Spatial Distribution of Aboveground Live Biomass in the Amazon Basin

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Abstract

The amount and spatial distribution of forest biomass in the Amazon basin is a major source of uncertainty in estimating the flux of carbon released from land-cover and land-use change. Direct measurements of aboveground live biomass (AGLB) are limited to small areas of forest inventory plots and site-specific allometric equations that cannot be readily generalized for the entire basin. Furthermore, there is no spaceborne remote sensing instrument that can measure tropical forest biomass directly. To determine the spatial distribution of forest biomass of the Amazon basin, we introduce a methodology based on spatial data, such as land cover, remote sensing metrics representing various forest structural parameters and environmental variables, and more than 500 forest plots distributed over the basin. A decision tree approach was used to develop the spatial distribution of AGLB in 7 distinct biomass classes in lowland old-growth forests with more than 80% accuracy. AGLB for other vegetation types such as the woody and herbaceous savanna and secondary forests were directly estimated from the regression analysis of satellite data.

Results show that AGLB is highest in the main Central Amazon and in regions to the east and north, including the Guyanas. Biomass is generally above 300 Mg/ha here except in areas of intense logging or open floodplains. In the Western Amazon from the lowland regions of Peru, Ecuador, and Colombia to the Andean elevational gradients, biomass ranges from 150-300 Mg/ha. Most transitional and seasonal forests in southern and northwestern edges of the basin have biomass ranging from 100-200 Mg/ha. The AGLB distribution has a significant correlation with the months of dry season and the annual mean rainfall patterns across the basin. We predict, the total carbon in forest biomass of the basin, including the dead and belowground biomass to be 77-96 Pg C that compares in magnitude with the range of carbon predicted by other models.

Keywords: Amazon, Biomass, Rainforest, Remote Sensing, Climate

Introduction

The distribution of forest biomass over large areas, such as the Amazon basin, is uncertain. Satellite measurements from active sensors (radars and lidars) may eventually be developed to determine aboveground biomass directly, but, to date, estimates of biomass vary widely (Fearnside, 1996; Brown, 1997; Houghton, 1997; Houghton et al., 2001; Eva et al., 2003; Fearnside et al., 2003), and contribute more than any other factor to the uncertainty of estimates of carbon flux from land cover and land use change in the region (Houghton et al. 2000). While extensive forest inventories would provide the data required for an accurate determination of the source and sinks of carbon from changes in land use, systematic on-the-ground measurements over the Amazon basin at the intensity required is not currently feasible. Partial inventories, such as the one carried out by RADAMBRAZIL in the 1970s and from measurements at individual plots, provide information on biomass in certain forest types, but they have been insufficient for the entire region.

For example, Houghton et al. (2001) compared seven methods that have been used to estimate forest biomass over the Brazilian Amazon. Different estimates were based on the RADAMBRAZIL inventory, on an interpolation of measurements from 44 plots, on empirical relationships between environmental factors and aboveground biomass, on percent tree cover from satellite data, and on estimates of biomass modeled with satellite-derived measurements of NPP. Basin-wide estimates of biomass (including dead, live, and belowground) ranged over more than a factor of two, from 39 to 93 PgC, with a mean value of 70 (±7) PgC. Average forest biomass was 177 (±17) MgC ha^{-1}.

Data from the RADAMBRAZIL inventory produced estimates of total biomass that varied between 62.5 PgC and 93.1 PgC, depending on the conversion factors used. The lower estimate was from of Brown and Lugo (1992) and the higher one, from Fearnside (1997). Most surprisingly, a spatial comparison of four of the most reasonable maps showed agreement over only 5% of the Brazilian Amazon (essentially random agreement).

Estimates of biomass for the region suffer from two sources of uncertainty: (1) uncertainties associated with measurements at individual plots and (2) uncertainties in extrapolating data from individual plots to the entire basin. Measurements at individual plots are often incomplete. Full accounting requires measurement of live and dead biomass, above- and belowground biomass, lianas, palms, small trees, and other components of biomass (Brown et al., 1995; Higuchi et al., 1994; Kaufman et al., 1996). Measurements at individual plots also suffer from other problems, such as the possible bias of inventory data towards low (accessible) biomass, the possible bias of small plots towards large biomass, the conversion factors used to calculate biomass from basal area or volume, and the species dependencies of allometric equations.

For example, estimates of average forest biomass for the Brazilian Amazon range from 155 to 352 Mg ha^{-1} (Brown et al., 1995) or from 290 to 464 Mg ha^{-1} as more biomass compartments are included (Fearnside, 1997; Houghton, 2000). All of these estimates have included the results of forest inventories conducted by FAO and the RADAMBRAZIl projects from 1950's through early 1980's. The use of allometric equations to convert volumes to biomass were largely responsible for the range of biomass estimates for undisturbed forests. Other analyses have documented the errors resulting from allometric equations and sampling schemes in secondary as well as old-growth forests (Brown et al., 1995; Keller et al., 2001; Nelson and Mesquita; 1998; Saatchi et al., 2004). Adding more plots will reduce the errors in biomass estimation to within 20% within a forest stand (Brown et al., 1995; Keller et al., 2001), but the number of plots required for the entire basin has not been estimated.

