Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models

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Abstract

In this paper, we present a methodology to map classes of degraded forest in the Eastern Amazon. Forest degradation field data, available in the literature, and 1-m resolution IKONOS image were linked with fraction images (vegetation, nonphotosynthetic vegetation (NPV), soil and shade) derived from spectral mixture models applied to a Satellite Pour L’observation de la Terre (SPOT) 4 multispectral image. The forest degradation map was produced in two steps. First, we investigated the relationship between ground (i.e., field and IKONOS data) and satellite scales by analyzing statistics and performing visual analyses of the field classes in terms of fraction values. This procedure allowed us to define four classes of forest at the SPOT 4 image scale, which included: intact forest; logged forest (recent and older logged forests in the field); degraded forest (heavily burned, heavily logged and burned forests in the field); and regeneration (old heavily logged and old heavily burned forest in the field). Next, we used a decision tree classifier (DTC) to define a set of rules to separate the forest classes using the fraction images. We classified 35% of the forest area (2097.3 km²) as intact forest. Logged forest accounted for 56% of the forest area and 9% of the forest area was classified as degraded forest. The resultant forest degradation map showed good agreement (86% overall accuracy) with areas of degraded forest visually interpreted from two IKONOS images. In addition, high correlation ($R^2 = 0.97$) was observed between the total live aboveground biomass of degraded forest classes (defined at the field scale) and the NPV fraction image. The NPV fraction also improved our ability to mapping of old selectively logged forests.

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Keywords: Mixture models; Forest degradation; Amazon; Nonphotosynthetic vegetation; Selective logging; Fire

1. Introduction

Selective logging and burning are considered the main causes of forest degradation in the Amazon upland forests (Nepstad et al., 1999). Numerous studies have measured the impacts of logging and burning activities on species diversity, carbon content, and economic value (e.g., Cochrane & Shulze, 1999; Gerwing, 2002; Holdsworth & Uhl, 1997; Johns, Barreto, & Uhl, 1996). While deforestation in the Amazon has been mapped (INPE, 2000), the extent of forest degradation is unknown. The total area of degraded forest, estimated from field surveys, is far larger than the area deforested each year. Annual deforestation rates range between 11,000 and 29,000 km², while it has been estimated that up to 8000–15,000 km² are logged, 80,000 km² are burned, and 38,000 km² are fragmented or degraded each year (Nepstad et al., 1999).

Spatial information on forest degradation would enhance the effectiveness of planning development, commercial activities, and conservation activities, as well as improve local and global ecological models and carbon budget estimates. For example, a forest degradation map could be used to improve fire risk models (e.g., IPAM et al., 1998), since degraded forests are highly fire-prone (Holdsworth & Uhl, 1997) and should be included in fire risk analysis. Forest law enforcement programs could also benefit from the use of a forest degradation map. For example, deforestation maps are combined with maps of property lines to identify areas of unauthorized deforestation and deforestation in areas of permanent protection (Firestone & Souza, 2002; Souza & Barreto, 2001). A forest degradation map could also be produced and used to identify forest plots that have not been properly managed for timber harvesting.
Due to the vast area of dense forest with difficult access, remote sensing is the most efficient and economically viable means of mapping forests in the region. Unlike deforestation, which is easily identifiable through visual interpretation (INPE, 2000) or automated processing of multispectral satellite images (Roberts, Batista, Pereira, Walker, & Nelson, 1998; Shimabukuro, Batista, Mello, Moreira, & Duarte, 1998) forest degradation is more difficult to identify. There is a range of degradation, and forest regeneration tends to obscure the spectral/spatial signature of the degraded forest. Additional complication arises from the complex spatial arrangement of the land cover components (i.e., dead vegetation, forest islands, bare soil) that makes up a degraded forest class (Fig. 1).

