Forest Resources Assessment Working Paper 161

CASE STUDIES ON MEASURING AND ASSESSING FOREST DEGRADATION

INTEGRATING FOREST TRANSECTS AND REMOTE SENSING DATA TO QUANTIFY CARBON LOSS DUE TO FOREST DEGRADATION IN THE BRAZILIAN AMAZON

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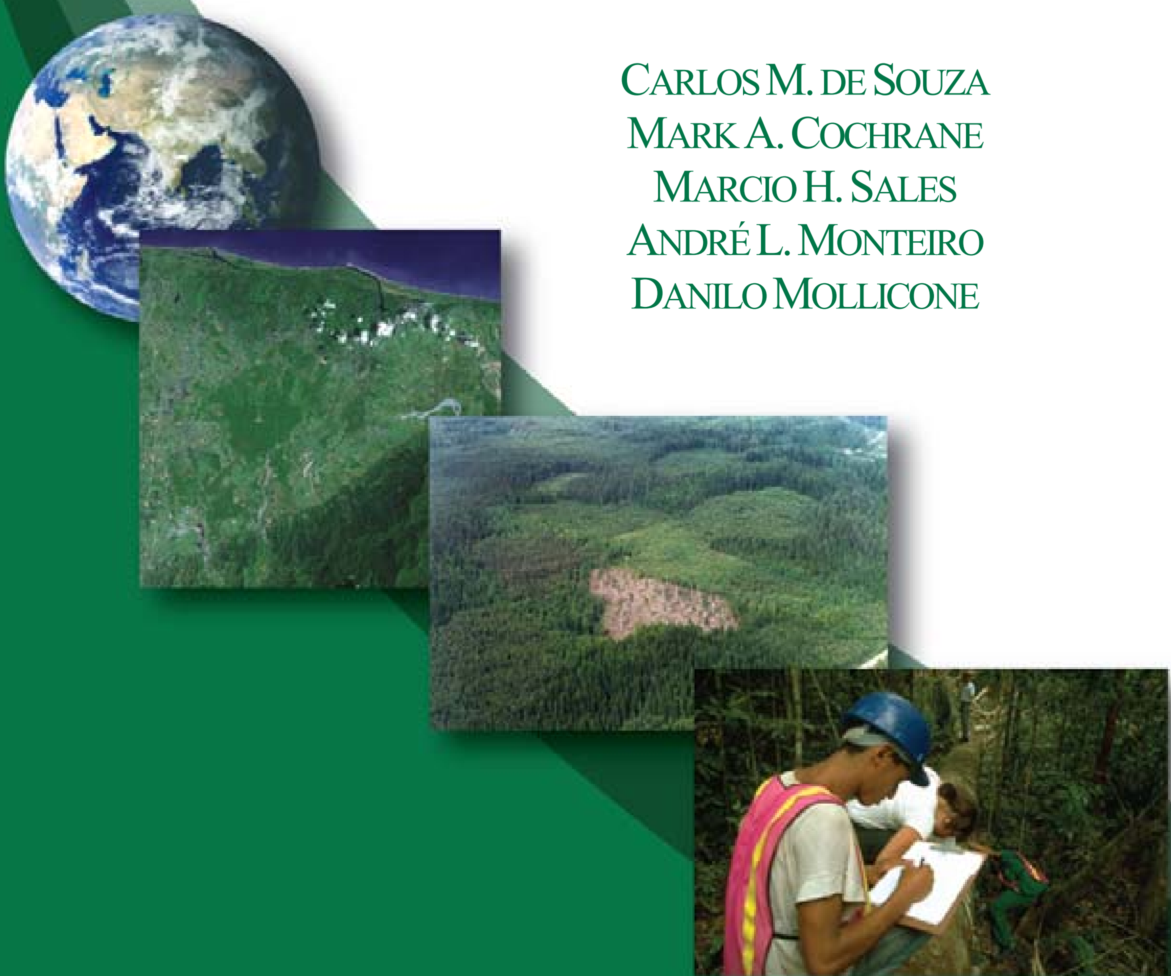

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Sustainably managed forests have multiple environmental and socio-economic functions which are important at the global, national and local scales, and they play a vital part in sustainable development. Reliable and up-to-date information on the state of forest resources - not only on area and area change, but also on such variables as growing stock, wood and non-wood products, carbon, protected areas, use of forests for recreation and other services, biological diversity and forests' contribution to national economies - is crucial to support decision-making for policies and programmes in forestry and sustainable development at all levels.

Under the umbrella of the Global Forest Resources Assessment 2010 (FRA 2010) and together with members of the Collaborative Partnership on Forests (CPF) and other partners, FAO has initiated a special study to identify the elements of forest degradation and the best practices for assessing them. The objectives of the initiative are to help strengthen the capacity of countries to assess, monitor and report on forest degradation by:

- Identifying specific elements and indicators of forest degradation and degraded forests;
- Classifying elements and harmonizing definitions;
- Identifying and describing existing and promising assessment methodologies;
- Developing assessment tools and guidelines

Expected outcomes and benefits of the initiative include:

- Better understanding of the concept and components of forest degradation;
- An analysis of definitions of forest degradation and associated terms;
- Guidelines and effective, cost-efficient tools and techniques to help assess and monitor forest degradation; and
- Enhanced ability to meet current and future reporting requirements on forest degradation.

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Case Studies on Measuring and Assessing Forest Degradation

Integrating Forest Transects and Remote Sensing data to Quantify Carbon Loss due to Forest Degradation in the Brazilian Amazon

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Abstract

Characterizing and quantifying carbon stocks due to forest degradation is one of the greatest challenges to advancing in climate change negotiation on carbon payments through the Reducing Emissions from Deforestation and Degradation (REDD) proposal. Defining forest degradation, in this context is fundamental, since this process can mean many things to different stakeholders. For the purpose of climate change negotiation, forest degradation must be defined in terms of loss of carbon stocks, even though there are other forest ecological and biophysical processes that can be degraded, such as biodiversity content, soil erosion and compaction, tree species extinction and changes in the forest microclimate and albedo. In the Brazilian Amazon, forest degradation is mainly caused by selective logging, fires and forest fragmentation. These degradation processes operate synergistically and recurrently, which can lead to even more drastic loss of original carbon stocks from the original forest. In the past ten years, our research team has been involved in projects to characterize forest degradation through forest inventories and remote sensing analysis. We have developed a methodology for assessing forest degradation based on field transects that allows us to estimate the intensity of forest degradation based on the loss of forest biomass stocks, forest canopy damage and soil disturbance, and as well as carbon sequestration due to regeneration of degraded forests. Additionally, we have developed a remote sensing methodology to detect and map the extent of forest degradation based on canopy damage and small clearings created by logging infrastructure, such as roads and log landings. These field and remote sensing methods have been applied extensively throughout the Brazilian Amazon, covering different logging, forest fragmentation and fire intensities. In this case study, we demonstrate how these methods have been applied and show new results of our recent efforts to integrate field and remote sensing data to improve the characterization and quantification of net carbon stocks associated with forest degradation in the Brazilian Amazon. Our results hold promise for contributing towards REDD negotiation, given that they can provide accurate estimations of carbon stock changes due to forest degradation and reliable information for defining baselines, as well as improving monitoring, reporting and verification (MRV) of REDD projects.

