



## ABSTRACT

As part of an integrated study aimed at modeling and mapping forest regrowth potential for the Amazon region, we conducted extensive field measurements of secondary forest structure in three areas across Amazonia and collected time series of remote sensing data from these same areas. We present results linking these field measurements and a time series of Landsat reflectance data. We compare the rates of succession of the stands by examining the stand level trajectories of reflectance over time. We also explore the feasibility of establishing a structural index created from the Landsat observations that is related to a combination of field-measured structural attributes. The thick and variable atmospheric conditions complicate the creation of a standard time series of reflectances from the Landsat data.

## REMOTE SENSING DATA

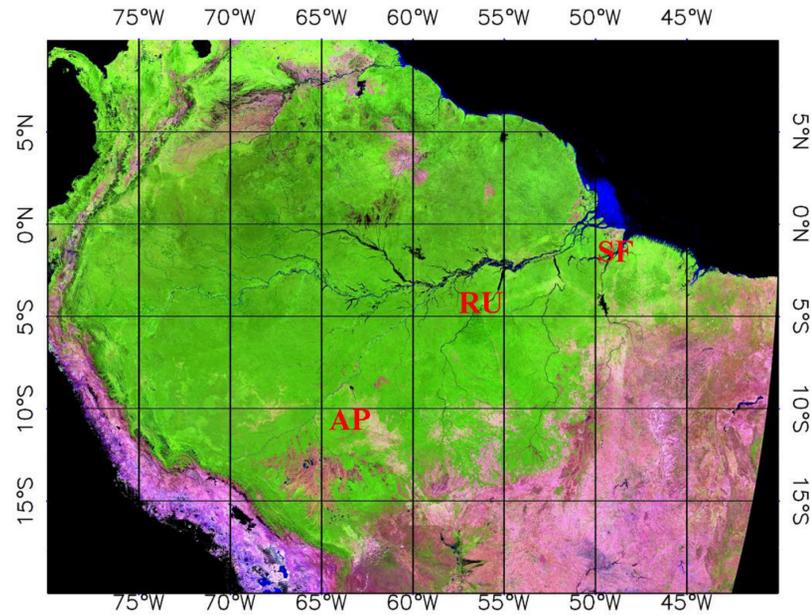


Figure 1: Composite of MODIS reflectances (R-SWIR, G-NIR, B-RED) taken in 2001 showing the northern part of South America. The three field campaigns are labeled in red (Alto Paraiso, Rondonia (AP), Rurópolis, Para (RU), and Sao Francisco, Para (SF)).

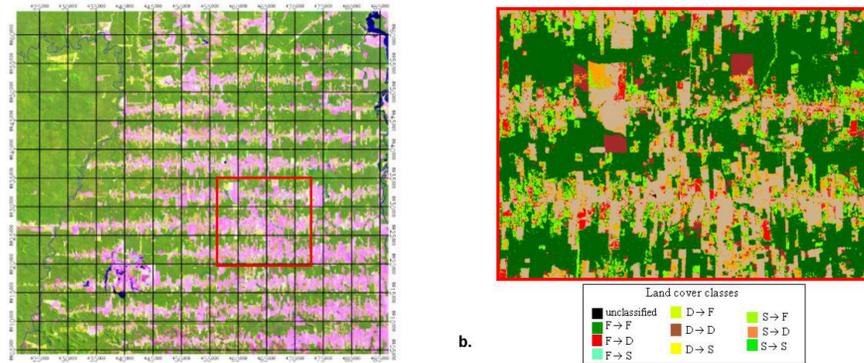


Figure 2: Landsat data from Rondonia, highlighting the Alto Paraiso study sites. The 30m reflectance data (a. R-SWIR, G-NIR, B-RED) are useful for classifying landcover. b. shows land cover change in the area near Alto Paraiso between 1999 and 2000. The change is estimated by classifying the 1999 and 2000 images separately, then overlaying them.

Atmospheric normalization is a critical challenge in developing time series of reflectances and spectral indices. We use an empirical process to convert TOA radiance to surface reflectance. Initially, we derived 2001 surface reflectance at the ETM scale using ETM radiance data and MODIS surface reflectance acquired the same day. Then, using the ETM 2001 image as a base, we normalize all other images in the time series band by band. The normalization is done using 295 forest stands near the field sites that were selected because a) they appear to be mature forest in the 1988 image and remain forest throughout our study and, b) they have low within stand spectral variance. This atmospheric correction process removes most of the “noise” generated by variability in the atmosphere, but not all of it. As Figure 6 shows, reflectances from areas known to be forest still vary significantly, especially in the visible wavelengths.

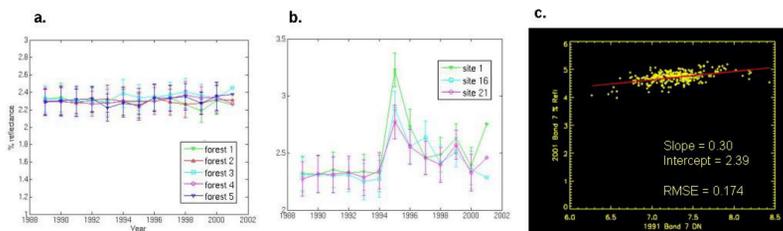


Figure 3: Time series of reflectance in the RED band for five mature forest stands (a), and three young secondary stands (b) after atmospheric correction. The error bars are created using the RMSE from the linear model (c).

