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New Satellites Help Quantify Carbon Sources and Sinks

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Deforestation and forest degradation account for between 7% and 30% of total anthropogenic carbon emissions [*Canadell et al.*, 2007; *Denman et al.*, 2007]. This wide range of values results from three major uncertainties: rates of deforestation, carbon stocks (biomass and soils) in forests prior to deforestation, and changes in carbon stocks within forests (i.e., both increases from growth and decreases from degradation). Historically, rates of deforestation and reforestation, together with estimates of forest biomass, have been used to calculate the net flux of carbon between terrestrial ecosystems and the atmosphere [*Woodwell et al.*, 1983; *Detwiler and Hall*, 1988; *Hall and Uhlig*, 1991; *Fearnside*, 2000; *DeFries et al.*, 2002; *Achard et al.*, 2004; *Houghton*, 2003]. This net flux is the difference between the sinks of carbon in growing and recovering forests and the sources from burning and decay associated with deforestation. Satellite imagery, particularly from Landsat, has long been used to sample deforestation rates [*DeFries et al.*, 2002; *Achard et al.*, 2004; *Skole and Tucker*, 1993; *Hansen et al.*, 2008]. Obtaining estimates of biomass, reforestation, and forest growth and degradation, however, has proven more difficult.

Recently, the capacity to estimate forest aboveground biomass over large areas has advanced substantially. Within the past few years, both radar and lidar (light detection and ranging) sensors have been carried aloft on satellites, notably the Geoscience Laser Altimetry System (GLAS) on board the Ice, Cloud, and land Elevation Satellite ICESat) and the Phased Array Synthetic Aperture Radar (PALSAR) on board the Japanese Advanced Land Observation System (ALOS). Other satellites more specifically dedicated to obtaining aboveground biomass are being designed, notably, the new NASA-led Deformation, Ecosystem Structure and Dynamics of Ice (DESDynI) mission and a European-led Biomass Monitoring Mission for Carbon Assessment (BIOMASS).

More than a decade of research—including past designs for NASA's Vegetation Canopy Lidar and related European missions—preceded the development of these satellite missions [*Dubayah et al.*, 1997] (see also http://www.cesbio.ups-tlse.fr/us/indexbiomass.html). Although documentation of the research is beyond the scope of this article, it is summarized in the literature [*Dubayah et al.*, 1997; *Lefsky et al.*, 2002], in workshop reports [*Bergen et al.*, 2006; *Zebker et al.*, 2007], and on the Internet (http://www.cesbio.ups-tlse.fr/us/indexbiomass.html). Radar has the advantage of penetrating clouds, making it particularly useful in many parts of the humid tropics. Lidar has the unique capability of providing data on forest canopy height and vertical structure, which are allometrically related to in situ biomass measurements [*Dubayah et al.*, 1997; *Lefsky et al.*, 2002].