Keywords: Selective logging, forest burning, forest fragmentation, remote sensing, biomass, Amazon.

Running head: Monitoring Forest Degradation
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1. Introduction

Tropical deforestation accounts for 6-28% of annual global anthropogenic emissions (Achard et al., 2002; Houghton et al. 2000) and future deforestation projections indicate that this level of carbon emissions will continue until 2100 (Sitch et al., 2005). Compensation for reduced emissions from deforestation and degradation (REDD) has received increasing attention in international climate change negotiations (Santilli et al., 2005; Shalamadinger et al., 2005) because avoided deforestation can reduce carbon emissions in a cost-effective and timely matter and help keep global climate change within tolerable limits (Santilli et al., 2003). There are also many co-benefits of keeping forests standing such as maintaining biodiversity, hydrological cycle, protecting soil against erosion, and providing medicine, food, and wood (Foley et al. 2007). However, technical challenges and uncertainties must be overcome to improve carbon accounting and support REDD compensation programs (Persson and Azar, 2007). Quantifying forest degradation is one of these challenges. In this paper, we show how forest degradation caused by selective logging and forest fires in the Brazilian Amazon is being characterized in terms of carbon loss by using forest transects, and detected and monitored using satellite images.

Forest degradation is a type of land modification in which the original land cover structure and composition are temporarily or permanently changed, but not replaced by other types of land cover (Lambin, 1999). Forest degradation became widespread in the Amazon with the boom of logging activity in the mid 1980's (Nepstad et al., 1999). Selective logging kills or damages 10-46% of living biomass in harvested forests (Uhl and Vieira, 1989; Verissimo et al., 1992), and directly affects 15-22% of ground area (Johns et al., 1996). Extensive road networks created by loggers also encourage unplanned development and increase deforestation rates (Verissimo et al., 1995). Logging impacts 10,000-20,000 km^2/year in the Brazilian Amazon (Asner et al., 2005; Nepstad et al., 1999; Matricardi et al., 2007), roughly equal to the area of annual deforestation. The area affected by forest fires can be much higher (Nepstad et al., 1999). Forest fires substantially increase the extent and intensity of forest degradation (Cochrane and Schulze, 1999) and recurrent fires and predatory logging interact synergistically to more severely degrade forests (Cochrane et al. 1999; Gerwing 2002).

In addition, deforestation fragments the landscape and creates more edges between forests and non-forested areas (Laurance et al., 2000). By 1988, the forest area at risk of edge effect (< 1 km from the forest edge) in the Amazon was about 150% larger than the total area deforested (Skole and Tucker, 1993). Forest edges are affected by solar radiation, wind (Laurance et al. 2000) and agricultural fires (Cochrane 2001), potentially causing extensive mortality and decreasing biomass drastically within 100 meters to several kilometers of the edges (Cochrane and Laurance 2002). Consequently, edge effects may contribute significantly to the emission of greenhouse gases, such as CO_2.

While advances have been made for detecting and mapping forest degradation in the Amazon (Cochrane and Souza 1998; Asner et al. 2005; Souza et al. 2005; Matricardi et al., 2007), estimation of carbon loss as a function of degradation intensity, and integration of remotely sensed data with field-collected biomass data have not yet been accomplished. In this paper, we demonstrate how remotely sensed data acquired in the optical part of the electromagnetic spectrum can be integrated with forest carbon stocks to characterize degraded forests in the

Brazilian Amazon. First we present a brief review of how remote sensing has been used to detect and map forest degradation. Then, we show how carbon stocks of degraded forests can be characterized using rapid forest transect surveys. We follow this by demonstrating how field data of forest carbon stocks can be integrated with optical remotely sensed data to regionally characterize forest degradation. Finally, we discuss the challenges to integrating field-derived carbon estimates with remotely sensed data.

2. Remote sensing of forest degradation

Detection and mapping of forest degradation with optical remotely sensed data is more challenging than mapping forest conversion due to deforestation because degraded forest 'pixels' are complex environments with mixtures of different land cover materials (i.e., vegetation, dead trees, bark, tree branches, soil, shade) (Souza and Roberts, 2005). Additionally, detectable degradation damage disappears within one to two years due to canopy closure and understory revegetation, making monitoring not possible after degradation scars disappear (Stone and Lefebvre, 1998); Asner et al., 2004; Souza, Jr et al. 2005). A detailed review of the available methods to detect and map forest degradation is provided elsewhere (GOFC-GOLD, 2009).

Several remote sensing techniques have been used to characterize forest degradation in the Brazilian Amazon. High spatial resolution sensors, such as Landsat (30 m) and SPOT (20 m) are the ones most used (Souza and Barreto, 2000; Souza et al. 2003; Asner et al. 2002, among others). At very high resolution (i.e., < 5 m pixel size), images acquired with orbital optical sensors, aerial photography and aerial videography have been used as well, for small scale analyses (Hurtt et al. 2003). Studies in the Brazilian Amazon have shown that Landsat reflectance data have limited capacity for detecting logged forests, with bands 3 and 5 providing the best spectral contrast between logged and intact forests (Stone and Lefebvre, 1998). Vegetation indices and texture filters also showed some potential for detection of logging impacts (Asner et al., 2002; Souza, Jr. et al. 2005). A recent study demonstrated that textural filters applied to Landsat band 5 can enhance detection of logging infrastructure (i.e., roads and log landings) (Matricardi et al., 2007).

Higher spatial resolution imagery is more suitable for detection of specific forest degradation impacts. For example, Ikonos imagery can easily detect forest canopy structural damage (Read et al., 2003; Souza, Jr et al., 2005), but, given the cost for image acquisition and computational challenges to extract information from these very high spatial resolution images, their use in operational applications such as monitoring logging is limited.