Prior studies have developed methods to map either logged (Souza & Barreto, 2000; Stone & Lefebvre, 1998; Watrin & Rocha, 1992) or burned forest in the Amazon (Cochrane & Souza, 1998). However, no study has proposed an all-encompassing classification scheme that can be meaningfully linked with field studies in the region. Without the ability to link mapped classes with data gathered in the field, the usefulness of mapping methods is limited. In this study, we evaluated the ability to link forest degradation classes mapped in the field with remotely sensed data. We tested our methodology using one Satellite Pour L’observation de la Terre (SPOT 4) multispectral image of Paragominas, acquired in August 1999.

2. Background

2.1. Causes and impacts of forest degradation in the Eastern Amazon

Forest degradation in the Amazon has been characterized through field studies, particularly in the arc of deforestation along the southern and eastern border of the Amazon (Cochrane et al., 1999; Gerwing, 2002; Johns et al., 1996; Uhl & Bushbacher, 1985). Degradation is generally grouped into classes based on the degrading activity and intensity. These activities include selective logging and burning, and the quantification of the impacts is measured in terms of forest structure and composition (Table 1).

Selective logging degrades forests during harvesting activities, causing extensive damage to nearby trees and soils (Johns et al., 1996), increasing the risk of species extinction.

Fig. 1. Forest degradation spatial arrangement and composition (vegetation as presented by intact forest and forest regeneration; NPV and soil) as seen from IKONOS Geo multispectral-panchromatic data fusion product [R (0.77–0.88 μm), G (0.64–0.72 μm) B (0.52–0.61 μm) and pan (0.45–0.90 μm)], acquired in November 2000 in the study area.
extinction (Martini, Rosa, & Uhl, 1994), as well as increasing carbon emissions (Houghton, 1995). In addition, timber extraction increases fire susceptibility (Holdsworth & Uhl, 1997) and open roads, which encourage unplanned development (Verissimo, Barreto, Tarifa, & Uhl, 1995). During harvesting, selective logging kills or damages 10–46% of living biomass (Gerwing, 2002; Verissimo, Barreto, Mattos, Tarifa, & Uhl, 1992; Verissimo et al., 1995), and damages an area of 1503–2276 m²/ha (Johns et al., 1996). The number of pioneer species can increase by 500% and the canopy cover can decrease to 63% of the original intact forest depending on the intensity and age of degradation (Gerwing, 2002).

Forest burning often occurs after forests have been opened through logging and are almost always started by human activities in adjacent areas (e.g., slash-and-burn). Forest fires can kill more than 45% of trees more than 20 cm in diameter the first time a forest is burned, opening the canopy by 30–50% and increasing the susceptibility of the forests to subsequent fires (Cochrane et al., 1999). In addition, pioneer species increase in density by 689%. Subsequent fires can then kill up to 98% of trees more than 20 cm in diameter and leave only 10–40% of the original canopy (Cochrane et al., 1999).

### 2.2. Mapping forest degradation in the Eastern Amazon using remote sensing

Prior studies in the Amazon have generally focused on detection of one or two types of degraded forests through remote sensing analysis. Mixture models (Adams et al., 1995) have been pointed out as one of the most appropriate techniques to map such degraded environments since it is capable of separating soil, vegetation, nonphotosynthetic vegetation (Roberts, Adams, & Smith, 1993; Roberts et al., 1998) and shade abundance at a sub-pixel scale. This technique enables the detection of subtle changes, and gives physical meaning to the spectral data provided by the satellite.

Soil fraction images, obtained through mixture models, also allow the detection of small areas (log landings) in the forest cleared to store timber (Monteiro, Souza, & Barreto, 2003; Souza & Barreto, 2000). Based on a site-specific harvesting radius, it is possible to estimate the area affected by selective logging (Souza & Barreto, 2000).

Besides its simplicity and applicability in forest surveillance programs, this methodology does not provide information on the degree of forest damage. On the other hand, the fraction of nonphotosynthetic vegetation (NPV) may allow estimates of forest degradation since it is associated with dead vegetation (Roberts et al., 1993). Cochrane and Souza (1998) used the NPV fraction image to map recently and old burned forests in the Eastern Amazon and pointed out its potential to map several levels of forest degradation.