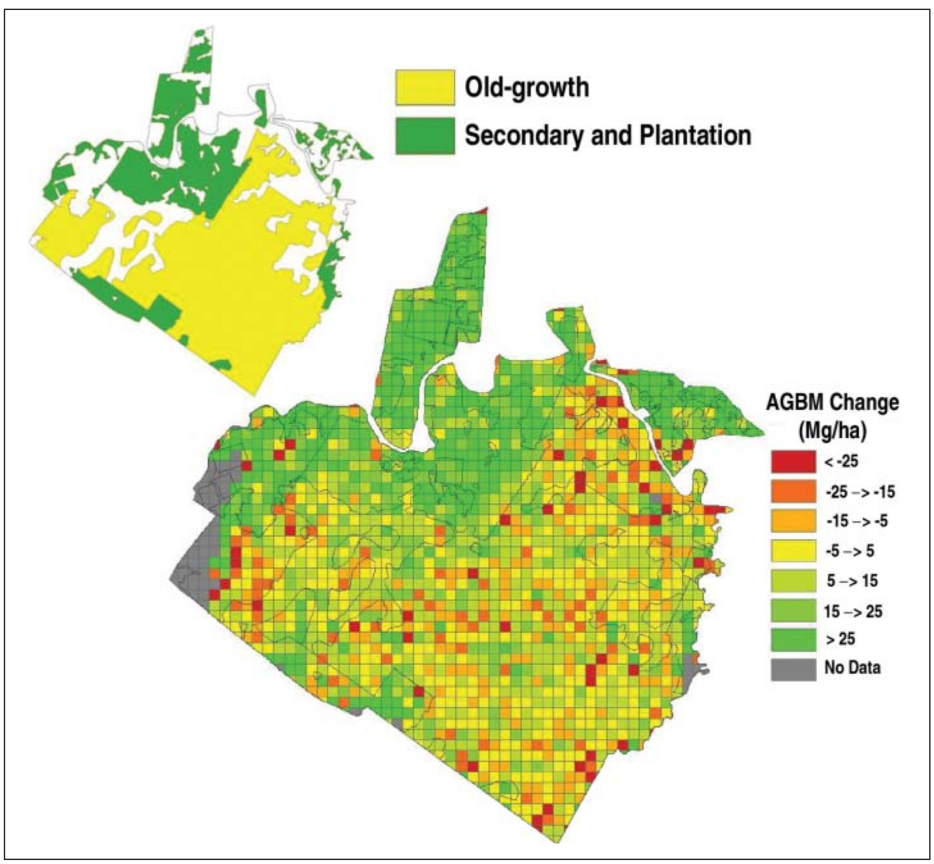

Fig. 1. Net change in aboveground biomass for La Selva Biological Station, Costa Rica, 1998–2005. The figure illustrates the approach of using new remote sensing technology to estimate directly changes in carbon stocks. Lidar data from NASA's airborne Laser Vegetation Imaging Sensor (LVIS) were acquired in 1998 and 2005. Changes in lidar metrics were related to field measurements of biomass accumulation and loss in 18 primary and two secondary forest plots. This relationship was then used to map biomass dynamics at 1-hectare resolution over the entire domain using LVIS data. The comparison with a land cover map (inset) shows primary forests as a heterogeneous mixture of sources and sinks, in contrast to secondary forests, which appear more uniformly as sinks. Image courtesy of Ralph Dubayah, University Maryland, using field data from David Clark and Robin Chazdon.

By R. A. Houghton and S. J. Goetz

A Focus on Carbon

These new satellite systems combining radar and lidar will change the way carbon emissions are determined, thereby increasing the accuracy and also reducing ambiguities of the current approach. Uncertainty about biomass density (megagrams per hectare) contributes as much as does uncertainty about rates of deforestation to the range of flux estimates [*Houghton*, 2005], particularly in the tropics where biomass density is greatest and where rates of deforestation are highest [*Houghton*, 2005; *Houghton et al.*, 2001]. Even in developed countries, with repeated systematic forest inventories, aboveground forest biomass is not spatially mapped. Rather, ground-based estimates of mean biomass are determined for administrative districts (counties, states, countries). But the forests that are actually deforested may not be "average" forests; their biomass may be systematically higher or lower than the average. Assigning an accurate estimate of biomass to the forests that are actually deforested will reduce the uncertainty of carbon emissions by as much as a factor of 2 [*Houghton*, 2005; *Houghton et al.*, 2001]. Spatially complete sampling also removes the need for assumptions about the distribution of deforestation and captures explicitly the heterogeneity of site factors that affect carbon dynamics, such as rates of decay and growth.

Mapping biomass from satellites will also remove a key arbitrary aspect of determining carbon emissions. A recurring discussion in United Nations Framework Convention on Climate Change meetings—in Nusa Dua, Bali, Indonesia; Bonn, Germany; and Accra, Ghana—over the past year has focused on reducing emissions from deforestation and degradation, with emphasis placed on refining the definitions of forest, deforestation, and forest degradation [*Noble et al.*, 2000; *United Nations Framework Convention on Climate Change*, 2006]. If forests are defined as having more than 20% tree cover, for example, the carbon released in reducing cover from 100% to 20% will not be counted as deforestation. And with a forest definition of 80% tree cover, the carbon emitted in reducing tree cover from 79% to zero will also not be counted. The arbitrariness in defining forest cover may also account for the apparent contradiction between the estimates of deforestation rates and changes in forest area from the Food and Agriculture Organization of the United Nations [*Grainger*, 2008]. Similar arbitrariness and ambiguity pertain to definitions of deforestation.

