

Biomass accumulation rates of Amazonian secondary forest and biomass of old-growth forests from Landsat time series and the Geoscience Laser Altimeter System

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Abstract. We estimate the age of humid lowland tropical forests in Rondônia, Brazil, from a somewhat densely spaced time series of Landsat images (1975–2003) with an automated procedure, the Threshold Age Mapping Algorithm (TAMA), first described here. We then estimate a landscape-level rate of aboveground woody biomass accumulation of secondary forest by combining forest age mapping with biomass estimates from the Geoscience Laser Altimeter System (GLAS). Though highly variable, the estimated average biomass accumulation rate of 8.4 Mg ha⁻¹ yr⁻¹ agrees well with ground-based studies for young secondary forests in the region. In isolating the lowland forests, we map land cover and general types of old-growth forests with decision tree classification of Landsat imagery and elevation data. We then estimate aboveground live biomass for seven classes of old-growth forest.

TAMA is simple, fast, and self-calibrating. By not using between-date band or index differences or trends, it requires neither image normalization nor atmospheric correction. In addition, it uses an approach to map forest cover for the self-calibrations that is novel to forest mapping with satellite imagery; it maps humid secondary forest that is difficult to distinguish from old-growth forest in single-date imagery; it does not assume that forest age equals time since disturbance; and it incorporates Landsat Multispectral Scanner (MSS) imagery. Variations on the work that we present here can be applied to other forested landscapes. Applications that use image time series will be helped by the free distribution of coregistered Landsat imagery, which began in December 2008, and of the Ice Cloud and land Elevation Satellite (ICESat) Vegetation Product, which simplifies the use of GLAS data. Finally, we demonstrate here for the first time how the optical imagery of fine spatial resolution that is viewable on Google Earth provides a new source of reference data for remote sensing applications related to land cover.

Keywords: tropical forest, forest disturbance, forest age, vegetation type, old growth, terra firme, várzea, cerrado, cerradão, igapó, change detection, image cubes, WBDI, deforestation.

1 INTRODUCTION

Forest age and carbon cycling are major features of tropical landscapes, but existing data are not comprehensive. This study presents an approach to improve data on patterns of tropical forest age and biomass accumulation rates in secondary forest. The approach uses Landsat image time series to map forest age. It then estimates forest biomass with data from the Geoscience Laser Altimeter System (GLAS), which is a space borne light detection and ranging (lidar) instrument.

Mapping forest age is important for many reasons. Older tropical forest is more diverse than secondary forest younger than about 50 yr. We know that the species composition of secondary tropical forest differs from nearby old-growth forest at least for decades [1-6]. Also, the genetic and species diversity of plants and animals in most old-growth tropical forests are poorly characterized. Well-dispersed networks of old-growth forests are probably desirable until we know more about the resilience of the diversity that these forests harbor. Planning and maintaining reserve networks of old-growth forest require, among other things, maps of forest age and disturbance.

Also critical is the carbon that tropical forests store in tree biomass, which differs with age. Land-use change accounts for a large but uncertain 15 to 40 percent of annual human-caused emissions of carbon dioxide (CO₂), to the Earth atmosphere. Most of these emissions are from tropical forest burning and clearing. Reducing their uncertainty requires better data on spatial variation in the biomass of the old-growth and secondary tropical forests that are cleared [7, 8]. Likewise, the carbon fluxes of secondary forests are uncertain. Their biomass accumulation rates vary with environmental conditions including land-use history [9-11]. We also need a way to map secondary forest age or biomass accumulation over large areas with as little supervision as possible. Labor-intensive ground studies of tropical old-growth forest biomass, and biomass accumulation rates in secondary forest, are limited.

Launched on the Ice, Cloud and Land Elevation Satellite (ICESat) on January 12, 2003, GLAS is the only global public source of continuous return lidar data [12]. Because GLAS waveforms gauge stand-level canopy height, they can also gauge aboveground live forest biomass (AGLB) [13]. They effectively form the most comprehensive sample of tropical forest biomass available. With GLAS biomass estimates, we can then model forest carbon storage and fluxes by mapping forest history since the 1970s or 1980s with Landsat image time series. Beginning December 8, 2008, all Landsat images in the U.S. archive became freely downloadable, which makes this approach more practical. In persistently cloudy regions, however, like humid tropical ones, the available clear scenes will have irregular temporal spacing and variable phenology. These factors complicate forest change mapping from image time series [14].

To make pan-tropical monitoring of forest age and carbon fluxes with Landsat-like imagery feasible, we need flexible ways to automate forest change mapping with image time series. Toward that goal, the specific objectives of this study are to 1) test the Threshold Age Mapping Algorithm (TAMA), which we describe here for the first time, that ages humid lowland tropical forest with a sequence of Landsat images, and 2) combine the resulting forest age map with coincident GLAS waveforms to estimate accumulation rates of AGLB in young lowland secondary forest. In isolating the lowland forests with decision tree classification of Landsat imagery and elevation data, we also map major old-growth forest types and estimate their AGLB with GLAS data. In addition, we briefly review how this work relates to other studies on mapping forest age, focusing mainly in the Neotropics.

2 BACKGROUND ON FOREST AGE MAPPING

Many methods exist to map forest age with satellite imagery, but past work is not both automated and widely applicable in tropical regions. A common method with Landsat imagery is post-classification merging. A related approach is to map forest change by classifying a time series stack of images. A third approach is to match trajectories of disturbance and succession. A fourth method is to use one classification model to classify one image date. Nearly all of these methods smooth final results in some way.

A post-classification approach to forest age mapping separately classifies each image in a time series and then merges the resulting maps, aging secondary forest based on its presence in the map sequence. Four studies in Amazônia map forest age with post-classification merging [15-18]. Others use the method to study the dynamics of forest clearing and

regrowth or track related soil changes [19-22]. Most of these studies track changes between three classes: mature forest, secondary forest/woody agriculture and pasture/cleared land.

Related to post-classification merging is simultaneously classifying a time series stack of images to map forest age, successional stage, disturbance, or land cover. Recent studies in tropical landscapes, for example, classify stacked multirate Landsat imagery. They map tropical forest age (old-growth vs. secondary forest), land cover, or forest clearing [23, 24]. Though effective, in tropical regions this approach has relied on manual identification of training data or visual labeling of unsupervised classes.

More recent studies in temperate regions automate some steps in forest disturbance mapping with image time series [25, 26], detecting change from differences in histogram position between images. Some of this work uses a time-series normalization method that also takes advantage of histogram position. That normalization method, known as ordinal conversion [27], assigns a new value to each pixel from its rank in the histogram for a given band. In using band or index differences between dates, these methods require image normalization through time and same-season imagery, so that images have similar phenology, and they generally use atmospherically corrected scenes. Unfortunately, the most cloud-free sets of available Landsat images in humid tropical locations are unlikely to all have similar phenology.

Another approach to mapping forest disturbance is to model spectral trajectories over an image sequence [28]. The algorithm finds which of a pre-defined set of possible disturbance histories agrees best with the spectral history of each pixel. An advantage of this method is that it may identify differences in rates of forest biomass accumulation that stem from different disturbance histories. Disadvantages of the trajectory approach in its current form are that, like the other automated methods, it requires image normalization through time and same-season imagery, because it uses band or index trends.

Approaches to map forest age also include regression or neural network classification models that are applied to one image date, as demonstrated in British Columbia and Brazil to map conifer stand age [29, 30]. Mapping forest age from one image date is problematic, however, because some lowland humid secondary forest can become spectrally similar to old-growth forest within 10-15 yr [31]. Older secondary tropical forest can remain spectrally distinct from old-growth forest for longer periods for some lowland humid forest associations, or where forests grow more slowly, as in some cloud or dry forest landscapes [23, 32]. However, avoiding confusion between secondary forest older than about 10-15 yr and old-growth forest may require a long image sequence.

The studies in temperate regions estimate forest age as time since last disturbance [33, 34]. This assumption may be accurate where forest clearing for agriculture is uncommon, as in many temperate landscapes. It may also be adequate in the tropical landscapes where agriculture is declining and forest cover is increasing as economies tilt toward industry and services [35]. In many tropical landscapes, however, as in Amazônia, people clear forest for agriculture or pasture that may last from one to many years. In such places, substituting time since last disturbance for forest age might greatly overestimate age.

3 METHODS

3.1 Study area and image data

Two to four percent of global CO₂ emissions may come from forest clearing in the Brazilian Amazon [36], the location of this study. Nevertheless, net emissions from the region may vary from a source to a sink. The main uncertainty in Amazonian forest carbon fluxes is, again, the biomass of the old-growth and secondary forests that are cleared [37-39]. Uncertainties also remain about rates of atmospheric CO₂ uptake and release via mature forest growth and respiration.

The study area extends over one Landsat scene in the Brazilian state of Rondônia, namely World Reference System 2, Path/Row 232/067 (10.1° S, 63.7° W) (Fig. 1). In Rondônia, large-scale clearing of old-growth tropical forest for agriculture began after construction of highways BR 364 and BR 421 in the mid 1970s; the clearing accelerated with settlement programs in the 1980s [22, 40]. Deforestation and logging have continued in Rondônia through the present [41-43]. Forest carbon dynamics and land-cover change have received considerable study in Rondônia, because forest clearing there has been extensive over the past 30 yr. Many of these studies have been summarized in recent work [22]. Published biomass accumulation rates from ground studies, and a long sequence of cloud-free and coregistered Landsat images, were available.

Forests in the study area are tropical and include broadleaf seasonal evergreen, semi-evergreen, and deciduous forests, forested wetlands, savannas, and woody savannas. Elevation in study area ranges from river levels of 70 m above sea level in lowlands in the north to about 1100 m on the Serra dos Pacaás Novos. Annual rainfall ranges from 1900 to 2700 mm yr⁻¹, with a wet season from November to April and a dry season from June to August [22, 44]. Major soil types include Latosols, Podzolic soils, Lithosols and Terras Roxas Estruradas (in U.S. soil taxonomy, Oxisols, Ultisols, Entisols and Alfisols) [45, 46].

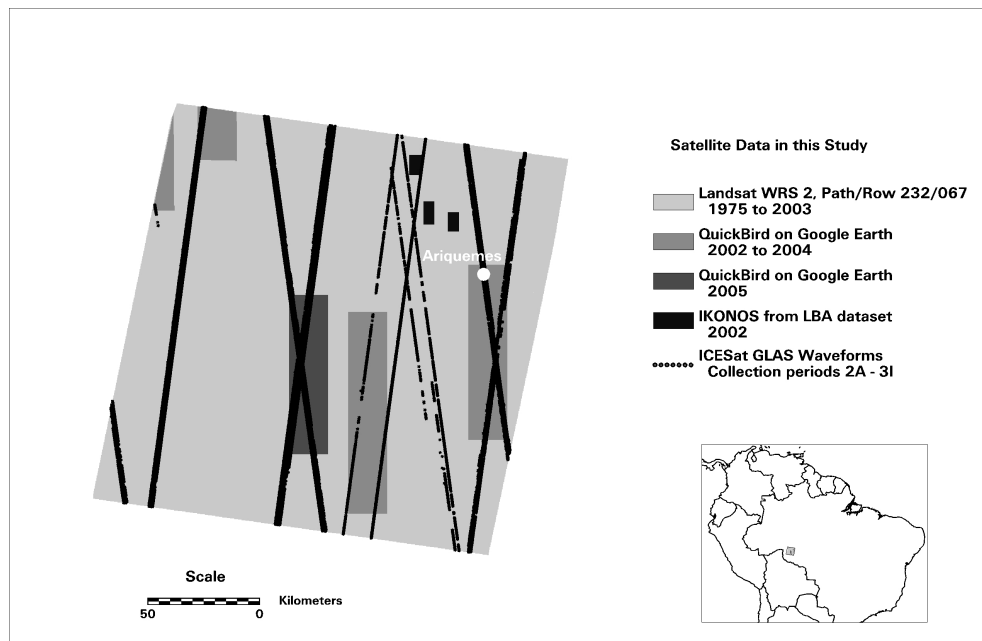


Fig. 1. Fine resolution imagery used for reference data covered 15% of Landsat Path/Row 232/067 and included 1) QuickBird imagery viewable on Google Earth, and 2) three areas of IKONOS imagery. Waveforms from GLAS collection periods 2A through 3I numbered to more than 30,000. The study area is located in southwestern Amazônia in Brazil, in the State of Rondônia.

Landsat imagery for the study included a previously assembled time series of Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) scenes dated from 1975 through 2000 [22] (Table 1). We coregistered additional images to this time series, from 1986, 2001, and 2003, to within < 0.5 pixels root mean square error, with nearest neighbor resampling. The data set (or "image stack," or "image cube") has a pixel size of 30 meters. The image data underwent no normalization or atmospheric

correction. Fine resolution reference data included three pan-sharpened IKONOS images dated from 2002 and Quickbird images, dated from 2002 to 2005, that were viewable on Google Earth (<http://earth.google.com>). The dates of the Quickbird images displayed on Google Earth are found by selecting the Digital Globe Coverage layer. Image dates appear that each include an associated Digital Globe logo. Clicking the logo gives access to the preview image for that date. Comparing the preview images for all dates available for a location reveals which date Google Earth displays at fine resolution.

