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S. Goetz, A. Baccini, N. Laporte, T. Johns, W. Walker, J. Kellndorfer, R. A. Houghton

Introduction

The monitoring requirements for reducing emissions from deforestation and forest degradation have been widely discussed and documented in a range of publications, including overviews of the general requirements to meet policy needs (UNFCCC 2006) as well as a variety of papers on the technical aspects and limitations of various monitoring approaches (Defries et al. 2002, Achard et al. 2007, Herold & Johns et al. 2007, Mollicone et al. 2007). The general consensus of these documents is that monitoring of forest cover change using satellite remote sensing is practical and feasible for determining baseline deforestation rates against which future rates of change can be based, provided that adequate validation and accuracy assessments are conducted and documented. The type of monitoring and baseline approach used has been the subject of much discussion, with a range of modifications proposed to deal with equity issues among countries with different historical rates of deforestation. Methods to map and monitor forest degradation, in which only a portion of the forest stock is removed, have also been developed. These range from straightforward visual interpretation of satellite imagery at multiple spatial scales (grain sizes) (e.g. Laporte et al. 2007) to semi-automated algorithmic techniques that require technical expertise to implement (e.g. Asner et al. 2005). Mapping and monitoring of carbon stocks, on the other hand, has been widely and routinely regarded as beyond the current capability of satellite remote sensing technology, primarily because most of the research on this topic has focused on field sampling approaches (Brown 1997). Nonetheless, mapping carbon stocks over large areas *without* satellite data is clearly problematic (Houghton et al. 2001). We revisit the potential for satellites to measure biomass and review a range of approaches that have been developed and used to map carbon stocks across a diverse set of conditions and geographic areas.



Above: Western Uganda, near Bwindi National Park. Courtesy of Nadine Laporte, Woods Hole Research Center (whrc.org).

Basing UNFCCC REDD (Reduced Emissions from Deforestation and Degradation) policies on a carbon stock mapping approach would have a number of benefits, not only in terms of improving estimates of carbon stored in forests for the emerging carbon markets, by providing spatially explicit information on the location of carbon stocks, but also with respect to avoiding the ambiguities of land cover type classifications and uncertainties in assigning relatively few field measurements to large areas while assuming little spatial variability within those areas (Houghton and Goetz 2008). This approach supports countries to report at a higher IPCC reporting tier through providing country-specific data and advanced methods and data for land conversions (GPG 1.7). A carbon stock monitoring approach could allow a country to report at Tier 3, which is defined in the Good Practice Guidance as including “models and inventory measurement systems tailored to address national circumstances, repeated over time, and driven by high-resolution activity data and disaggregated at sub-national to fine grid scales (GPG 3.17).” Tier 3 is identified as increasing certainty and having a closer link between biomass and soil dynamics. A carbon stock monitoring approach is directly linked with biomass dynamics. Since such an approach does not depend upon the determination of land use/cover types as a step in estimating biomass, the uncertainty associated with these classifications is removed. Land classifications may still be applied to the biomass map for the purposes of accounting and reporting, but they are no longer a necessary step in the determination of the biomass of the land area. A carbon stock monitoring approach will introduce different, and perhaps additional, sources of uncertainty than other more traditional methods, but can reduce the overall uncertainty level below Tier 1 methods, and depending on the specific situation, is also likely to reduce uncertainties below Tier 2 methods, in addition to providing geographically explicit information on changes in carbon stocks. This approach could be used to obtain estimates for above-ground biomass (AGB) in all of the categories of LULUCF reporting, including categories where land classification

Cover photo of forest canopy, Mato Grosso, Brazil. Courtesy of Michael T. Coe, Woods Hole Research Center (whrc.org).

remains the same (i.e. Forest Land Remaining Forest Land) and in categories defining changes in land use (i.e. Land Converted to Forest Land). Additionally, this approach would also allow a Tier 2 key category analysis (GPG 5.30), as it can provide specific uncertainty estimates for each category measured with this approach.

In the remainder of this overview we use carbon stock and above-ground biomass terminology interchangeably (carbon is typically 50% of above-ground biomass), although we recognize that carbon stocks can refer to below-ground biomass and soil carbon as well – neither of which are directly discussed here.

