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Aboveground biomass assessment in Colombia: A remote sensing approach

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ABSTRACT

This paper presents a method to increase the level of detail of aboveground biomass estimates at a regional scale. Methods are based on empirical relationships while materials are based on MODIS products and field measurements; the area covers from 4° south up to 12° north of the Equator with a total of 1,139,012 km^2 corresponding to the continental area of Colombia. Vegetation was classified in three broad classes: grasslands, secondary forests and primary forests which have been proved to enhance biomass estimates. MOD44 vegetation continuous fields (VCFs) was used as an explanatory variable for primary and secondary forests following an exponential relationship, while MOD13A1 enhanced vegetation index (EVI) was used as explanatory variable for grasslands following a linear relationship; biomass for this vegetation class was estimated every 16 days given its large variation throughout the year. EVI–biomass relationships were established from 2001 to 2006. Vegetation maps were used to separate primary forests from secondary forest, since the latter has shown lower biomass levels. Confidence intervals of the exponential regression are larger as the biomass values increases, for this reason the uncertainty is quite high ranging from 3.7 to 25.2 millions of Mg with a mean of 16.2 million of Mg. Despite the uncertainty our biomass results are within the estimates of previous studies.

1. Introduction

Dry aboveground biomass (AGB) studies are important to determine biosphere–atmosphere interactions. Existing biomass stocks are considered a carbon sink while biomass burning is considered a source of atmospheric carbon. The last report of the Intergovernmental Panel on Climate Change has outlined the importance to determine a base line for organic carbon. This protocol has valuated the carbon as a producer good and the net primary productivity as a resource of future economical benefits (Cihlar, 2007). This requires developing scientific methods to delineate biomass distribution at scales from local and regional to global with their respective uncertainty (Moutiño and Schwartzman, 2005; Herold et al., 2006; DeFries et al., 2007; Gibbs et al., 2007; Pearson et al., 2008). However, estimates of carbon sinks have shown a particularly large degree of uncertainty (Houghton et al., 2001; Achard et al., 2004; Hese et al., 2005).

There are different methods to approach regional biomass estimates for forests: field measurements (inventories), patterns of greenness derived from vegetation indexes, vegetation models simulating the global carbon cycle, e.g. CASA (van der Werf et al., 2006), and tree cover data sets combined with potential biomass density. In the case of herbaceous mean annual precipitation and climatic indexes are commonly used.

Regional studies of biomass estimation could be classified in three vegetation groups: grasslands, secondary forests and primary forests. This classification of biomass reduces the uncertainties in estimations since there is a large relationship between structure and ecosystem dynamics (Keeling and Phillips, 2007). In the case of grasslands, AGB changes rapidly especially when subject to grazing and is highly related to precipitation (Menaut et al., 1991; Privette et al., 2002; Baruch, 2005; Scanlon et al., 2005; San José and Montes, 2007). On the other hand AGB in secondary forest is only of importance when considered at the inter-annual basis. Sierra et al. (2007) estimated an AGB in secondary forest of 46 Mg/ha increasing up to 249 Mg/ha in approximately 50 years. Finally, primary forests AGB increments are insignificant since potential biomass equals real biomass (Scheller and Mladenoff, 2004). For this reason primary forests are considered important carbon pool but without the capacity of increasing additional AGB.

Ground-based quantification methods of AGB are destructive (harvest and weighing) being more complex for forest than for grasslands. In the case of forests it is required to fell trees, palms

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and vines, oven-dry large volumes of material and weight several Mg of trunks, roots, branches and leaves from the overstory and understory individuals.

As a mean to facilitate this process allometric equations are generated from direct measurements. These equations have biomass as the dependent variable and height, diameter at breast height (DBH) and wood density as the independent variables. Height and diameter are easily measured in the field while density is usually measured at a laboratory based on volume and dry weight of wood samples. Malhi et al. (2006) and Nogueira et al. (2008) discussed the effect of basal area and wood density spatial distribution on the overall biomass estimates at the Brazilian Amazonia.

Another vegetation type of great interest at the study area is the tropical savanna, not only for the large extensions it covers but also for the high inter-annual biomass dynamics. Colombia has two large savanna formations, to the north along the Magdalena River and to the east along the tributaries of the Orinoco River. The latter; is the most important and is known as *Llanos Orientales*. Relevant studies have been made in this area by several authors (Jimenez et al., 1998; Rippstein et al., 2001; San José and Montes, 2007). Savanna formations are related to climates with low precipitation seasons, fire occurrence, and grazing. Both, Rippstein et al. (2001) in Colombia and Scurlock et al. (2003) in Venezuela have determined biomass with a maximum around 3–4 Mg/ha without fertilization treatments. From these studies it can be drawn that phenologic changes of the Llanos are closely related to rainy seasons. As a matter of fact, the amount of rainfall during the growing season has been found to be the best single predictor of grasslands aboveground net primary productivity (Nippert et al., 2006; Wessels et al., 2006).

Remote sensing is the best approach to estimate biomass at a regional level where field data is scarce. Almost two decades have passed since the pioneers like Sader et al. (1989) related biomass to reflectance. Since then, several studies in different regions have found strong correlations between biomass and reflectance at different wavelengths: in India (Roy and Ravan, 1996), in Bolivia and Brazil (Steininger, 2000), in Malaysia (Phua and Saito, 2003), in Eastern Brazil (Lu et al., 2004), and in Wisconsin, USA (Zheng et al., 2004). Other studies have used a measure of greenness or cumulative greenness as a means to estimate biomass. Greenness is based on reflectance bands and calculated using vegetation index equations like the normalized difference vegetation index (NDVI) in Eq. (1) or the enhanced vegetation index (EVI) in Eq. (2). The cumulative greenness is the sum over a period of time of vegetation index values, usually representing a phenological stage like the growing season (Myneni et al., 2001; Dong et al., 2003; Lu et al., 2004; Wessels et al., 2006).

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{R}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{R}}} \qquad (1)$$

where NDVI is the normalized difference vegetation index.

$$\mathrm{EVI} = G\left[\frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{R}}}{(\rho_{\mathrm{NIR}} + \mathrm{C1}\,\rho_{\mathrm{R}} - \mathrm{C2}\,\rho_{\mathrm{B}} + L)}\right] \qquad (2)$$

where EVI is the enhanced vegetation index; C1 = 6.0, atmosphere resistance red correction coefficient; C2 = 7.5, atmosphere resistance blue correction coefficient; L = 1.0, canopy background brightness correction factor; G = 2.5, gain factor.

Huete et al. (1997) analyzed several indexes (NDVI, SAVI, EVI and the ratio NIR/Red) in order to determine biomass estimation accuracy at different leaf canopy densities. These indexes are built upon reflectance values of near infrared (ρ_{NIR}), red (ρ_{R}) and blue (ρ_{B}) that might be calculated with any sensor (vegetation, ETM+, MODIS), except for EVI which is calibrated exclusively for MODIS data. Huete et al. (1997, 2002) found that the NDVI saturated in high biomass regions like the Amazon while the EVI was sensitive to canopy variations.

There are two drawbacks of biomass estimation using remote sensing: field plots are rarely designed to be related to spaceborne data and saturation at dense leaf canopies restricts estimates to low biomass levels when passive sensor data is used. Biomass is a three-dimension feature of vegetation and has been estimated using popular optical sensors like Landsat or Spot. However, the ability of these sensors is limited to two dimensions only, i.e. the upper layers of vegetation. Steininger (2000) found that the canopy reflectance–biomass relationship saturated at around 150 Mg/ha or over 15 years of age. These drawbacks result in large uncertainties and the methods that are used may not generalize accurately in space and time (Foody et al., 2003). Houghton et al. (2001) found that AGB, belowground biomass and necromass for large geographic extensions like the Brazilian Amazon vary from the lowest estimates of 78 billion Mg up to the highest of 186 billion Mg.