Alternatively, spectral mixture analysis (SMA) has been used to overcome the mixed pixel problem in Landsat imagery (Cochrane and Souza 1998). Fraction images derived from SMA enhance detectability of logging infrastructure and canopy damage. For example, soil fractions enhance log landings and logging roads (Souza and Barreto 2000), while non-photosynthetic vegetation (NPV) fractions enhance forest damage (Cochrane and Souza 1998; Souza, Firestone et al. 2003) and the green vegetation (GV) fraction is sensitive to canopy gaps (Asner et al. 2004).

A novel spectral index combining the information from these fractions, the Normalized Difference Fraction Index (NDFI) (Souza, Jr et al. 2005), was developed to more accurately map selective logging. The NDFI is computed as:

$$\mathrm{NDFI} = \frac{\mathrm{GV_{Shade}} - (\mathrm{NPV} + \mathrm{Soil})}{\mathrm{GV_{Shade}} + \mathrm{NPV} + \mathrm{Soil}} \qquad (1)$$

where GV_{shade} is the shade-normalized GV fraction given by,

$$\mathrm{GV_{Shade}} = \frac{\mathrm{GV}}{100 - \mathrm{Shade}} \qquad (2)$$

NDFI values range from -1 to 1. For intact forests, NDFI values are expected to be high (i.e., about 1) due to the combination of high GV_{shade} (i.e., high GV and canopy Shade) and low NPV and Soil values. As forest becomes degraded, the NPV and Soil fractions are expected to increase, lowering NDFI values relative to intact forest (Souza, Jr et al. 2005). Canopy damage detection caused by forest degradation caused by factors such as logging and forest fires can be detected with Landsat image within a year of the degradation event with 90.4% overall accuracy (i.e., for three land cover classes, Non-Forest, Forest and Canopy Damage) (Souza, Jr et al. 2005).

3. Methods

3.1 Forest transect characterization of degraded forests

Forty-nine transect inventories were conducted across a range of degraded forest classes most common in the Brazilian Amazon: Non-mechanized Logging (NML), Managed Logging (ML), Conventional Logging (CL), Logged and Burned Forest (BF) and Forest Fragment (FF) (Table 1). An additional 12 inventories in Undisturbed Forest (UF) transects were conducted as a reference to carbon stock changes in these degraded forest environments. The transects were conducted in five regions of the Brazilian Amazon that undergo forest degradation due to logging, forest fires and forest fragmentation, and low intensity of degradation in areas of reduced impact logging (Table 1). These transects are located in the following regions: Paragominas and Santarém, in the state of Pará; Sinop in Mato Grosso; Ji-Paraná, in Rondônia; and Itacoatiara in Amazonas.

Table 1. Forest classes defined at the field scale.

Forest class (Total number of Transects)	**Field description**	**Transect location** (number of transects)
Undisturbed Forest (UF) (n=15)	Consists of mature, undisturbed forest dominated by shade tolerant tree species.	Itacoatiara, Manaus (n=2) Ji-Paraná, Rondônia (n=3) Santarém, Pará (n=3) Sinop, Mato Grosso (n=4)
Non-mechanized logging (NML) (n=9)	Logged forest without the use of heavy vehicles such as skidders and trucks, also known as traditional logging. Logging infrastructure (log landings, roads and skid trails) are not built.	Santarém, Pará (n=4) Sinop, Mato Grosso (n=5)
Managed Logging (ML) (n=14)	Planned selective logging where the tree inventory is conducted, followed by road and log landing planning to reduce harvesting impacts.	Itacoatiaiara, Manaus (n=3) Paragominas, Pará (n=5) Santarém, Pará (n=1) Sinop, Mato Grosso (n=5)
Conventional Logging (CL) (n=10)	Conventional unplanned selective logging using skidders and trucks. Log landings, roads and skid trails are built causing extensive canopy damage. Low intensity understory burning may occur, but forest canopy is not burned.	Paragominas, Pará (n=3) Santarém, Pará (n=6) Sinop, Mato Grosso (n=3)
Logged and burned (LB) (n=6)	Either non-mechanized logging or logged forests where forest canopy has been intensively burned.	Santarém, Pará (n=3) Sinop, Mato Grosso (n=3)
Forest Fragment (FF) (n=8)	Isolated forest patch created by deforestation with abrupt changes on edges to pasture and agriculture lands, or with partial transitional edges to secondary forests. Fragments in the study area usually subject to recurrent NML and fires.	Ji-Paraná, Rondônia (n=8)

The forest transects were conducted following a detailed protocol to characterize biophysical properties of degraded forests (Gerwing, 2002). All trees with Diameters at Breast Height (DBH) > 10 cm were mapped along 10 m by 500 m transects (i.e. 0.5 ha). Additionally, sub-parcels (10 m x 10 m; 0.1 ha) were created every 50 meters along each transect and all trees < 10 cm DBH were mapped with total ground cover and canopy gaps estimated using a hemispherical lens and densitometer. Aboveground live biomass (AGLB), for each transect (trees > 10 cm DBH), was estimated using allometric equations available in the literature (Gerwing 2002). Additionally, information on land use and disturbance history was collected during the field surveys. A total of 15 forest transects were conducted in UF; 9 in NML; 14 in ML; 10 in CL; 8 in FF; and 6 in BF (Table 1).

3.2. Remote Sensing

Landsat and Spot images available for the transect areas were selected for this study. We selected images no longer than one year after the forest degradation event to integrate with field transects. The images were georeferenced to the NASA GeoCover 2000 Mosaic (https://zulu.ssc.nasa.gov/mrsid/), followed by radiometric and atmospheric correction. Atmospheric correction was performed using Atmospheric Correction Now 4.0 (ACORN: Analytical Imaging & Geophysics, Boulder, CO). The next steps were to perform SMA and calculate NDFI. Detailed information of all these procedures can be found elsewhere (Souza, Jr et al. 2005).

We next plotted GPS coordinates acquired during field surveys to conduct the forest transects on the geo-rectified satellite images in order to extract pixel values of fractions and NDFI. To do that, regular polygons of 30x30 pixels were drawn on these images using the GPS coordinates of the forest transects as cancroids. Then, 30 random pixels were selected within these polygons to extract SMA fractions and NDFI values of the transect areas for the degraded and intact forest classes. A regression analysis of forest carbon stocks against NDFI was conducted using the field and satellite images data of published results (n = 28; (Souza Jr. et al., 2003; Souza, Jr. et al. 2005) because we have not completed the pre-processing of all satellite images for all transect areas yet.