A biomass satellite mission eliminates these ambiguities by directly measuring aboveground carbon stocks. The most important information in determining sources and sinks of carbon, from both scientific and policy perspectives, is the accurate estimation of changes in carbon stocks. If the stocks are greater (or lesser) at time 2 than they were at time 1, then the sinks (or sources) of carbon can be determined directly (Figure 1), without arbitrary definitions of forests, deforestation, or degradation and without having to monitor changes in land use and land cover. Admittedly, determining changes in land cover may be critical for other purposes, such as documenting the causes of degradation [*Laporte et al.*, 2007], but the primary goal of carbon accounting is to determine changes in carbon stocks.

Limitations and Remaining Uncertainties

There are still some issues about the new approach that need to be resolved. For example, aboveground carbon stocks do not include the large stocks of carbon in belowground biomass and soils, and a full accounting of changes in carbon will require terrestrial ecosystem models. Despite the larger stocks of carbon below ground, however, changes above ground accounted for nearly 90% of the emissions of carbon calculated from changes in land use over the period 1850–2000 [*Houghton*, 2005].

More important, it is unclear what accuracies are achievable from satellites over different temporal and spatial scales. It will be much easier, for example, to observe the large reductions in aboveground carbon that result from deforestation than the small accumulations (or losses) that result from forest growth (or degradation) (see Figure 1). The biomass satellites will undoubtedly miss small losses and accumulations of carbon in aboveground biomass, and "small" is so far undefined. Current estimated emissions of carbon from forest degradation range between zero and a magnitude equivalent to the emissions from deforestation [*Houghton*, 2005]; and the residual terrestrial carbon sink is greater than the emissions from deforestation [*Canadell et al.*, 2007]. Simply identifying what fraction of the world's forests (and where) are losing or gaining carbon at rates that can be observed over a multiyear mission would be a substantial improvement over current estimates.

We conclude that the general approach for estimating terrestrial sources and sinks of carbon can be redesigned as a consequence of the ability to map biomass from satellites. Rates of deforestation will no longer be of primary interest. Instead, measurements can focus on the appropriate target for carbon emissions, namely, change in carbon storage, whether or not deforestation is involved. With the new approach, both the accumulations of carbon in growing forests and the losses through degradation would be directly assessed within the limits of spaceborne instruments.

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Not to Worry: Solar Magnetic Activity for Cycle 24 Is Increasing

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Several academic sources have noted that the current sunspot minimum seems to be unusually long. Indeed, sunspot counts are at a 50-year low. As of 27 September, the Sun has had no visible sunspots for 200 days this year, the most of any year since 1954. Unfortunately, this has been interpreted in some media sources as showing that there is something wrong with the Sun. Some reports have even suggested that we should prepare for a widespread cooling due to a lack of sunspots and even that a new mini ice age is on the way (see "Sorry to ruin the fun, but an ice age cometh," by P. Chapman, at http://www.theaustralian.news.com.au/story/0,25197,23583376-5013480,00.html).

True, the total solar irradiance at Earth has dropped to a minimum that is lower than seen in the previous two cycles (see *Lockwood and Fröhlich* [2008] for a description of the trends in total solar irradiance). And the length of the minimum in solar activity may actually have some important implications. The most extreme solar minimum was the 70-year-long Maunder Minimum of 1645–1715 that coincided with the Little Ice Age. This period consisted of extremely severe winters in the Northern Hemisphere. While evidence such as this indicates a possible link between the solar cycle and Earth's climate, it is not known what the mechanism could be.

Perhaps more pertinent to our current technology-based society is the fact that a less active Sun means fewer solar storms; solar storms pose a threat to astronauts and various satellites, including GPS and weather satellites. Further, radio bursts from solar flares can interfere with cell phones. The strongest solar storms are caused by coronal mass ejections (CMEs) hitting the Earth, and these events can even threaten ground-based electronics, aircraft navigation, and power grids. All of these events occur less frequently during solar minimum.