### 3. Study area

Paragominas is a logging center in the northeast of Pará, covering 19,310 km² with a population of 76,095 inhabitants (IBGE, 2000) (Fig. 2). It was founded in 1965 after the opening of the Belém-Brasília highway, one of the first and only major roads connecting north and south of Brazil. Through the 1970s and 1980s, ranching was the dominant land use in the area. However, the 1990s brought a boom in the logging industry, which bought wood from the land of large ranches and extracted it at extremely high rates (35–40 m³ wood/ha; Verissimo et al., 1992). Since the logging boom, the municipality has experienced a collapse of the timber industry, damaging the local economy (Schneider, Arima, Verissimo, Barreto, & Souza, 2002).

The natural vegetation is almost entirely dense, closed upland forest. The dry season extends from June–November, with annual temperatures averaging 25 °C. This area was chosen because its long history of logging, ranching and agricultural activity allowed for the inclusion of all forest degradation types. In addition, numerous field studies in the area allow for characterization of forest degradation classes and determination of the history and age of forest stands (Gerwing, 2002; Johns et al., 1996; Uhl & Bushbacher, 1985; Verissimo et al., 1992).

### 4. Methods

#### 4.1. Data set and preprocessing

Data acquired for this study included one multispectral SPOT 4 scene (bands: 0.50–0.59, 0.61–0.68, 0.79–0.89, 1.58–1.75 μm; 20 m pixel size) acquired in August of 1999.

<table>
<thead>
<tr>
<th>Forest degradation class</th>
<th>Physical characteristics</th>
<th>Biomass (tons/ha)</th>
<th>Canopy cover</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intact forest (%)</td>
<td>Wood debris (%)</td>
<td>Disturbed soil (%)</td>
</tr>
<tr>
<td>Intact forest</td>
<td>99 (1)</td>
<td>1 (1)</td>
<td>&lt; 1 (0)</td>
</tr>
<tr>
<td>Moderately logged</td>
<td>72 (6)</td>
<td>11 (8)</td>
<td>17 (8)</td>
</tr>
<tr>
<td>Heavily logged</td>
<td>38 (4)</td>
<td>32 (9)</td>
<td>30 (6)</td>
</tr>
<tr>
<td>Lightly burned</td>
<td>27 (10)</td>
<td>26 (3)</td>
<td>10 (5)</td>
</tr>
<tr>
<td>Heavily burned</td>
<td>2 (2)</td>
<td>42 (5)</td>
<td>13 (8)</td>
</tr>
</tbody>
</table>
Fig. 2. Map of the study area showing the location of the SPOT 4 and IKONOS images.

Fig. 3. Methods used to map forest degradation in the study area.
Four Landsat Thematic Mapper (TM) images acquired in 1988 (16 August), 1991 (24 July), 1995 (05 July) and 1996 (03 June) were used to aid in the identification of forest degradation age for the purpose of the collection of training samples. The images cover an area of 3666 km², mostly within the boundaries of Paragominas County in the northeast of Pará (Fig. 2). The SPOT 4 image was geometrically corrected using a set of 18 ground control points extracted from topographic maps (Diretoria do Serviço Geográfico—DSG/IBGE). Additionally, two IKONOS fusion scenes (1 × 1 m pixels; 15 × 15 km each scene), acquired in November 2000 within the study area, were used in combination with field data to identify samples to train a decision tree classifier, and to generate test fields to evaluate the accuracy of the final classification (Figs. 1 and 2).

4.2. Forest mask

The first step was to separate forest and nonforest pixels (i.e., pasture, secondary growth, plantation, cloud/shadow and water classes). We tested different methods proposed in the literature to perform this task such as segmentation of the shade fraction image (Shimabukuro et al., 1998), tasseled-cap brightness index (Cochrane & Souza, 1998) and unsupervised classification. The ISODATA unsupervised classification algorithm produced the best result for a forest/nonforest map. Areas that presented spectral ambiguity (<5%) between burned pasture and burned forest; and forest regeneration and secondary forest, were corrected using post-classification manual editing. Forest areas of less than 1 ha were also automatically reclassified as nonforest and a mean filter (5 × 5 pixels) was used to close forest gaps. These procedures allowed us to isolate the forested pixels from the other land cover classes (Fig. 3).