4. Results

4.1 Forest Transects

The mean AGLB of UF was 377 $Mg.ha^{-1}$with minimum biomass for the Ji-Paraná site (273 $Mg.ha^{-1}$) and maximum for Santarém (497 $Mg.ha^{-1}$). This result is compatible with field AGLB estimates using very large forest plots (Keller et al. 2001) and within the range of average values reported for the Brazilian Amazon region (Malhi et al., 2006 ; Saatchi et al., 2007) NML was found only at the Sinop (301 $Mg.ha^{-1}$) and Santarém (418 $Mg.ha^{-1}$) sites. NML showed a 15% reduction in the original AGLB in Santarém and Ji-Paraná. However, if we compare the change in mean AGLB stocks in NML sites relative to the mean AGLB of UF (377 $Mg.ha^{-1}$), the decrease was only 6% (Table 2).

The ML degradation class was found in all sites except Ji-Paraná. The mean AGLB of this class was 343 $Mg.ha^{-1}$ which represents a reduction of 8% relative to the mean AGLB of UF. However, we found higher AGLB reduction when compared to the AGLB of each site. For example, ML reduced the AGLB stocks relative to UF by 18% in Sinop and 12% in Itacoatiara. For the other sites, the changes were similar to the mean reduction value (Table 2).

A greater mean AGLB reduction (11%) was found for CL (335 $Mg.ha^{-1}$) relative to the mean AGLB of UF. The highest change was found in Santarém where CL reduced 28% of the original UF AGLB. FF also consumed the original AGLB. In Ji-Paraná, the only site that we sampled in this class, showed 27% of reduction relative to the mean AGLB of UF. The class of forest degradation that showed the highest change in the original AGLB was BF, with an average reduction of 30% but reaching 44% in Santarém and 34% in Sinop (Table 2).

We ran a non-parametric test (Wicoxon rank test) to test whether the changes in AGLB of the UF and the forest degradation classes are statistically different. The results of this test did not show a statistically significant difference of the AGLB means among the classes UF, NML, ML and CL. The other degradation classes (BF = 274 $Mg.ha^{-1}$ and FF = 260 $Mg.ha^{-1}$), showed statistically significant mean biomass values between each other, and among all other degradation classes (Table 2). These preliminary results imply that UF, NML, ML CL could not be statistically separated at the field level based only on AGLB, but FF and BF could. We believe that using average AGLB values to run this test minimizes the difference in changes of biomass stocks due to degradation. Having this test run for each site could potentially show more differences, as has been demonstrated for Paragominas (Gerwing 2002). Because of the limited number of transects for each forest degradation class, and because we could not conduct the forest transect surveys before the degradation event to estimate the original AGLB of the undisturbed forest, we were not able to generate site-specific statistical analysis.

Assuming that carbon makes up 50% of the AGLB, we can then demonstrate how carbon stocks vary with degradation intensity (Figure 1). These changes are similar to the AGLB mean changes presented above. The FF and BF degradation classes had significantly reduced carbon stocks (i.e., 28 and 30%, respectively), whereas the NML, ML and CL degradation classes each had <10% carbon loss. However, as previously noted, these results must be interpreted with caution because using a regional average of aboveground forest carbon stocks can hide the effect of change in carbon stocks due to forest degradation. For example, we found that in Santarém, the site with the largest AGLB for UF (496 $Mg.ha^{-1}$, i.e., 248 $MgC.ha^{-1}$), the carbon stocks of the NML, and CL disturbance classes decreased by 15 and 28% relative to UF class. In addition, AGLB varies among the forest transect sites. Therefore, using global mean AGLB values can be misleading because of the high spatial variability of biomass across the landscape (Houghton, 2005). Nonetheless, our preliminary results show that mean of carbon stocks decreases with degradation intensity.

Table 2. Remote sensing capability to detect undisturbed forest and various forest degradation classes with Landsat type of sensors.

Class (# Transects[1])	**Class Description**	**Aboveground Forest Live Biomass[2]** (ton/ha)	**Remote Sensing Detectability**
(1) Undisturbed Forest (n=15)	Consists of mature, undisturbed old growth forest dominated by shade tolerant tree species.	376.00 (100.00) (5),(6)	Easily detected. Forest type differentiation is challenge.
(2) Non-mechanized logging (n=9)	Timber removal without the use of heavy vehicles such as skidders and trucks for various purposes such as wood consumption and fuel production. Gradual forest biomass loss occurs. Logging infrastructure (log landings, roads and skid trails) is not built.	353.00 (66.50) (5),(6)	Not directly detectable.
(3) Managed Logging (n=14)	Planned selective logging where the tree inventory is conducted, followed by road and log landing planning to reduce collateral harvesting impacts.	343.00 (91.30) (1),(2),(3),(4)	Forest canopy damage marginally detected. Logging infrastructure (i.e., roads and log landings) are visible and may be used as a proxy to estimate forest area degraded.
(4) Conventional Logging (n=10)	Conventional unplanned selective logging using skidders and trucks. Log landings, roads and skid trails are built causing extensive canopy damage and tree mortality. Low intensity understory burning may occur, but forest canopy is not burned	335.00 (66.90) (1),(2),(3),(4)	Forest canopy damage and logging infrastructure easily detected up to 2 years since disturbance event..
(5) Forest Fragment (n=8)	Isolated forest patch created by deforestation with abrupt changes on edges to pasture and agriculture lands, or with transitional edges to secondary forests. Fragments in the study area usually subject to recurrent disturbances cause by logging and fires.	274.00 (77.15) (1),(2),(3),(4)	Isolated forest patches > 2 ha easily detected.
(6) Burned Forest (n=6)	Any type of degraded forests heavily and/or recurrently burned causing extensive canopy damage and tree mortality.	260.90 (43.60) (1),(2),(3),(4)	Canopy forest scars easily detected up to 2 years since disturbance event.

[1] We mapped all trees with Diameter at Breast Height (DBH) greater than 10 cm along a 10 m by 500 m transect. In addition, ten sub-parcels (10 m x 10 m) were created every 50 meters along each transect. All trees where mapped within the sub-parcels and ground cover and canopy cover were estimated. Aboveground biomass was estimated using allometric equations available in the literature, adapted specifically by Gerwing (2002), for degraded forests and estimating vine biomass.