Overview of Satellite Measurements useful for Carbon Stock Mapping

Synthetic Aperture Radar (SAR) Since the 1960's, SAR has been used to produce images of earth-surface features based on the principles of radio detection and ranging (radar¹) and has been widely used to map AGB. SAR systems are active, which means they transmit microwave energy and measure the amount of energy reflected back to the sensor. As a result, SAR sensors can operate day or night while penetrating through haze, smoke, and clouds. The microwave energy transmitted by a SAR also penetrates into forest canopies, with the amount of backscattered energy largely dependent on the size and orientation of canopy structural elements, such as leaves, branches and stems. The sensitivity of SAR sensors to different AGB components is a function of the wavelength of the sensor, with shorter-wavelengths (X and C band) being sensitive to smaller canopy elements (leaves and small branches) and longer wavelengths (L and P band) sensitive to large branches and stems. Measuring the orientation (polarization) of the transmitted and received electro-magnetic waves allows for further sensitivity to AGB measurements. Also, the application of interferometric SAR (InSAR) is employed to further retrieve AGB estimates through proxies of vegetation height (Walker). A number of radar satellites are currently in operation, including the Canadian RADARSAT 1/2 (C-band), the Japanese ALOS/PALSAR (L-band), and the European ENVISAT/ASAR (C-band), the German TerraSAR-X (X-band), and the Italian Cosmo/SkyMed (X-Band). Several others are planned for launch within 5-10 years, including the ALOS follow-on mission (L-Band), the NASA DESDynI mission (L-band), the European BIOMASS (P-band), the German Tandem-X (X-band InSAR), and the German/Brazilian MAPSAR (L-Band).

Lidar Light Detection and Ranging (lidar), like radar, is based on the concept of actively sensing the vegetation using a pulse of energy, in this case from a laser operating at optical wavelengths (rather than at radio wavelengths). Lidar does not penetrate clouds but has the unique capability of measuring the three-dimensional vertical structure of vegetation in great detail, sometimes with hundreds of measurements in the vertical dimension for each location on the Earth. Whereas lidar has only been used commercially for a little more than a decade, primarily for forestry operations using aircraft-based sensors, it has revolutionized the way vegetation, particularly biomass, is measured from satellites (Lefsky et al. 1999, Hurtt et al. 2004, Drake et al. 2002). The only lidar instrument currently operating from a satellite platform is a sampling instrument known as the Geoscience Laser Altimetry System (GLAS) onboard ICESAT, but several new missions are planned for the next few years, including ICESAT2 and a lidar on DESDynI.

Optical Optical remote sensing, i.e., passive sensing of visible and near-infrared reflectance from the earth, forms the basis for much of current global scale mapping (GoogleEarth, for example, is based on a combination of observations from the Landsat and Quickbird series of satellites). Optical measurements have been widely used in studies that link AGB measurements from the field to satellite observations, but these have not proven to be consistent over large areas because surface conditions change more rapidly than the repeat time of the cloud-free satellite observations, producing artifacts in the derived maps. This has been overcome using frequent repeat measurements from new sensors such as the Moderate Resolution Imaging Sensors (MODIS) onboard the AQUA and TERRA satellites (e.g. Baccini et al. 2008, Hansen et al. 2008). Despite some issues with the continuity of optical satellite missions (Goetz 2007) a wide range of sensors are expected to be operational well into the future.

Multi-sensor Synergy No single sensor on any satellite mission, whether radar, lidar or optical, can be expected to provide consistently infallible estimates of biomass, but use of these measurements in a synergistic way provides a powerful way to overcome the limitations of each (whether radar saturation, lidar sampling modes or optical temporal mismatches).

Methods to Produce Carbon Stock Maps from Satellite Observations

A number of approaches have been developed to map carbon stocks and AGB from the satellite observations and data products described above. Each of the approaches relies on calibrating the satellite measurements to *in situ* estimates of AGB at field study plots. AGB is often determined using a combination of well documented allometric relationships between simple plot-level measurements (e.g. stem diameter, density and sometimes canopy height and/or depth) and AGB, where the latter is determined from trees that have been carefully dissected, oven-dried and weighed (e.g. Brown et al. 1997, Brown et al. 1989, Chave et al. 2005). This type of allometry has a long history and is routinely used in daily forestry operations worldwide.