4.3. Mixture models

We estimated the amount of shade, soil, green vegetation and NPV within each pixel of the SPOT 4 image. Candidate pixels for pure spectra of these materials were found using the Pixel Purity Index—PPI (Boardman, Kruse, & Green, 1995). The PPI results were inspected in terms of the shape of the spectral curves and field context (e.g., soils are mostly

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**Table 2**
Characterization of forest degradation image classes in terms of field classes

<table>
<thead>
<tr>
<th>Image classification scheme</th>
<th>Field description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intact forest</td>
<td>Consists of mature, undisturbed forests dominated by shade tolerant species</td>
</tr>
<tr>
<td>Logged forest</td>
<td>Recently moderate logged (up to 1 year) or old heavily logged forest (&gt;5 years) which have experienced extensive damage due to harvesting activities, such as road creation, small clearings for timber piles, and structural damage to nearby trees and soil</td>
</tr>
<tr>
<td>Degraded forest</td>
<td>Includes recently burned, heavily burned or heavily logged forest (up to 2 years)</td>
</tr>
<tr>
<td>Forest regeneration</td>
<td>Regeneration of old heavily burned and burned forests</td>
</tr>
</tbody>
</table>

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**Fig. 4.** Fraction image composition of the forest degradation classes defined at the field scale plotted in a triangular space. Vertices of the ternary diagram (clockwise from top) represent 100% of NPV, shade and vegetation endmembers.
associated with roads) to define the final set of image pure spectra, known as image endmembers. The final green vegetation endmember was extracted from green pasture and the shade endmember was extracted from a dark water body. The soil endmember was extracted from road and NPV was acquired from senesced grass found in a pasture.

We applied least-square linear mixture modeling (Adams, Smith, & Gillespie, 1993) to estimate the proportion of each endmember within the SPOT 4 pixels. The sum of the fractions should add up to 1, but our mixture modeling did not use this condition as a constraint. The mixture modeling equations are given by

\[ \text{DN}_b = \sum_{i=1}^{n} F_i \text{DN}_{i,b} + \varepsilon_b \]

for

\[ \sum_{i=1}^{n} F_i = 1 \]

where \( \text{DN}_b \) is encoded radiance in band \( b \), \( F_i \) the fraction of endmember \( i \), \( \text{DN}_{i,b} \) encoded radiance for endmember \( i \) in band \( b \), and \( \varepsilon_b \) is the residual error for each band.

The mixing model results were evaluated as proposed by Adams et al. (1995). First, we evaluated the root-mean-square (RMS) image. Our final model showed very low RMS (<1 DN values). Next, fraction images were evaluated and interpreted in terms of field context and spatial distribution. The fraction image inspections also allowed us to evaluate the spectral separability of NPV and soil endmembers. For example, the final mixture model generated soil

![Binary decision tree](image)

**Fig. 5.** Binary decision tree used to classify forest degradation and intact forest classes using the fraction images derived from the SPOT 4 spectral mixture model. The decision tree divides a data set into progressively more homogeneous classes based on a series of hierarchical binary decisions. In the decision tree shown, the first branch splits at 22.5% NPV and branches left if this is true, right if false. Following this split, intact forest would follow the left branch with less than 68% green vegetation and less than 15.5% NPV.
fraction values slightly negative in forested pixel and high fraction values along roads and bare soil values. The NPV fraction was high in pasture and degraded forest areas.

Finally, we inspected the histograms of the fraction images to quantify the percentage of pixels laying outside the range of 0% to 100%. Our endmembers modeled about 95% of the pixels within the physically meaningful range. After acquiring a good model, we normalized the NPV, green vegetation and shade fractions to fit within the range from 0% to 100%. The normalization procedure was necessary because forested pixels are composed essentially of green vegetation, NPV and shade endmembers.