Another approach to biomass estimates using remote sensing applications are based on canopy density (Suganuma et al., 2006) which is represented by tree cover percentage maps. The main advantage of tree cover percentage maps over traditional maps of discrete classifications is to represent the internal variability of vegetation distribution. Two maps of proportional per pixel tree cover estimates, or continuous field of percent tree cover, have been published at a global scale, the AVHRR tree cover (DeFries et al., 2000) and the MODIS VCF, with spatial resolutions of 1 km and 500 m, respectively. The 500-m MODIS VCF represents the amount of skylight obstructed by tree canopies equal or greater than 5 m in height (Hansen et al., 2003a), and was estimated using metrics from the seven MODIS bands, NDVI and AVHRR brightness temperature. Hansen et al. (2003a) found that increasing canopy density is correlated with lower red reflectance values due to shadowing and chlorophyll absorption. More recently, Saatchi et al. (2007) used a series of metrics including vegetation indexes, leaf area index and percent tree cover maps to determine the distribution of aboveground live biomass in the Amazon basin, they calculated a total of 86 Pg C with a 20% uncertainty of total carbon in forest biomass.

State of the art of biomass estimates using remote sensing is based on LiDAR data (light detection and ranging), designed to allow the penetration of the signal through the canopy. During the last 10 years there is a growing interest for airborne and spaceborne LiDAR in order to estimate biomass (Lefsky et al., 1999; Drake et al., 2002; Patenaude et al., 2004; Hese et al., 2005; Lefsky et al., 2005). Successful spaceborne LIDAR has not yet been implemented, but allows measuring forest height and deriving its profile or vertical structure. This active sensor is, by far, the best option to estimate biomass at a local scale. Radar data has also been used to estimate biomass, Quiñones (2002) has a well documented discussion of the best radar bands to estimate AGB in the Colombian Amazon.

No active sensors data was available for this study, and thus LIDAR and radar data were disregarded. Medium and high spatial resolution images were also disregarded, since the spatial extent and temporal availability was insufficient. High temporal resolution was required not only to follow biomass trends but also to obtain pixels as free of clouds as possible. MODIS products were selected from the spaceborne available data, this program offers adequate temporal resolution with an appropriate spatial resolution to describe vegetation distribution at a national level. Additionally, MODIS products have a robust validation assessment per pixel which allows both, reducing noise and eliminating clouds when building composites.

Current nation's agreements in a global context like the Kyoto protocol require better estimates of biomass. The overall goal of this paper is to determine the spatial distribution of biomass in Colombia. Previous studies in Colombia and cited in this document are extremely detailed and covering a low percentage of local vegetation. While, on the other hand, there are extremely general studies at a national level with tabular data or pixels over 50 km (Olson et al., 1985, 2003; FAO, 2006). Increasing the detail level in a regional context allows understanding the processes affecting biomass (logging, fire occurrence, road building) and to assess current biomass sources and sinks. Remote sensing offers readily available and updated information to estimate biomass at regional level. The goals of this paper are: (i) model AGB as a function of VCF maps or vegetation indexes; (ii) evaluate intra-annual biomass trends for grasslands; (iii) provide AGB estimates for natural regions in Colombia, and (iv) increase the spatial detail level of previous biomass estimates.

2. Methods

2.1. Study area

Colombia is a tropical country in Northern South America with a total area of 1,139,012 km^2 and a large primary forest carbon pool. Humid conditions and warm temperatures promote fast vegetation regeneration at low lands in most of the country. Climate is driven by the intertropical convergence zone (ITCZ), although there is also a fair amount of moisture coming from the Pacific Ocean that raises along the western Andes resulting in annual precipitations over 8000 mm. Colombia has been divided in five natural regions (Fig. 1): Amazon, which contains the largest carbon pool; Orinoquía, characterized by savannas and large inter-annual fire occurrence; Andes, with the most threatened forests and intensive agricultural activity; Pacific, the second carbon pool of the country, highly deforested due to the presence of rivers and coasts; finally, the Caribbean region, having large formations of savannas and the driest region of the country, this region also has the highest Colombian snow peak at the Sierra Nevada de Santa Marta above 6000 m above sea level. The Andean and Caribbean regions present the largest conversion from forest to agriculture (Etter et al., 2006).

2.2. Remote sensing data

The Moderate Resolution Imaging Spectroradiometer was launched on board Terra satellite in 1999 followed by Aqua

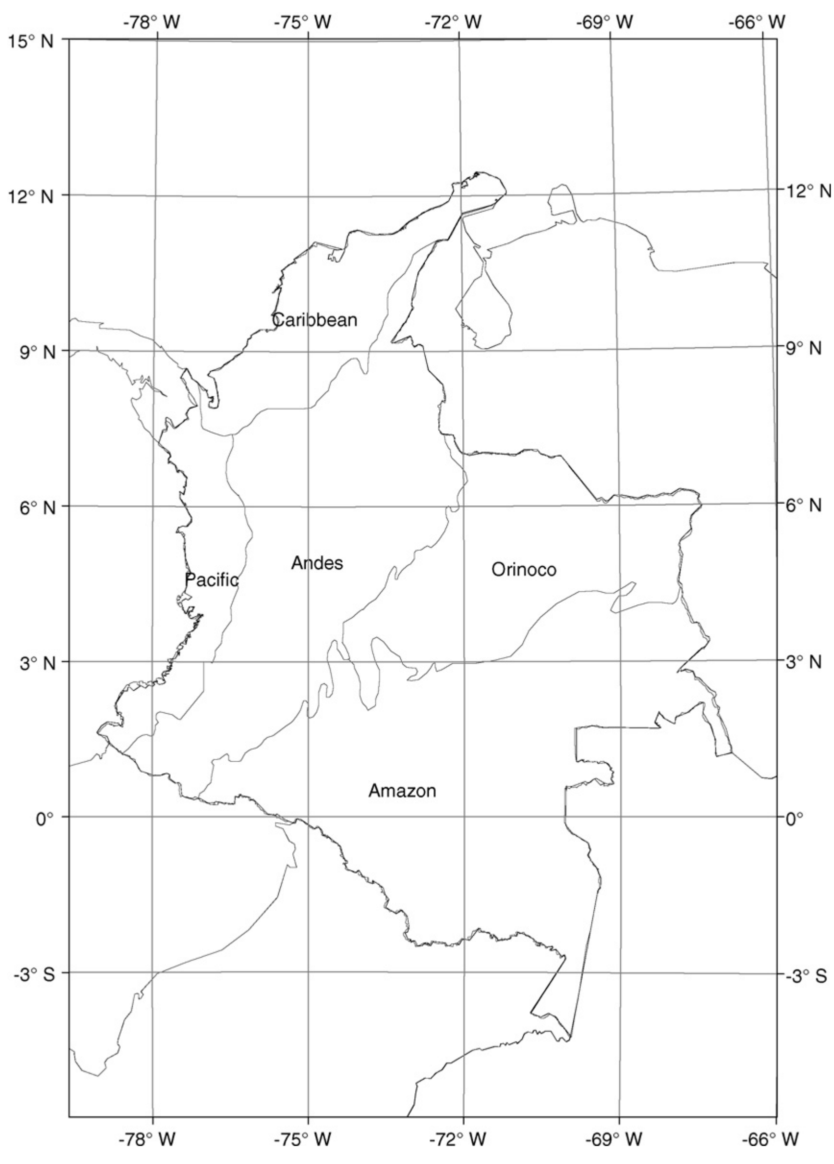

Fig. 1. Five major biogeographic regions of Colombia.

satellite in 2002. Both satellites are part of the Earth Observing System of NASA. The goal of this program is to provide a series of global atmosphere, oceans and land http://modis.gsfc.nasa.gov/. This sensor has 36 channels in the optical and thermal domain with resolutions of 250, 500 and 1000 m. The best of a series of observations is selected within a time period at a certain location (Mayaux et al., 2004; Schwarz et al., 2004). Time periods are commonly 8 days or 16 days. The selected product for assessing biomass is MOD13A1, a 16 days composite with 500 m spatial resolution

A total of 828 tiles were processed to build 138 mosaics, each covering the study area for a 16-day period. The 138 dates were built upon six tiles (H10V07, H11V07, H10V08, H11V08, H10V09, and H11V09) to complete the 2001–2006 time-series of satellite data. MODIS tools (DAAC, 2004) were used to download, reproject, mosaic and extract quality assessment values. A nearest neighbour reprojection was used with a pixel size of 500 m. Low quality pixels of composite (t) were replaced with the average value of adjacent temporal composites $t-1$ and $t+1$, afterwards a directional low pass filter with a 5×5 kernel size was applied to the temporal domain of the 138 dates.