Table 1. Time series of Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper (ETM+) scenes for World Reference System 2 (WRS2) Path/Row 232/067. The scenes are from 1) Roberts et al. (2002) (many from the Instituto Nacional de Pesquisas Espaciais, Brazil), 2) the US Geological Survey Center for EROS, and 3) the University of Maryland GLCF.

Scene date ^{source}	Landsat scene type
19 June 1975 ¹	Landsat 2 MSS
24 June 1984 ¹	Landsat 4 TM
16 July 1986 ²	Landsat 5 TM
12 August 1990 ¹	Landsat 5 TM
22 June 1992 ¹	Landsat 4 TM
7 October 1993 ¹	Landsat 4 TM
7 July 1995 ¹	Landsat 5 TM
17 July 1998 ¹	Landsat 5 TM
28 June 2000 ¹	Landsat 7 ETM+
19 September 2001 ³	Landsat 7 ETM+
20 May 2003 ²	Landsat 7 ETM+

3.2 Overview of mapping

We first mapped forest age from the 11-image sequence of Landsat images with the Threshold Age Mapping Algorithm (TAMA). Unique to TAMA is that it does not assume that forest age equals time since disturbance; and it does not require image normalization through time, same season imagery or atmospheric correction. This first version of TAMA applies to the simple case of basically evergreen forest on gentle terrain, and human disturbance in the study area mainly impacts these lowland forests. Consequently, after applying TAMA, we isolated the lowland forests by separately mapping land cover and old-growth forest types with two decision tree classifications of the Landsat imagery and topographic data. An added benefit of the resulting land-cover and forest-type map was that it allowed us to estimate AGLB of the different old-growth forest types with coincident GLAS data. We combined the age map from TAMA with the land-cover and forest-type map by replacing all lands mapped as secondary forest in the land-cover and forest-type map with secondary forest age from the age map. We extracted forest age or type for each GLAS waveform from the combined map (Fig. 2).

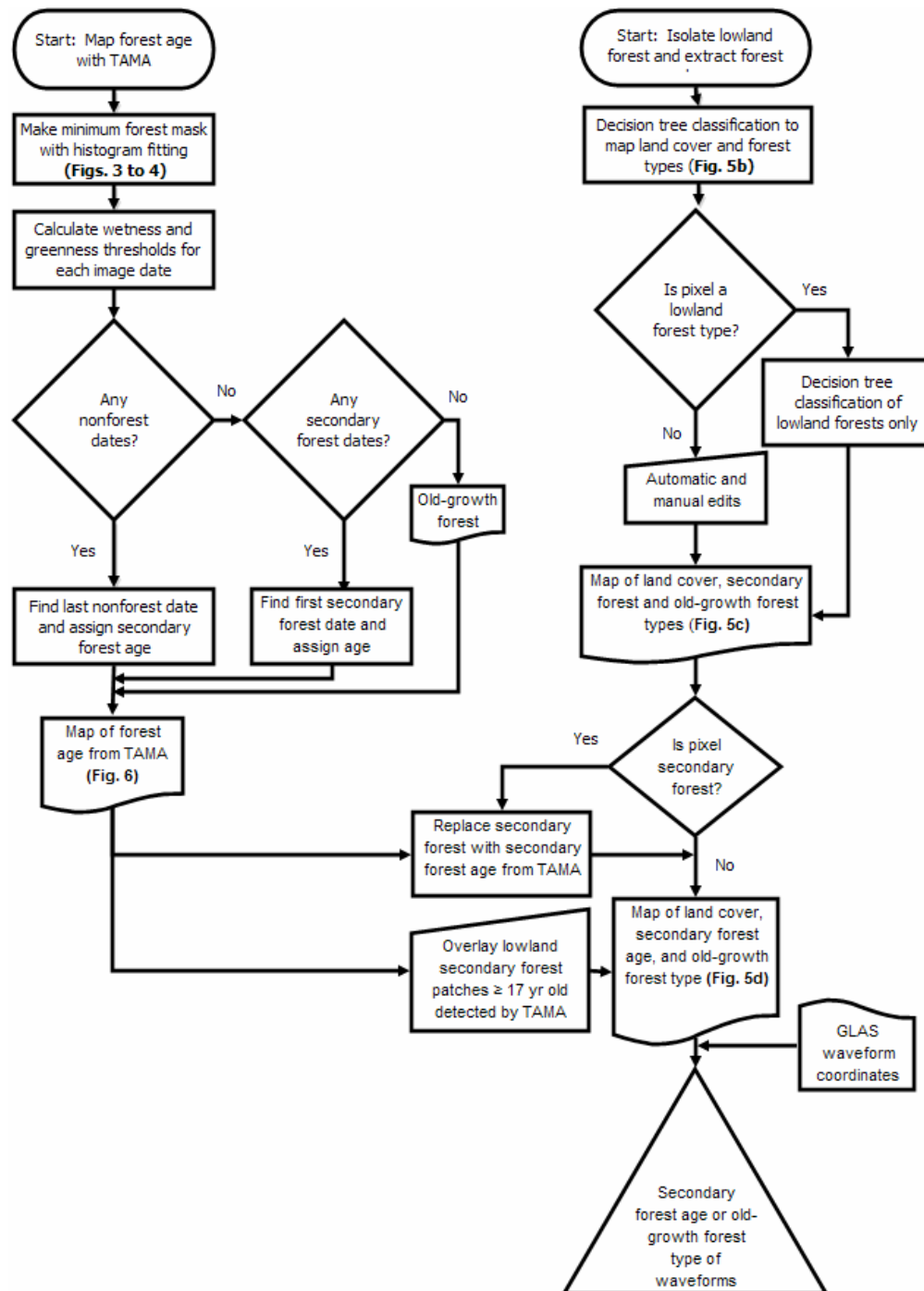


Fig. 2. Flow chart of steps to extract secondary forest age or old-growth forest type of GLAS waveforms.

3.3 The Threshold Age Mapping Algorithm (TAMA) to map lowland forest age

The Threshold Age Mapping Algorithm maps the age of lowland humid tropical forest from a sequence of Landsat images. For the Landsat Path/Row of this study, TAMA is automatic. The algorithm finds and ages secondary forest, including post-agricultural secondary forest, heavily logged but not entirely cleared forest, and forest where recent river disturbance was stand replacing. It classifies lightly logged forest as old-growth forest. The algorithm has five steps (Table 2). The first step maps forest for the scene in the time series with near the minimum forest cover (the minimum forest mask). General knowledge of land-use trends in the region under study determines this date. In this landscape, the most recent image is most likely to have the least forest. The second step applies the minimum forest mask to all images in the time series to find thresholds for forest and mature forest that are specific to each date. Here *forest* refers to forest of any age and *mature forest* refers to forest that is old enough to be spectrally similar to old-growth forest.

The third and fourth steps in the algorithm apply the image-specific thresholds and assign forest age. Pixels that do not qualify as forest in the last image are labeled as nonforest. Forested pixels that are nonforest at some point in the image sequence are assigned an age based on the last date they were nonforest. If no nonforest dates occur, then these pixels are assigned an age based on the first date they became secondary forest. If forested pixels are never nonforest or secondary forest, then TAMA assigns the oldest class, having found no major disturbance since the earliest image. For the study area, the oldest class is nearly all old-growth forest, subject only to natural or small-scale human disturbances at least in recent decades, but probably longer. The final step is application of a majority filter over a 90-m window (3x3-pixel), mainly to minimize a speckling of misclassified secondary forest amid the old-growth forest.

The reasoning behind using one minimum forest mask to define the thresholds for forest and mature forest is that most of the area that is forested when forest cover is least is also likely to be forest in the other image dates. This assumption comes from the concept that the spatial patterns of tropical forest recovery tend to proceed like deforestation in reverse, as described in a recent synthesis [5]. Over the long term, forest recovery spreads outwards from existing forest patches and fills in cleared areas surrounded by forest. The least fertile or accessible forests are generally cleared later and abandoned sooner. These patterns emerge because the overriding spatial controls on tropical forest clearing and recovery are accessibility, arability and spatial contagion, though the relative influences of these factors depend on economic conditions and opportunities. Accessibility and arability determine 1) the spatial patterns of forest clearing and subsequent agricultural abandonment that permit forest recovery, and 2) where humans leave old-growth forest remnants. Spatial contagion spurs both forest clearing and recovery. It spurs forest clearing because deforestation or logging makes nearby forest more accessible. It spurs forest recovery because nearby forest is a source of seeds and seed vectors and makes microclimate more conducive to forest regeneration.

The minimum forest mask, then, is a general forest mask that includes secondary forest of various ages and some recently cleared land in each image. In any one image, however, the amount of recently cleared land or very young secondary forest that falls within the minimum forest mask will be small. Consequently, the thresholds assume that recently cleared land or very young secondary forest will cover no more than about 2% of the minimum forest mask in any date. Below we detail methods for creating the minimum forest mask and finding the thresholds.

Table 2. The Threshold Age Mapping Algorithm (TAMA) has five major steps.

Step and Description	
1	Create the minimum forest mask with <i>Histogram Fitting for Mapping (HFM)</i> Fit the histogram of the Tasseled Cap (TC) <i>Wetness-Brightness Difference Index</i> (WBDI) for the scene date with the least forest cover. Define forest as the range of the dominant peak in this histogram. ¹
2	Find date-specific thresholds for forest and mature forest For each image date t_i (in yr), mask areas outside of the minimum forest mask to calculate: a. The date-specific, minimum TC wetness threshold for forest² as $W(t_i) = W_{AVG}(t_i) - 2SD_W(t_i)$ b. The date-specific, maximum TC greenness threshold for mature² forest as $G(t_i) = G_{AVG}(t_i) + 2SD_G(t_i)$ Where $W(t_i)$ is the wetness threshold for image t_i , i indexes the sequence number of the image date, $W_{AVG}(t_i)$ is the average wetness under the minimum forest mask for image t_i , and $SD_W(t_i)$ is the standard deviation of W for image t_i . Likewise, $G(t_i)$ is the greenness threshold for image t_i , $G_{AVG}(t_i)$ is the average greenness under the minimum forest mask for image date t_i and $SD_G(t_i)$ is the standard deviation of G for image t_i .
3	Find the last date each pixel was not forest and first date each pixel became secondary forest a. Work backwards through the time series to find the last date each pixel was not forest. b. Work forwards through the time series to find the first date each pixel became secondary forest.
4	Find forest age Combine dates of last nonforest and first secondary forest to map forest age.
5	Smooth results Apply 3x3-pixel majority filter.

¹For scenes from the late wet season or early dry season, use WBDI in the HFM procedure. For scenes from the mid- to late dry season, use TC wetness. The minimum wetness threshold in the last image can determine final forest vs. nonforest. When recently burned areas are present, intersect the mask from WBDI or TC wetness with a mask that results from separately applying HFM to TC greenness.

²Here *forest* refers to all forest ages including very young secondary forest, and *mature forest* refers to forest that is old enough to be spectrally similar to old-growth forest.

3.3.1 Minimum forest mask

To create the minimum forest mask from TM or ETM+ imagery, TAMA uses histogram fitting for mapping (HFM), first described here. The method fits the dominant peak in the histogram of an index from the image date with the minimum forest cover. In the study area, the most recent image is likely to have the least forest cover and is dated from May 2003. For scenes from the late wet season to early dry season, including those dated in November through June in Rondônia, TAMA uses the wetness-brightness difference index (WBDI), which we introduce here. The WBDI forms from the Tasseled Cap [47-49] (TC) indices. It is TC wetness (W) minus TC brightness (B):

$$WBDI = W - B \quad (1)$$

We rescaled the WBDI to eight bits. Like linear mixture models of several Landsat bands [22, 50], or other combinations of TC bands [51], the WBDI uses more of the dimensionality of TM imagery than single TC bands or simpler TM indices. In preliminary work on wet-season scenes, forest and nonforest form more distinct peaks in histograms of the WBDI than in histograms of single bands or indices or other TC band combinations. With distinct peaks for forest vs. nonforest in a forest-dominated image area, fitting the dominant peak in a histogram of WBDI finds thresholds that automatically separate forest from most nonforest for the minimum forest mask.

Pixels that fall within the range of the second and dominant peak in the histogram of the index used for the minimum forest mask (Fig. 3) are mostly forest. We find the range of this second histogram peak with a procedure in Interactive Data Language software (<http://www.itlvis.com/idl>) that parameterizes a Gaussian model to a histogram. With the procedure, called GAUSSFIT, we used a three-term fit, which yields the height, mean and standard deviation of the dominant (forest) peak in the WBDI histogram. Another way to parameterize this peak is to visually interpret the WBDI histogram. To approximate the thresholds where the upper and lower limits of this peak cross the origin, the range that defines forest is calculated as the mean of this second peak ± 3.29 times the standard deviation of this mean. The standard deviation multiple of 3.29 comes from the standard normal distribution, in which this multiple encompasses 99.9% of the values under a standard normal peak. The upper and lower thresholds defined by this range are used to make the minimum forest mask (Fig. 4).