4.4. Forest degradation classification

We acquired GPS coordinates at the 14 research sites used by Gerwing (2002) in his forest degradation characterization study to identify the following classes of degraded forest: “heavily logged forest, moderately logged forest; heavily burned forest and burned forest” (Table 1). The forest inventories were conducted in November 1999 (Gerwing, personal communication). The GPS coordinates were collected, in a nondifferential mode, using a 12 channel Trimble Pathfinder unit (Trimble Navigation, Chandler, AZ). These coordinates were superimposed on the SPOT 4 image and used as a reference to select areas (3 × 3 pixels) to extract fraction values of NPV, green vegetation, and shade of each field class of degraded forest.

We did not attempt to extract pixels from the forest transects (10 × 500 m) used by Gerwing (2002) because the forest canopy did not enable us to accurately locate the forest transects with our GPS unit. However, the procedure we chose to extract fraction values from the image did not

Fig. 6. Fraction images obtained from the SPOT 4 mixture model. Shade fraction is low in deforested areas and high in canopy gaps (a). Heavily logged forest shows high NPV percent as well as areas that were logged and burned (b). Vegetation fraction can also enhance canopy gap damage areas due to logging (c—low values). Log landings, skid trails and roads can be identified from the soil fraction images (d—high values).
represent a problem to our analysis because the transects were representative of the degraded forest areas (Gerwing, 2002). Additional geolocated points acquired from field surveys ($n = 17$) and high-resolution IKONOS ($n = 4$) were combined with the forest transect data. Classes representing burning regeneration and old logged forest (>5 years) were also included in the analysis.

We then used box plots, scatter matrices and ternary diagrams to evaluate which fraction image could be used to separate the forest degradation classes defined by Gerwing (2002). This preliminary exploratory data analysis allowed us to evaluate whether or not it would be possible to distinguish the field classes defined by Gerwing using the SPOT 4 image.

Fraction images, when plotted in a ternary diagram, revealed that a direct linkage could not be established for all degradation classes (Fig. 4). Heavily logged, heavily burned and burned field classes were grouped into the forest degradation image class. Intact forest and burning regeneration could be mapped at the SPOT 4 scale. However, old logging and logged forest were also combined to form the logging image class (Table 2).

### 4.5. Forest degradation classification

The forest fraction images derived from the mixture models were classified into intact forest, degraded forest, forest regeneration and logged forest using a decision tree classifier (DTC) (Friedl & Brodlley, 1997; Roberts et al., 1998) available in the statistical software package S-Plus. We used the same training samples extracted for the exploratory data analysis (45 pixels/class), except that the outliers were excluded before running the DTC. The final forest degradation map was obtained after applying a majority filter ($5 \times 5$) to eliminate small isolated classes.

![Fig. 7. Map of forest degradation of the study area derived from fraction images using the decision tree classification rules.](image)

<table>
<thead>
<tr>
<th>Classes</th>
<th>Area (km²)</th>
<th>Percent of the study area</th>
<th>Percent of the forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonforest</td>
<td>1569.3</td>
<td>42.8</td>
<td>–</td>
</tr>
<tr>
<td>Intact forest</td>
<td>728.8</td>
<td>19.9</td>
<td>34.7</td>
</tr>
<tr>
<td>Degraded forest</td>
<td>185.6</td>
<td>5.1</td>
<td>8.9</td>
</tr>
<tr>
<td>Regeneration</td>
<td>11.8</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Logged forest</td>
<td>1171.1</td>
<td>31.9</td>
<td>55.8</td>
</tr>
<tr>
<td>Total</td>
<td>3666.6</td>
<td>100.0</td>
<td>100</td>
</tr>
</tbody>
</table>

**Table 4:** Area of the image classes estimated from the forest degradation map.
4.6. Accuracy assessment analysis

In order to evaluate the classification accuracy, 300 points were randomly generated for each of the forest degradation classes and the nonforest class within the area covered by the two IKONOS images (Fig. 2). Accuracy assessment for the intact forest class was not possible because the two IKONOS images were acquired in areas where there was no such class. Visual inspection of IKONOS data, at a 1:10,000 scale, was used to identify the reference class of each point within an area equivalent to the SPOT 4 pixel (i.e., 20 × 20 m). Because the IKONOS and SPOT 4 images were not acquired on the same dates (1 year apart), we had to use a color composite of the SPOT 4 (R4, G3, B2) to help to assign the final class to the randomly selected points. Points were only used if the class could be confidently identified in the IKONOS images. We also eliminated points that fell on cloud/shadow areas in the IKONOS images.