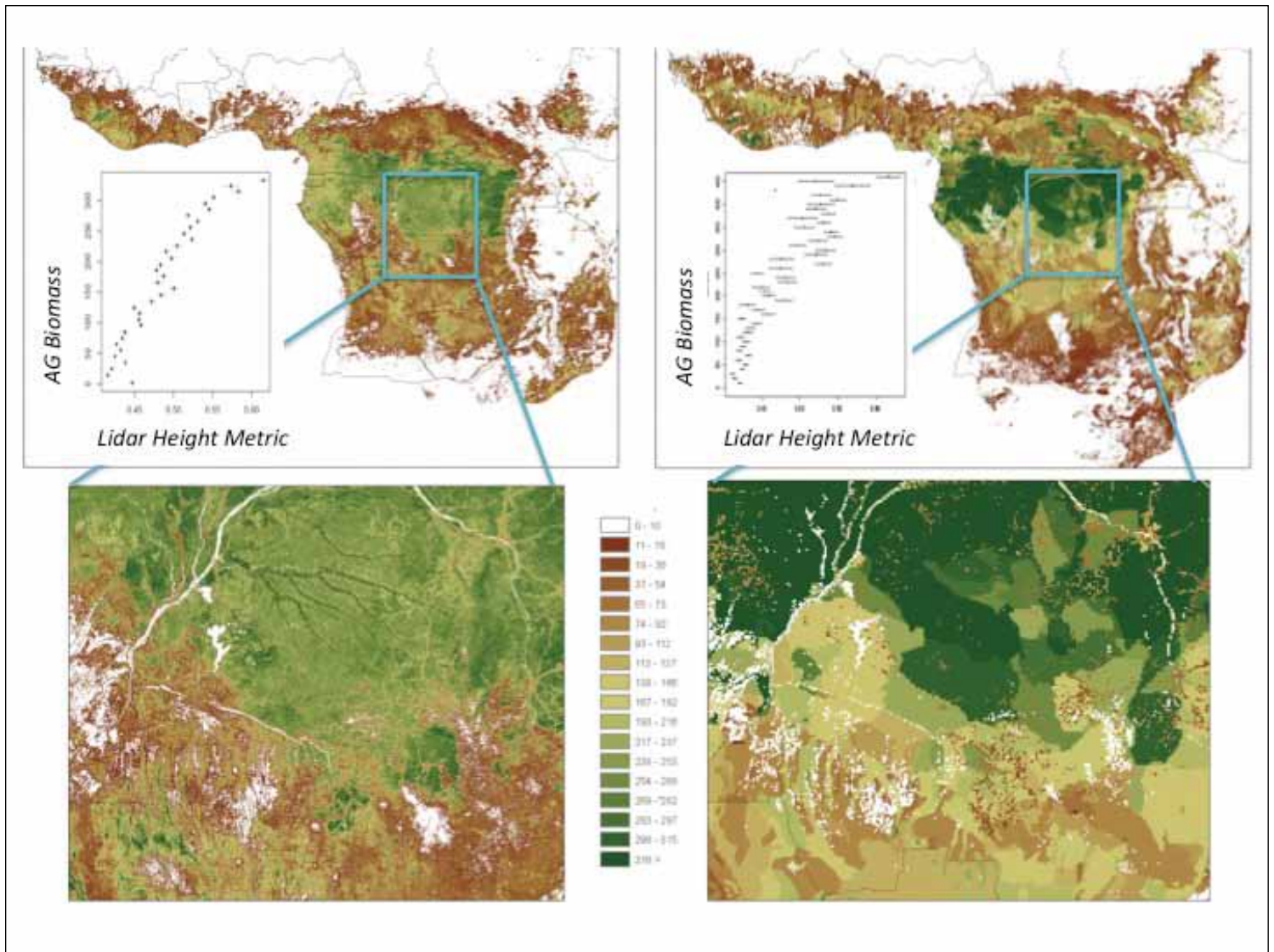
Stratify & Multiply (SM) approach The simplest approach to derive carbon stock maps is to assign a single value (or a range of values) to each of a number of land cover, vegetation type, or other thematic map classes that have been derived from satellite data (or other map sources) and placed into categories (such as Evergreen Lowland Forest, Deciduous Forest, and the like). These thematic class areas are then multiplied by the assigned values to estimate total carbon stock values. Land cover maps are widely available from a number of sources, with the most consistent and best-documented effort to date being the Global Land Cover 2000 maps produced by a broad consortium of research groups (e.g. Mayaux et al. 2004). This “stratify & multiply” approach is limited in a number of ways, but primarily by the wide range of AGB variability within any given thematic type class, and by ambiguities in the definition of those type classes (which is difficult to make universal and thus has consumed the better part of many workshops over the years).