For mid- to late dry-season scenes, including the months of July through October in the study area, the minimum forest mask is based on the wetness index. The simpler wetness index forms a forest peak that is relatively distinct from nonforest during the dry season. More importantly, recently burned areas can be common in imagery from the mid- to late dry season and, being dark rather than bright in the visible bands as with other nonforest, they are indistinct from forest in the WBDI. The most recently burned areas can also be indistinct from forest in the wetness index. Applying HFM to TC greenness, and then intersecting the result with the mask from applying HFM to TC wetness or WBDI, excludes such areas from the minimum forest mask.

For clear TM or ETM+ scenes of largely forested landscapes like those in Amazônia, the second and tallest peak in a histogram of WBDI values, or of TC wetness values in mid- to late dry-season scenes, represents mostly forest. Some woody agriculture, as well as pixels reflecting a mixture of forest and water, may also form part of this peak. The first peak includes mostly bare, urban, or agricultural land, pasture or recently cleared land, and some young secondary forest. Pixels with values beyond the range of the second histogram peak are water, but they also include some topographic shadow. The histogram of TC greenness in dry-season imagery is similar, though water is dark. In the study area, the mean of the second histogram peak in 2003, as estimated with histogram fitting, was about 199, and the mean of the WBDI for the whole scene histogram was about three percent smaller at 193. Moreover, the scene-wide standard deviation for WBDI is 2.5 times larger than for the forest peak alone, which would make a threshold determination less clear cut.

Because forest does not dominate all scenes in humid tropical landscapes, it will not always form the tallest peak in scene-wide histograms of these indices. In these cases, we anticipate that forest will, however, dominate the intersection between the scene with minimum forest cover and forest cover from an external source. Global external sources of data on forest or land cover are available from Moderate Resolution Imaging Spectroradiometer (MODIS) products.

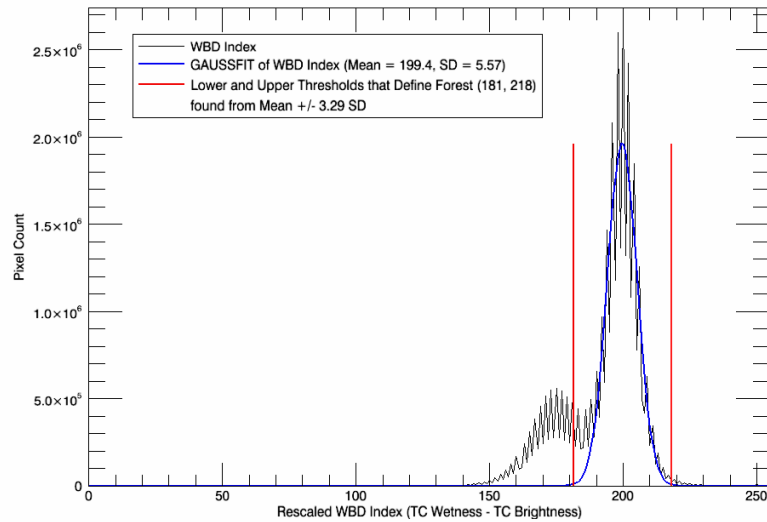


Fig. 3. *Histogram Fitting for Mapping (HFM)* involves fitting a histogram of an image area dominated by an image element of interest. Here, the *wetness-brightness difference index (WBDI)* finds the range of WBDI values that define forest for a minimum forest mask based on wet season imagery. For a forest-dominated landscape, a three-term Gaussian fit of the *WBDI* histogram yields the mean and standard deviation for the second and largest peak in the histogram, which represents forest. The range that defines forest is calculated as the mean of this second peak ± 3.29 times the standard deviation of this mean (99.9% of the values under this peak).

3.3.2 Last date each pixel was not forest

To find the last date that a pixel is not forest, TAMA uses a minimum wetness threshold for forest that is specific to each date. It then works backwards through the image sequence to find the last date that each pixel was not forest. In other words, pixels are assigned age based on the last date they were nonforest. The threshold comes from the range of TC wetness for other forest in the landscape, as defined from the intersection of the minimum forest mask with the wetness band for the particular image date. Using a wetness threshold instead of a *WBDI* threshold detects young secondary forest in its earliest stages. In using a wetness threshold, we build on the knowledge that indices that contrast near infrared with shortwave infrared spectral response, like TC wetness and the band 4:5 ratio, are sensitive to forest structure and successional stage [52]. In humid tropical forest succession, the TC wetness index tends to increase with forest age [23, 53]. One of the exceptions to this general rule is that old-growth forest consistently includes scattered pixels with TC wetness values as small as young secondary forest. Because the minimum forest mask includes these scattered old-growth forest pixels as well as secondary forest of various ages, the wetness range of the minimum forest mask can define a minimum wetness threshold for forest including secondary forest. The threshold calculation is as follows:

$$W(t_i) = W_{AVG}(t_i) - 2SD_W(t_i) \quad (2)$$

Where $W(t_i)$ is the wetness threshold for forest for image date t_i in yr, i indexes the year of the image, $W_{AVG}(t_i)$ is the average wetness under the minimum forest mask for image date t_i , and $SD_W(t_i)$ is the standard deviation of W for image date t_i . Age is then calculated as the midpoint between $(t_n - t_i)$ and $(t_n - t_{i+1})$, where t_n is the year of the last image date in the sequence and n indicates that the index for the year is the last one.

In using an image-specific range for forest spectral response, TAMA is *self calibrated*. Consequently, the algorithm avoids the requirement that images in the sequence be phenologically similar, atmospherically corrected, or normalized. In other words, the algorithm calculates an image-specific threshold for each scene date. For the earliest, MSS scene, we defined forest with a maximum threshold in the red band from the masked scene, calculated as the mean of the red band plus two times its standard deviation. In the study area, calculating these thresholds after removing most nonforest leads to wetness thresholds that are three to nine percent greater than if these thresholds came from histograms of whole scenes, with the difference increasing as forest cover decreases. The threshold calculation also assumes that recently cleared land, including the darkest and most recently burned areas, will be detected as nonforest or secondary forest in later images if not detected initially.

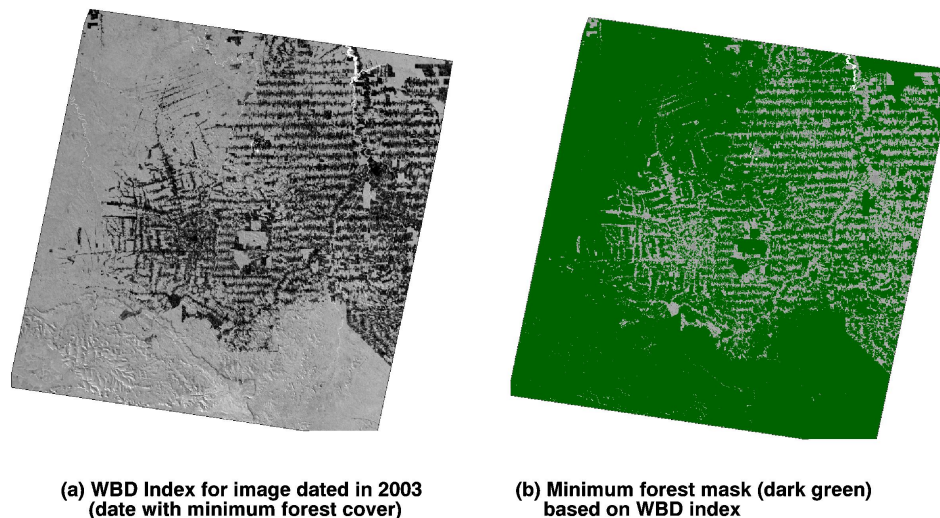


Fig. 4. An image of the Wetness-Brightness Difference Index (WBDI) (image a), and the minimum forest mask that results from applying Histogram Fitting for Mapping (HFM) to WBDI (image b). TAMA intersects the forest mask with each image date to find the minimum wetness and maximum greenness thresholds for mapping forest age.

3.3.3 First date each pixel became secondary forest

If the wetness test finds no nonforest dates, TAMA looks for the first date that forest became secondary forest. For this test, we build on the fact that in humid tropical zones, young secondary forest can quickly produce a dense vegetation canopy with little shadow and bright signatures in TC greenness that gradually fade with age [23, 31, 53]. The young regrowth generally has brighter greenness than most other lowland forest in the landscape, including most of the greenest mature forest pixels. Exceptions in steep terrain include that mature forest on brightly sunlit slopes can be as green as young secondary forest. Also, secondary

forest greenness is subdued on shadowed slopes. These exceptions are mainly why we limit our current scope of inference to lowland forests.

The greenness test serves only as a backup to the wetness test because it can fail for two reasons. First, young secondary forest may be no greener than mature forest in some peak dry-season scenes. Second, if the wetness threshold does not detect recleared forest, TAMA will overestimate the age of forest formed after reclearing, because it only uses the first date that greenness exceeds that of mature forest. Phenology, however, impacts the relative greenness of secondary forest strongly, making age estimates unstable if derived from working backwards through a sequence of greenness images. The main reasons for the greenness test are to detect the following: 1) secondary forest that the wetness threshold does not detect because of a long gap in the image sequence; and 2) initial regrowth that the wetness threshold does not detect because a combination of wet season phenology and lush regrowth after old-growth forest clearing have given the pixel larger than typical values in both wetness and greenness; and 3) recently burned areas that the wetness threshold does not detect that undergo little or no cultivation before forest regrowth begins.

If TAMA finds no disturbance with the wetness threshold, it works forward through the sequence to find when a pixel first became secondary forest. For this date TAMA finds the first date that the TC greenness of a pixel exceeds a threshold value for most other forest in the landscape. This threshold is calculated separately for each masked image as follows:

$$G(t_i) = G_{AVG}(t_i) + 2SD_G(t_i) \quad (3)$$

Where $G(t_i)$ is the greenness threshold for forest for image date t_i , in yr, i indexes the image date, $G_{AVG}(t_i)$ is the average greenness in image date t_i of all pixels under the minimum forest mask, and $2SD_G(t_i)$ is the standard deviation of G for image t_i . Age is then calculated as the midpoint between $(t_n - t_i)$ and $(t_n - t_{i-1})$. For the earliest, MSS scene, we defined secondary forest as forest that fell below a minimum threshold in the Normalized Difference Vegetation Index (NDVI) from the masked scene, calculated as the mean of NDVI minus two times its standard deviation. In the study area, masking each image date with the minimum forest mask increases these greenness thresholds by only one to three percent compared with scene-wide averages.

3.4 Old-growth forest types

To isolate lowland forests in the study area, we mapped old-growth forest types with two successive decision tree classifications of multirate Landsat imagery. Recent studies show that decision tree classification of Landsat imagery and topographic data can accurately map forest physiognomic classes in complex tropical landscapes [35, 54, 55]. Those works more thoroughly discuss the topic. The first of the two decision tree classifications mapped land cover, two spectral classes of secondary forest (whether terra firme or not), and the following four classes of old-growth forest: 1) lowland seasonal evergreen to semi-evergreen forest; 2) forests that were not terra firme forests, including lowland floodplain forested wetlands (várzea) and swamp (igapó); 3) hill and submontane semi-evergreen forest, and 4) hill and submontane, semi-evergreen to deciduous, woody savanna (cerradão) to forest (Fig. 5b). Band data for this classification included all six optical bands and the TC brightness, greenness, wetness and haze indices from each of three image dates (1998, 2000 and 2003), as well as elevation, slope, aspect and topographic shading (in the 2003 image) from Shuttle Radar Topography Mission (SRTM) [56] data. Though correlated, we included all of these bands because an advantage of decision tree analysis is that it determines which input variables yield the most accurate classification. In preliminary work, decision tree models with the three image dates gave a more accurate classification than models from only one or