5. Results

5.1. Mixture models

The fraction images derived from the mixture model provided useful information to map degraded forests (i.e., heavily burned, heavily logged and burned forest field classes; Table 2, Figs. 4 and 6) in the study area. NPV and shade fractions increased in areas that were heavily burned or heavily logged, whereas vegetation content de-

![Graphs and tables showing relationships between NPV and total live aboveground biomass, and NPV and wood debris combined with burned vegetation.]
creased (Fig. 6). Degraded forests showed NPV fractions higher than 20% (Table 3, Fig. 5). This result agrees with the threshold value found by Cochrane and Souza (1998) to separate forest from recently burned forest in Taillândia, a county neighboring Paragominas in the Eastern Amazon. The heavily burned field class showed the highest NPV fraction values (mean = 38.4%), whereas heavily logged forest and burned forest had similar NPV mean values (mean = 29.3% and 29.6%, respectively—Table 3, Figs. 5 and 6). The main difference between the heavily logged class and burned forest class is in the green vegetation fraction. The heavily logged forests showed a lower shade (mean = 33.8%) content than the burned forests (mean = 31.9%; Table 3).

Intact forest showed good correlation between field and image scales. This class was characterized by NPV values lower than 17%, a vegetation fraction varying from 39% to 60%; and shade content ranging from 26% to 48% (Table 3, Fig. 5). Logged forest exhibited a decrease in shade (mean = 27.8%) and a subtle increase in the NPV content (mean = 19.9%) which allowed its separability from intact forest (Table 3, Figs. 5 and 6). Logged forest (Table 4) showed a higher range of green vegetation (43–60%) than intact forest because selective logging creates a heterogeneous environment composed of intact forest, canopy-reduced areas, small cleared areas, liana-rich areas, and areas that forest regeneration took place.

Regeneration of degraded forest resulted in a strong decrease in the shade fraction (mean = 11%) and increase in vegetation (mean = 69.8%) when compared to intact forest. This class is generally associated with older degraded forest areas. Visual inspection of the Landsat TM images showed that some of these areas are more than 10 years old.

Soil fractions were slightly negative in the intact forest class and all forest degradation classes (Fig. 6). However, important spatial information was obtained from the soil fraction image. For example, small areas of land cleared for temporary storage of logs in the forest (log landings) were detected in the soil fraction (Fig. 6). This information can be used to separate recently logged forest from old logged forest by applying a harvesting radius from the log landings (180 m; Souza & Barreto, 2000). Using this approach we estimated that 1676 ha of forest had been recently logged (about 1.5% of the total logged forest). Log landings were not associated with old logged and degraded forest because regeneration and canopy closure erases this spatial signature. In addition, logging roads and skid trails were also identified in the soil fraction images. This information can be useful to model logging economic extent (Souza, Monteiro, Salomão, & Valente, 2001) and map forest areas that are economically accessible (Veríssimo, Souza, Stone, & Uhl, 1997).

5.2. Forest degradation map

As the statistics in Table 4 show, a simple forest/nonforest characterization of an area such as Paragominas would drastically misrepresent the extent of intact forests. Of the entire area (3666 km²), about 57% of the area would be classified as intact forest, whereas only 20% (729 km²) is actually intact forest when the degraded forest classes are included as a class (Table 4, Fig. 7).

