fig. 4. Height map of mangrove forest in Nigeria and Cameroon derived from SRTM and GLAS.

2.4 Biomass measurement error

There are several types of error that can arise and need to be considered when working with remote sensing data to estimate biomass: For optical remote sensing, classification errors due to omissions and commissions, and clouds are the most prevalent. In Fatoyinbo et al (2008), we found that the Landsat-derived mangrove map did have a high accuracy of 93%, however, there was still some misclassification of mangrove areas as nonmangrove and vice versa, with 3.6% commissions and 10.6% omissions. For active remote sensing, a systematic error can be introduced from sensor error and there is also a certain amount of random error due to biases in measurements. Additional error is introduced by the utilization of different datasets: each dataset has a different resolution and was taken at a different time, which results in differences in measurement. Geolocation errors are introduced when using radar/lidar fusion of datasets in addition to error introduced due to the differing interaction of the radar and lidar signal with the canopy, soil and water in mangrove forests.

When using InSAR, Lidar and/or field data to estimate mangrove structure, there is also the possibility of geolocation error between the data. For example both SRTM and ICESat have mean geolocation errors of better than 20 m and 2.4 m +/- 7.4 m respectively (Carabajal, 2005). The error in geolocation can result in large differences in height measurements, which increases the total error. Furthermore, the natural variability of canopy height and structure

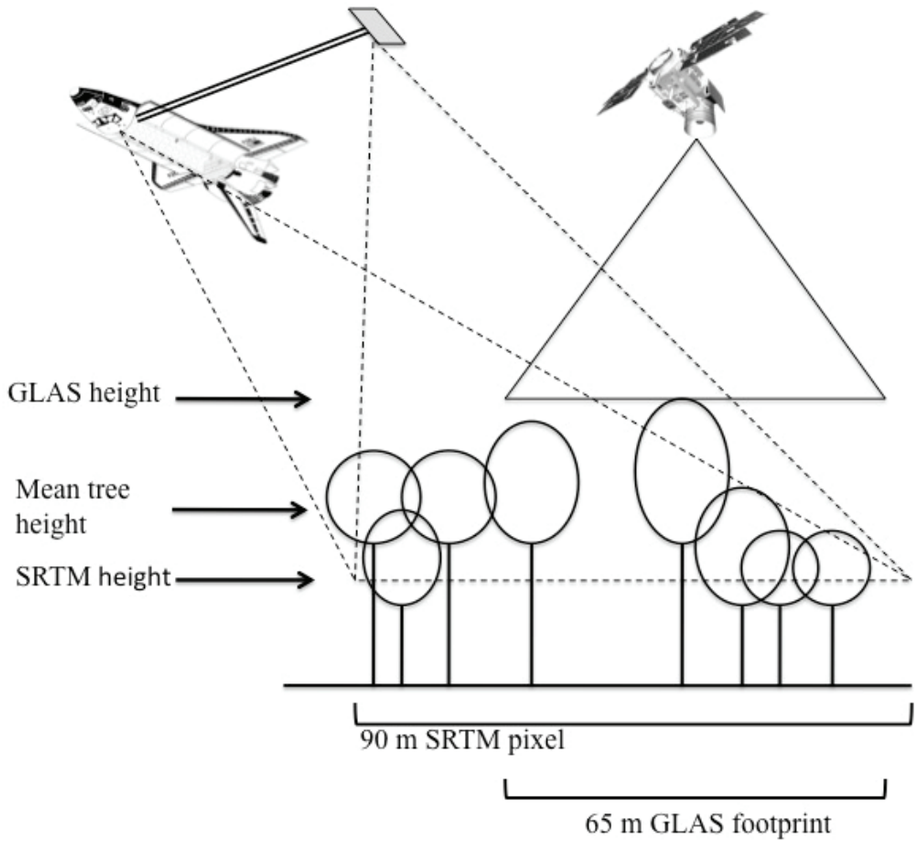

Fig. 5. Illustration of the differences in measurement carried out by SRTM and GLAS instruments.

within a forest increases possible measurement errors between the two datastets. This is compounded by the natural variability of canopy height within a forest. Therefore, if the trees measured by each method are not exactly the same, the differences between the height measurements and therefore the error of the measurement can be high. The differences in physical parameters measured by radar and lidar, in addition to differences in resolution also increase the height and biomass estimation error. In their 2006 study in the Florida Everglades, Simard et al. were able to calculate mean tree height within 2.0 m RMSE and Fatoyinbo et al. (2008) were able to estimate mean tree height within 1.6 m RMSE. Although this RMSE is very good when looking at forests at a whole, this methodology is not applicable to very short forests as the error can in this case be larger than the actual tree height. The combinations of sources of error are illustrated in figure 5.

Finally, when estimating the actual biomass of the mangroves from tree height, a large error can be introduced. The global height- biomass equation developed by Saenger and Snedaker (1993) for example, has a root mean square error of 65.4 Mg/ha due to the large variability of methodologies used to derive biomass in the dataset. Because the equation is applicable globally, it does not take into account local variations in species composition, height and biomass, thereby introducing potential error into the biomass estimate.

3. Conclusions

Measurement of aboveground biomass in forest ecosystems, including mangroves, is important for Carbon storage and cycling studies, mitigation of climate change and management of natural resources. In recent years, accurately quantifying biomass and carbon storage has become increasingly important for financial mechanisms of carbon emission mitigation such as Reduced Emissions from Deforestation and Degradation (REDD). In particular the UNFCCC and IPCC are pushing for increased large scale forest monitoring and development of carbon assessment methodologies. In this chapter, we highlight how field and remote sensing data can be used to estimate mangrove forest biomass. In particular, we concentrate on field measurement techniques and the application of active remote sensing using radar and lidar to better estimate mangrove height and biomass. While estimates of mangrove biomass have been achieved, even on a large scale, using different field and remote sensing techniques, challenges still remain. In particular, the potentially large error introduced by the combination of multiple datasets is a challenge when trying to estimate biomass with a low error. We therefore look forward to future satellite missions where radar and lidar data will be recorded simultaneously, such as the proposed NASA DesDynI mission.

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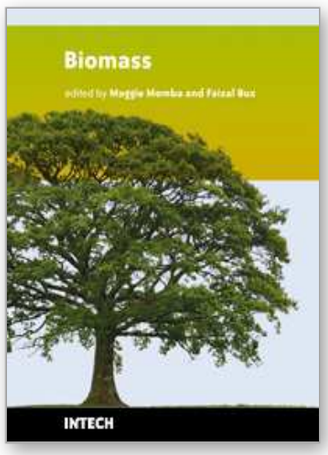

Biomass

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Due to demands placed on natural resources globally and subsequent deterioration of the environment, there is a need to source and develop appropriate technology to satisfy this requirement. For decades mankind has largely depended on natural resources such as fossil fuels to meet the ever increasing energy demands. Realizing the finite nature of these resources, emphasis is now shifting to investigating alternate energy source governed by environmentally friendly principles. The abundance of biomass and associated favorable techno-economics has recently changed global perceptions of harnessing biomass as a valuable resource rather than a waste. To this end this book aims to make a contribution to exploring further this area of biomass research and development in the form of a compilation of chapters and covering areas of ecological status of different types of biomass and the roles they play in ecosystems, current status of biomass utilization and deriving energy and other value added products from biomass. In this context biomass can be defined as large plants and trees and different groups of microorganisms. This book will serve as an invaluable resource for scientists and environmental managers in planning solutions for sustainable development.

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