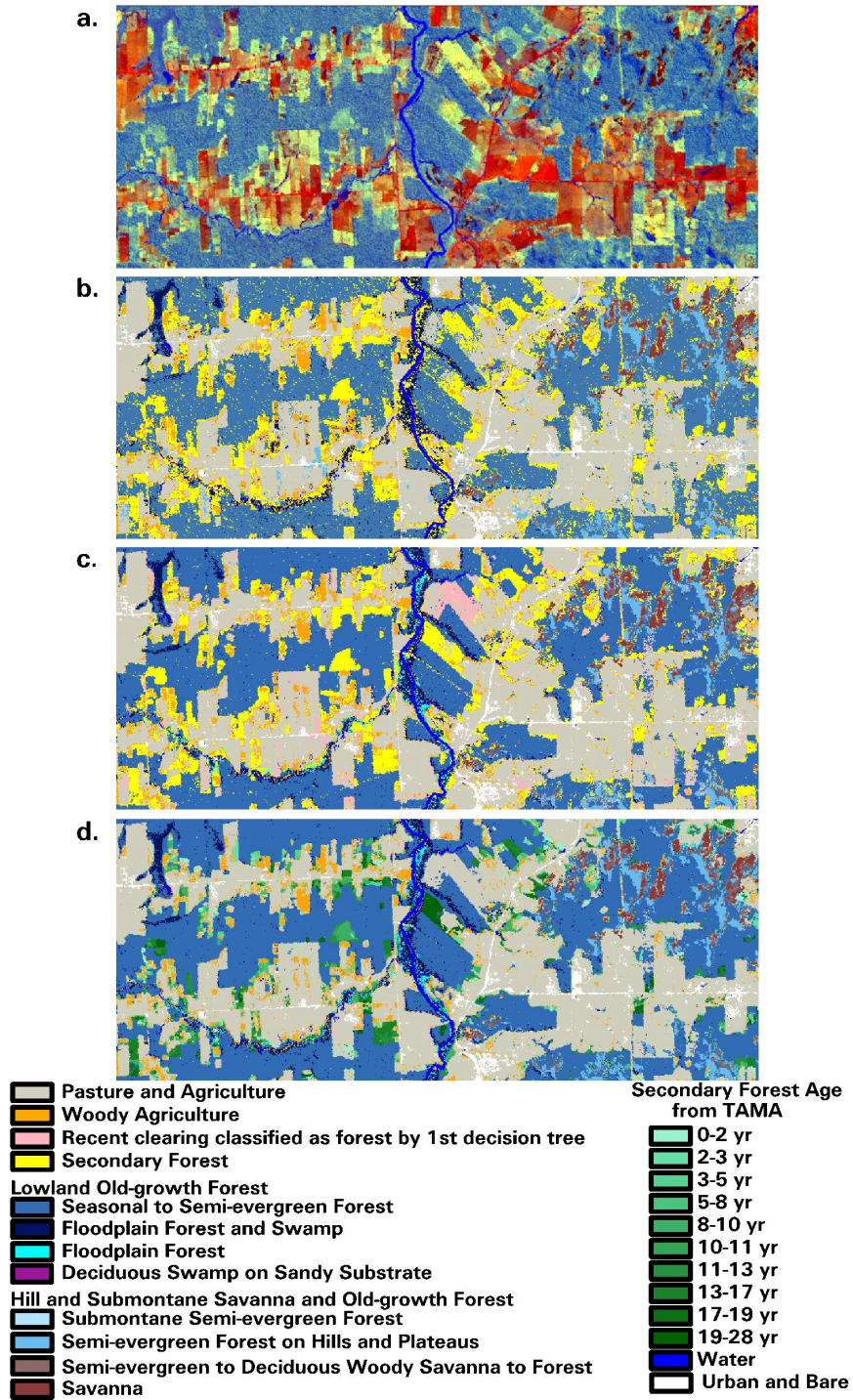


Fig. 5. The mapping sequence for a subset of the area. Fig. 5a – Landsat imagery from 2003, Tasseled Cap transform. Fig. 5b – Land cover from the first decision tree classification. Fig 5c – Lowland and secondary forests reclassified with the second decision tree classification and then overlain onto the map from the first decision tree classification. Fig 5d. TAMA-mapped secondary forest age overlain onto the map from the two decision tree classifications.

two dates, confirming other work in the region [20]. We applied two automated recodes. First, at elevations <175 m, hill and submontane semi-evergreen and deciduous forest and semi-evergreen to deciduous woody savanna to forest were reclassified to woody agriculture to reduce confusion between those classes. Second, above 500 m elevation, hill and submontane semi-evergreen forest, and some misclassified secondary forest, were recoded to a new class, submontane semi-evergreen forest. Hill and submontane semi-evergreen forest below 500 m elevation was then labeled semi-evergreen forest on hills and plateaus. We also manually recoded some large patches in the north from barren and pasture to wet savanna and deciduous swamp on sandy substrate, respectively.

The goal of the second decision tree classification was to reduce confusion between secondary forests, recently cleared land, and lowland old-growth forests. It further classified only these classes: lowland old-growth seasonal to semi-evergreen forest, the old-growth floodplain forest and swamp that was not terra firme forest, and secondary forests (which are mainly not terra firme forest but include some wetlands) (Fig. 5c). This second classification separated training data for old-growth forested wetland into two spectral classes: a brighter floodplain forest class and a darker class of floodplain forest and swamp, in which an underlying water signal was visible in the imagery. It also added two new classes to identify those areas classified as secondary forest in the first classification that were actually forest cleared between the years 2000-2001 and 2001-2003. The image stack for this second decision tree classification included band data from all of the other images. Their inclusion provided spectral data for the second decision tree model to better distinguish the brighter floodplain forest class and the old-growth forest.

As in previous work [35, 54, 55], classification training data for both decision tree classifications included about 40 to >100 multi-pixel patches for each class. The training data included separate classes for sunlit and shadowed versions of each hill and submontane class. We identified these data with the optical satellite imagery of fine spatial resolution. This imagery covered about 15% of scene (Fig. 1). We supplemented this training data with training data visually interpreted from the Landsat imagery for areas that the fine resolution imagery did not cover. Training data for the classes of recently cleared forest also consisted of > 40 multi-pixel patches of forest cleared between specific dates as seen in the Landsat imagery. The resulting data trained a See5 (<http://www.rulequest.com/>) decision tree model for each classification. Each model also used a costs file, developed through trial and error, to minimize confusion between some classes. Applying each model from See5 [57] to the stack of image bands and topographic data yielded the two classified maps. For the final land-cover and forest-type map, we overlaid the results of the second decision tree classification, of lowland forest types, onto the first one. For the map from which we extracted forest age or type of GLAS waveforms, we replaced secondary forest in the land-cover and forest-type map with secondary forest age from TAMA. Patches of old secondary forest that TAMA found, but that were misclassified as old-growth or floodplain forest by the decision tree classifications, were manually transferred to the combined map (Fig. 5d).

3.5 Accuracy assessment

Accuracy assessment for the land-cover and forest-type map relied on a stratified random sample of about 50 pixels for each mapped class but secondary forest. All of these samples were only from the areas in the map covered by fine resolution imagery dated within one yr of the image from 2003 (12% of the mapped area). We created a kml file of validation points, and loaded it into Google Earth to locate and identify the land cover or forest type of points viewable at fine resolution only in Google Earth. Because we eliminated duplicate points, some classes had few observations for error assessment. Pixels for error assessment of secondary forest were limited to those within patches larger than about 0.7 ha, because we would relate secondary forest age to biomass estimated from GLAS waveforms. Because

some forest ages were rare, we supplemented the validation data for secondary forest age with a randomly selected 5-10 percent of pixels used for training data in the decision tree classification that were from areas not covered by the fine spatial resolution imagery. At least half of the accuracy assessment data for all ages was randomly selected from areas covered by the fine resolution imagery. With these data we calculated error statistics for a stratified random sample [58], including overall percent of correctly classified pixels, the Kappa coefficient of agreement [59], and producers' and users' accuracy. We combined all secondary forest ages in assessing the land-cover and forest-type map.

Secondary forest age for the accuracy assessment was inferred by simultaneously viewing, for each age, 1) the entire Landsat image sequence as red-green-blue (RGB) color composites of TC wetness, and 2) the two single-date TC images flanking the interval under evaluation. The RGB-TC wetness color composites display wetness from three sequential images in RGB color space. An example is displaying in one viewer TC wetness from 1984, 1986 and 1990 in Red, Green and Blue, and displaying in the next viewer TC wetness from 1986, 1990 and 1992. We displayed enough viewers to cover all three-band sequential combinations. This display reveals where forest regrowth lasts through the sequence as well as the date interval when the regrowth began. Interpreting RGB-NDVI color composites of forest disturbance and regrowth [60] is similar to interpreting the RGB-TC wetness composites in this study. Forest clearing between dates one and two of each composite appears magenta, and forest clearing between dates two and three appears yellow. Lowland old-growth and old secondary forest are grey, and water is white. Forest regrowth that begins between dates one and two and continues through dates two and three appears cyan. With growth, however, the difference between the average TC wetness of mature forest and secondary forest decreases. As a result, secondary forests first pale from cyan to dark grey and then gradually brighten toward the lighter grey of mature forest in the sequence of RGB-TC wetness composites. Simultaneously displaying the TC images for the interval under evaluation then confirms the interpretation.

3.6 Forest biomass estimates from GLAS and secondary forest biomass accumulation rate

The Geoscience Laser Altimeter System (GLAS), onboard the Ice, Cloud, and land Elevation Satellite (ICESat), is a waveform sampling lidar sensor. GLAS emits short duration (5 ns) laser pulses towards the land surface and records the echo of those pulses as they reflect off the ground surface. When that surface is vegetated, the return echoes, or waveforms, are a function of the vertical distribution of vegetation and ground surfaces within the area illuminated by the laser. The vertical extent of each waveform increases as a function of terrain slope and footprint size (the area on the ground that is illuminated by the laser), as modified by the spatial pattern of ground surfaces visible to the laser. Over sloped terrain, returns from both canopy and ground surfaces can occur at the same elevation. As a result, information on the vertical extent of the waveform is insufficient to make estimates of tree height on more steeply sloped terrain. However, for forests on level ground, discrete peaks in the waveform separate the height distribution of reflecting canopy surfaces from that of the underlying ground. In these cases, forest stand height can be calculated as the difference between the elevations of the first returned energy minus the mean elevation of the ground return.

We estimated canopy height and AGLB from GLAS waveforms for collection periods 2A through 3I, which extend from November 2003 through November 2007. The method used to process the data and estimate canopy height from the GLAS data is described elsewhere [13]. The equation that we used to estimate AGLB of Amazonian humid forest from GLAS-measured forest canopy height, which is updated from that publication (M. Lefsky, unpublished data), is the following:

$$AGLB \text{ (Mg ha}^{-1}\text{)} = -8.84 + 10.23 \text{ GLAS Height} \quad (4)$$

About 38,000 waveforms fell within the study area (Fig. 1). Of those, 31 waveforms were centered where the surrounding 150-m window was at least 85% secondary forest. Three of these waveforms had no or very low biomass. We assumed that these waveforms fell on land that had undergone clearing since 2003 and excluded them from further analysis. We also excluded a waveform that fell on logged forest that was not subsequently cleared and two waveforms that were statistical outliers (one of which was woody agriculture misclassified as secondary forest). Forest age for each waveform was the sum of 1) the average mapped age of secondary forest pixels in the circular 150-m window surrounding each waveform center, and 2) the time difference between the last Landsat scene, from May 2003, and the GLAS waveform collection. For estimating biomass of old-growth forest types, we first masked all pixels on lands with a 30 percent slope or steeper. In addition, we used only pixels centered in 210-m windows of the same forest class for most classes. For classes with many observations, we only summarized waveforms from Collection Periods 2A through 2C to minimize the influence of land-cover changes since 2003. Hill and submontane semi-evergreen to deciduous woody savanna to forest, and deciduous swamp on sandy substrate, had few observations centered in a uniform 210-m window. For these classes, we used waveforms surrounded by a minimum of 90% of the same class in a 210-m surrounding window. We separately summarized GLAS-estimated biomass values for hill and submontane semi-evergreen to deciduous woody savanna to forest above vs. below 500 m elevation, though we did not divide this class in the land-cover and forest-type map.

4 RESULTS

4.1 Map of secondary forest age and land-cover and forest-type map

The map of forest age (Fig. 6) has an overall accuracy of 88%. The Kappa coefficient of agreement of 0.62 (Table 3) is generally considered good [61]. The forest age mapping algorithm mapped some of the land cleared land from 2000 to 2003 as secondary forest. Some of this land had dense vegetation or large amounts of slash in the fine resolution imagery. Some of it also was clearly pasture or woody agriculture in later fine resolution imagery from 2005. To assure that the algorithm was accurately aging secondary forest younger than 3 yr that was not recently cleared, we excluded recently cleared land from the error assessment of lowland forest age.

The final map of land cover and major forest types (Fig. 7), which resulted from the two decision tree classifications and the editing, has an overall classification accuracy of 69% and a Kappa coefficient of agreement of 0.56 for the 14 classes (Table 4), which is also considered good. Although overall accuracy was good, it reflects the fact that the error matrix merges secondary forest with lands cleared in the last three years, because, similar to the age mapping algorithm, about one-third of the land that was cleared in the last three years was classified as secondary forest. Woody agriculture also showed confusion with secondary forest. Remaining errors included confusion between the following classes: pasture vs. savanna; secondary forest vs. semi-evergreen to deciduous woody savanna to forest; and forested wetlands vs. other classes. Other old-growth forest classes had users' and producers' accuracies ranging from 52 to 98%.