## FIELD DATA COLLECTION

We collected structure field data from 36 secondary forest stands in two levels of detail, high intensity/ extensive detail (category A) and moderate intensity/moderate detail (category B). The following figures illustrate data collected in one Category A stand, a 20-year old capoeira located in Para. From left to right: stem map of all trees >5cm DBH in a 60x60m area (snags shown in red); crown map of trees >5cm DBH (solid crowns measured; dotted crowns estimated by regression/imputation); and vertical crown profiles. Field data also include spatially explicit density and size measures on trees <5cm DBH, vines and lianas, herbaceous layer vegetation, and downed woody material.

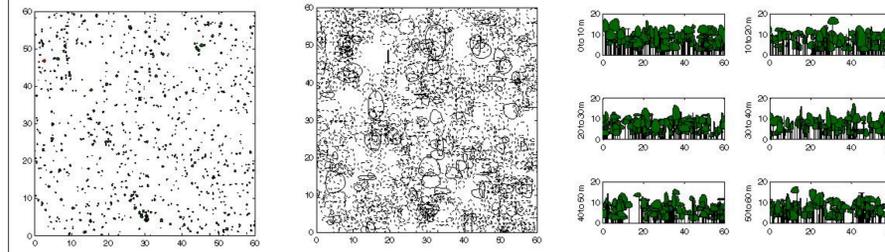


Figure 4

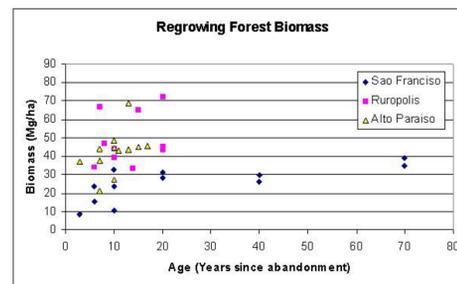


Figure 5: Stand age vs. accumulated above ground biomass as measured in the field. While it is clear that biomass generally increases with stand age, other factors have a significant influence on the rate of biomass accumulation after deforestation and abandonment.

## DEVELOPING RELATIONSHIPS BETWEEN OPTICAL REMOTE SENSING DATA AND FOREST STRUCTURE

**Approach:** While previous studies indicate that several successional age classes can be mapped, we are using a different approach by developing coupled estimates of successional stage and regrowth rate. This enables us to use remote sensing technologies to assess not only the current stage of a successional stand but also the dynamics and future of regional biomass and carbon accumulation. The basis of our approach is the combination of multi-temporal land cover change data with multi-temporal spectral trajectories. Based on the multi-temporal analysis of annual TM data from late 1980s to 2003 we have mapped land use patterns, secondary growth persistence, and secondary growth stand age. Rates of succession are mapped using several multi-temporal spectral indices to enhance sensitivity at different stages of succession.

**MODEL:** We used a nonlinear regression technique (i.e. artificial neural network) to identify relationships between the 2001 remote sensing data and field measure forest structure data. By employing a stepwise regression technique coupled with an n-fold validation, we identified the optimal model as defined by the lowest out-of-sample error. This model uses as input the GRN, NIR, and SWIR1 bands together with the standard deviation of the NIR band as input to predict three structural variables: **trees per hectare**, **standard deviation of dbh**, and **crown competition factor**.

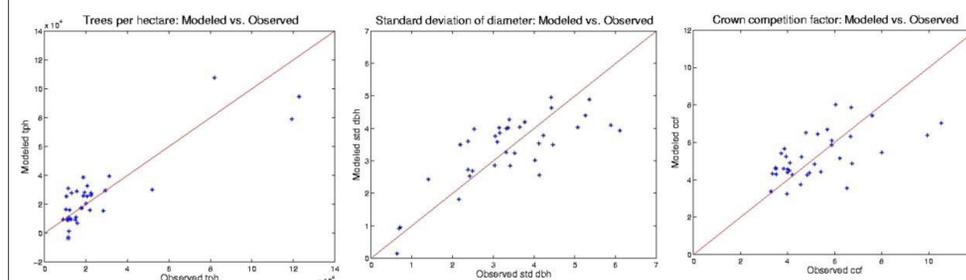


Figure 6: The multiple nonlinear regression model produces out-of-sample estimates (i.e. n-fold validation) of structural variables that measure up well with field observed structure. The rmse and r2 metrics for the three structural variables are as follows:

	R <sup>2</sup>	RMSE
tph	0.75	13268
sdd	0.58	0.86
ccf	0.34	1.42

## MULTITEMPORAL ANALYSIS

We extended our single date analysis to a 12 image time series of atmospherically corrected reflectances covering the period between 1988 and 2001 for the area around the city of Rurópolis, Para. By extending the secondary forest structure model fit to the 2001 remote sensing data, we estimated structural characteristics over time for 8091 secondary forest plots of at least one hectare in the region (Figure 6, red pixels). These secondary forest plots were chosen using the classified 12 layer land cover transition matrix. We analyzed plots that were classified as secondary forest for at least five consecutive years. We examined the predicted structural characteristics against time since abandonment as well as against time since original clearing (TSOC).

