# Biomass accumulation rates of Amazônian secondary forest and biomass of old-growth forests from Landsat and GLAS

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## Abstract:

With a new method, the *Threshold Age Mapping Algorithm (TAMA)* [1], we mapped forest age from a Landsat image time series over Rondônia, Brazil. Combining mapped forest age with aboveground live biomass (AGLB) estimated from coincident GLAS waveforms yielded a regional biomass accumulation rate in secondary forest (See Summary Figure). We also mapped old-growth forest types and estimated their AGLB with GLAS.

## Introduction:

Major uncertainties in the global forest carbon budget include the biomass of tropical forests that are cleared and the biomass accumulation rates of secondary forest [2]. Maintaining reserve networks of old-growth tropical forests also require automated ways to map forest age and disturbance.

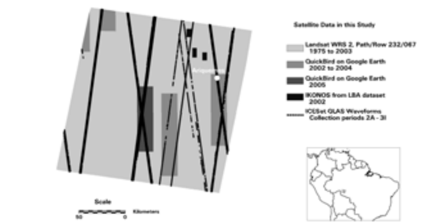


Figure 1.Study area, reference data, and GLAS tracks.

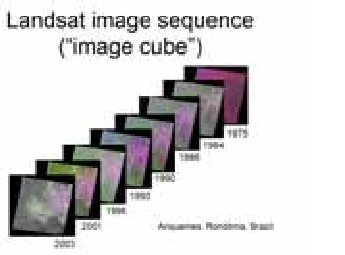



Figure 2. Landsat image time series.

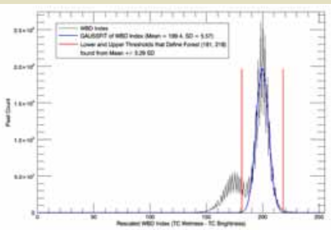


Figure 3. The *Histogram Fitting for Mapping* (HFM) procedure.

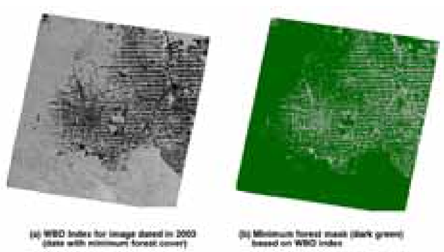



Figure 4. Grey-scale image of the Wetness-Brightness Difference Index (WBDI) and the forest mask that results from applying HFM to WBDI.

## Methods:

With the new *Threshold Age Mapping Algorithm (TAMA)* [1], we mapped the age of lowland forests from a Landsat image time series for a southwestern Amazon study area (Figs. 1-2). TAMA is self-calibrated and was automatic for the study area.

TAMA first uses *Histogram Fitting for Mapping* (HFM) to map forest vs. non-forest in the image with about the minimum forest cover. HFM is a novel way to automatically map forest vs. non-forest (Figs. 3-4 and Table 1). TAMA then uses the minimum forest mask to find image-specific minimum wetness and maximum greenness thresholds that define forest and secondary forest in each date. It combines these results to map forest age (Fig. 5 and Table 1). Pixels that are never non-forest or secondary forest are in the oldest class, which is mostly old-growth forest in this region.

We also mapped other old-growth forest types with decision trees and elevation data (Fig. 6). For more on forest formation mapping in complex tropical landscapes with decision tree classification of Landsat imagery, see [3-5].

Accuracy assessment used Google Earth (Fig. 7), demonstrating for the first time its usefulness as reference data for land-cover remote sensing.

Forest height was estimated from GLAS waveforms [6]. Next, forest AGLB was estimated from GLAS-measured forest height as
*AGLB* (Mg ha-1) = -8.84 + 10.23 *GLAS Height* (M. Lefsky, unpublished data).

Waveforms surrounded by ≥ 85% secondary forest in a 150-m window were used to estimate biomass accumulation rate of secondary forest (Fig. 8). To estimate AGLB of most old-growth forest classes, we used waveforms surrounded by 90-100% of the same class in a 210-m window (Table 2).