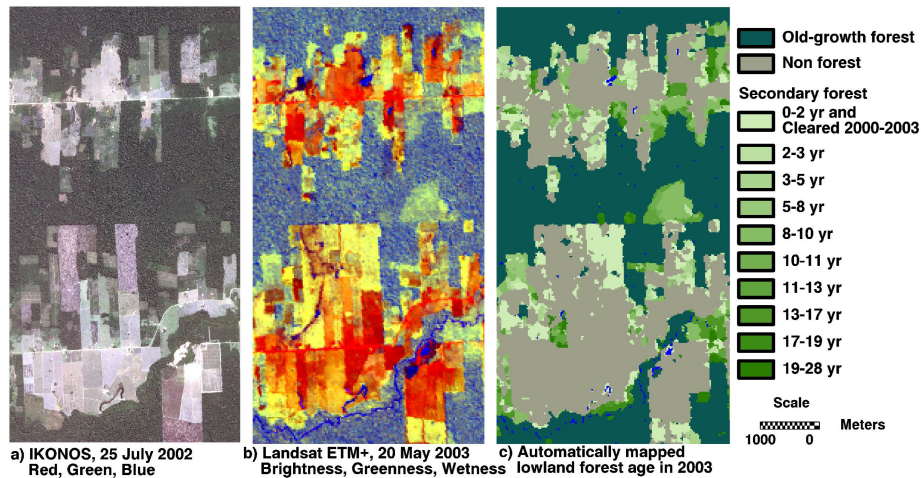


Fig. 6. A close-up view of a lowland part of the study area, including a) pan-sharpened IKONOS imagery, b) Landsat imagery transformed to the Tasseled Cap indices, and c) forest age as mapped with the self-calibrating algorithm, TAMA, and an 11-date image sequence. The map distinguishes old-growth from secondary forest older than 19 yr. Images in the time series varied phenologically, but they underwent neither atmospheric correction nor normalization.

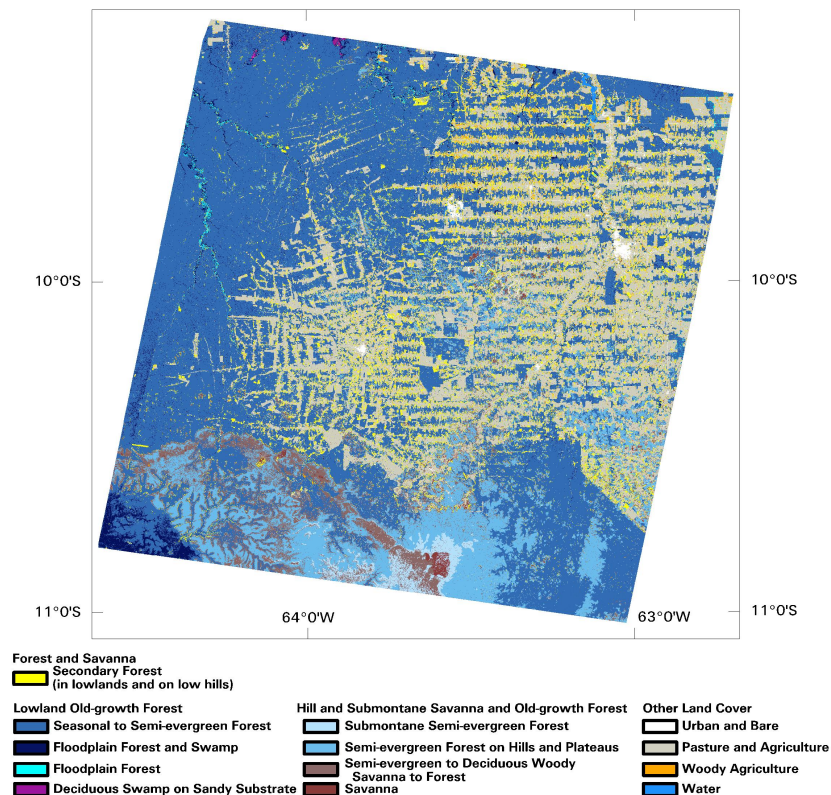


Fig. 7. Two decision tree classifications of Landsat imagery yielded a land-cover and forest-type map for the year 2003 for WRS Path/Row232/067.

Table 3. Accuracy assessment points for the map of forest age (Fig. 6) resulting from applying the Threshold Age Mapping Algorithm (TAMA). Error statistics are calculated for a stratified random sample [58] (see Appendix A). The Kappa coefficient is 0.62¹. Overall accuracy (P_o) is 88%. Lowland old-growth forest classes are: OG = Old-growth Lowland Seasonal to Semi-evergreen Forest; WF2 = Floodplain Forest and Swamp; and WF1 = Floodplain Forest. Users' Acc. = Users Accuracy; Producers Acc. = Producers' Accuracy. P_o = Overall Accuracy.

Class (Age in yr)	Reference class										Lowland Old-Growth Forest			Area (000 ha)	Users Acc. (%)
	Secondary Forest Age in yr										OG	W F1	W F2		
	0-2	2-3	3-5	5-8	8- 10	10- 11	11- 13	13- 17	17- 19	19- 28					
0-2	12	11	3	2	0	0	0	0	0	0	1	0	0	84	41
2-3	4	5	2	0	2	1	2	0	0	0	0	1	0	20	29
3-5	1	5	42	3	1	0	0	1	0	0	0	3	0	22	75
5-8	1	2	4	26	0	0	2	0	0	0	0	0	0	14	74
8-10	1	2	0	3	54	0	1	0	0	0	0	0	1	10	87
10-11	0	1	0	2	3	19	0	0	0	0	0	0	0	6	76
11-13	0	0	0	0	7	3	29	2	0	0	0	0	0	9	71
13-17	0	0	0	0	1	1	2	32	1	0	1	2	0	6	80
17-19	0	0	0	0	1	0	0	0	10	1	0	1	0	4	77
19-28	0	0	0	0	1	0	3	0	1	11	0	0	0	19	69
OG	0	1	0	0	0	0	0	0	0	0	51	0	3	1,612	93
WF1	0	0	0	0	0	0	0	0	0	0	1	1	1	15	33
WF2	0	0	0	0	1	0	0	0	0	0	7	0	35	72	81
Pro- ducers', Acc. (%)	86	8	56	57	52	71	47	85	72	97	99	62	39	1,893	P _o = 88%

¹Accuracy calculated according to Czaplewski (2003). The calculations differ from those for a random sample and are area-weighted by mapped class and sample area. For an example calculation, see Appendix A.

Table 4. Validation data for the land-cover-forest type map (Kappa coefficient = 0.56)¹. Urbn/Bare = Urban or bare; Past = Pasture and agriculture; Sav = Savanna; WAg = Woody Agriculture; SF/RctClr = Secondary Forest and Land cleared since 2000. LowlSeasEvF = Lowland Seasonal to Semi-evergreen Forest; SemiEvF = Semi-Evergreen Forest on hills and plateaus; SDecidDF = Hill and Submontane Semi-evergreen to Deciduous Woody Savanna to Forest; SubmF = Submontane Semi-Evergreen Forest; WetSav = Emergent Wetland and Wet Savanna; WetlF3 = Deciduous Swamp on Sandy Substrate; WetlF2 = Floodplain Forest and Swamp; WetlF1 = Floodplain Forest. P_o = Overall Accuracy.

Mapped Class	Reference Class							
	Urbn	Past	Sav	WAg	SF/RctClr	Lowl Seas EvF	Semi EvF	SEvDecF
Urbn/Bare	29	18	0	1	1	0	0	0
Past	1	37	0	0	30	0	0	0
Sav	0	11	6	0	10	0	0	2
WAg	1	10	1	15	14	0	0	0
SF/RctClr	0	17	0	35	339	2	1	3
Lowl SeasEvF	0	0	0	0	4	52	1	5
SemiEvF	0	0	0	0	3	4	35	5
SEvDecF	0	6	1	1	5	1	5	20
SubmF	0	0	0	0	0	0	4	1
WetSav	0	0	0	0	0	0	0	0
WetlF3	0	0	0	0	0	0	0	0
WetlF2	1	0	0	1	2	7	0	0
WetlF1	0	0	0	2	13	1	1	0
Water	0	1	0	0	1	0	0	0
<i>Producers' % Accuracy</i>	51	84	44	35	32	98	52	37

Mapped Class	Reference Class							<i>Users' Acc. (%)</i>
	SubmF	WetSav	WetlF3	WetlF2	WetlF1	Water	Area (000 ha)	
Urbn/Bare	0	0	0	0	0	0	20	59
Past	0	0	0	0	2	0	601	53
Sav	0	0	0	0	0	0	19	21
WAg	0	0	1	2	0	2	73	33
SF/RctClr	0	0	0	2	3	1	47	84
Lowl SeasEvF	0	0	0	3	1	2	239	76
SemiEvF	2	0	0	0	0	0	1,653	71
SEvDecF	1	0	0	0	0	0	155	50
SubmF	33	0	0	0	0	0	32	87
WetSav	0	4	3	0	0	0	0.1	57
WetlF3	0	1	24	0	0	0	1.1	96
WetlF2	0	0	1	35	2	2	73	69
WetlF1	0	0	0	1	3	0	24	14
Water	0	0	1	1	0	38	13	90
<i>Producers' % Accuracy</i>	80	40	28	39	7	18	2,951	$P_o = 69\%$

¹Accuracy calculated according to Czaplewski, 2003 [58]. The calculations differ from those for a random sample and are area-weighted by mapped class and sample area. For an example calculation, see Appendix A.

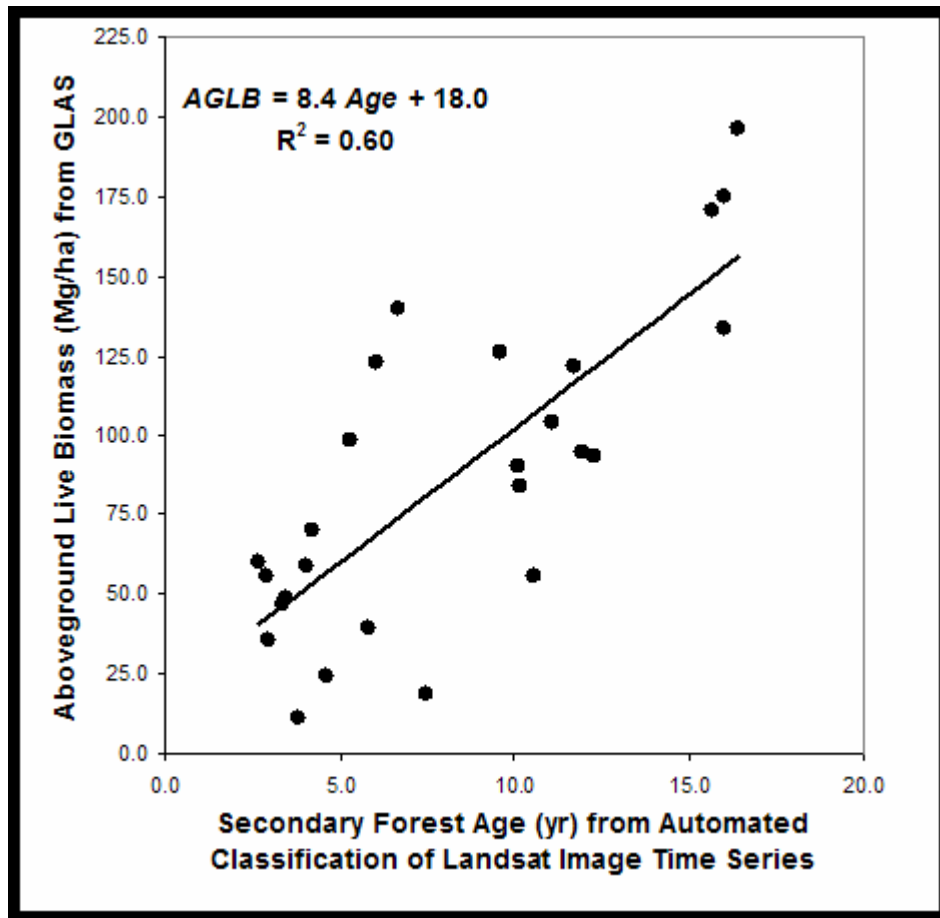


Fig. 8. The average age of secondary forest pixels in the 150-m window surrounding GLAS waveform centers explained 60% of the variance in GLAS-estimated canopy height and biomass (Aboveground Live Biomass, AGLB, in Mg ha^{-1} dry weight). The standard error of the slope and intercept are 1.4 and 13.2, respectively, for 26 observations.