The remaining forested areas are in some stage of forest degradation, which includes logged forest (1171 km²; 5% of the forested area) and degraded forest (185.6 km²; 9% of the forested area). Severely degraded forests are forests which have recently been heavily burned or drastically damaged by selective logging and have not had time to regenerate. Less than 1% of the forested area was mapped as regeneration (Table 4).

Even though there was not a one-to-one relationship between the field and image classes, we found a strong correlation between NPV and total live aboveground biomass and combined wood debris and burned vegetation (Fig. 8). There is a negative linear relationship between the mean NPV fraction values and mean total live aboveground biomass (R² = 0.97) measured in the field. NPV content showed a positive correlation with the combined wood debris and burned vegetation percents (R² = 0.89).

5.3. Accuracy assessment

The accuracy was high for the forest/nonforests map (93%; Table 5). However, when trying to assess the accuracy of the forest degradation classes, the difference in the acquisition date of the SPOT 4 image and the IKONOS image imposed some difficulties due to regeneration of previously degraded areas and the appearance of new degraded areas. The overall classification of the forest degradation classes was 86%. Areas that were classified as logged forest showed 92.2% and 73.8% users and producers accuracy, respectively. Degraded forest was satisfactorily mapped (65.5% and 83.7% users and producers accuracy; Table 5). No estimate is provided for the burning regeneration class because only a few randomly selected points (n = 6) were representative of this class.

<table>
<thead>
<tr>
<th>IKONOS reference image</th>
<th>Forest degradation map</th>
<th>Total Users accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Nonforest</td>
<td>Degraded forest</td>
</tr>
<tr>
<td>Nonforest</td>
<td>132</td>
<td>6</td>
</tr>
<tr>
<td>Degraded forest</td>
<td>2</td>
<td>36</td>
</tr>
<tr>
<td>Logged forest</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>138</td>
<td>43</td>
</tr>
</tbody>
</table>

Producers accuracy = 0.86
Kappa coefficient = 0.78
Forest/nonforest accuracy=((132/142)+(113a/119))/2 = 0.93

* Degraded forest = logged forest.
6. Discussion

6.1. Field and satellite scale linkage

We cannot compare directly the forest composition measured at the field scale (Table 1) and at the pixel scale (Table 3). For example, the percentage of intact forest measured in the field represents the amount of vegetation that had not been disturbed by logging and/or burning, and not the percentage of green vegetation. Additionally, the intact forest field class is composed of leaves (green vegetation), barks and branches. The percentage of intact forest is high for the intact forest class and drops in degraded forests, reaching 2% in heavily burned forests.

As a result, there is an increase in wood debris and burned vegetation (NPV) as intact forest becomes more degraded (Table 1).

At the satellite pixel scale, the intact forest is characterized by a mixture of green vegetation (mean = 49%), shade (mean = 36%) and NPV (mean = 13%; Table 3). The highest green vegetation fraction values is found in regeneration class (mean = 69%), followed by old logged class (mean = 56%) and logging class (mean = 52%; Table 3). This pattern occurs because the forest gaps caused by logging activity closes rapidly (Johns et al., 1996; Verissimo et al., 1992) causing a decrease in shade content. As a result, green vegetation fraction increases in logged forests. For this reason, green vegetation estimated at the sub-pixel scale should not be interpreted as a measure of disturbance of forested areas.

The other differences observed at the field and satellite scales are associated with NPV estimates. These differences occur because the natural NPV contents (i.e., bark, branches, stems, and dead leaves) were not measured at the field scale. The NPV reported in Table 1 refers to wood debris and burned vegetation resulted from logging and/or burned activities. The NPV estimated with the mixture models represents the total NPV content (i.e., natural and anthropogenic). The offset observed in the regression line of wood debris and burned vegetation versus NPV fraction (Fig. 8b) is due to the different methodologies used to estimate NPV content in the field and in the satellite image.

6.2. Fraction image classification

Our SPOT 4 mixture model results agree with prior studies that used fraction images, derived from Landsat TM, to map burned forest (Cochrane & Souza, 1998), log landings created by selective logging (Souza & Barreto, 2000), and intact forest (Adams et al., 1995; Cochrane & Souza, 1998; Roberts et al., 1998) in the Amazon.