[2] Biomass mean and standard deviations within brackets. In the biomass values, forest class numbers in brackets indicating statistical separability at 10% significance level, using the Wicoxon non-parametric rank test. For example, the biomass mean of Undisturbed Forest (class 1) is statistically different from the biomass means of Forest Fragments (class 5) and Burned (class 6).

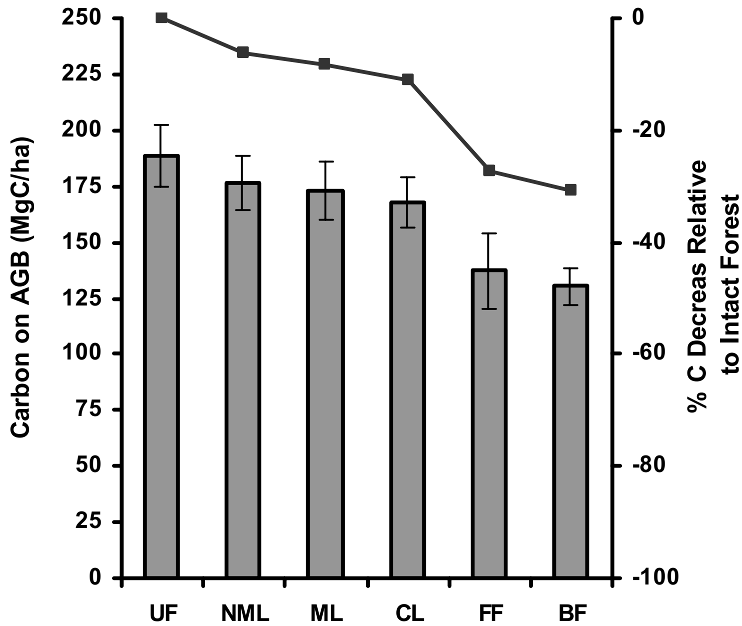

Figure 1. Change in above ground live biomass as a function of degradation intensity. Bars represent standard error of the mean value and line the percent change of C mean relative to intact forest.

4.2 Integration of satellite data and transect data

Previous study showed that NDFI is more sensitive than individual SMA fractions to these types of canopy changes described above (Souza and Roberts, 2005). As an example, Figure 2 shows a NDFI time-series for a region with three forest transects for the Sinop site. Selective logging first occurred in this area in 1998 as pointed out by disconnected linear features indicating logging roads and canopy damage scars highlighted by yellow to orange colors (Figure 2a). NDFI values of the selectively logged forest in 1998 increased (i.e., dark green color) in 1999 as canopy gaps closed. A new 1999 logging signal appeared in the NDFI image adjacent to the 1998 logged area. In 2000, both logged forest areas were subjected to a severe fire event, burning approximately 5,000 hectares (Figure 3c), which lowered NDFI values more drastically. Two years later, in 2003, nearly all detectable forest degradation signals had disappeared, implying that forests are intact.

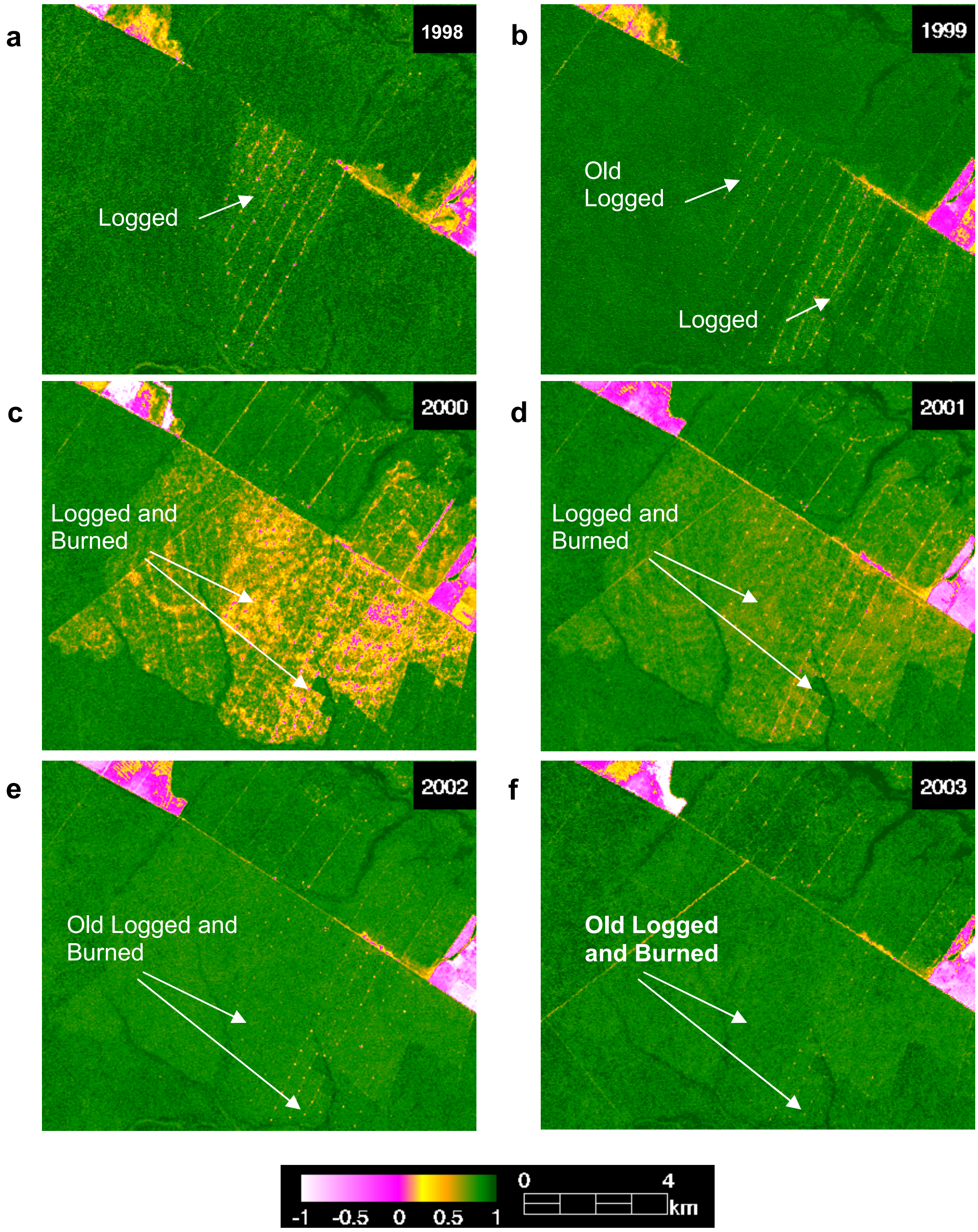

Figure 2. Time-series of NDFI images showing forest degradation due to logging and forest fires in Sinop, Mato Grosso. The NDFI degradation signal (yellow to orange colors) change within one to two years. Dark green colors are forests undamaged by selective logging and/or burning (NDFI values >0.75). Orange to yellow colors indicate a range of forest canopy damage (0 > NDFI < 0.75). Areas in white have negative NDFI values (<50% of GV) and represent bare soil.