0.25	0.25	0.00	0.25	0.25

This helped to reduce time-series noise (atmospheric, residual cloud and views). Original images were downloaded following standard MODIS tiles and reprojected to UTM (zone 18N) using WGS84 as a reference ellipsoid.

In order to describe biomass spatial distribution the VCF map, or proportional tree cover estimate per pixel, MOD44B Collection 3 was also included. The map is available for download at http://glcf.umiacs.umd.edu/data/vcf/ (Hansen et al., 2002, 2003b) and includes three layers: tree, herbaceous/shrub and bare soil percentages. The only layer used was the proportional tree cover, from now on VCFt, and the other two layers were disregarded due to the large multicollinearity. There are no means to build a time-series out of this product since it is a single date map representing the year 2001, but it is probably the best representation of continuous vegetation distribution at a spatial resolution of 500 m.

Secondary forest and primary forest were discriminated with a map of forests made by the Geographic Agustín Codazzi Insititute (IGAC) (Hacienda-IGAC, 1985). This map of polygons was made with expert's knowledge using aerial photography and satellite image interpretation and updated for this work using Landsat images. The level of detail is 1:1:500,000 and the map have 24 categories. In addition to this, maps of precipitation were also used to evaluate previous reported relationships between biomass and precipitation (Nippert et al., 2006; Wessels et al., 2006). The TRMM (tropical rainfall measurement mission) described by Kawanishi et al. (2000) provides adequate spatial and temporal rainfall information to follow the biomass intra-annual changes we want to describe.

2.3. Field data

Biomass ground data for forests is based on allometric relationships for each field plot with sizes varying from 0.01 up to 0.1 h. There are large differences among measurements for several reasons. Saldarriaga et al. (1998) found that biomass measured at primary forest was four times larger than in secondary forest. Large variations of biomass are also reported by Lovelock et al. (2005) depending on the distance of trees to the shore in the Panamá Mangroves. Edaphic, climatic, and orographic conditions as well as specie composition are also known to influence biomass values. On the other hand, pasture biomass varies according to fertilization treatments, use, soils, and more important: intra-annual precipitation pattern. Table 1 provides information of 44 field plots in Colombia, Panamá, and Venezuela including vegetation types from pasture to primary forests. Ground-based data and derived remote sensing data were related spatially through plot coordinates at a pixel level in areas of homogeneous vegetation coverage (Fig. 2).

2.4. Empirical models

There are no practical methods to measure all carbon stocks across a country. However, ground based and remote sensing data can be converted into national estimates using allometric relationships (Gibbs et al., 2007). Here, we established empirical relationships between all the plots and EVI or VCFt based on the hypothesis that larger EVI or VCFt (canopy cover) values result in larger biomass values. Several assumptions were made on the basis of biomass distribution in space and time. First, primary forests are in a steady state, i.e. these forests have reached its potential biomass. Second, growth and extraction in secondary forests are in balance. For these reasons, we assumed that primary and

Table 1
Biomass field data.

X	*Y*	Vegetation type	Biomasa (Mg/ha)	Reference
71°18′W	4°34′N	Grassland	0.60	Rippstein et al. (2001)
71°16′W	4°28′N	Grassland	1.00	Rippstein et al. (2001)
75°4′W	6°46′N	Grassland	3.00	Orrego and Del Valle (2001)
75°8′W	6°51′N	Grassland	3.00	Orrego and Del Valle (2001)
71°19′W	4°28′N	Grassland	5.00	Rippstein et al. (2001)
75°8′W	6°48′N	Grassland	6.00	Orrego and Del Valle (2001)
75°5′W	6°46′N	Grassland	8.00	Orrego and Del Valle (2001)
67°25′W	8°59′N	Grassland	3.20	San Jose and Montes (1998)
72°33′W	2°24′N	Grassland	10.00	Quiñones (2002)
75°9′W	6°49′N	Secondary forest	11.00	Orrego and Del Valle (2001)
74°21′W	6°17′N	Secondary forest	24.00	Benitez and Serna (2004)
75°6′W	6°45′N	Secondary forest	26.00	Orrego and Del Valle (2001)
75°7′W	6°43′N	Secondary forest	30.00	Orrego and Del Valle (2001)
75°9′W	6°48′N	Secondary forest	31.00	Orrego and Del Valle (2001)
75°6′W	6°45′N	Secondary forest	32.00	Orrego and Del Valle (2001)
75°8′W	6°47′N	Secondary forest	35.00	Orrego and Del Valle (2001)
75°8′W	6°46′N	Secondary forest	50.00	Orrego and Del Valle (2001)
74°18′W	6°25′N	Secondary forest	68.00	Benitez and Serna (2004)
75°4′W	6°46′N	Secondary forest	82.00	Orrego and Del Valle (2001)
75°5′W	6°45′N	Secondary forest	86.00	Orrego and Del Valle (2001)
75°32′W	6°3′N	Secondary forest	87.00	CORNARE (2002)
75°7′W	6°47′N	Primary forest	98.00	Orrego and Del Valle (2001)
66°0′W	9°59′N	Primary forest	140.00	Houghton et al. (2001)
75°6′W	6°44′N	Primary forest	154.00	Orrego and Del Valle (2001)
77°17′W	4°33′N	Primary forest	194.00	Lovelock et al. (2005)
77°0′W	3°55′N	Primary forest	195.00	Houghton et al. (2001)
75°34′W	6°2′N	Primary forest	217.00	CORNARE (2002)
67°4′W	1°58′N	Primary forest	218.00	Saldarriaga et al. (1998)
67°3′W	1°55′N	Primary forest	221.00	Houghton et al. (2001)
75°8′W	6°50′N	Primary forest	239.00	Orrego and Del Valle (2001)
73°55′W	6°49′N	Primary forest	252.00	Houghton et al. (2001)
74°21′W	6°23′N	Primary forest	257.00	Benitez and Serna (2004)
67°2′W	1°58′N	Primary forest	264.00	Saldarriaga et al. (1998)
67°9′W	1°49′N	Primary forest	271.00	Saldarriaga et al. (1998)
70°0′W	9°30′N	Primary forest	296.0	Houghton et al. (2001)
72°32′W	2°25′N	Primary forest	297.00	Quiñones (2002)
75°6′W	6°45′N	Primary forest	298.00	Orrego and Del Valle (2001)
70°52′W	10°23′N	Primary forest	314.00	Houghton et al. (2001)
73°32′W	6°24′N	Primary forest	325.81	DAAC (2002)
67°7′W	1°53′N	Primary forest	326.00	Saldarriaga et al. (1998)
72°10′W	0°39′S	Primary forest	343.00	Houghton et al. (2001)
78°7′W	8°45′N	Primary forest	397.00	DAAC (2002)