In the absence of direct measurement of forest biomass from remote sensing data, most efforts for quantifying the distribution of biomass have focused on interpolation techniques (Mahli et al. 2002; Baker et al., 2004), aimed at providing patterns of biogeographical variation of forest biomass (Baker et al., 2005). In this paper, we introduce a new approach for extrapolation of biomass plots over the Amazon basin. By collecting data from a large number of forest plots in a variety of forest types distributed over the basin, and by using remote sensing data sensitive to forest characteristics and environmental variables, we develop a series of metrics for extrapolating the plot data to the basin. The approach combines the strengths of both sets of data: 1) forest plots, although limited in spatial coverage, provide more accurate measurement of biomass, and 2) remote sensing data, although less accurate in measuring biomass directly, cover the entire region with a variety of spatial resolutions and with different sensitivities to forest structural attributes. By integrating these two properties, we have produced a 1-km map of forest aboveground live biomass for discrete classes. To cover the wide range of biomass values across the basin, our methodology concentrates on all vegetation types present, from old growth terra firme forests, to floodplains, woody and herbaceous savanna, and small forest patches along the western Andes and Atlantic coast. We also include the most recent land cover map of the region (1 km resolution) in order to separate the undisturbed vegetation from those impacted by human activities (secondary and degraded forests). The region chosen for study included all tropical vegetation types in South America between 14^{o} N and 20^{o} S latitude.

The paper is divided into several sections. The first section describes the biomass plots and the remote sensing data used in this study. The section on methodology describes the approach for extrapolating the plot data over the basin with the aid of remote sensing metrics and a decision rule algorithm. The last section presents the biomass distribution at 1 km resolution, estimates the accuracy from cross-validation, and discusses the sources of errors and uncertainties.

Methods

Inventory Plots

The number of biomass plots for different regions of the basin and over different vegetation types has increased in recent years. Although plot size, sampling schemes, allometric equations, number of components measured (e.g. aboveground live and dead and belowground) and uncertainties associated in each case may vary, the measurements represent the largest dataset on forest and woody vegetation biomass in the basin. For this study, we identified and collected 544 biomass plots sampled in different vegetation types throughout the basin (Figure 1). Many of the data are unpublished. The individual scientists who contributed these data are too numerous to mention, but clearly the analysis would not have been possible without their cooperation. In Table 1, we summarize the general information about the forest plots and provide references or the name of the main scientist and the dates for publications or data collection.

INSERT FIGURE 1 (About Here)

The forest plots include 216 terra firme old-growth forests, 191 secondary forests of different ages, 59 low and high density woodland savannas, 40 floodplain forests, and more than 38 sites over submontane and montane tropical forests (Table 2). The plots included in this study meet the following criteria: (1) Biomass measurements were made after 1990. All secondary forests plots included the age since abandonment. (2) Plots were representative of larger areas. All plots, except a few in secondary forests, were sampled within a larger forest patch and thus could be integrated with the remote sensing data at 1 km resolution. (3) Location of plots were given with geographical coordinates. We located all plots on high resolution (30 meter) Landsat ETM imagery acquired in late 1990s and early 2000s and if necessary, we modified the geographical locations slightly to make sure they fell in described vegetation types and represented larger forest patches within 1 km pixel resolution.

INSERT TABLE 1 (About Here)

All plots contained information on AGLB, but measurements were variable and included different components of forest biomass, such as live and dead and belowground biomass, structural information such as the basal area and height, and average wood density. The most consistent quantity provided for each plot was the aboveground live biomass (AGLB). For this reason, we limit our analyses to distribution of this quantity over the basin. However, relationships derived from available data and those published in literature are used to calculate the total biomass over the basin (Brown et al., 1995; Crains et al., 1997; Houghton et al., 2001). These relationships may be a function of AGLB. For example, Houghton et al. (2001) found that for sites with given biomass components, the aboveground dead biomass (AGDB) and the belowground biomass (BGB) averaged 9% and 21% of AGLB respectively. Crains et al (1997) also showed a direct relationship between AGLB and the below ground biomassBGB based on 85 studies of forest plots around the world.

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Remote Sensing Metrics

We compiled a set of remote sensing data and products over the Amazon basin from various earth observing sensors in order to compile spatial information about various attributes of the Amazonian landscape and its vegetation cover. We derived metrics sensitive to the structural attributes of vegetation, landscape, or environmental variables. The most recent land cover map derived from remote sensing data (Saatchi et al. 2004) was used to separate general categories of vegetation present in the basin. Table 3 summarizes the remote sensing data used in this study. The optical data are derived from four years of MODIS 32-day composite products. The normalized difference vegetation index (NDVI) images at 1 km resolution are from Huete et al. (2002) and the LAI data are from Myneni et al.(2002). In order to reduce redundancy, the number of data layers, and the effects of cloud cover, we computed 4 metrics from these data sets that included the maximum, mean, mean of 4 driest months (corresponded to July, August, September, October), and mean of 4 wettest months (corresponded to December, January, February, and April) over 4 years. These data sets provided measures of vegetation greenness, seasonality (deciduousness, optical properties), leaf properties and heterogeneities. MODIS derived percentage tree cover from continuous field approach (Hansen et al., 2002) was also used as an indictor of forest density separating areas of heterogeneous tree cover and identifying fragmentation.