Yet there is nothing amiss with the current solar minimum. NASA solar physicist David Hathaway at the NASA Marshall Space Flight Center was quoted saying, "the ongoing lull in sunspot number is well within historic norms for the solar cycle" (see "What's wrong with the Sun? (Nothing)" at http://science.nasa.gov/headlines/y2008/11jul_solarcycleupdate.htm). For example, there were 6 years in the past century with more spotless days than 2008, including 1913, which had more than 300 spotless days. Further, examination of the interplanetary magnetic field (IMF) activity supports this conclusion and shows that while the sunspot number may still be low, IMF activity this solar cycle appears to be increasing as expected, with solar maximum predicted for 2010.

Boxcar Averages of the Interplanetary Magnetic Field

IMF data can be analyzed in a manner identical to that used to calculate the sunspot number. This is important in that IMF activity is indicative of overall solar activity. In fact, IMF activity seems to lead the overall activity, presenting the possibility that it can serve as an early indicator of upcoming solar activity.

Keating et al. [2001] and *Keating and Jaeger* [2003] described how a long-term average, consisting of a smoothed, 13-month "boxcar" mean of the magnitude of the *z* component of the magnetic field ($B_z(m)$), demonstrated a cyclical pattern similar to the solar cycle with approximate correlation to the solar sunspot cycle. The boxcar method of averaging is useful for smoothing the data in order to eliminate short-term variations. The method consists of summing $B_z(m)$ averages of 11 consecutive months, beginning with the month 5 months prior to the month being examined and ending with the month 5 months after the month being examined. A final term is then added to this sum: one half of the data average for the month that falls 6 months previous plus one half of the data average for the month that falls 6 months following.

This method takes the average data from 13 months and yields a sum of 12 full months of averaged data. This sum is then divided by 12 to give a monthly running average $B_z(m)$. For instance, the boxcar average for June would consist of the sum

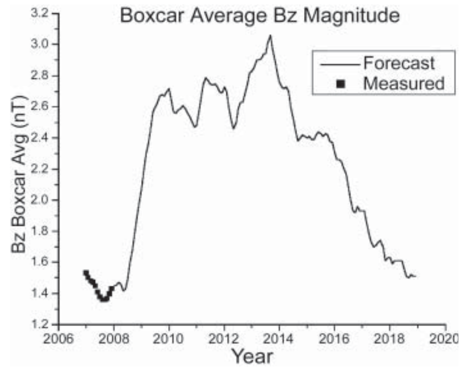

Fig. 1. Actual boxcar averages for measured B_z(m) *magnitude and the forecast results of applying the McNish-Lincoln technique. Actual data are represented by solid squares, while the calculated results are shown as a curve. The correlation between the two is due to the fact that the McNish-Lincoln method uses actual data when available. The calculated forecast is performed only for the time period after the end of the actual data. This plot shows that* B_z(m) *reached its minimum average magnitude in mid-2007 and has begun to increase in magnitude. The forecast is that it will continue to increase slowly through the first part of 2008, but will then begin to rapidly increase in magnitude beginning in the latter part of this year, reaching its first peak in late 2009.*

Table 1. Results of the McNish-Lincoln Technique Forecast for the $B_z(m)$ Boxcar Average Monthly Values for 2008 and 2009[a]

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2008	$B_z(m)$ averages	1.45	1.45	1.47	1.46	1.42	1.43	1.49	1.60	1.68	1.78	1.89	1.9
	Uncertainty	0.06	0.11	0.12	0.20	0.39	0.30	0.25	0.25	0.24	0.17	0.09	0.07
2009	$B_z(m)$ averages	2.08	2.19	2.30	2.37	2.46	2.57	2.60	2.63	2.67	2.68	2.67	2.70
	Uncertainty	0.12	0.11	0.13	0.16	0.14	0.11	0.22	0.27	0.26	0.27	0.28	0.36

[a]Adding and subtracting the uncertainty estimates to the predicted value yields the upper and lower bounds to the 90% confidence interval. All values are in nanoteslas.