## Results and Discussion:

TAMA estimated forest age with an overall accuracy of 88% and a Kappa coefficient of agreement of 0.62. The average biomass accumulation rate of 8.4 Mg ha$^{-1}$ yr$^{-1}$ for lowland forests averaging 3 to 16 yr old (Fig. 8) agrees well with ground based estimates from Rondônia. The AGLB of the old-growth forest classes significantly differed from each other. The average biomass of lowland seasonal to semi-evergreen old-growth forest, of 185 Mg ha$^{-1}$ dry weight (Table 2), is smaller, however, than field estimates in the area, but it agrees with map-based estimates from other studies.

## Conclusions:

Forest age mapping with TAMA, and AGLB estimates from GLAS, allow estimation of regional rates of secondary forest biomass accumulation.

- The systematic distribution of GLAS waveforms means that forest biomass accumulation rates estimated in this way can be considered weighted averages that incorporate the different regrowth rates of secondary forest that stem from varied disturbance histories.
- TAMA, a self-calibrating forest age mapping algorithm, does not use band or index differences or trends among image dates, consequently:
  - TAMA requires neither atmospheric correction, image normalization through time, nor same-season imagery; and
  - TAMA makes cloud-minimized image composites or mosaics unnecessary, solving a recalcitrant problem in forest remote sensing.
- Unlike other automated algorithms, TAMA does not assume that forest age equals time since disturbance; this assumption would be invalid for many tropical landscapes.
- Google Earth will be an important new source of reference data for remote sensing of land-cover mapping.

Photo: T. J. Brandeis

Table 1. The Threshold Age Mapping Algorithm (TAMA) has five steps.

| Step and Description |
|---|
| 1 Create the minimum forest mask with *Histogram Fitting for Mapping* (HFM) [illegible] |
| 2 Find date-specific thresholds for forest and mature forest [illegible] |
| 3 [illegible] |
| 4 [illegible] |
| 5 Smooth results with a 3x3 pixel majority filter |

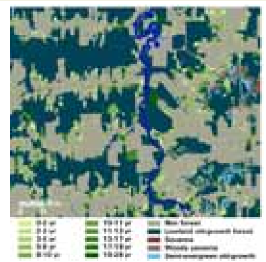


Figure 5. Lowland forest age and hill forest types (forested wetlands shown in Fig. 6).

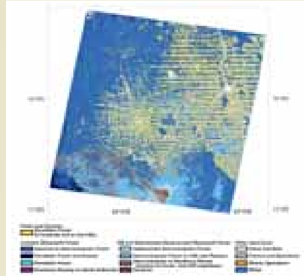


Figure 6. Old-growth forest types and land cover.

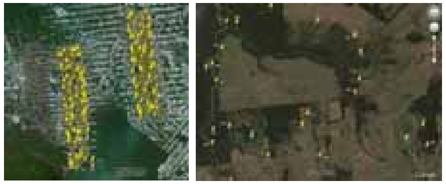


Figure 7. Using Google Earth for accuracy assessment data.

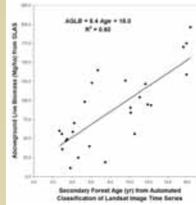
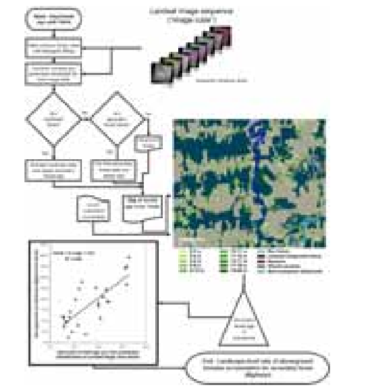



Figure 8. Secondary forest productivity.

Table 2. [illegible]

| Old-growth forest type | Mean AGLB (Mg/ha) | SE AGLB (Mg/ha) | N |
|---|---|---|---|
| [illegible] | [illegible] | [illegible] | [illegible] |

*AGLB = Aboveground live forest biomass (dry weight)



Summary Figure: Estimating secondary forest productivity.

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