The microwave data sets from spaceborne radar measurements were used as a surrogate for forest structure and biomass. JERS-1 backscatter image mosaics for dry and wet seasons at 100 meter resolution were aggregated to 1 km to produce the mean backscatter and first order texture (coefficient of variation). Backscatter measurement and texture at L-band (1.25 GHz) from this instrument is sensitive to forest structure and biomass for low density forests and woodland savannas (Saatchi et al., 1997; Saatchi et al., 2000; Podest and Saatchi, 2002; Luckman et al., 1997). Global QUIKSCAT data, available in 3-day composites at 2.25 km resolution (Long et al., 2001), were used, first, to create monthly composites at 1 km resolution from 4 years of data. The data were further processed to produce 4 metrics at both HH and VV polarizations (H: horizontal, and V: vertical) that included maximum and minimum, and the mean of dry and wet season radar backscatter. QUIKSCAT radar measurements are at KU band (12 GHz) and are sensitive to surface moisture, leaf water content, and other seasonal attributes such as deciduousness and water availability. In savanna vegetation, measurements at different polarizations correspond to aboveground biomass (Long et al., 2002). We also included the SRTM (Shuttle Radar Topography Mission) digital elevation data, aggregated from 100-meter resolution to 1 km. In addition to the mean elevation, the coefficient of variation as a surface ruggedness factor was included in the data set as an indicator of landscape features. Overall, 23 remote sensing image layers representing vegetation and landscape features were used in classifying the vegetation biomass types.

INSERT TABLE 3 (About Here)

Climate Data

A series of climate metrics were chosen to examine the relationship between biomass distribution and climate variables over the Amazon basin. The climate surfaces were created from a number of databases by R. Hijmans et al. (2004) and are available from WorldClim website (http://biogeo.berkeley.edu/). These climate metrics, known also as the bioclimatic variables, were derived from monthly temperature and rainfall values in order to generate biologically meaningful variables that could be used for habitat characterization. The metrics included 11 temperature and 8 precipitation metrics at 1 km spatial resolution (Table 4). The databases used to produce these climate metrics were obtained mainly from the Global Historical Climatology Network (GHCN), the FAO, the WMO, the International Center for Tropical Agriculture (CIAT), R-HYdronet, and additional country-base stations. The station data were interpolated to climate surfaces by using three independent variables: latitude, longitude, and elevation and the thin plate smoothing spline technique (ANUSPLIN, Hutchinson 1999). Elevation (from SRTM data) was incorporated because temperature, and often rainfall, are dependent on elevation and inclusion of elevation in the model reduced statistical error (Hutchinson 1999).

INSERT TABLE 4 (About Here)

Vegetation Map

To improve the extrapolation of the biomass plots over the basin, we used a vegetation map recently produced by Saatchi et al. (2004) from the fusion of several remote sensing data. This map is an improvement over other remote sensing based vegetation map of the Amazon (Saatchi et al., 2004; Saatchi et al., 2001), and its primary application was to improve the land surface parameterization of ecosystem models over the Amazon basin during the LBA project. The vegetation cover was divided in four categories and 16 types based on structure (relative density), phenology, and surface inundation conditions. The categories are: Terra firme forest (1.dense closed forest, 2.open forest, 3.bamboo dominant forest, 4.liana or dry forest, 5.seasonal forest), savanna vegetation (6.dense woodland, 7.open woodland, 8.park or shrubland, 9.grassland), wetlands (10.closed forest, 11.open forest, 12.herbaceous, 13.mangrove, 14.open water), and anthropogenic vegetation (15.secondary forest and plantation, 16.nonforest including pasture, crops, and bare fields). In our study, the vegetation map was used to separate forest from nonforest types, to locate the biomass plots associated with each vegetation type (Figure 2), and to allocate AGLB to land cover types in the Amazon basin.

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Analysis Methodology

Our goal was to integrate the remote sensing data (metrics) with the inventory biomass plots to produce the distribution of AGLB over the Amazon basin. A direct method for achieving this goal is to develop relationships between remote sensing metrics and AGLB from forest plots, and use these relationships to estimate AGLB over the entire basin. We tested several techniques, such as the multivariate regression analyses, and a maximum likelihood estimator (MLE). Both methods performed poorly when verified against the field data (R^2 <0.3) because of high spatial variability of biomass at local scale and, thus, weak correlations between remote sensing metrics and biomass values. Given the uncertainties in location and magnitude of biomass associated with the forest plots, methodologies for allocating biomass values for each 1 km pixel produced noisy results and unknown uncertainties. For this reason, we adopted a biomass classification approach in order to classify the 1 km pixels into different ranges of AGLB with higher accuracy. Our methodology can be summarized in three steps: 1) classification, 2) validation, and 3) correlation with environmental variables.

1. Classification: For biomass classification, we use the decision tree method (DTM) described in Simard et al. (2000). The classification methodology is based on the algorithm of Breiman et al (1984), in which, a hierarchical set of rules from a training data set are developed to successfully split the input data layers into clusters associated with the class definition. DTM has been successfully applied to remote sensing data in the past because of its simplicity, efficiency, and robustness (Simard et al., 2000, 2001; Saatchi et al., 2000, 2004;, 1998; Hansen et al., 2000). It is simple because once the rules are determined, the classification can be readily performed by using a simple program. Its efficiency is primarily due to the fact that unlike traditional approaches (e.g. MLE) it uses only input data layers that are important in deciding the class. Finally the methodology is robust because it does not assume any a priori statistical characteristics for the input data layers and therefore can be applied when using remote sensing data from different sensors. Moreover, the decision tree rules are explicit and allow for identification of data layers relevant to distinguish class types.