Prior studies have shown that a unique set of thresholds obtained with DTC can be used to map land cover classes locally and that the rules cannot be extended to other regions without considering natural vegetation type variations (Roberts et al., 1998, in press). The classification thresholds obtained in our study to map classes of degraded forest must not be interpreted as general rules to map degraded forest. Variation on harvesting intensity, forest burning dynamics, and logging and fire recurrence regime will also affect the portability of the DTC thresholds. Additionally, regeneration of degraded forest can contribute to change the class thresholds. However, in areas like Paragominas, that underwent drastic forest structure and composition changes due to logging and fire activities, the threshold might also show temporal instability. A time series analysis of degraded forest area is required to evaluate the temporal portability of the DTC thresholds.

6.3. Mapping of forest degradation

The NPV endmember was the most important endmember to separate classes of degraded forests at the SPOT 4 image scale. Given the low spectral resolution of SPOT 4 and spectral resemblance with soil spectra, locating the NPV endmember was not a straightforward process. We used three approaches to identify the NPV endmember and separate NPV from soil. First, we computed the PPI algorithm to identify potential endmember candidates. Second, we compared the PPI results with field knowledge to identify areas more likely to find NPV (e.g., pastures with senesced grass) and soil (associated with roads and bare areas). Finally, we evaluated the fraction image results in terms of expected class composition (e.g., intact forest must have no soil and low to moderate NPV values).

The NPV fraction image improved the mapping of old logged forest when compared to soil fraction image used by Souza and Barreto (2000). The rapid regeneration of log landing areas (Gerwing, 2002; Johns et al., 1996; Stone & Lefebvre, 1998) limits the use of soil fraction images to mapping selective logging no more than 2 years old. Moreover, information about the harvesting radius is needed in order to estimate the area affected by logging using soil fractions. Additionally, soil fraction images also fail to identify log landing in highly disturbed forest areas because the spatial signal of the log landing is confused with other types of cleared areas. The NPV fraction allowed us to map selectively logged forest up to 10 years old. It is important to highlight that most of these forests were logged at least twice. For that reason, the NPV fraction may not improve the mapping of very old logged forest in areas that logging intensity is low (>20 m3/ha), such as Sinop, in Mato Grosso state (Monteiro et al., 2003) where soil fraction images have also proved to be effective to map selectively logged areas up to 2 years old.

Our analysis did not include information on edge effects and minimum size of a forest patch that would still function as a forest. The total area of intact forests would be reduced if information on edge effects and minimum forest area had been included in the analysis. There are three main blocks of intact forest in the eastern portion of the study area (Fig. 7). These forest blocks show evidence of selective logging and
deforestation activities along the border with deforested areas. This may lead to the conclusion that these forest blocks are no longer pristine. As a final consideration, our classification procedure may be improved by using images acquired at different dates, ideally every year. Old degraded forest (>10 years) may have regenerated and misclassified at old logged forest. Having been used images acquired in different dates, disallowed class transitions could have been defined to avoid this type of classification error.

7. Conclusions

This study showed that a partial linkage of field classes with moderate-resolution satellite images such as SPOT 4 (20 m IFOV), and potentially Landsat TM (30 m IFOV), can be achieved by deriving information at a sub-pixel scale associated with field materials. Improvements can be made to fully integrate these scales by including both temporal and spatial information.

Our results reinforce the need for a more complete characterization of forests in areas of the Amazon where logging centers and agricultural activities play an important economic role. A classification scheme that is reflective of basin-wide degraded forest types found in the field is needed for integration of data over time and scale. In order to accomplish this task, more field studies must be conducted covering other forest types than have been selectively logged, as for example, transitional forest in Mato Grosso (Monteiro et al., 2003). Field inventories and map of degraded forests in the region are needed for local and state governments to identify resource bases and effectively plan conservation and development activities. Additionally, more accurate estimates of the extent and type of degraded forests are needed to incorporate into ecological, economic and carbon models for the basin.

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