4.2 Relationship between forest biomass from GLAS and secondary forest age or old-growth forest type

Secondary forest age, as estimated with TAMA, was significantly related to AGLB, as estimated from GLAS ($p < 0.0001$, $R^2 = 0.60$, $N = 26$, $\text{SE slope} = 1.4$, $\text{SE intercept} = 13.2$), yielded the following relationship (Fig. 8):

$$\text{AGLB (Mg ha}^{-1}\text{)} = -8.4 \text{ Age} + 18.0 \quad (4)$$

Average AGLB of woody savanna to forest, below and above 500 m elevation, respectively, was 63 and 90 Mg ha^{-1} . We combined AGLB estimates of floodplain forest and swamp, which averaged 146 Mg ha^{-1} . Deciduous swamp forest averaged 91 Mg ha^{-1} . Lowland seasonal evergreen to semi-evergreen forest averaged 185 Mg ha^{-1} , which was slightly larger than an average of 166 Mg ha^{-1} for semi-evergreen forest at mid elevations and on hills (Table 5). Semi-evergreen forest at elevations above 500 m averaged 165 Mg ha^{-1} .

Table 5. The mean and range of stand height and aboveground live forest biomass for old-growth or naturally disturbed forest types were estimated from GLAS waveforms coincident with 210-m windows of uniform forest type (100 percent of pixels in the same class, or 90 percent in the case of hill and submontane semi-evergreen to deciduous woody savanna to forest and drought deciduous swamp on sandy substrate). Mean elevations are those estimated from the GLAS waveform. Hill and submontane semi-evergreen to deciduous woody savanna to forest was mapped as one class, but we separately summarized the biomass estimates for this class above vs. below 500 m elevation.

Forest type (Old-growth and natural disturbance regime)	Mean AGLB Mg ha ⁻¹	SD AGLB Mg ha ⁻¹	N	Median AGLB Mg ha ⁻¹	AGLB 5th %ile	AGLB 95th %ile	Mean Ht. m	Mean Elev. m	Laser Period
<i>Lowland forests</i>									
Lowland Seasonal to Semi-evergreen Forest	185	52	1898	182	114	261	19	179	2A-2C
Floodplain Forest and Swamp ¹	146	48	25	157	51	227	15	156	2A-2C
Deciduous Swamp on Sandy Substrate	68	49	6	77	11	119	7	116	2A-3I
<i>Hill and submontane forests and woody savanna</i>									
Semi-Evergreen Forest on Hills and Plateaus	166	60	71	162	57	265	17	385	2A-2C
Hill and Submontane Submontane Semi-Evergreen Forest (≥500 m elevation)	166	34	18	165	85	208	17	723	2A-3I
Hill and Submontane Semi-evergreen to Deciduous, Woody Savanna to Forest									
<500 m elevation	63	43	22	52	17	144	7	337	2A-3I
≥500 m elevation	91	83	19	59	9	320	10	790	

¹This estimate includes waveforms from two of the mapped classes: 1) floodplain forest, and 2) floodplain forest and swamp.

5 DISCUSSION

5.1 Mapping forest age with TAMA

The algorithm here finds thresholds that separately classify images in a time series, and then it merges the results to map forest age. The method is akin to post-classification change detection. The main difference between TAMA and past post-classification merging is that TAMA has the potential to be fully automatic. It is automatic for the scene in this study once lowlands are isolated, but TAMA still requires testing in humid lowlands with different seasonality or disturbance histories. Another difference with TAMA is that although error accumulation from post-classification change detection is problematic with both approaches,

it may be less of an issue with forest age mapping, because age is ordinal. We observed that forest misclassified as one age tends to be confused with the next one to three older or younger classes as opposed to other ages. This tendency would reduce precision when estimating parameters like biomass accumulation rate, but it may not greatly reduce accuracy.

Unique to TAMA is that atmospheric correction, image normalization, and same-season imagery are unnecessary, because it does not detect change with band or index differences or trends among images. The criteria for classifying a given image come from the image itself instead of from two or more images. This feature of TAMA may help address the recalcitrant problem of detecting forest change with Landsat image time series where cloud cover is persistent. The algorithm lends itself to separately identifying nonforest and secondary forest in the clear areas of two or more scenes that can form a time step and then merging the results for each time step. The only requirement is that the clear data in each of the scenes that form a time step are sufficient to estimate valid thresholds for each scene. In addition, the HFM procedure automates forest cover mapping for the self-calibrations.

Classification and change detection based on automated self-calibration, like that in TAMA, could become a paradigm-shift in remote sensing of forest disturbance. The demand for fully automatic, operational forest monitoring leaves less room for difficulties normalizing between-date differences in atmospheric conditions or vegetation phenology. Existing methods that help normalize vegetation phenology between images are either meant for creating cloud-minimized image mosaics across space [55], or they require imagery with high temporal resolution like that from MODIS [62, 63]. The approach of using high temporal resolution imagery to normalize Landsat scenes from different dates has not been tested with high temporal resolution imagery dated from before MODIS.

5.2 Error sources and topics for further study in threshold age mapping

One error source in aging lowland secondary forest with TAMA is spectral overlap between recently cleared land, woody agriculture and secondary forest. The algorithm relies on the tendency for TC wetness to increase during tropical forest succession. An exception to this rule is recently cleared land in wet season imagery. Whether the vegetation on such land is young secondary forest, pasture, or woody agriculture, it may have bright TC wetness or greenness values in wet season imagery, because it has moister soil with vigorous vegetation growth. Unless all of the images in the sequence are from the wet season, which is unlikely, recently cleared land that remains clear in one or two subsequent dates will not qualify as forest in later images. Accordingly, this error source mainly affects 1) whether recently cleared and active herbaceous agricultural or pasture land is considered secondary forest in the most recent images, 2) whether TAMA will detect recleared forest that quickly reverts to secondary forest, and 3) whether the age of secondary forest that was once woody agriculture is overestimated. When using wetness to delineate forest for the last date, the youngest classes in the final map may include some recently cleared lands. Waveforms from GLAS that fall on these lands will need to be manually removed when estimating biomass accumulation rates. Fitting the histogram of the *WBDI* to map forest cover in the last image eliminates recently cleared land from the youngest forest class. We did not use this approach because we observed that it may misclassify scattered pixels of secondary forest as nonforest. However, the optimal methods for mapping forest cover in the most recent image, and for detecting forest reclearing in wet season scenes, merits further work.

The other exception to a general increase in TC wetness with tropical forest age is that dense, intermediate-aged tropical forest stands with little height variation can have slightly greater average wetness than old-growth forest (personal observation). Because such stands are old enough to already be identified as forest, however, this circumstance does not affect forest age mapping with TAMA. Future work should also test alternatives to the greenness threshold based on the minimum forest mask that we use here. Phenology strongly impacts

TC greenness. As a result, the youngest secondary forest in peak dry-season imagery is not always greener than most other forest in the landscape.

Another aspect of TAMA that needs development is a way for TAMA to age forests in more rugged topography. In this study we limit the age mapping to lowland areas. Landsat image classifications can easily confuse secondary forest with old-growth forest on slopes that are sunlit in imagery [22, 31]. The decision tree classification of land cover and forest type that used topographic data distinguished secondary forest from old-growth forest on sunlit slopes fairly successfully. In the age mapping, however, TAMA classified some old-growth forest on sunlit slopes as older secondary forest. Conceivably, topographically normalizing images with digital elevation data might alleviate this problem, but addressing that issue was beyond the scope of this study.

When estimating biomass accumulation rates from forest age maps generated with TAMA, an additional source of uncertainty arises. Confusion exists between post-agricultural secondary forest and logged forest that is not entirely cleared. This confusion could lead to overestimation of biomass accumulation rates. Outright forest clearing often follows logging in Amazônia [50], which would minimize the impact of this uncertainty. However, we found it necessary to manually eliminate, from the dataset of biomass and forest age, an observation that was logged forest that did not undergo conversion to agriculture. A final potential error source with TAMA is long temporal gaps between the images in a sequence. In as few as five to 10 years, the TC greenness of secondary forest may fade into the range of greenness for old-growth forest. The temporal gaps between the oldest Landsat data available may sometimes be longer than five to 10 yr. Consequently, another important topic is ensuring that TAMA identifies secondary forest when image temporal gaps are long.

5.3 Mapping tropical forest types with decision tree classification of satellite imagery and elevation data

In this study, two successive decision tree classifications of optical satellite imagery and elevation data allowed us to distinguish five broadly-defined forest classes, some of which were spectrally similar. Elevation data allowed us to distinguish a sixth class, submontane semi-evergreen forest, and we mapped a seventh class, drought deciduous swamp on sandy substrate, with manual recoding. Mapping vegetation types with such an approach is now common in remote sensing. In tropical landscapes, an early application of expert systems to map Eucalypt forest types [64] has been followed by work to map spectrally similar but physiognomically distinct forest types over large areas or steep environmental gradients. For example, recent work in the Caribbean, where forests range from dry deciduous forests to wet cloud forests, produced the first decision tree classification of Landsat imagery and ancillary data that mapped an entire commonwealth or country [35]. Maps of other complex tropical islands have followed [54, 55]. Across larger areas, decision tree classification of multitemporal SPOT-4 Vegetation data yielded forest formation maps for the state of Mato Grosso, Brazil [65].

5.4 Google Earth as reference data

The fine resolution imagery viewable on Google Earth was critical to this study. Over the study area, this imagery was QuickBird imagery from Digital Globe. It allowed us to distinguish many land-cover types for classification training and error assessment, including lowland old-growth forest, secondary forest, pasture, woody agriculture, urban lands, roads, savanna, and recently cleared land (dead wood or moister soils were often visible). Drawbacks of this approach include that the date of fine resolution imagery on Google Earth may not be optimal for an application. Yet that same drawback is common with other reference data. Some forested areas were cleared or disturbed, for example, between the

dates of the IKONOS imagery and the most recent Landsat image. Another issue is that having full coverage of fine resolution imagery for training data collection may yield the best classification results. Misclassifications were more common in areas that the fine resolution imagery did not cover, because our training data were sparser there. These results confirm previous observations that distributing training data throughout an image greatly benefits decision tree classification of land cover and forest type [55]. Nevertheless, for many areas, there has never been such a convenient and finely-scaled source of reference data.

5.5 Forest biomass and biomass accumulation rate

The regeneration potential of tropical secondary forests is high [66, 67]. Their pattern of biomass accumulation is an asymptotic curve that begins to level off after about 20 yr, but land-use history, edaphic conditions, climatic zone, and probably landscape structure, all affect biomass accumulation rates over the short or long term [11, 68]. The GLAS waveforms amount to a systematic sample across tropical landscapes. Assuming they give a representative sample of secondary forest, the biomass accumulation rates estimated with the method in this study might be considered weighted averages that incorporate the different regrowth rates of secondary forest that stem from varied disturbance histories.

The average biomass accumulation rate of $8.4 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for lowland forests with an average age ranging from 3 to 16 yr agrees well with ground based estimates from Rondônia and other places. Field-measured rates of biomass accumulation for 2-18 yr old secondary forest in Rondônia, after short-term clearing, varied from 6.6 to $8.7 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ [69]. The estimate is also similar to a field estimate of $9.1 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for 4-12 yr old secondary forest after light use in Amazonas, Brazil, but larger than an estimate of $5.9 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for 15 to 30 yr old forest growing after six to 10 yr of land use as pasture [70]. It is slightly smaller than another estimate from Amazonas of $11.0 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for <1-14 yr old forest [71]. Repeated field measurements in that same area yielded biomass accumulation rates of 4.4 , 5.7 and $9.9 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for <1-5, 6-10 and 11-14 yr old secondary forest, respectively [72]. The estimate from this study falls between two estimates for early rates of biomass accumulation in humid tropical forest in general of $6.2 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ [68] and $10 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ [67].

The average biomass of lowland old-growth forest, of 185 Mg ha^{-1} dry weight, is smaller than field-based estimates in southwestern Amazônia of 276 to 409 Mg ha^{-1} dry weight [69, 73, 74]. Our estimate agrees, however, with recent Amazon-wide mapping results [75] that may better reflect spatial variation in climate and forest biomass. Our estimate is similar to the estimate in the Amazon-wide map of 200 Mg ha^{-1} for Open Terra Firme forest. That study found that transitional and seasonal forest in the southern and northwestern edges of the Amazon basin range from 100 to 200 Mg ha^{-1} . The present study area extends over an ecotone from nearly evergreen forest in the north to semi-evergreen forest with deciduous forest patches in the south. The field-based measurements appear to be concentrated in the more humid northern parts of the ecotone, which may partially explain the disparity. Also, in ensuring that field measurements were of stands without recent human disturbance, investigators may have inadvertently selected stands with larger trees and fewer canopy gaps, possibly biasing the field estimates toward larger values.

6 SUMMARY

In this study we first map secondary forest age with a new self-calibrating algorithm, TAMA, from an 11-image sequence extending from 1975 through 2003 for a study area in the state of Rondônia, Brazil. We then map major old-growth forest types and land cover with decision tree classification of the Landsat imagery. Third, we use coincident GLAS waveforms to 1) estimate an average biomass accumulation rate for post-agricultural secondary forest, substituting space for time, and 2) estimate the AGLB of the old-growth forest types.