The example of Figure 2 shows how dynamic the forest degradation process is and the need to monitor these changes in an annual basis. Additionally, NDFI decreases with degradation intensity. Given these characteristics, we hypothesized that NDFI values should respond to changes in AGLB stocks due to forest degradation processes as indicated by the field measurements (Figure 1). We investigated this relationship for transect sites where satellite imagery [SPOT 4 and Landsat; Souza et al. 2003 and Souza, Jr et al. 2005, respectively] was available within less than one year of the occurrence of forest disturbance. We then found out a negative linear relationship between NDFI and AGLB as expected (Figure 3). This means that we found higher NDFI for UF and lower ones for the most degraded type of forest (BF). However, if we use satellite images acquired more than one year after the degradation event, this strong relationship disappears. Therefore, these preliminary results indicate that monitoring AGLB changes caused by forest degradation may be possible with optical remotely sensed data as long as the images are acquired within the time frame in which the degradation event can be detected.

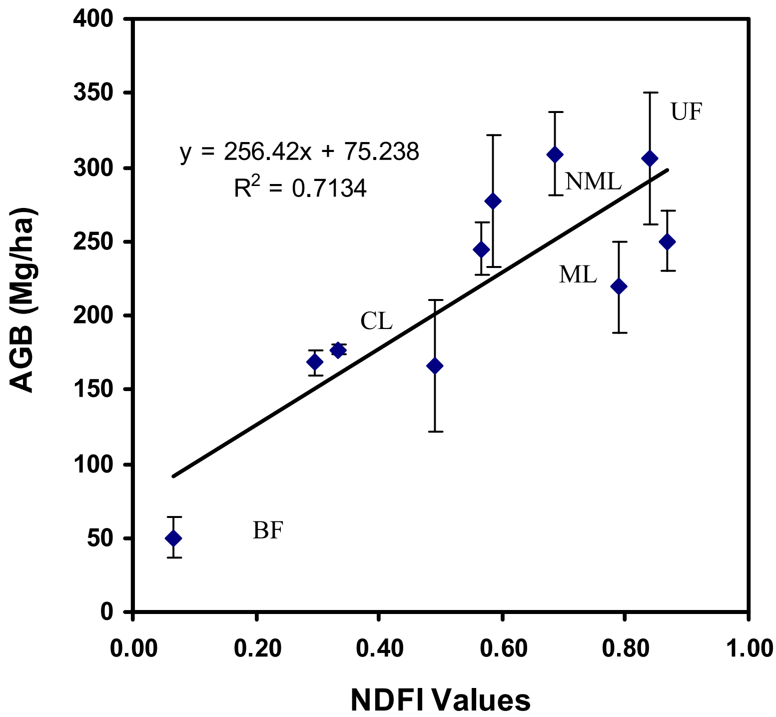

Figure 3. Relationship between AGB and NDFI values for degraded forest of Paragominas (Pará) and Sinop (Mato Grosso).

5. Challenges to monitoring forest degradation

Although forest degradation can be detected and mapped and degradation intensity can be inferred from satellite images, technical challenges and limiting factors remain that need to be overcome in order to adequately monitor forest degradation in REDD projects:

- **Quantifying biomass in degraded forests**. Methods for measuring and estimating carbon stock changes for different carbon pools in forested areas are well-established in the scientific literature and some have already been approved by the United Nations Framework Convention on Climate Change **(**UNFCCC). However, monitoring forest degradation requires documenting forest disturbance history well, specifically recurrent degradation events and time since last disturbance. This information is crucial for quantifying carbon stock changes. However, in many cases it is not possible to reconstruct the land use and forest degradation history of a particular site, as was the case for some of the forest transect sites surveyed in this study. Another factor that should be taken into account is the spatial variability of biomass. In this study, we used the mean biomass value for UF as a reference to estimate carbon loss due to different intensities of forest degradation. While this approach is useful for demonstrating how carbon stocks vary with degradation intensity, using local estimates of carbon in UF is preferred because forest biomass stocks vary across regions (Houghton, 2005).
- **Detection and mapping of forest degradation**. There have been substantial advances toward remote sensing of forest degradation in recent years, and new sensors are being tested or planned that may allow biomass to be monitored directly (GOFC-GOLD 2009). Previous studies demonstrated that the sub-pixel approach using SMA is more sensitive than 'whole-pixel' classifiers in detecting degraded forest environments (Asner et al. 2005); Souza, Jr et al. 2005). There are, however, limitations to applying these types of techniques to monitor forest degradation. Monitoring degradation requires annual acquisition of satellite images because the rapid changes in degraded forests inhibit detection and mask out the intensity of the degradation after one year (Cochrane and Souza, 1998; Souza and Roberts 2005). The optical remote sensing techniques presented here cannot be applied in cloudy conditions, making some regions impossible to monitor. Finally, detection and mapping of low intensity forest degradation (i.e., NML, ML) is limited to imagery with very high spatial resolution. The cost of such imagery is still prohibitive for operational monitoring projects over large areas.
- **Field-satellite integration.** Monitoring changes in carbon stocks due to forest degradation requires integration of remotely sensed data with site-specific biophysical field attributes. NDFI, a continuous remote sensing variable, can respond to biomass changes due to forest degradation. However, it is important to highlight that this type of correlation collapses one year after the degradation event. This happens because the NDFI value of degraded forests changes rapidly as new foliage closes forest gaps, but the biomass of the degraded forest, most of which is in woody stems, does not recover at the same rate. Therefore, caution, must be taken when using this approach so that detailed information of the degradation history of the project area is established and verified with initial field inspections. Ideally, it is also best to calibrate the remote sensing variables with local forest biomass, instead of using regional means as presented in this study. Limited transect data covering all degradation intensities and the lack of an established REDD project area prevented us doing so in this study.