The structure of the decision tree is determined by optimizing a cost function iteratively to assign a final node to a thematic class that is the biomass range. The optimization works in a global sense such that it uses the best decisions in order to optimize the cost function for the entire group of classes rather than individual classes. This process is performed by selecting a random sample of the training data to develop the decision tree rules and assess the accuracy by predicting the class of the rest of the training data. The optimization will allow the choice of a decision tree with highest accuracy. The optimized tree is a combination of binary splits of input data layers which are obtained by selecting the best univariate splits in order to correctly classify the training data. The optimized decision tree uses the most relevant data layers, and the least number of splits to arrive at each class (Simard et al., 2000). Once the decision rules applied on the input data layers, a classification image is produced.

We have used DTM to classify the biomass of terra firme and floodplain forest types. For areas with savanna vegetation, deforested, and secondary forests, we have developed direct regression equations from the field plots and the remote sensing layers that resulted in biomass classification in much finer range (0-25, 25-50, 50-75, 75-100, 100-150 Mg/ha). The combination of these two approaches classifies the entire Amazon basin and all its vegetation types into AGLB classes.

2. Validation: We do not have an independent data set to test the accuracy of the Amazon biomass distribution. Therefore, the validation is performed only at two levels: 1) by assessing the biomass classification accuracy and the internal consistency of the methodology by predicting the biomass of pixels used in the training data, and 2) by comparing the total biomass with published results.

3. Correlation with Climate: The relationship between AGLB and the environmental variables is important for understanding both the formation and function of the Amazonian tropical forests. Forest structure, density, and biomass accumulation and dynamics are often explained by variations availability of water and light (Pires and Prance, 1985). In general, rainfall, seasonality, and landscape features, such as soil and topography are among the most important factors affecting the structure and biomass accumulation (Mahli et al., 2004; Clark and Clark 2000). By using the bioclimatic layers introduced earlier we examine the statistical correlation of climatic metrics with aboveground live biomass.

Analysis and Results

The distribution of AGLB over the Amazon basin was derived with two approaches as described in the methodology section: 1) for old growth or high density forests with biomass values above 150 Mg/ha, we used the decision rule classification approach, and 2) for savanna and anthropogenic or low density forest types, with biomass values less than 150 Mg/ha we used a direct estimation approach. The results from the two steps were combined to generate a wall-to-wall AGLB distribution over the basin. These two steps are discussed separately.

Dense Forests

Before using the decision rule approach to develop a biomass classification of dense old growth forests, we performed the following analysis:

1. Using the geographic coordinates, we identified the land cover types of 256 forest plots (216 terra firme and 40 inundated) on the vegetation map of the Amazon basin (1 km resolution). All old growth forest plots were identified correctly among dense, open (degraded), bamboo or deciduous, dry, and floodplain or swamp forests in the classification map. Several plots were co-located on the same pixels which reduced the number of plots from 256 to 228. For co-located

plots, we used the average AGLB to represent the pixel value. The purpose of this step was to make sure that the forest plots which were used as training data for classification were correctly located on the map and represented dense forests. From the vegetation map, we created a mask for the class types of dense and old growth forests.

2. The plot locations were used to create a training dataset from 23 remote sensing data layers introduced earlier. We divided the training plots into seven biomass class types with 50 Mg/ha increments (i.e. 0-150, 150-200, 200-250, 250-300, 300-350, 350-400, >400.) The number of forest plots in each class types ranged from 10-30 points. For those plots that were in the middle of a large contiguous forest stand and had similar landscape features (no change in elevation and land cover type), the training data were extracted from 3x3 pixels around the plot location. This approach increased the training dataset to 50-100 points for each biomass class and allowed the development of input statistics for the DTM classifier.

3. DTM classifier was used to generate a biomass map with seven classes over areas masked by the vegetation map as dense or old growth forest types (Figure 3). The decision rules used to determine the class types are shown in figure 4. Out of

INSERT FIGURE 4 (About Here)

the 23 remote sensing layers, only 12 were used to generate the map. These layers, and the associated binary decisions are explicitly shown in figure 4. DTM produced 29 nodes for the classification. Each node is associated to one of the 7 biomass classes and was used to choose the pixel class in the biomass map. However, among these nodes, only 8 had the largest accuracy and highest probability for choosing the class types. The rest, shown in brackets, are considered weak nodes and have very low accuracy in classifying the image pixels. In the final map, the pixels associated with these nodes were corrected by applying a majority filter that renamed the class based on the probability of classes within a 3x3 box centered around the pixel with low accuracy.

The class validation was performed after the final map was produced. As described earlier, the DTM internally validates the performance of the rules and the accuracy by using a random sample of the original training data as independent test sites. This validation, shown in Fig. 5, produced a classification accuracy of R^2=0.78. The largest error was for the biomass class exceeding 400 Mg/ha. Given the limited sensitivity of the input data layers to high biomass values, such results were expected. As expected, the low and the medium biomass classes had the largest number of points and the highest accuracy. Furthermore, the classification accuracy was within the error of the biomass of old growth forests measured in the field (Brown et al. 95).