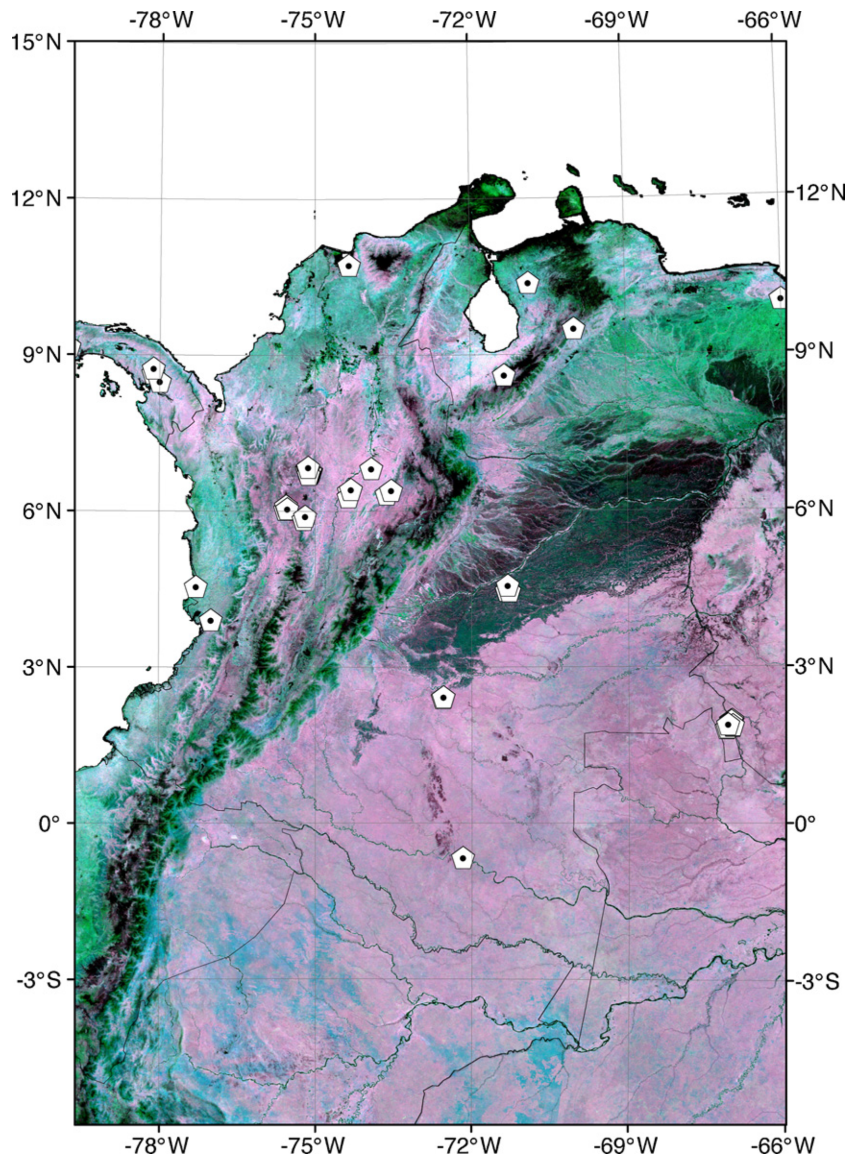

Fig. 2. Color composite of maximum, minimum and mean EVI values for the study period (2001–2006) and biomass field plots location.

secondary forests have constant biomass during the study period. Third, it is assumed that field plots are representative of a 25 ha pure pixel values. Fourth, pasture biomass changes rapidly within a year and the temporal resolution of 16 days composite data is sufficient to depict these changes.

3. Results

3.1. Biomass model for primary and secondary forests

Linear and exponential models were fitted to the primary forests and secondary forest with VCFt and EVI metrics as explanatory variables (Table 2 and Fig. 3). The statistical significance of F value is lower than 0.05 just in those equations were the VCFt term was included, which means that the variation explained by the model is not at random. However, the inclusion of the cumulated EVI or maximum EVI reduces the significance level and for this reason was discarded as explanatory variable. The linear model seems more appropriate for the ground-data, however it predicts negative biomass values when tree percentage is close to zero Eqs. (3) and (4). On the other hand, the exponential model overestimate biomass at the upper range with 1062 and 187 Mg/ha for primary forests Eq. (5) and secondary forests Eq. (6). We consider the exponential model more appropriate to describe biomass increase as the percentage of tree percentage increases, the larger the VCFt value the larger the probability of a pixel to belong to a forests with large AGB values (less fragmented and less extraction levels). In order to avoid unrealistic estimations we restricted the model to the maximum ground-based value of 397 Mg/ha.

Residuals were calculated for the exponential model in order to evaluate any systematic patterns along a fitted line between measured and estimated values. In the case of secondary forest there is a tendency to underestimate field values as VCFt value increases, although more observations are required to confirm this trend (Fig. 4).

Table 2
Biomass equations estimated for forests, R^2 coefficient of determination, variable significance and forest type.

AGB model (Mg/ha)	R^2	Sig.	Forest type
4.3149 (VCFt) − 80.202	0.82	0.000	Primary
1.6397 (VCFt) − 76.006	0.55	0.009	Secondary
$1.951 \times \exp(0.063 \times \text{VCFt})$	0.78	0.000	Primary
$0.419 \times \exp(0.061 \times \text{VCFt})$	0.72	0.001	Secondary

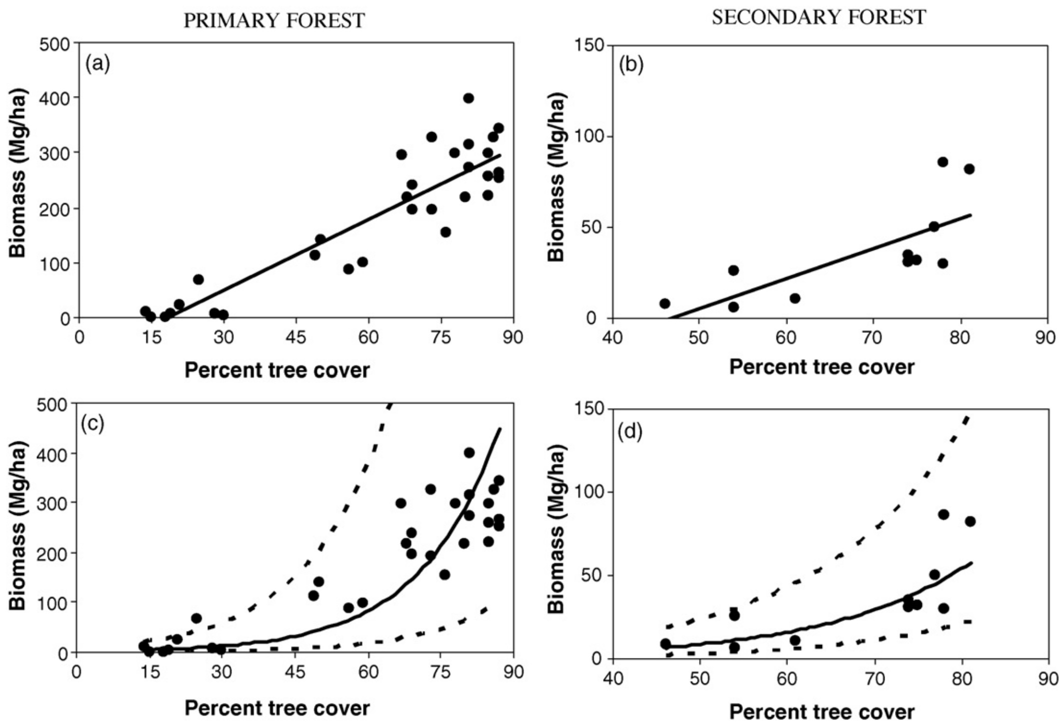

Fig. 3. Linear and exponential models for primary and secondary forests. The dotted line represents the confidence interval at (90%).

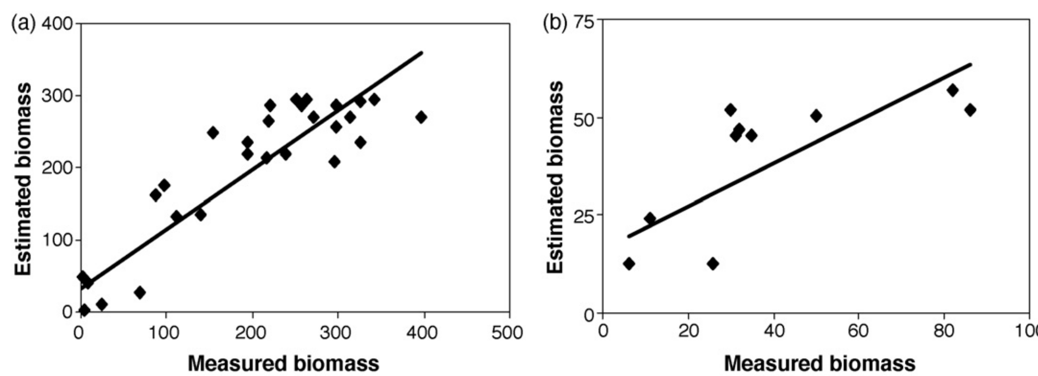

Fig. 4. Validation plot for exponential models, measured and estimated biomass value. Primary forest (a) and secondary forest (b).