6. Conclusions

Reduced emissions from deforestation and degradation (REDD) has recently gained acceptance as an approach for mitigating climate change (FCCC/SBSTA/2007/L.10). The concept behind REDD is that countries that prevent destruction likely to occur to portions of their tropical forests will reduce their expected carbon emissions, thereby moderating climate change and warranting recompense or credit for defensible mitigation activities. REDD has the potential to substantially reduce carbon emissions in a cost-effective and timely manner, helping to keep global climate change within tolerable limits. However, degradation of standing forests needs to be addressed when calculating reduced emissions from deforestation and the overall feasibility of implementing REDD during the post-Kyoto commitment period must be evaluated. We demonstrate how the full range of forest degradation intensity in the Brazilian Amazon can be quantified and characterized in space and time. We have provided a short review of tested and validated remote sensing methods for mapping and monitoring forest degradation and discussed the current challenges and limitations to implementation of operational systems to keep track of forest degradation. Our results show that the effects of forest degradation, if they are not accounted for, can result in substantial overestimation of the carbon 'protected' by projects that reduce deforestation.

In the Brazilian Amazon, only 36% of forests that are logged in any given year are deforested within the next five years (Asner et al. 2006). This means that the area of forest degraded by logging tends to increase every year. The forest area degraded by fires has not yet been fully mapped, but can potentially be much larger than the annual area logged (Nepstad et al. 1999). Forest degradation in our study sites reduced aboveground carbon stocks by up to 30% on average, but areas of recurrent disturbance by fires and logging can be reduced by >50% (Gerwing, 2002; Cochrane and Schulze, 1999). Potential disturbance-related carbon stock changes in forests can reduce the effectiveness of any mitigation activity under REDD, leading to questions or doubts about a project's additionality (i.e. are mitigation activities beyond business as usual) and permanence (i.e. the likelihood that mitigating activities will be effective over the long term). To ensure that emissions from tropical forests will really decrease, it is critical that REDD mechanisms account for emissions from forest degradation. This requires national or regional forest monitoring systems able to assess carbon stock changes due to degradation processes. We have related possible technical solutions for monitoring changes in remaining forests that should be applied in future. But historical data on forest degradation are rare and, even in Brazil where deforestation is being monitored since the late 1980's, including emissions from forest degradation in the emission historical reference scenario for REDD is problematic. Thus, the magnitude of historical forest degradation processes will have to be estimated through modeling and/or other indirect methods in order to minimize risks of overestimating avoided emissions to the atmosphere under REDD. Because the amount of carbon removed and the annual area affected can be significant, forest degradation needs to be recognized as one of the major GHG emission sources in tropical forests and targeted for mitigation activities, similar to what is being done for deforestation, in order to effectively address climate change and ensure the sustainability of all forest lands.

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References

Achard, F., H. D. Eva, H. J. Stibig, P. Mayaux, J. Gallego, T. Richards and J. P. Malingreau (2002). Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583): 999-1002.

Asner, G. P., E. N. Broadbent, P. J. C. Oliveira, M. Keller, D. E. Knapp and J. N. M. Silva 2006. Condition and fate of logged forests in the Brazilian Amazon. 10.1073/pnas.0604093103 PNAS : 0604093103.

Asner, G.P., Keller, M., Pereira, R., and Zweede, J.C. 2002 Remote sensing of selective logging in Amazonia - Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis. Remote Sensing of Environment 80 (3) 483-496.

Asner, G. P., M. Keller, R. Pereira and J. C. Zweede (2002). Remote sensing of selective logging in Amazonia - Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis. Remote Sensing of Environment 80 (3): 483-496.

Asner, G. P., M. Keller, R. Pereira, J. C. Zweede and J. N. M. Silva (2004). Canopy damage and recovery after selective logging in Amazonia: Field and satellite studies. Ecological Applications 14 (4): S280-S298.

Asner, G. P., M. Keller and J. N. M. Silva (2004). Spatial and temporal dynamics of forest canopy gaps following selective logging in the eastern Amazon. Global Change Biology 10 (5): 765-783.

Asner, G. P., D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller and J. N. Silva (2005). Selective logging in the Brazilian Amazon. Science 310 (5747): 480-482.
Cochrane, M. A. (2001). In the line of fire - Understanding the impacts of tropical forest fires. Environment 43 (8): 28-38.

Cochrane, M. A., A. Alencar, M. D. Schulze, C. M. Souza, D. C. Nepstad, P. Lefebvre and E. A. Davidson (1999). Positive feedbacks in the fire dynamic of closed canopy tropical forests. Science (Washington D C) 284 (5421): 1832-1835.

Cochrane, M. A. and W. F. Laurance (2002). Fire as a large-scale edge effect in Amazonian forests. Journal of Tropical Ecology 18 : 311-325.

Cochrane, M. A. and M. D. Schulze (1999). Fire as a recurrent event in tropical forests of the eastern Amazon: Effects on forest structure, biomass, and species composition. Biotropica 31 (1): 2-16.

Cochrane, M. A. and C. M. Souza (1998). Linear mixture model classification of burned forests in the Eastern Amazon. International Journal of Remote Sensing 19 (17): 3433-3440.

Foley, J. A., G. P. Asner, M. H. Costa, M. T. Coe, R. DeFries, H. K. Gibbs, E. A. Howard, S. Olson, J. Patz, N. Ramankutty and P. Snyder (2007). Amazonia revealed: forest degradation and loss of ecosystem goods and services in the Amazon Basin. Frontiers in Ecology and the Environment 5 (1): 25-32.

Gerwing, J. J. (2002). Degradation of forests through logging and fire in the eastern Brazilian Amazon. Forest Ecology and Management 157 (1-3): 131-141.

GOFC-GOLD (2009). Reducing greenhouse gas emissions from deforestation and degradation in developing countries: a sourcebook of methods and procedures for monitoring, measuring and reporting. GOFC-GOLD Project Office, Natural Resources Canada, Alberta, Canada: 185p.

Houghton, R.A. 2005 Aboveground Forest Biomass and the Global Carbon Balance. Global Change Biology 11 (945-958.

Houghton, R. A., D. L. Skole, C. A. Nobre, J. L. Hackler, K. T. Lawrence and W. H. Chomentowski (2000). Annual fluxes of carbon from deforestation and regrowth in the Brazilian Amazon. Nature (London) 403 (6767): 301-304.