The new algorithm, TAMA, maps forest age in lowland humid tropical landscapes. Based on the results of this study, TAMA has the potential to fully automate forest age mapping in lowland Amazônia. One advantage of TAMA is that it includes the HFM procedure, an automated way to map forest cover for finding the thresholds that it uses. Histogram fitting is common in medical and other image analysis [76], but it is new to land-cover mapping with Landsat imagery. A second advantage of TAMA is that it is self-calibrating, automatically finding classification thresholds specific to each date in an image sequence. Third, TAMA incorporates MSS imagery. A fourth advantage is that it does not use band or index differences or trends among images. Consequently, it does not require atmospherically corrected or temporally normalized scenes; scenes can also vary phenologically. This feature of TAMA points toward a way to map forest age in persistently cloudy regions without the need for cloud-minimizing image composites or mosaics. Fifth, unlike single-date classification of forest age, TAMA distinguishes lowland humid secondary forest older than 19 yr from old-growth forest in gentle terrain. The largest continuous tracts tropical forests on Earth extend over humid lowland forests. Whether the approach is effective in more complex, drier, or less forested landscapes, is unknown. Optimizing the method for these situations should occur in the context of image time series from several locations. Finally, we show here how the optical imagery of fine spatial resolution that is viewable on Google Earth provides a new source of reference data for land-cover remote sensing.

Many recent breakthroughs are allowing unprecedented monitoring of tropical forest resources, and we take advantage of some of them here. For one thing, all Landsat imagery in the U.S. archive became freely downloadable in December 2008. Second, GLAS has made available a global public source of continuous return lidar data. Third, elevation data at moderate spatial resolution are now publicly available for much of the globe. Fourth, the fine resolution imagery that is viewable on Google Earth is a new source of reference data for land-cover mapping.

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Appendix A. Example calculation of error statistics for a stratified random sample with the method and notation from [58]. That publication gives more detail on the method and includes variance formulas. The example is for one secondary forest age class from the data in Table 3, except for the calculation of overall accuracy for all classes. The Kappa coefficient of agreement was calculated from an error matrix in which the counts for each cell are replaced by the proportions of the sampled population that they represent ($\hat{p}_{ij}$).

Symbol	Description	Example for Age 13-17 yr ¹
i	Row subscript designating stratum i , the mapped class in the error matrix	$i = 8$
j	Column subscript designating the reference class in the error matrix	$j = 8$
n_{ij}	Number of sample population in row i and column j	32
$n_{i\bullet}$	Total number of sample population in row i	40
A	Total area of sampled population from the map	1,892,831
$A_{i\bullet}$	Total area of sampled population in class i	5,973
$p_{i\bullet}$	Proportion of sampled population mapped as class i $p_{i\bullet} = A_{i\bullet} / A$	$5,973 / 1,892,831 = 0.0032$
$\hat{p}_{ij}$	Proportion of the sampled population mapped as class i that is in reference class j $\hat{p}_{ij} = (n_{ij} / n_{i\bullet})(p_{i\bullet})$	$(32/40)(0.0032) = 0.0025$
$\hat{p}_{\bullet j}$	Proportion of sampled population in reference class j estimated from the mapped area $p_{\bullet j} = \sum_i \hat{p}_{ij}$	Sum over all rows in column 8 the values for $\hat{p}_{ij}$ $\sum_i \hat{p}_{ij} = 0.003$
$\hat{p}_{j=Y i=X}$	Users' accuracy for a given class. For $X=Y$, proportion of sampled population in reference class Y given that the mapped class is X $\hat{p}_{j=Y i=X} = \hat{p}_{ij} / p_{i\bullet}$	$0.0025 / 0.0032 \sim 0.8^1$
$\hat{p}_{i=X j=Y}$	Producers' accuracy for a given class. For $X=Y$, proportion of sampled population mapped as class X given that the reference class is Y $\hat{p}_{i=X j=Y} = \hat{p}_{ij} / p_{\bullet j}$	$0.0025 / 0.003 \sim 0.85^1$
$\hat{p}_{i=j}$	Overall accuracy for all classes. Proportion of sampled population where the map and reference class agree, i.e. the sum of all $\hat{p}_{ij}$ in the diagonal of the matrix (i.e. P_o) in Tables 3-4). $\hat{p}_{i=j} = \sum_i \hat{p}_{ij}$ for all cells where $i = j$	For accuracy over all classes: $\sum_i \hat{p}_{ij}$ for all cells where $i = j$ $= 0.88$

¹Values differ slightly from Table 4 due to rounding error.

References

- [1] E. Marin-Spiotta, R. Ostertag, and W. L. Silver, "Long-term patterns in reforestation of tropical pastures: plant community composition and aboveground biomass accumulation," *Ecol. Appl.* **17**, 828-839 (2007) [doi: 10.1890/06-1268].
- [2] I. M. Turner, Y. K. Wong, P. T. Chew, and A. b. Ibrahim, "Tree species richness in primary and old secondary tropical forest in Singapore," *Biodiversity Conservation* **6**, 537-543 (1997) [doi: 10.1023/A:1018381111842].
- [3] F. Q. Brearley, S. Prajadinata, P. S. Kidd, J. Proctor, and Suriantata, "Structure and floristics of an old secondary rain forest in Central Kalimantan, Indonesia, and a comparison with adjacent primary forest," *Forest Ecol. Manag.* **195**, 385-397 (2004) [doi: 10.1016/j.foreco.2004.02.048].
- [4] C. Gehring, M. Denich, and P. L. G. Vlek, "Resilience of secondary forest regrowth after slash-and-burn agriculture in central Amazonia," *J. Trop. Ecol.* **21**, 519-527 (2005) [doi: 10.1017/S0266467405002543].
- [5] E. H. Helmer, T. Brandeis, A. E. Lugo, and T. Kennaway, "Spatial controls on tropical forest age and implications for carbon storage and species diversity of the forests cleared for land development," *J. Geophys. Res. Biogeosci.* **113**, G02S04 (2008) [doi: 10.1029/2007JG000568].
- [6] J. Thompson, N. Brokaw, J. K. Zimmerman, R. B. Waide, E. Everham III, D. Lodge, C. Taylor, D. García-Montiel, and M. Fluet, "Land use history, environment and tree composition in a tropical forest," *Ecol. Appl.* **12**, 1344-1363 (2002) [doi: 10.1890/10510761(2002)012[1344:LUHEAT]2.0.CO;2].
- [7] R. Houghton, "Revised estimates of the annual net flux of carbon to the atmosphere from changes in land use and land management 1850 - 2000," *Tellus* **55B**, 378-390 (2003) [doi: 10.1034/j.1600-0889.2003.01450.x].
- [8] D. A. Clark, "Detecting tropical forests' responses to global climatic and atmospheric change: current challenges and a way forward," *Biotropica* **39**, 4-19 (2007) [doi: 10.1111/j.1744-7429.2006.00227.x].
- [9] D. Lawrence, "Biomass accumulation after 10-200 years of shifting cultivation in Bornean rain forest," *Ecology* **86**, 26-33 (2005) [doi: 10.1890/03-0564].
- [10] C. Uhl, R. Buschbackher, and A.S. Serrão, "Abandoned pastures in eastern Amazonia I. patterns of plant succession," *J. Ecol.* **75**, 663-681 (1988).
- [11] D. J. Zarin, E. A. Davidson, E. Brondizio, I. C. G. Vieira, T. Acute, T. Feldpausch, E. A. G. Schuur, R. Mesquita, E. Moran, P. Delamonica, M. J. Ducey, G. C. Hurtt, C. Salimon, and M. Denich, "Legacy of fire slows carbon accumulation in Amazonian forest regrowth," *Front. Ecol. Environ.* **3**, 365-369 (2005) [doi: 10.1890/15409295(2005)003[0365:LOFSCA]2.0.CO;2].
- [12] H. J. Zwally, R. Schutz, C. Bentley, J. Bufton, T. Herring, J. Minster, J. Spinhirne, and R. Thomas, "GLAS/ICESat L2 altimetry data (Digital media)," in (Boulder, CO, 2007).
- [13] M. A. Lefsky, M. Keller, Y. Pang, P. B. D. Camargo, and M. O. Hunter, "Revised method for forest canopy height estimation from Geoscience Altimeter System waveforms," *J. Appl. Remote Sens.* **1**, 1-18 (2007) [doi: 10.1117/1.2795724].
- [14] C. Song and C. E. Woodcock, "Monitoring forest succession with multitemporal Landsat images: factors of uncertainty," *IEEE Trans. Geosci. Rem. Sens.* **41**, 2557-2567 (2003) [doi: 10.1109/TGRS.2003.818367].
- [15] D. S. Alves, J. L. G. Pereira, and C. L. D. S. J. V. S. F. Yamaguchi, "Characterizing landscape changes in central Rondonia using Landsat TM imagery," *Int. J. Rem. Sens.* **20**, 2877-2882 (1999) [doi: 10.1080/014311699211859].

- [16] R. M. Lucas, M. Honzak, G. M. Foody, P. J. Curran, and C. Corves, "Characterizing tropical secondary forests using multi-temporal Landsat sensor imagery," *Int. J. Rem. Sens.* **14**, 3061-3067 (1993) [doi: 10.1080/01431169308904419].
- [17] R. F. Nelson, D. S. Kimes, W. A. Salas, and M. Routhier, "Secondary forest age and tropical forest biomass estimation using Thematic Mapper imagery," *Biosci.* **50**, 419-431 (2000) [doi: 10.1641/0006-3568(2000)050[0419:SFAATF]2.0.CO;2].
- [18] G. M. Foody, G. Palubinskas, R. Lucas, P. J. Curran, and M. Honzak, "Identifying terrestrial carbon sinks: classification of successional stages in regenerating tropical forest from Landsat TM data," *Rem. Sens. Environ.* **55**, 205-216 (1996) [doi: 10.1016/S0034-4257(95)00196-4].
- [19] I. Numata, J. V. Soares, D. A. Roberts, F. C. Leonidas, O. A. Chadwick, and G. T. Batista, "Relationships among soil fertility dynamics and remotely sensed measures across pasture chronosequences in Rondônia, Brazil," *Rem. Sens. Environ.* **87**, 446-455 (2003) [doi: 10.1016/j.rse.2002.07.001].
- [20] K. A. Budreski, R. H. Wynne, J. O. Browder and J. B. Campbell, "Comparison of segment and pixel-based non-parametric land cover classification in the Brazilian Amazon using multitemporal Landsat TM/ETM+ imagery," *Photogramm. Eng. Rem. Sens.* **73**, 813-827 (2007).
- [21] S. F. de Barros Ferraz, C. A. Vettorazzi, D. M. Theobald, and M. V. R. Ballester, "Landscape dynamics of Amazonian deforestation between 1984 and 2002 in central Rondonia, Brazil: assessment and future scenarios," *Forest Ecol. Manag.* **204**, 69-85 (2005) [doi: 10.1016/j.foreco.2004.07.073].
- [22] D. A. Roberts, I. Numata, K. Holmes, G. Batista, T. Krug, A. Monteiro, B. Powell, and O. A. Chadwick, "Large area mapping of land-cover change in Rondônia using multitemporal spectral mixture analysis and decision tree classifiers," *J. Geophys. Res. Atmos.* **107**, 8073 (2002) [doi: 10.1029/2001JD000374].
- [23] E. H. Helmer, W. B. Cohen, and S. Brown, "Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery," *Int. J. Rem. Sens.* **21**, 2163-2183 (2000) [doi: 10.1080/01431160050029495].
- [24] L. S. Guild, W. B. Cohen, and J. B. Kauffman, "Detection of deforestation and land conversion in Rondônia, Brazil using change detection techniques," *Int. J. Rem. Sens.* **25**, 731-750 (2004) [doi: 10.1080/01431160310001598935].
- [25] J. G. Masek, C. Huang, R. Wolfe, W. Cohen, F. Hall, J. Kutler, and P. Nelson, "North American forest disturbance mapped from a decadal Landsat record," *Rem. Sens. Environ.* **112**, 2914-2926 (2008) [doi: 10.1016/j.rse.2008.02.010].
- [26] M. A. Wulder, C. R. Butson, and J. C. White, "Cross-sensor change detection over a forested landscape: Options to enable continuity of medium spatial resolution measures," *Rem. Sens. Environ.* **112**, 796-809 (2008) [doi: 10.1016/j.rse.2007.06.013].
- [27] T. Nelson, H. G. Wison, B. Boots, and M. A. Wulder, "Use of ordinal conversion for radiometric normalization and change detection," *Int. J. Rem. Sens.* **26**, 535-541 (2005) [doi: 10.1080/01431160512331314065].
- [28] R. E. Kennedy, W. B. Cohen, and T. A. Schroeder, "Trajectory-based change detection for automated characterization of forest disturbance dynamics," *Rem. Sens. Environ.* **110**, 370-386 (2007) [doi: 10.1016/j.rse.2007.03.010].
- [29] J. R. Jensen, F. Qiu, and J. Minhe, "Predictive modelling of coniferous forest age using statistical and artificial neural network approaches applied to remote sensor data," *Int. J. Rem. Sens.* **20**, 2805-2822 (1999) [doi: 10.1080/014311699211804].
- [30] M. A. Wulder, R. S. Skakun, W. A. Kurz, and J. C. White, "Estimating time since forest harvest using segmented Landsat ETM+ imagery," *Rem. Sens. Environ.* **93**, 179-187 (2004) [doi: 10.1016/j.rse.2004.07.009].