3.2. Biomass model for savannas

As explained before pasture biomass values are highly variable within a year and this variability must be modeled. In order to model intra-annual variation we used field data elaborated by San Jose and Montes (1998) which were collected and made available by Scurlock et al. (2003). This dataset has monthly biomass values for pastures at El Calabozo Station (Llanos of Venezuela) and has similar characteristics to the Llanos of Colombia and are considered representative for the study area. The 16 days

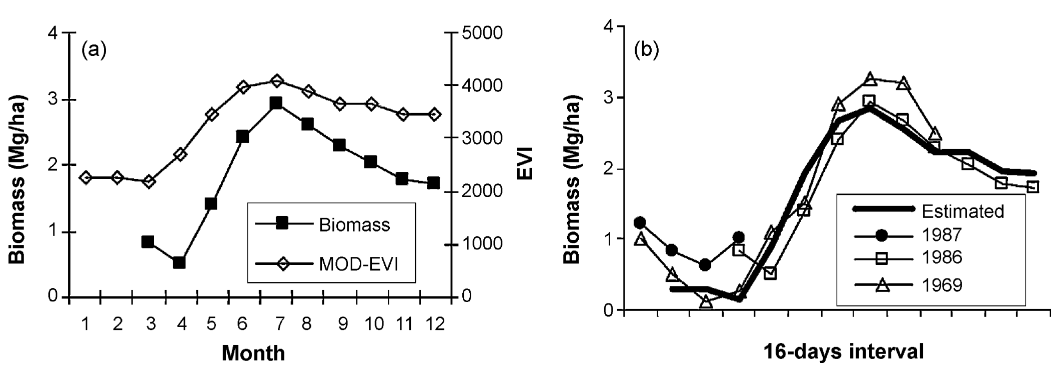

Fig. 5. Pastures productivity and EVI values at the Calabozo station (8.93N, 67.42W). (a) MOD13A1 EVI for 2004 and measured biomass values in 1986; (b) estimated biomass as a function of EVI and measured values for 3 different years.

MOD13A1 EVI of the year 2004 was related to the changes measured in the field during 3 years: 1969, 1986 and 1987. Despite the temporal discrepancy between remote sensing data and field data these results are useful in depicting the inter-annual biomass variability (Fig. 5).

Here, it is important to note that this relationship is only valid for pastures, i.e. 0% tree or bare soil. If an important amount of bare soil is present EVI will be low and will result in negative biomass values (which translates as no biomass), but on the other hand, if the percentage of tree cover is different than zero a correction factor must be applied to account for forest biomass. Eq. (7) accounts for changes in pastures based on EVI but also include a VCFt term that becomes more important as the percent tree cover increases. This is particularly important at tree savanna formations.

$$\begin{aligned} AGB = {} & (0.0014 \times EVI - 2.8911) \times (100 - VCFt)/100 \\ & + (4.3149 \times (VCFt) - 80.202) \times VCFt/100 \end{aligned} \tag{7}$$

EVI is the enhanced vegetation index, scale factor 10,000.

Biomass values for the three vegetation classes are estimated using Eqs. (5)–(7) and the stratification based on Fig. 6. The distinction of classes was based on the distribution of VCF values

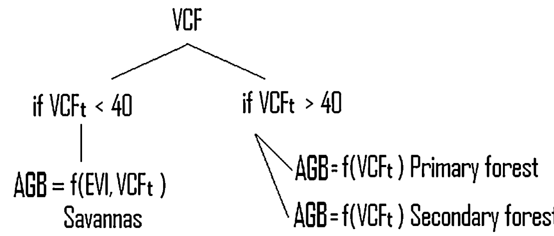

Fig. 6. Biomass estimation flow chart based on VCFt (percent tree cover) and map of forests.

and the map of forests; both sources were used to benefit from the structural information of the VCF and the vegetation interpretation of the map of forests. The distribution of VCF values at the forest class was defined as $40 < VCFt < 100$ while the distribution of VCF values for savannas was defined as $0 < VCFt < 40$.

3.3. Biomass spatial distribution

Biomass distribution is determined as a surface with a pixel size of 500 m (Fig. 7). In order to describe biomass spatial distribution, information is aggregated using two different maps: map of forests

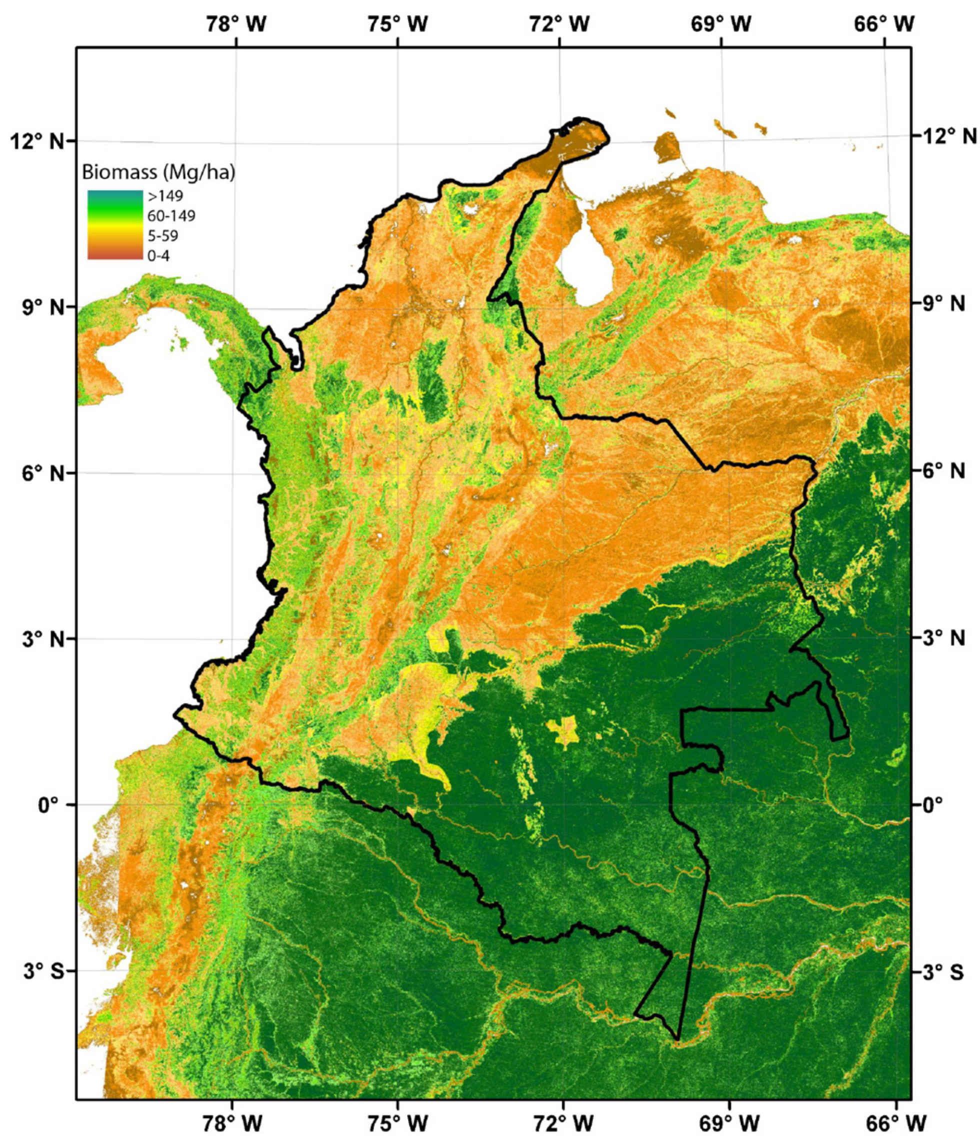

Fig. 7. Aboveground live biomass derived from the relationship of VCFt, EVI and field data.

Table 3
Model statistics by vegetation class.

	Area by vegetation class (km^2)[a]	Average AGB (Mg/ha)	Confidence intervals 90%	Biomass (million of Mg)
Primary forest	576,968	264	61–1246[b]	15,231
Secondary forest	78,899	35	12–81	276
Savannas	359,830	21	2–46	755

[a] Water bodies and bare soils are excluded.
[b] 397 Mg/ha was set as a maximum biomass value.