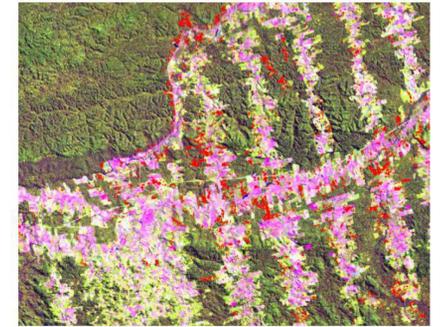


Figure 7: False color composite of the Rurópolis, Para region overlaid with the secondary forest stands of at least one hectare (red).

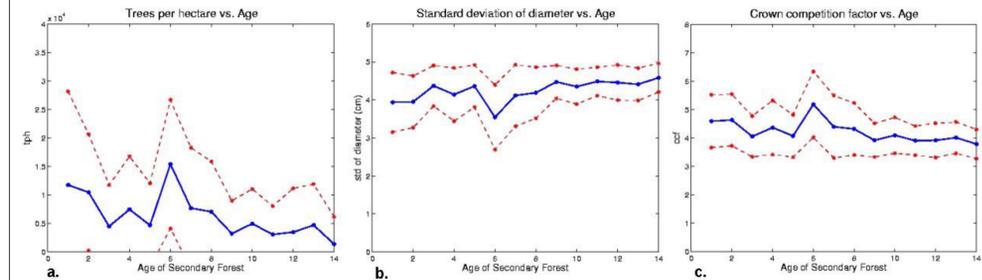


Figure 8: Plots of mean structural attributes versus the age of the secondary forest, with plus and minus one standard deviation. We see that, as the secondary forest ages, the number of trees per hectare generally decreases (a) and the standard deviation of the dbh generally increases (b). Also, the stand's crown competition factor decrease with age (c). While these results are expected, we also note the considerable amount of noise associated with the means. These high standard deviations suggest that secondary forest age isn't the only factor controlling our estimates of structure.

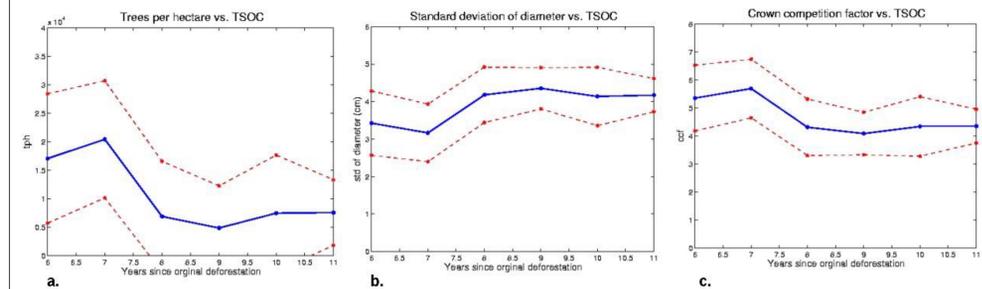


Figure 9: Other possible factors controlling secondary forest structural development (and our estimates of it) include intensity of use prior to abandonment, presence or absence of burning, edaphic conditions, climate conditions, and residual cloud contamination in the remote sensing data. We use time since original clearing (TSOC) as a proxy for intensity of use, arguing that a plot of secondary forest that was originally cleared 10 years ago is likely to have undergone more intense use than a plot of the same age that was originally cleared 5 years ago. The three plots show the estimates of structure for all 6 year old secondary forest plots against the years since original deforestation. We see slight trends masked by large uncertainties. Trees per hectare (a) and crown competition factor (c) decrease with our proxy for more intense use, while standard deviation of dbh (b) increases with increasing intensity of use.

## SUMMARY

We present results from a project that combines an intense field campaign with an innovative method of modeling secondary forest structure to identify controlling factors in the regeneration of these forests. Non-linear regression using neural networks allows us to more accurately capture the relationship between optical remote sensing data and field measured forest structure. The land cover transition histories assembled from multi-year stacks of classified Landsat imagery and their associated reflectance data provide a unique tool for following the regeneration pathways of thousands of secondary forest stands. This study provides more evidence that structure doesn't change uniformly with age; that is, factors other than just time since abandonment determine the structural properties of secondary forests. Some of these factors include edaphic conditions, climate, intensity of use, and presence of fire (Brown et al. 1992). Furthermore, this study establishes a method of mapping secondary forest structure over large regions. By adding information layers related to the controlling factors (i.e. soil maps, precipitation data, etc.), we will quantify the effect of these factors on secondary forest structure during regeneration.

## ACKNOWLEDGMENTS

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