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The results show several interesting features of AGLB distribution in the basin: 1. The areas in the northeastern Amazonian region, including the Brazilian coast and the Guyanas, have high biomass (300-400 Mg/ha). This region has distinct floristic and structural features, separated from the interior lowland forests by the Guianan highlands (Prance, 1989). The region includes one of the relatively intact forests because of its low human population, low agricultural potential as a result of infertile and highly weathered forest soils, low commercial timber volume, and inaccessibility. The climate is hot and wet and strongly influenced by the northeastern trade winds from the ocean and the intertropical convergence zone. The forest structure is multi-tiered with height reaching 40 meter and emergents up to 50 meter. Despite patches of savannas and low density marsh forests around the river, the lowland forest in this region is expected to be less dynamic and have high biomass values (Lindeman and Mori, 1989).

2. Central areas west of Trombeta river to the west of Rio Negro, containing the main geomorphological features of the Amazon basin, with high rainfall, and elevation less than 100 meter are also classified as high biomass. The forests in this region are on well-drained clay or loam soil with no shortage of water and are high in diversity with 150 to 300 tree species in a single hectare and more than 500 tree species. The canopy structure is irregular, with heights ranging from 25 to 45 meter and the presence of emergent taller trees and many palms and pole-sized trees. According to the biomass map, the biomass in this region ranges from 300 to 400 Mg/ha with occasional low stature forests on sandy soil and biomass of less than 300 Mg/ha. The main channel of the Amazon River, all major tributaries, and the large extent of varzea and igapo floodplains with biomass as high 250-300 Mg/ha also fall in this region. Along the Amazon river, the high biomass forests can extend to the eastern regions of the state of Para and the Marajo island.
3. 3. The Western region of the Amazon basin covering a large area of the lowlands of Peru, Ecuador, Colombia, and Bolivia has biomass values lower than the Central Amazon region ranging from 200-300 Mg/ha. This region extends to the

submontane and transitional forests of along the Andean elevational gradients and is covered by forests with open canopy, with low density of large trees, mixed with semi-deciduous, deciduous, bamboo, and liana forests. Data from permanent plots in this region suggest the forests are more dynamic, have a higher productivity than their counterparts in the central and eastern Amazon, and have a higher number of smaller and medium sized trees (Mahli et al., 2004; Baker et al., 2004; Fearnside, 1997).

***Savanna and Low Density Forest*s**

To complete the mapping of biomass distribution over the Amazon basin, we included areas of woody savanna and park savanna in or surrounding the basin, disturbed or secondary forests, and tree plantations. These areas, although less extensive than the dense old growth forests, are becoming an increasingly important part of the basin, and their biomass distribution and changes play a major role in the global carbon cycle. The extent and the biomass density of secondary forests depend on the extent of deforestation and land use change. Most areas of secondary forest are small compared to the resolution of the images used in this study. However, pixels with a mixture of secondary, old growth and non-forested land were identified as anthropogenic or open forests. Similarly, the woodland savanna pixels are mixtures of forest and non-forested areas. We combined these pixels from the vegetation map with the areas of the lowest biomass class (0-150 Mg/ha) from the dense forest biomass map, to create a new vegetation mask for the low-density forest biomass estimation.

The estimation algorithm was developed first by extracting spectral information from the remote sensing data layers for pixels representing the forest plots with 0-150

Mg/ha of biomass. Similar to the dense forest case, we combined all those plots that fell on the same 1 km pixel and used an average biomass to represent the pixel. After combining the pixels, we were able to create a spreadsheet of spectral information and biomass for 214 pixels that included 100 in secondary forests, 58 in woodlands and non-forest savanna class, and 4 in mixed open forest and herbaceous swamps. By analyzing the data and creating relations between biomass and spectral information, we found 4 spectral data that showed the highest correlation with the field plots (Fig. 6).

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The best correlations, as expected, were based on radar backscatter measurements. In the case of JERS-1 data, the backscatter was measured at L-band (25 cm wavelength) and at 38 degrees from nadir where the radar signal has the potential of penetrating through the forest canopy and scattering off the stems. As shown in Fig. 6a, the sensitivity to biomass declines at values above 80 Mg/ha and almost saturates between100 and 150 Mg/ha. Similar results have been reported in the literature from other studies over tropical forests (Luckman et al., 1997; Saatchi et al. 1997; Rignot et al., 1997).

The second best correlations were found for the annual mean of the QuikSCAT scatterometer measurements at the polarizations (Horizontal and Vertical). For QuikSCAT radar, the backscatter was measured at KU Band (2 cm wavelength) at incident angles of 46 and 54 degrees for the H and V polarizations respectively. At this angle, and the short wavelength, the radar return is highly sensitive to forest crown structure, roughness, leaf density and moisture. According to Fig. 6b, these parameters are good surrogates for aboveground biomass in sparse woodlands and low-density forests up to 80 to 100 Mg/ha. Similar results with the spaceborne scatterometer data have been observed over savanna woodlands (?). Often, the seasonal changes due to deciduousness of trees or moist surface condition may affect the scatterometer data, but these effects did not appear in the annual mean backscatter data used in this study.