Table 4
Biomass distribution by region.

Region	Area (km^2)	Average AGB (Mg/ha)	Biomass (million of Mg)
Caribbean	110,014	19	209
Andes	306,010	54	1,652
Pacific	81,280	95	772
Orinoquía	202,618	37	749
Amazon	439,090	291	12,777
Total	1,139,012		16,160

(Table 3) and natural regions (Table 4). In the case of savannas each date has different biomass values but an inter-annual average was calculated. Primary forest accounts for 93.7% of the total biomass while savannas and secondary forest accounts for only 6.3%. Total secondary biomass is low mainly because the small fraction of this vegetation type with respect to the total area. Most of the biomass pools of the country are, by far, located at the Amazon region, followed by the Pacific and Andes regions. The Amazon not only has a large percentage of the country in terms of area but it also has the largest biomass estimates. After the Amazon, the Pacific region has a large carbon pool. This region has high rainfall rates distributed evenly during the year, which is important since production in tropical forests are highly dependent on moisture availability during the dry season where light and radiation are available (Malhi et al., 2006). The Andes region has an important amount of cropping (here considered as secondary forests or savannas) and infrastructure. However, some forests still remain in the north, east and west sides of the Andes mountain range. Lower concentrations of biomass are found in the savannas of the

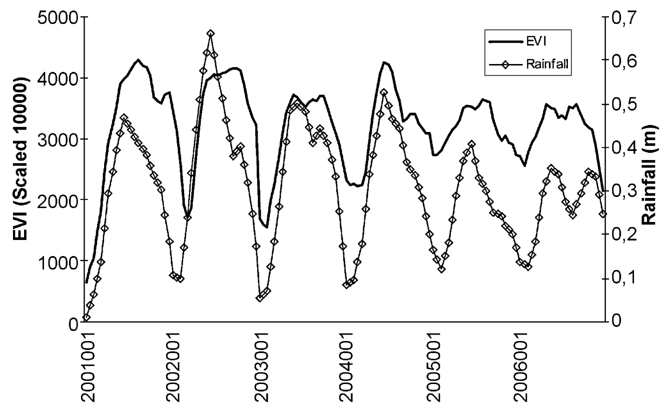

Fig. 8. Tropical rainfall measurement mission and enhanced vegetation index time-series from January 2001 to December 2006.

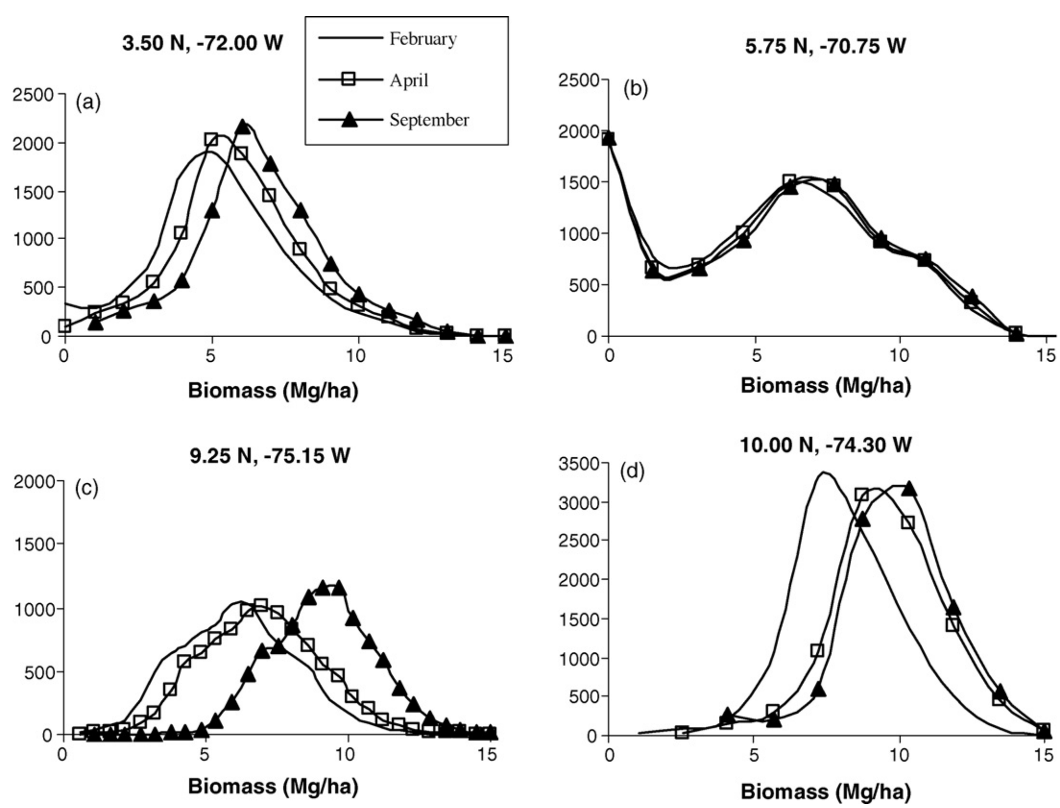

Fig. 9. Intra-annual modeling of pastures biomass distribution at different latitudes. Each figure has the biomass distribution for three different months: February (dry season), April (first wet season) and September (after mild dry season); (a) and (b) are located in the Caribbean regions and (c) and (d) in the Orinoco plains.

Orinoquía characterized by the presence of grasslands (e.g. Trachypogon vestitas and Trachypogon plumosus) and dedicated to cattle farming. The Caribbean region also presents low biomass values due to the arid conditions in the north and the presence of savannas along the Magdalena River; the main concentrations of biomass is located in the North of the Sierra Nevada de Santa Marta.

3.4. Biomass temporal distribution

Savannas are highly dynamic within a year and thus a description of the temporal biomass distribution is needed. As expected, these trends are closely related to rainfall (Fig. 8), where February represents the dry season with a large occurrence of biomass burning (Chuvieco et al., 2008); April represents the start of the wet season followed by a mild dry season in June and July; from September to November there is a second rainy season that decreases towards December to start a new cycle.

The year 2004 was selected to illustrate intra-annual savanna biomass trends at four sites of 2500 km^2 chosen at different latitudes. In general, the distribution shifts towards larger biomass values from February to September where it reaches a maximum. The southern sites Fig. 9(a) and (b) have a content of pixels with no biomass, i.e. pixels located at zero, meaning bare soil or water bodies. This is more evident in site (b) where large amounts of pixels are located at biomass zero and thus related to small biomass changes throughout the year. On the other hand, the northern sites (c) and (d) are characterized for larger biomass values where shrub lands and cropping are common.

4. Conclusions

VCF maps provide a spatial detail large enough to estimate AGB distribution in the context of biogeochemical modeling, especially in the tropics where data is scarce. Although there are no means to estimate stand heights, distribution values of AGB could be approached using detailed ground-based data and continuous vegetation maps. Ground-based measurements of AGB and VCFt pixel values were related to fit empirical equations. This method was used based on the assumption that large contents of trees per pixel (canopy density) must be associated to larger biomass values. Empirical equations were fit independently for three types of vegetation: primary forest, secondary forest and savannas. Canopy density based on VCFt maps and AGB field data allows a large improvement for biomass spatial distribution at a national level. Biomass assessment in Colombia is challenging given the large diversity of vegetation types.

No significant empirical relationship was found between EVI and forest biomass values, despite of the fact that successful results had been found in non-tropical regions. There are two reasons to support these results, first the growing season is difficult to be defined in broad leaf tropical environments, and second, the variability in magnitude of EVI values is lower in the tropical forest than in temperate forests; EVI values for Colombian forests of the Amazon ranges from 4250 to 5500 while in temperate forests like East Asia ranges from 1000 to 5000 (Boles et al., 2004). On the other hand, in the case of pastures, we found that intra-annual productivity of field data behaves similar to the phenology captured by EVI. For this reason we argued that pasture phenology is closely related to intra-annual biomass changes and thus EVI is statistically significant to explain intra-annual biomass changes. These observations are confirmed by the TRMM precipitation patterns which are similar to those found by Wessels et al. (2006).