- [31] M. K. Steininger, "Tropical secondary forest regrowth in the Amazon: age, area and change estimation with Thematic Mapper data," *Int. J. Rem. Sens.* **17**, 9-27 (1996) [doi: 10.1080/01431169608948984].
- [32] I. C. G. Vieira, A. S. de Almeida, E. A. Davidson, T. A. Stone, C. J. Reis de Carvalho, and J. B. Guerrero, "Classifying successional forests using Landsat spectral properties and ecological characteristics in eastern Amazonia," *Rem. Sens. Environ.* **87**, 470-481 (2003) [doi: 10.1016/j.rse.2002.09.002].
- [33] M. A. Lefsky, D. P. Turner, M. Guzy, and W. B. Cohen, "Combining lidar estimates of aboveground biomass and Landsat estimates of stand age for spatially extensive validation of modeled forest productivity," *Rem. Sens. Environ.* **95**, 549-558 (2005) [doi: 10.1016/j.rse.2004.12.022].
- [34] J. G. Masek and G. J. Collatz, "Estimating forest carbon fluxes in a disturbed southeastern landscape: Integration of remote sensing, forest inventory, and biogeochemical modeling," *J. Geophys. Res.* **111**, G01006 (2006) [doi: 10.1029/2005JG000062].
- [35] T. Kennaway and E. H. Helmer, "The forest types and ages cleared for land development in Puerto Rico," *GISci. Rem. Sens.* **44**, 356-382 (2007) [doi: 10.2747/1548-1603.44.4.356].
- [36] G. Carvalho, P. Moutinho, D. Nepstad, L. Mattos, and M. Santilli, "An amazon perspective on the forest-climate connection: opportunity for climate mitigation, conservation and development?" *Environ. Dev. Sustain.* **6**, 163-174 (2004) [doi: 10.1023/B:ENVI.0000003635.86980.c0].
- [37] A. I. Hirsch, W. S. Little, R. A. Houghton, N. A. Scott, and J. D. White, "The net carbon flux due to deforestation and forest re-growth in the Brazilian Amazon: analysis using a process-based model," *Global Change Biol.* **10**, 908-924 (2004) [doi: 10.1111/j.15298817.2003.00765.x].
- [38] R. A. Houghton, D. L. Skole, C. A. Nobre, J. L. Hackler, K. T. Lawrence, and W. H. Chomentowski, "Annual fluxes of carbon from deforestation and regrowth in the Brazilian Amazon," *Nature* **403**, 301-304 (2000) [doi: 10.1038/35002062].
- [39] N. Ramankutty, H. K. Gibbs, F. Achard, R. DeFries, J. A. Foley, and R. A. Houghton, "Challenges to estimating carbon emissions from tropical deforestation," *Global Change Biol.* **13**, 51-66 (2007) [doi: 10.1111/j.1365-2486.2006.01272.x].
- [40] J. O. Browder, M. A. Pedlowski, and P. M. Summers, "Land use patterns in the Brazilian Amazon: comparative farm-level evidence from Rondônia," *Hum. Ecol.* **32**, 197-224 (2004) [doi: 10.1023/B:HUEC.0000019763.73998.c9].
- [41] J. M. B. Carreiras, J. M. C. Pereira, M. L. Campagnolo, and Y. E. Shimabukuro, "Assessing the extent of agriculture/pasture and secondary succession forest in the Brazilian Legal Amazon using SPOT VEGETATION data," *Rem. Sens. Environ.* **101**, 283-298 (2006) [doi: 10.1016/j.rse.2005.12.017].
- [42] G. P. Asner, D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller, and J. N. Silva, "Selective logging in the Brazilian Amazon," *Science* **310**, 480-482 (2005) [doi: 10.1126/science.1118051].
- [43] J. C. Brown, M. Koeppe, B. Colse, and K. P. Price, "Soybean production and conversion of tropical forest in the Brazilian Amazon: the case of Vilhena, Rondônia," *Ambio* **34**, 462-469 (2005) [doi: 10.1639/0044-7447(2005)034[0462:SPACOT]2.0.CO;2].
- [44] A. D. Culf, G. Fisch, J. Lean, and J. Polcher, "A comparison of Amazonian climate data with general circulation model simulations," *J. Clim.* **11**, 2674-2773 (1998) [doi: 10.1175/1520-0442(1998)011<2764:ACOACD>2.0.CO;2].
- [45] F. H. Beinroth, "Relationship between U.S. soil taxonomy, the Brazilian soil classification system, and FAO/UNESCO soil units," in *Soil Management in*

- Tropical America*, pp. 92-108, E. Bornemisza and A. Alvarado, Eds., Cali, Columbia,(1975).
- [46] EMPRABA, "Mapa de solos do Brazil, Empresa Brasileira de Investigações Agropecuárias," in *Landscape Ecology as a Tool for Sustainable Development in Latin America*, Sioux Falls, SD (1981).
 - [47] E. P. Crist and R. C. Cicone, "A physically-based transformation of Thematic Mapper data - the TM tasseled cap," *IEEE Trans. Geosci. Rem. Sens.* **22**, 256-263 (1984) [doi: 10.1109/TGRS.1984.350619].
 - [48] E. P. Crist, R. Laurin, and R. C. Cicone, "Vegetation and soils information contained in transformed Thematic Mapper data," *Int. Geosci. Rem. Sens. Symp.*, 1465-1470 (1986).
 - [49] C. Huang, B. Wylie, C. Homer, L. Yang and G. Zylstra, "Derivation of a Tasseled Cap transformation based on Landsat 7 at-satellite reflectance," *Int. J. Rem. Sens.* **23**, 1741-1748 (2002) [doi: 10.1080/01431160110106113].
 - [50] G. P. Asner, D. E. Knapp, A. N. Cooper, M. M. C. Bustamante, and L. P. Olander, "Ecosystem structure throughout the Brazilian Amazon from Landsat observations and automated spectral unmixing," *Earth Interact.* **9**, 1-31 (2005) [doi: 10.1175/EI134.1].
 - [51] S. P. Healey, W. B. Cohen, Y. Zhiqiang, and O. N. Krankina, "Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection," *Rem. Sens. Environ.* **97**, 301-310 (2005) [doi: 10.1016/j.rse.2005.05.009].
 - [52] M. Fiorella and W. J. Ripple, "Determining successional stage of temperate coniferous forests with Landsat satellite data," *Photogramm. Eng. Rem. Sens.* **59**, 239-246 (1993).
 - [53] A. Aguilar, "Remote Sensing of Forest Regeneration in Highland Tropical Forests," *GISci. Rem. Sens.* **42**, 66-79 (2005) [doi: 10.2747/1548-1603.42.1.66].
 - [54] E.H. Helmer, T.A. Kennaway, D.H. Pedreros, M.L. Clark, H. Marciano-Vega, L.L. Tieszen, T.R. Ruzyski, S. Schill and C.M.S. Carrington, "Land cover and forest formation distributions for St. Kitts, Nevis, St. Eustatius, Grenada and Barbados from decision tree classification of cloud-cleared satellite imagery," *Caribb. J. Sci.* **44**, 175-198 (2008)
 - [55] E.H. Helmer and B. Ruefenacht, "A comparison of radiometric normalization methods when filling cloud gaps in Landsat imagery," *Can. J. Rem. Sens.* **33**, 325-340 (2007)
 - [56] T.G. Farr and M. Kobrick, "Shuttle Radar Topography Mission produces a wealth of data," *Trans. Am. Geophys. Union* **81**, 583-585 (2000) [doi:10.1029/2005RG000183].
 - [57] B. Ruefenacht, "CART Tools," in, RSAC Imagine Module, Salt Lake City, UT (2007).
 - [58] R. L. Czaplewski, "Accuracy assessment of maps of forest condition, statistical design and methodological considerations," in *Remote Sensing of Forest Environments : Concepts and Case Studies*, pp. 115-140, M. A. Wulder and S. E. Franklin, Eds., Norwell, MA (2003).
 - [59] J. Cohen, "A coefficient of agreement for nominal scales," *Educ. Psychol. Meas.* **20**, 37-46 (1960) [doi: 10.1177/001316446002000104].
 - [60] S. A. Sader and J. C. Winne, "RGB-NDVI colour composites for visualizing forest change dynamics," *Int. J. Rem. Sens.* **13**, 3055-3067 (1992) [doi:10.1080/01431169208904102]
 - [61] J. Landis and G. Koch, "The measurement of observer agreement for categorical data," *Biometrics* **33**, 159-174 (1977) [doi:10.2307/2529310]

- [62] F. Gao, J. G. Masek, M. Schwaller, and F. Hall, "On the blending of the Landsat and MODIS surface reflectance: predicting daily Landsat," *IEEE Trans. Geosci. Rem. Sens.* **44**, 2207-2208 (2006) [doi: 10.1109/TGRS.2006.872081].
- [63] D. P. Roy, J. Ju, P. Lewis, C. Schaaf, F. Gao, M. Hansen, and E. Lindquist, "Multitemporal MODIS-Landsat data fusion for relative radiometric normalization, gap filling, and prediction of Landsat data," *Rem. Sens. Environ.* **112**, 3112-3130 (2008) [doi:10.1016/j.rse.2008.03.009].
- [64] A. K. Skidmore, "An expert system classifies eucalypt forest types using thematic mapper data and a digital terrain model," *Photogramm. Eng. Rem. Sens.* **55**, 1449-1464 (1989).
- [65] J. Carreiras, J. M. C. Pereira, and Y .E. Shimabukuro, "Land-cover mapping in the Brazilian Amazon using SPOT-4 Vegetation data and machine learning methods," *Photogramm. Eng. Rem. Sens.* **72**, 897-910 (2006).
- [66] M. R. Guariguata and R. Ostertag, "Neotropical secondary forest succession: changes in structural and functional characteristics," *Forest Ecol. Manag.* **148**, 185-206 (2001) [doi: 10.1016/S0378-1127(00)00535-1].
- [67] S. Brown and A. E. Lugo, "Tropical secondary forests," *J. Trop. Ecol.* **6**, 1-32 (1990).
- [68] W. L. Silver, R. Ostertag, and A.E. Lugo, "The potential for carbon sequestration through reforestation of abandoned tropical agricultural lands," *Restor. Ecol.* **8**, 394-407 (2000) [doi: 10.1046/j.1526-100x.2000.80054.x].
- [69] D. Alves, J. V. Soares, S. Amaral, E. Mello, S. Almeida, O. F. Da Silva, and A. Silveira, "Biomass of primary and secondary vegetation in Rondônia, Western Brazilian Amazon," *Global Change Biol.* **3**, 451-461 (1997) [doi:10.1046/j.13652486.1997.00081.x].
- [70] M. K. Steininger, "Satellite estimation of tropical secondary forest above-ground biomass: data from Brazil and Bolivia," *Int. J. Rem. Sens.* **21**, 1139-1157 (2000) [doi:10.1080/014311600210119].
- [71] T. R. Feldpausch, "Carbon and nutrient accumulation in secondary forests regenerating on pastures in Central Amazonia," *Ecol. Appl.* **14**, S164-S176 (2004)[doi: 10.1890/01-6015].
- [72] T. R. Feldpausch, C. D. C. Prates-Clark, E. C. M. Fernandes, and S. J. Riha, "Secondary forest growth deviation from chronosequence predictions in central Amazonia," *Global Change Biol.* **13**, 967-979 (2007) [doi: 10.1111/j.1365-2486.2007.01344.x].
- [73] D. L. Cummings, J. Boone Kauffman, D. A. Perry, and R. Flint Hughes, "Aboveground biomass and structure of rainforests in the southwestern Brazilian Amazon," *Forest Ecol. Manag.* **163**, 293-307 (2002) [doi: 10.1016/S0378-1127(01)00587-4].
- [74] T. R. Feldpausch, A. J. McDonald, C. A. M. Passos, J. Lehmann , and S. J. Riha, "Biomass, harvestable area, and forest structure estimated from commercial timber inventoriesand remotely sensed imagery in southern Amazonia," *Forest Ecol. Manag.* **233**, 121132 (2006) [doi: 10.1016/j.foreco.2006.06.016].
- [75] S. S. Saatchi, R. Houghton, R. C. Dos Santos Alvala, J. V. Soares, and Y. Yu, "Distribution of aboveground live biomass in the Amazon basin," *Global Change Biol.* **13**, 816-837 (2007) [doi: 10.1111/j.1365-2486.2007.01323.x].
- [76] J. Kay, "The EM algorithm in medical imaging," *Stat. Meth. Med. Res.* **6**, 55-75 (1997)[doi: 10.1177/096228029700600105].