From MODIS data layers, NDVI metrics, LAI metrics, and the percent tree cover all showed reasonable correlations with the ground data. However, the best correlations with the AGLB were found for the maximum NDVI of the dry season (R^2=0.43), and the percent tree cover derived from the continuous field approach (DeFries et al., 2000) (R^2=0.56). The low correlation with NDVI may be related to its high sensitivity to leaf greenness, density, and seasonality. The mean NDVI for the dry season carries more information about the woody vegetation as the grasslands and dry herbaceous understory are mostly absent during this season.

By combining these four measurements (JERS-1, QUIKSCAT, dry season NDVI, and percent tree cover), we developed a multivariate regression equation between the logarithm of AGLB and the four variables in the following form:

$$\log(AGLB) = 2.99 + 0.0467QH + 0.218QV + 0.00059VI + 0.0133TF \qquad (1)$$

where LHH is the JERS-1 radar backscatter in dB, QH and QV respectively represent the scatterometer H and V polarized backscatter in dB, VI the mean dry season NDVI (ranging between 0 and 1), and TF is the fraction of tree cover. Equation (1) was developed by using a random sub-sample of the ground data, and was tested with the residual ground data to determine the estimation accuracy (Fig. 7). The overall R^2

obtained from comparison of measured and estimated values was almost 0.77, which is approximately the same as what we obtained over the dense forests. In Figure 7, we also provide the accuracy for each biomass class by comparing the measured and estimated results within each class separately. As expected, the error associated with classes increase with the biomass to almost 50% accuracy for the highest class category.

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The spatial distribution of AGLB over areas of low density forests shows that the entire area of herbaceous, park savanna, caatinga and parts of open woodlands fall in the first biomass class (0-25 Mg/ha). The area includes savanna regions of eastern and southern Amazon basin extending to the Atlantic Ocean, savannas of Roraima in northern Brasil, La Gran Sabana of southern Venezuela, and the areas along the Andes extending to northwestern region of Venezuela. Majority of woodland savanna, secondary forests and regions of mixed pasture and forests fall in the second and third categories of 25 to 75 Mg/ha. The combined distribution map has also segmented the regions of 0-150 Mg/ha class of the high density forests into the sub-categories with majority of pixels in 100-150 Mg/ha (Fig. 8). Areas on the high elevation of Andes and regions west of Andeas appear to have reasonable biomass values as expected from the vegetation map. However, these regions are outside of the Amazon basin and our forest plot data do not extend to those region. Therefore, we cannot verify the distribution of AGLB over these regions.

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Discussion

By producing the distribution of AGLB in distinct classes, we can start examining the underlying factors impacting the distribution pattern over the basin. These include: 1) the relation between the regional variation of biomass and the vegetation types of the Amazon basin, 2) the correlation of environmental variables such as rainfall and temperature with the patterns of AGLB, 3) comparison of the total stock of carbon obtained from this study with published results, and 4) the uncertainties associated with the value and spatial variations of AGLB.

Biomass of Vegetation Types

To quantify the allocation of the AGLB to vegetation types of the Amazon, we intersected the vegetation map (Saatchi et al., 2004) with the biomass distribution map and for each vegetation types, we estimated the percentage of area covered by each biomass category. The results are shown in table 4. The old growth terra firme forests include 5 class types in the vegetation map including dense, open, bamboo, liana, and seasonal forests. This class occupies approximately 62% of the legal Amazon basin and represents the undisturbed or selectively logged forests. The biomass for this combined class was almost evenly distributed between 150 to 350 Mg/ha. A similar biomass range was observed when only the areas of the dense forest class were examined. The analysis also showed that for this category the area of AGLB greater than 350% was very small (4.5% of the area of the combined class). Given the reasonable accuracy of the vegetation map and the biomass distribution obtained in this study, the results clearly show that 1) the Amazonian forest biomass is extremely diverse, 2) the average biomass is much lower than expected but in the range of some earlier results (Brown et al., Baker et al., 2004), and 3) the spatial variation of the biomass is important to reduce the uncertainty in estimating the Amazonian carbon flux as a result of deforestation or disturbance.

INSERT FIGURE 9 (About Here)

The inundated forests including the closed and open floodplain forests and the estuary and coastal mangroves occupy almost 4% of the basin and have lower biomass than terra firme types ranging primarily from 150 to 300 Mg/ha. The secondary forest class is approximately 1.7% of the basin and is primarily classified in the lower biomass range of 0-50 Mg/ha. The accuracy of this result cannot be independently verified from published data. However, this result is similar to what has been reported for the Brazilian Amazon (Alves et al., 1997) and it implies that secondary forests are a small portion of the total biomass of the basin. Woodlands, on the other hand play a major role in total biomass distribution within the basin because of their area coverage and biomass as high as 100 to 150 Mg/ha.