Combine & Assign (CA) approach An extension of the stratify & multiply approach is a “combine & assign” approach, which essentially makes use of a wider range of data sets and spatial information to extend the field AGB estimates. For example, population estimates (or maps derived from interpolating population location data) can be used together with vegetation type classes and any of a number of other spatial data layers in a geographic information system (GIS) to provide finer-grained units over which the field data can be applied (given that adequate field data exist to characterize each of the basic map units). A substantial advantage to this approach, besides finer spatial units of aggregation, is that different weights can be applied to various data layers in order to capture information that is known (such as locations where forests are more degraded around settled areas) or to average gradients across large areas (such as variations in vegetation density within type classes). Another advantage of this type of simplified GIS “modeling” is that values can be aggregated and provided for specific political jurisdictions (Gibbs et al. 2007)(see Figure). Despite these advantages, the combine & assign approach suffers from some of the same limitations as the stratify & multiply approach, particularly in that a representative value (or range of values) is assigned to, and assumed to be representative of, a given spatial unit and adequate field data may not be available to adequately characterize those units.

Direct Remote Sensing (DR) approach A more spatially consistent way to produce carbon stock maps is to extend the satellite measurements directly to maps by calibrating them to field estimates of AGB using any of a number of statistical or so-called “machine learning” techniques, such as neural networks or regression trees (Breiman 2001, Baccini et al. 2004). In the simplest terms this approach makes use of a set of field measurements to “train” an algorithm to develop a set of rules by which any combination of satellite observations (whether radar, lidar, optical, or a combination of these) produce a unique solution in terms of “observed” (i.e., field estimated) AGB. The approach is typically done in an iterative manner, repeatedly passing through the data sets to produce an optimized set of rules that account for the greatest amount of variability in the training data and, by so doing, produce the smallest error in the satellite-derived estimates of AGB. For example, maps have been produced across all of Africa at 1km resolution using MODIS imagery, and validated using independent lidar data sets (Baccini et al. 2008)(see Figure). A related analysis has been done for the Amazon basin using a similar approach (Saatchi et al. 2007). Multi-sensor synergy has been used with a network of forest inventory data to produce ca. 1 hectare resolution biomass maps for tropical Costa Rica (see Houghton and Goetz 2008) and is in progress for the conterminous U.S. (www.whrc.org/nbcd). Once the optimized rules are established for the training data, they are then applied to the satellite images to produce wall-to-wall maps with nearly continuous values of AGB for each cell (pixel) of the image (or map). A key advantage of this approach is that the rules, once established, are easy to understand and can be adapted to a monitoring framework.



Tropical forest in Costa Rica. Photo courtesy of Scott Goetz, Woods Hole Research Center (whrc.org).



Map of above-ground biomass (AGB) across Africa produced using a "Direct Remote Sensing" approach (left) and a "Combine and Assign" approach (right). The top images show maps of AGB for the tropical forest regions of Africa, with boxes indicating those areas shown in the bottom images. The DR approach shows more detail across the region, characterized by transitions between vegetation types ranging from dense humid forest in the Congo Basin to more open woodlands to the south. Note the more continuous nature of the map on the left, and the more aggregated spatial units in the map on the right. The inset line graphs in the top images show how the range of AGB relates to independent Lidar metrics that are closely related to field estimates of AGB. Note the Lidar values in the left graphic have a narrower range of variability within each AGB value than the right graphic, indicating less uncertainty at any given location in the continuous fields map.

The AGB maps shown above can be summarized by land cover type. Table 1 shows the average AGB by cover type (based on the Global Land Cover 2000 product, Mayaux et al 2004). Although most of the classes show a similar average AGB, note how the averages based on the "combine and assign" map tend to be higher than those derived using the direct remote sensing approach, indicating difficulties in assigning field plot measurements to more generalized land cover categories that are often modified by human land use.

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Footnotes

¹ The term “radar” is often used as a synonym for SAR.

For more information, contact:

Scott Goetz
Senior Scientist
sgoetz@whrc.org
508 540 9900, x131



The Woods Hole Research Center

149 Woods Hole Road
Falmouth, MA 02540
USA

whrc.org