Hurtt, G., X. Xiao, M. Keller, M. Palace, G. P. Asner, R. Braswell, E. S. BrondÃ-zio, M. Cardoso, C. J. R. Carvalho, M. G. Fearon, L. Guild, S. Hagen, S. Hetrick, B. Moore, III, C. Nobre, J. M. Read, T. SÃ¡, A. Schloss, G. Vourlitis and A. J. Wickel (2003). IKONOS imagery for the Large Scale Biosphereâ€Atmosphere Experiment in Amazonia (LBA). Remote Sensing of Environment . 88: 111-127.

Johns, J. S., P. Barreto and C. Uhl (1996). Logging damage during planned and unplanned logging operations in the eastern Amazon. Forest Ecology and Management 89 (1-3): 59-77.

Keller, M., M. Palace and G. Hurtt (2001). Biomass estimation in the Tapajos National Forest, Brazil - Examination of sampling and allometric uncertainties. Forest Ecology and Management 154 (3): 371-382.

Lambin, E.F. 1999 Monitoring forest degradation in tropical regions by remote sensing: some methodological issues doi:10.1046/j.1365-2699.1999.00123.x. Global Ecology and Biogeography 8 (3-4) 191-198.

Laurance, W. F., H. L. Vasconcelos and T. E. Lovejoy (2000). Forest loss and fragmentation in the Amazon: implications for wildlife conservation. Oryx 34 (1): 39-45.

Malhi, Y., Wood, D., Baker, T.R., Wright, J., Phillips, O.L., Cochrane, T., Meir, P., Chave, J., Almeida, S., Arroyo, L., Higuchi, N., Killeen, T.J., Laurance, S.G., Laurance, W.F., Lewis, S.L., Monteagudo, A., Neill, D.A., Vargas, P.N., Pitman, N.C.A., Quesada, C.A., Salomao, R., Silva, J.N.M., Lezama, A.T., Terborgh, J., Martinez, R.V., And Vinceti, B. 2006 The regional variation of aboveground live biomass in old-growth Amazonian forests. doi:10.1111/j.1365-2486.2006.01120.x. Global Change Biology 12 (7) 1107-1138.

Matricardi, E., Skole, D., Cochrane, M.A., Pedlowski, M., and Chomentowski, W. 2007 Multi-temporal assessment of selective logging in the Brazilian Amazon using Landsat data. International Journal of Remote Sensing 28 (1) 63-82.

Nepstad, D. C., A. Varissimo, A. Alencar, C. Nobre, E. Lima, P. Lefebvre, P. Schlesinger, C. Potter, P. Moutinho, E. Mendoza, M. Cochrane and V. Brooks (1999). Large-scale impoverishment of Amazonian forests by logging and fire. Nature 398 (6727): 505-8.

Nepstad, D. C., A. Verissimo, A. Alencar, C. Nobre, E. Lima, P. Lefebvre, P. Schlesinger, C. Potter, P. Moutinho, E. Mendoza, M. Cochrane and V. Brooks (1999). Large-scale impoverishment of Amazonian forests by logging and fire. Nature 398 (6727): 505-508.

Persson, U.M. and Azar, C. 2007 Tropical deforestation in a future international climate policy regime - lessons from the Brazilian Amazon. Mitigation and Adaptation Strategies for Global Change (12) 1277-1304.

Read, J.M., Clark, D.B., Venticinque, E.M., and Moreira, M.P. 2003 Application of merged 1-m and 4-m resolution satellite data to research and management in tropical forests. Journal of Applied Ecology 40 (3) 592-600.

SAATCHI, S.S., HOUGHTON, R.A., DOS SANTOS ALVALA, R.C., SOARES, J.V., and YU, Y. 2007 Distribution of aboveground live biomass in the Amazon basin. Global Change Biology 13 (4) 816-837.

Santilli, M., Moutinho, P., Schwartzman, S., Nepstad, D., Curran, L., and Nobre, C. 2005 Tropical Deforest and Kyoto Protocol. 71 (267-276.

Santilli, M., Moutinho, P., Schwartzman, S., Nepstad, D., Curran, L., and Nobre, C. 2003 Tropical Deforest and Kyoto Protocol: a new proposal. in 9th Conference of the Parties to the UNFCCC of Conference Milan, Italy.

Shalamadinger, B., Ciccaree, L., Dutschke, M., Dutschke, M., Fearnside, P.M., Brown, S., and Murdiyarso, D. 2005. Should we include avoidance of deforestation in the international response to deforestation? In Proceedings from the Workshop on Carbon Sequestration and Sustainable Livelihoods Conference Bogor, Indonesia.

Sitch, S., Brovkin, V., von Bloh, W., van Vuuren, D., Eickhout, B., and Ganopolski, A. 2005 Impacts of future land cover changes on atmospheric CO2 and climate,. Global Biogeochem. Cycles 19 (GB2013, doi:10.1029/2004GB002311.

Skole, D. and C. Tucker (1993). Tropical Deforestation and Habitat Fragmentation in the Amazon - Satellite Data from 1978 to 1988. Science 260 (5116): 1905-1910.

Souza, Jr. C.M. and P. Barreto (2000). An alternative approach for detecting and monitoring selectively logged forests in the Amazon. International Journal of Remote Sensing 21 (1): 173-179.

Souza, Jr. C. M., Firestone, L. M. Silva and D. Roberts (2003). Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models. Remote Sensing of Environment 87 (4): 494-506.

Souza, Jr. C. M., D. A. Roberts and M. A. Cochrane (2005). Combining spectral and spatial information to map canopy damage from selective logging and forest fires. Remote Sensing of Environment. 98: 329-343.

Souza, Jr. C. M. and D. Roberts (2005). Mapping forest degradation in the Amazon region with Ikonos images. International Journal of Remote Sensing 26 (3): 425-429.

Stone, T. A. and P. Lefebvre (1998). Using multi-temporal satellite data to evaluate selective logging in Para, Brazil. International Journal of Remote Sensing 19 (13): 2517-2526.

Uhl, C. and I. C. G. Vieira (1989). Ecological Impacts of Selective Logging in the Brazilian Amazon - a Case Study from the Paragominas Region of the State of Para. Biotropica 21 (2): 98-106.

Verissimo, A., P. Barreto, M. Mattos, R. Tarifa and C. Uhl (1992). Logging Impacts and Prospects for Sustainable Forest Management in an Old Amazonian Frontier - the Case of Paragominas. Forest Ecology and Management 55 (1-4): 169-199.

Verissimo, A., P. Barreto, R. Tarifa and C. Uhl (1995). Extraction of a High-Value Natural-Resource in Amazonia - the Case of Mahogany. Forest Ecology and Management 72 (1): 39-60.