Total Amazon Biomass

To estimate the total biomass of the Amazon basin, and compare the results with other studies, we used published ratios for the above ground dead biomass (AGDB) and the below ground biomass (BGB) derived from forest plots (Houghton et al., 2001). The AGDB ranged from 2% to 17% with an average of 9% of the AGLB. The BGB average ratio was 21% of AGLB with a range of 13% to 26%. We used the same ratios for all vegetation types of the basin and calculated the total biomass range for each biomass class, the total biomass in terra firme forest, and the total biomass in terms of carbon and the mean total biomass weighted by area. To quantify the full range of the biomass (or carbon) stock, we used the area of each biomass class and computed three total AGLB values by multiplying the minimum, maximum, and the mid biomass value for each class range with the area. We then used the ratios for adding the biomass components and computing the total biomass (TB) for each class and for the entire basin, To find the extreme ranges of the total biomass and carbon stock, we used the minimum and maximum ratios of BGB and AGDB with the minimum and maximum range of the AGLB. The results are shown in figure 9 for the biomass class type. The uncertainties in quantifying TB or the carbon stock in the Amazon basin are mainly due to uncertainties in mid to high range biomass classes. These class types are spatially extensive in the basin and they contain high AGLB and when used with the wide range of ratios for AGDB and BGB, they produce large errors.

Including the dead and belowground biomass calculated from the mean biomass of each class in the unit of carbon (half of biomass) yielded the total carbon stored in the forest in PgC (10^{15} g) and the mean carbon in MgC/ha). These numbers including the range of biomass using the minimum and maximum range of biomass for each class are shown in Table 6. Comparing these values with the those given in Houghton et al. (2001) , the total carbon, the range and the mean biomass are

Biomass and Climate Variables

Environmental variables such as topography, geomosphology, soil types, solar radiation, wind, temperature and rainfall are important factors affecting the formation of the tropical forests, their diversity, density, and productivity. In this section, we examine the relationship between biomass distribution and the average bioclimatic variations over the Amazon basin. To quantify this relationship, we intersected the BIOCLIM variables interpolated with the digital elevation model of SRTM data at 1km grid cells with the AGLB map. For each AGLB class, we calculated the average and standard deviation of the climate variables and analyzed the relationship for each climate variables separately. Furthermore, we combined the biomass classes into 4 levels (0-100, 100-200, 200-300, and > 300) in order to improve the correlations with climate variables and to limit the analysis to only few biomass ranges.

From 21 BIOCLIM layers, only the rainfall variables showed significant correlations with the biomass classes. Among these variables, we have chosen three to demonstrate these correlations, the annual mean rainfall, the number of months rainfall stays below 100 mm and the number of months rainfall exceeds 300 mm. These variables pick up the total water availability, the dry condition, and the magnitude and seasonality of moisture as the controlling factors for the biomass density in the basin. The results are shown in figure 10. All 4 biomass levels are clearly separated in figure 10a by the number of dry months (rainfall less than 100 mm). The areas of low biomass density that are often associated with the transitional forests with deciduous semi-deciduous trees and with geographical distribution around the margins of the basin demonstrate a seasonal behavior. Biomass values less than 100 Mg/ha occur largely in regions with long dry season (around 6 months) and forests with 100-200 Mg/ha in areas with shorter dry season (almost 4 months). The area of forests with high biomass density decrease as the number of dry months increases indicating the consistency of moist condition for their distribution. On the contrary, there was no distinct relationship between biomass classes and the high monthly rainfalls. All four biomass categories showed similar behavior with the number of months the rainfall exceeded 300 mm (Figure 10b) suggesting the intensity of rainfall a less important factor in controlling the biomass density. Most pixels in each biomass category coincided with areas that had less months with high rainfall. The results are confirmed when examining the relationship between the annual mean rainfall and the above ground biomass. Figure 10c shows the mean and standard deviation of annual rainfall for the 11 original biomass class types. It From the overall trend of mean annual rainfall and the number of dry months with biomass density, it appears that majority of high biomass stocks in the basin are in regions with consistent moisture and with high rainfalls distributed evenly throughout the year.

INSERT FIGURE 10 (About Here)

Similar analysis with the land surface temperature variables showed no significant correlation with the patterns of biomass distribution. In general, the temperature remains isothermal and does not vary significantly over the Amazon basin. Except in areas with higher elevation near Andes where temperature may change slightly along the elevation gradient or diurnally, most of the basin remains between 24^o-27^o Celsius throughout the year.

Conclusion

In this paper, we have compiled a large dataset of AGLB from available forest plots and spatial data from remote sensing satellites to quantify, for the first time, the distribution of Amazonian forest biomass on a fine spatial resolution. The quality and quantity of datasets allowed us to examine several approaches to estimate or extrapolate the forest plots over the basin, and to understand the fundamental problems, and the uncertainties associated with each approach. We produced a forest biomass class map at 1 km spatial resolution with reasonable accuracy (better than 70%) that enabled us to also examine the total carbon stock of the basin, including the dead and belowground biomass. Our estimate of the total carbon content of the Amazon forests ranged between 77 and 95 PgC with the average of 86 PgC which was within the range of published results from different approaches (Houghton et al., 2001). Given the uncertainties associated with our technique and those published in the literature and the errors associated with areas of land use and deforestation, it appears that we are arriving at a quantity close to 85 PgC for the total carbon in biomass of Amazon forests. As we used the extreme ranges of dead wood and belowground biomass ratios with low and high AGLB, obtained in this study, to compute the total biomass, the range (77-95 PgC) must reasonably bound the total carbon stock of the basin.

Several questions, however, remain outstanding and must be addressed and examined in future work. These are primarily associated with the uncertainty in datasets used in the study and the results.