With this methods and materials we estimated a total of 16.2 million Mg of aboveground biomass in Colombia. With the 90% confidence intervals of the exponential equation upper and lower biomass values are within 3.7 and 25.2 million Mg, the confidence intervals are extremely large given the nature of the exponential models. Linear models were also evaluated but these models are unable to depict biomass distribution at the lower range. Our results agree with FAO's Forestry Resources Assessment Programme where 15.4 million Mg are reported for forest lands (FAO, 2006). Moreover, based on (Olson et al., 2003) carbon density estimates are 8.1 million Mg for the whole country, resulting in 16.2 million Mg of biomass, where 97% (15.7 million Mg), correspond to primary forests. These results are within the range of previous studies and with a major improvement in spatial detail.

VFC maps are a useful representation of vegetation with an appropriate detail level at regional scale but temporal resolution is scarce. New versions of annual VCF product are required to track vegetation change in terms of land use and biomass change assessment. On the other hand, more research is required to adequately design biomass field plots that are to be related with canopy density information derived from remote sensing observations.

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References

Achard, F., Eva, H., Mayaux, P., Stibig, H.-J., Belward, A., 2004. Improved estimates of net carbon emissions from land cover change in the tropics for the 1990s. Global Biogeochemical Cycles 18, 1–12.

Baruch, Z., 2005. Vegetation–environment relationships and classification of the seasonal savannas in Venezuela. Flora-Morphology, Distribution, Functional Ecology of Plants 200, 49–64.

Benitez, P.A., Serna, J.C., 2004. Deforestación y flujos de carbono en los bosques asociados con ciénagas del Magdalena Medio. Universidad Nacional de Colombia, Medellín, Colombia.

Boles, S.H., Xiao, X., Liu, J., Zhang, Q., Munkhtuya, S., Chen, S., Ojima, D., 2004. Land cover characterization of Temperate East Asia using multi-temporal VEGETATION sensor data. Remote Sensing of Environment 90, 477–489.

Cihlar, J., 2007. Quantification of the regional carbon cycle of the biosphere: policy, science and land-use decisions. Journal of Environmental Management 85, 785–790.

CORNARE, 2002. Modelo de financiación alternativo para el manejo sostenible de los bosques de San Nicolás. Universidad Nacional de Colombia, Cornare, Medellín.

Chuvieco, E., Opazo, S., Sione, W., Del Valle, H., Anaya, J., Di Bella, C., Cruz, I., Manzo, L., Lopez, G., Mari, N., Gonzalez, F., Morelli, F., Setzer, A., Csiszar, I., Karpandegui, A., Bastarrika, A., Libonari, R., 2008. Global burned land estimation in Latin America using MODIS composite data. Ecological Applications 18, 64–79.

DAAC, 2002. NPP Data. Global Change Master Directory.

DAAC, 2004. LDOPE Tools User's. Release 1.4.

DeFries, R., Achard, F., Brown, S., Herold, M., Murdiyarso, D., Schlamadinger, B., de Souza Jr., C., 2007. Earth observations for estimating greenhouse gas emissions from deforestation in developing countries. Environmental Science & Policy 10, 385–394.

DeFries, R.S., Hansen, M.C., Townshend, J.R., Janetos, A.C., Loveland, T.R., 2000. A new global 1-km dataset of percentage tree cover derived from remote sensing. Global Change Biology 6, 247–254.

Dong, J., Kaufmann, R.K., Myneni, R.B., Tucker, C.J., Kauppi, P.E., Liski, J., Buermann, W., Alexeyev, V., Hughes, M.K., 2003. Remote sensing estimates of boreal and temperate forest woody biomass: carbon pools, sources, and sinks. Remote Sensing of Environment 84, 393–410.

Drake, J.B., Dubayah, R.O., Knox, R.G., Clark, D.B., Blair, J.B., 2002. Sensitivity of large-footprint lidar to canopy structure and biomass in a neotropical rainforest. Remote Sensing of Environment 81, 378–392.

Etter, A., McAlpine, C., Wilson, K., Phinn, S., Possingham, H., 2006. Regional patterns of agricultural land use and deforestation in Colombia. Agriculture Ecosystems & Environment 114, 369–386.

FAO, 2006. Global Forest Resources Assessment 2005, Main Report. Progress Towards Sustainable Forest Management. FAO Forestry Paper 147, Rome.

Foody, G.M., Boyd, D.S., Cutler, M.E.J., 2003. Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. Remote Sensing of Environment 85, 463–474.

Gibbs, H.K., Brown, S.O., Niles, J., Foley, J.A., 2007. Monitoring and estimating tropical carbon stocks: making REDD a reality. Environmental Research Letters 2, 1–13.

Hacienda-IGAC, M.d., 1985. Mapa de Bosques. Instituto Geográfico Agustín Codazzi, Bogotá.

Hansen, M.C., DeFries, R.S., Towndsend, J.R.G., Carroll, M., Dimiceli, C., Sohlberg, R., 2003a. Global percent tree cover at a spatial resolution of 500 meters: first results of the MODIS vegetation continuous algorithm. Earth Interactions 7, 1–15.

Hansen, M.C., DeFries, R.S., Townshend, J.R., Carroll, M., Dimiceli, C., Sohlberg, R., 2003b. MOD44B: vegetation continuous fields collection 3, version 3.0.0. Earth Interactions 1–20.

Hansen, M.C., DeFries, R.S., Townshend, J.R.G., Marufu, L., Sohlberg, R., 2002. Development of a MODIS tree cover validation data set for Western Province, Zambia. Remote Sensing of Environment 83, 320–335.

Herold, M., Achard, F., De Fries, R.S., Skole, D., Brown, S., Townshend, J.R., 2006. Report of the workshop on monitoring tropical deforestation for compensated reductions. In: GOFC-GOLD Symposium on Forest and Land Cover Observations. pp. 1–33.

Hese, S., Lucht, W., Schmullius, C., Barnsley, M., Dubayah, R., Knorr, D., Neumann, K., Riedel, T., Schröter, K., 2005. Global biomass mapping for an improved understanding of the CO_2 balance—the Earth observation mission carbon-3D. Remote Sensing of Environment 94, 94–104.

Houghton, R.A., Lawrence, K.T., Hackler, J.L., Brown, S., 2001. The spatial distribution of forest biomass in the Brazilian Amazon: a comparison of estimates. Global Change Biology 7, 731–746.

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 83, 195–213.

Huete, A., Liu, H., Leeuwen, W., 1997. The use of vegetation indices in forested regions: issues of linearity and saturation. IEEE 1966–1968.

Jimenez, J., Moreno, A.G., Lavelle, P., Decaens, T., 1998. Population dynamics and adaptive strategies of Martiodrilus carimaguensis (Oligochaeta, Glossoscolecidae), a native species from the well-drained savannas of Colombia. Applied Soil Ecology 9, 153–160.

Kawanishi, T., Kuroiwa, H., Kojima, M., Oikawa, K., Kozu, T., Kumagai, H., Okamoto, K., Okumura, M., Nakatsuka, H., Nishikawa, K., 2000. TRMM precipitation radar. Advances in Space Research 25, 969–972.

Keeling, H.C., Phillips, O.L., 2007. The global relationship between forest productivity and biomass. Global Ecology and Biogeography 0, 1–14.

Lefsky, M.A., Harding, D., Cohen, W.B., Parker, G., Shugart, H.H., 1999. Surface lidar remote sensing of basal area and biomass in deciduous forests of Eastern Maryland, USA. Remote Sensing of Environment 67, 83–98.

Lefsky, M.A., Turner, D.P., Guzy, M., Cohen, W.B., 2005. Combining lidar estimates of aboveground biomass and Landsat estimates of stand age for spatially extensive validation of modeled forest productivity. Remote Sensing of Environment 95, 549–558.

Lovelock, C.E., Feller, I.C., McKee, K.L., Thompson, R., 2005. Variation in mangrove forest structure and sediment characteristics in Bocas del Toro, Panama. Caribbean Journal of Science 41, 456–464.

Lu, D., Mausel, P., Brondízio, E., Moran, E., 2004. Relationships between forest stand parameters and Landsat TM spectral responses in the Brazilian Amazon Basin. Forest Ecology and Management 198, 149–167.