1. To what extent the uncertainty in ground measurements impact the biomass distribution over the basin? In this study, we did not address the errors associated with the above ground biomass of forest plots. The differences in plot size, the size of sampled trees, allometric equations, and the biomass components in dead and belowground are important in both the allocation of carbon for the forest stand and estimating the regional distribution. We are unfortunately, limited to the available datasets compiled from different experiments using

different methodologies. To understand the errors, how they propagate in the analysis, and to consolidate these datasets, the access to the original tree level data and a standard approach is required. However, this is not a trivial task and the question remains if there is a standard approach that can be used on forest plots with different species composition and geographical and environmental characteristics. Is it possible that by choosing a large number of forest plots from different sources and with unknown but limited errors, we may have a better statistics and less uncertainty in magnitude and distribution of the Amazon biomass?

2. Is it possible to reduce the uncertainty by improving the spatial resolution of data layers? This is can be readily tested by incorporating all available high resolution satellite imagery and employing a multi-scale approach for estimating or extrapolating the biomass. One of the main sources of uncertainty in our study was the discrepancy between the resolution of images and the size of the forest plots. The spectral information obtained from 1 km resolution data will not represent the forest plot biomass or structure in the presence of slight surface heterogeneity within the pixel. By incorporating images at 30-100 meter resolutions, we will be able to locate the plots directly on the images and remove location uncertainty, to incorporate the surface heterogeneity in our calculations, and to improve the separation of the anthropogenic landscapes from forests. By using a multiscale approach, the final biomass map can be produced at 100 meter or better resolutions, providing datasets than can be readily used in estimating

the area and impact of deforestation on the carbon stock and changes in the basin.

3. What are the controlling or limiting environmental variables responsible for the magnitude and distribution patterns of biomass density over the basin? The validation of our results shows a very good agreement with the forest plot data, and the general distribution of vegetation types and climate conditions. However, we cannot completely explain the distribution of the biomass everywhere. It is important to know weather the environmental and landscape variables are playing a role in forest biomass stock and dynamics. To what extent the climate, soil, geomorphology, radiation and hydrological features impact the forest structure, species composition, and biomass? These questions can be addressed in future as soon as the environmental data layers for the Amazon basin are compiled. We expect the LBA GIS (Geographical Information System) data, forest plots in conjunction with other ground measurements obtained from permanent and carefully organized forest plots such as RAINFOR will contribute to these studies in future.

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Table Captions:

Table 1. List of field data used in this study with general locations, number of plots, vegetation types, and sources.

Table 2. Distribution of number of plots and biomass ranges for general vegetation types across the Amazon basin.

Table 3: List of remote sensing data and metrics used as direct measures or surrogates of vegetation structure or environmental variables. CV refers to coefficient of variations. Ruggedness factor is the coefficient of variation of elevation data when aggregated from SRTM 3 arcsec (approximately 100 m) resolution to 1 km.

Table 4. Description of long term averaged climate surfaces (Hijmans, et al. 2004).

Table 5. Area of the biomass classes within each general vegetation category of the Amazon basin. The percent area of each vegetation type is with respect to the total Area of Legal Amazon (8235430 km2) and the percent cover of biomass class is given with respect to the area of each vegetation class type.

Table 6. The area and the biomass carbon components (AGLB, AGDB, and BGB) of terra firme and floodplain forests in the Amazon.

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Figure Captions:

Figure 1. Location of forest plots in the Amazon basin. Each location on the map represents several plots.

Figure 2. Vegetation map of the Amazon basin, at 1 km spatial resolution, derived from remote sensing data (Saatchi et al., 2004). The map divides the basin into 16 land cover types and open water bodies.

Figure 3. AGLB class map of terra firme old growth forests derived from the decision rule classifier and multiple layers of remote sensing data.

Figure 4. Optimized decision tree rules used in the classification of the dense forest biomass map. The name of remote sensing data layers are at shown at the top of branches with their binary rules. The final nodes derived from the rules are shown at the end of each branch, with the red nodes representing the weak rules that will be finally removed by using a majority filter around the pixels associated with the weak rules.

Figure 5. Validation of biomass classification map performed internally by the DTM classifier using the a subsample of the training pixels. The number of pixels correctly classified created an overall R^2=0.786.

Figure 6. The relationship between five remote sensing data and the AGLB of low-density forests and savanna woodlands: (a) JERS-1 radar data at L-band HH polarization with R^2=0.68, (b) QuikSCAT V- and H-polarized channels with R^2=0.69, and R^2=0.68 respectively, (c) Maximum NDVI of dry season with R^2=0.43, (d) MODIS continuous field percent tree cover with R^2=0.56.

Figure 7. Validation of biomass estimation of low density forests and savanna vegetation using the linear regression of combined remote sensing data (equation 1).

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Figure 8. Aboveground live biomass classification map of the Amazon basin from combined DTM and regression analysis with 11 class range and with overall accuracy of R^2=0.78.

Figure 9. Contribution of biomass classes to the total biomass of the legal Amazon basin and uncertainty calculated by using the minimum, maximum, and middle range of each class.

Figure 10. Relationship between rainfall variations and the biomass distribution across the Amazon basin: (1) percent area of biomass categories falling in rainfall metric representing the number of months rainfall is less than 100 mm, (b) percent area of biomass falling in areas of rainfalls with number of months exceeding 300 mm, (c) the relationship between mean annual rainfall and the biomass class types.

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