Malhi, Y., Wood, D., Baker, T.R., Wright, J., Phillips, O.L., Cochrane, T., Meir, P., Chave, J., Almeida, S., Arroyo, L., Higuchi, N., Killeen, T.J., Laurance, S.G., Laurance, W.F., Lewis, S.L., Monteagudo, A., Neill, D.A., Nuñez Vargas, P., Pitman, N.C.A., Quesada, C.A., Salomao, R., Silva, J.N.M., Torres Lezama, A., Terborgh, J., Vásquez Martínez, R., Vinceti, B., 2006. The regional variation of aboveground live biomass in old-growth Amazonian forests. Global Change Biology 12, 1–32.

Mayaux, P., Bartholomé, E., Fritz, S., Belward, A., 2004. A new land-cover map of Africa for the year 2000. Journal of Biogeography 31, 861–877.

Menaut, J.C., Abbadie, L., Lavenu, F., Loudjani, P., Podaire, A., 1991. Biomass burning in West African savannas. In: Levine, J.S. (Ed.), Global Biomass Burning. The MIT Press, Cambridge, MA, pp. 133–142.

Moutiño, P., Schwartzman, S. (Eds.), 2005. Tropical Deforestation and Climate Change. Amazon Institute for Environmental Research, Belem.

Myneni, R.B., Dong, J., Tucker, C.J., Kauffman, R.K., Kauppi, P.E., Liski, J., Zhou, L., Alexeyev, V., Hughes, M.K., 2001. A large carbon sink in the woody biomass of Northern forests. Proceedings of the National Academy of Sciences of the United States of America 1–7.

Nippert, J.B., Knapp, A.K., Briggs, J.M., 2006. Intra-annual rainfall variability and grassland productivity: can the past predict the future? Plant Ecology 184, 56–74.

Nogueira, E.M., Nelson, B.W., Fearnside, P.M., França, M.B., Oliveira, Á.C.A.d., 2008. Tree height in Brazil's [']arc of deforestation': shorter trees in south and southwest Amazonia imply lower biomass. Forest Ecology and Management 255, 2963–2972.

Olson, J.S., Watts, J.A., Allison, L.J., 1985. In: Millemann, R.E., Boden, T.A. (Eds.), Major World Ecosystems Complexes Ranked by Carbon in Live Vegetation: A Database. US Department of Energy, Carbon Dioxide Information Center, Information Resources Organization, Oak Ridge National Lab, p. 18.

Olson, J.S., Watts, J.A., Allison, L.J., 2003. LBA Regional Carbon in Live Vegetation, 0.5-Degree (Olson) Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, TN, USA. , http://www.daac.ornl.gov.

Orrego, S.A., Del Valle, J.I., 2001. Existencias y tasas de incremento neto de la biomasa y del carbono en bosques primarios y secundarios de Colombia. In: Simposio Internacional Medición y Monitoreo de la Captura de Carbono en Ecosistemas Forestales, Valdivia, Chile, pp. 1–31.

Patenaude, G., Hill, R.A., Milne, R., Gaveau, D.L.A., Briggs, B.B.J., Dawson, T.P., 2004. Quantifying forest above ground carbon content using LiDAR remote sensing. Remote Sensing of Environment 93, 368–380.

Pearson, T., Harris, N., Shoc, D., Pandey, D., Brown, S., 2008. Estimation of carbon stocks. In: A Sourcebook of Methods and Procedures for Monitoring, Measuring and Reporting GOFC-GOLD, Alberta, Canada (Chapter 4).

Phua, M.-H., Saito, H., 2003. Estimation of biomass of a mountainous tropical forest using Landsat TM data. Canadian Journal of Remote Sensing 29, 429–440.

Privette, J.L., Myneni, R.B., Knyazikhin, Y., Mukelabai, M., Roberts, G., Tian, Y., Wang, Y., Leblanc, S.G., 2002. Early spatial and temporal validation of MODIS LAI product in the Southern Africa Kalahari. Remote Sensing of Environment 83, 232–243.

Quiñones, M., 2002. Polarimetric Data for Tropical Forest Monitoring. Studies at the Colombian Amazon. Wageningen University, Wageningen.

Rippstein, G., Escobar, G., Motta, F., 2001. Agroecología y Biodiversidad de las Sabanas en los Llanos Orientales de Colombia. CIAT, no. 322, 302 pp.

Roy, P.S., Ravan, S.A., 1996. Biomass estimation using satellite remote sensing data—an investigation on possible approaches for natural forest. Journal of Biosciences 21, 535–561.

Saatchi, S.S., Houghton, R.A., Dos Santos Alvala, R.C., Soares, J.V., Yu, Y., 2007. Distribution of aboveground live biomass in the Amazon basin. Global Change Biology 13, 816–837.

Sader, S.A., Waide, R.B., Lawrence, W.T., Joyce, A.T., 1989. Tropical forest biomass and successional age class relationships to a vegetation index derived from Landsat TM data. Remote Sensing of Environment 28, 143–156.

Saldarriaga, J.C., Darrell, C.W., Tharp, M.L., Uhl, C., 1998. Long-term chronosequence of forest succession in the upper Rio Negro of Colombia and Venezuela. Journal of Ecology 76, 938–958.

San Jose, J., Montes, R.A., 1998. NPP Grassland: Calabozo, Venezuela, 1969–1987. Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, TN, USA Data set: http://Www.Daac.Ornl.Gov.

San José, J.J., Montes, R.A., 2007. Resource apportionment and net primary production across the Orinoco savanna-woodland continuum. Venezuela. Acta Oecologica 32, 243–253.

Scanlon, T.M., Caylor, K.K., Manfreda, S., Levin, S.A., Rodrigues, I., 2005. Dynamic response of grass cover to rainfall variability: implications for the function and persistence of savanna ecosystems. Advances in Water Resources 28, 291–302.

Scurlock, J.M., Johnson, K.R., Olson, J.S., 2003. NPP Grassland: NPP Estimates from Biomass Dynamics for 31 Sites, 1948–1994. Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, TN, USA Data set available online: http://www.daac.ornl.gov.

Scheller, R.M., Mladenoff, D.J., 2004. A forest growth and biomass module for a landscape simulation model, LANDIS: design, validation, and application. Ecological Modelling 180, 211–229.

Schwarz, M., Zimmermann, E., Waser, L.T., 2004. MODIS based continuous fields of tree cover using generalized linear models. IEEE 2377–2380.

Sierra, C.A., del Valle, J.I., Orrego, S.A., Moreno, F.H., Harmon, M.E., Zapata, M., Colorado, G.J., Herrera, M.A., Lara, W., Restrepo, D.E., Berrouet, L.M., Loaiza, L.M., Benjumea, J.F., 2007. Total carbon stocks in a tropical forest landscape of the Porce region, Colombia. Forest Ecology and Management 243, 299–309.

Steininger, M.K., 2000. Satellite estimation of tropical secondary forest aboveground biomass: data from Brazil and Bolivia. International Journal of Remote Sensing 21, 1139–1157.

Suganuma, H., Abe, Y., Taniguchi, M., Tanouchi, H., Utsugi, H., Kojima, T., Yamada, K., 2006. Stand biomass estimation method by canopy coverage for application to remote sensing in an arid area of Western Australia. Forest Ecology and Management 222, 75–87.

van der Werf, G.R., Randerson, J.T., Collatz, G.J., Giglio, L., Kasibhatla, P.S., Arellano, A.F., Olsen, S.C., Kasischke, E.S., 2006. Interannual variability of global biomass burning emissions from 1997 to 2004. Atmospheric Chemistry and Physics Discussions 6, 3175–3226.

Wessels, K.J., Prince, S.D., Zambatis, N., Macfadyen, S., Frost, P.E., Van Zyl, D., 2006. Relationship between herbaceous biomass and 1-km^2 advanced very high resolution radiometer (AVHRR) NDVI in Kruger National Park, South Africa. International Journal of Remote Sensing 27, 951–973.

Zheng, D., Rademacher, J., Chen, J., Crow, T., Bresee, M., Le Moine, J., Ryu, S.-R., 2004. Estimating aboveground biomass using Landsat 7 ETM + data across a managed landscape in northern Wisconsin, USA. Remote Sensing of Environment 93, 402–411.