**A 22 year assessment of deforestation and restoration in riparian forests in the eastern Brazilian Amazon**

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## Methods

### Satellite imagery data

To cover the study area, 57 Landsat TM and ETM+ images, 30-metre spatial resolution, acquired between 1988 and 2010, were used (Table S1). The path/rows that cover Paragominas municipality are 223/62, 223/63, 222/62 and 222/63 (Table S1; Figure 1 in main manuscript). The images were acquired through the National Institute for Space Research (INPE, in Portuguese). In order to build the mosaic of RapidEye images, we acquired 55 orthorectified (3A level) scenes from 2009 (n=45) and 2010 (n=10), with a 5-metre spatial resolution (Table S2; Figure 1a in main manuscript).

Table S1: Landsat TM/ETM+ data used to cover study area.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Year** | **223/62** | | **223/63** | | **222/62** | | **222/63** | |
| **Date** | **Sensor** | **Date** | **Sensor** | **Date** | **Sensor** | **Date** | **Sensor** |
| **1988** | 22/07/1988 | TM | 22/07/1988 | TM | 31/07/1988 | TM | 16/08/1988 | TM |
| **1990** | 28/07/1990 | TM | 25/05/1990 | TM | - | - | - | - |
| **1991** | - | - | - | - | 24/07/1991 | TM | 24/07/1991 | TM |
| **1992** | 02/08/1992 | TM | 02/08/1992 | TM | - | - | - | - |
| **1994** | 23/07/1994 | TM | 07/07/1994 | TM | 18/09/1994 | TM | 01/08/1994 | TM |
| **1995** | - | - | - | - | - | - | - | - |
| **1996** | 25/05/1996 | TM | 10/06/1996 | TM | 05/07/1996 | TM | 03/06/1996 | TM |
| **1997** | - | - | - | - | - | - | - | - |
| **1998** | - | - | 19/08/1998 | - | 28/08/1998 | TM | 28/08/1998 | TM |
| **1999** | 13/07/1999 | ETM | - | - | - | - | - | - |
| **2000** | 31/07/2000 | ETM | 31/07/2000 | ETM | 06/06/2000 | ETM | 06/06/2000 | ETM |
| **2001** | - | - | - | - | - | - | - | - |
| **2002** | 07/09/2002 | ETM | - | - | 28/06/2002 | ETM | 28/06/2002 | ETM |
| **2003** | - | - | 16/07/2003 | TM | - | - | - | - |
| **2004** | 15/05/2004 | TM | 15/05/2004 | TM | 15/10/2004 | TM | 09/06/2004 | TM |
| **2006** | 09/08/2006 | TM | 09/08/2006 | TM | 15/06/2006 | TM | 15/06/2006 | TM |
| **2008** | 14/08/2008 | TM | 29/07/2008 | TM | 20/06/2008 | TM | 20/06/2008 | TM |
| **2010** | 03/07/2010 | TM | 05/09/2010 | TM | 26/06/2010 | TM | 26/06/2010 | TM |

Table S2: RapidEye data used to cover study area.

|  |  |  |  |
| --- | --- | --- | --- |
| **Path/Row** | **Date** | **Path/Row** | **Date** |
| 2337901 | 05/09/2009 | 2337607 | 04/09/2009 |
| 2337902 | 05/09/2009 | 2237525 | 26/06/2010 |
| 2337905 | 02/08/2009 | 2237526 | 26/06/2010 |
| 2337906 | 03/08/2009 | 2237527 | 26/06/2010 |
| 2337907 | 04/09/2009 | 2237528 | 21/07/2009 |
| 2337908 | 14/08/2009 | 2337501 | 21/07/2009 |
| 2337801 | 21/07/2009 | 2337501 | 21/07/2009 |
| 2337802 | 21/07/2009 | 2337502 | 27/07/2009 |
| 2337803 | 02/08/2009 | 2337503 | 27/07/2009 |
| 2337804 | 02/08/2009 | 2337504 | 11/07/2009 |
| 2337805 | 27/07/2009 | 2337505 | 04/09/2009 |
| 2337806 | 04/09/2009 | 2237424 | 03/07/2009 |
| 2337807 | 14/08/2009 | 2237425 | 26/06/2010 |
| 2337701 | 21/07/2009 | 2237426 | 26/06/2010 |
| 2337702 | 21/07/2009 | 2237427 | 26/06/2010 |
| 2337703 | 02/07/2009 | 2237428 | 21/07/2009 |
| 2337704 | 27/07/2009 | 2337401 | 21/07/2009 |
| 2337705 | 27/07/2009 | 2337402 | 02/08/2009 |
| 2337706 | 04/09/2009 | 2337403 | 02/08/2009 |
| 2337707 | 13/06/2009 | 2337404 | 02/07/2009 |
| 2237627 | 20/08/2009 | 2337405 | 02/08/2009 |
| 2237628 | 21/07/2009 | 2237325 | 26/06/2010 |
| 2337601 | 21/07/2009 | 2237326 | 26/06/2010 |
| 2337602 | 21/07/2009 | 2237327 | 26/06/2010 |
| 2337603 | 02/07/2009 | 2237328 | 21/07/2009 |
| 2337604 | 27/07/2009 | 2337301 | 21/07/2009 |
| 2337605 | 27/07/2009 | 2337301 | 04/09/2010 |
| 2337606 | 04/09/2009 | - | - |

### Satellite imagery processing

### Pre-processing

Landsat ETM+ images acquired in 2000 were georeferenced using control points extracted from GeoCover 2000 mosaic of NASA (National Aeronautics and Space Administration available at https://zulu.ssc.nasa.gov/MrSID/mrsid.pl). Images from other years were then registered based on the georeferenced images from 2000, using ENVI 4.7 software. Accurate georeferencing and registration is important to detect small scale changes over time. Both processes were based on the nearest-neighborhood resampling method, available in the Environment for Visualizing Images software - ENVI 4.7, using at least 40 image control points. The root-mean-squared-error (RMSE) maximum acceptable was 0.5 of a pixel.

The effects of haze and smoke were corrected in all images using a haze equalization algorithm (Carlotto, 1999). This method corrects the spectral bands in the visible region (1, 2 and 3) that are most affected by haze and smoke, using the bands that are free from this effect (4, 5 and 7). Then, images were radiometrically corrected using the calibration values (gains and offsets) of ETM+ (Chander *et al.*, 2009).

The images were then converted from radiance into absolute reflectance using FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) 4.7, the ENVI atmospheric correction module. The parameters of visibility and water vapor in the atmosphere were estimated from the reflectance of targets with known reflectance values (water and vegetation). The initial values of water vapor and atmospheric visibility to optimize the atmospheric correction model were 45 mm and 45 km, respectively.

### Spectral Mixture Analysis (SMA)

The next step was to estimate the abundance of pure components (pure pixels of vegetation - GV, bare soil, Non-Photosynthetic Vegetation - NPV, cloud and shade) at each pixel by applying the spectral mixture analysis (SMA) (Adams *et al.*, 1993) in the reflectance images. The SMA estimates the fraction of pure components in the image using the reflectance of each pixel, which is modeled by a linear combination of the reflectance product of the N pure components by their respective fractions, as shown in Equation 1:

|  |  |
| --- | --- |
| for | (1) |
|  | | |  |

Where, *Rb* is the reflectance measured in the band *b*; *Fi* is the fraction of component *i*; *Ri,b* is the reflectance measured for the component *i* in band *b*; *εb* is the residual error for each band, which indicates the portions of the spectrum not modeled, and *n* is the number of bands (Roberts *et al.*, 1998). The error of the SMA is given by Equation 2:

|  |  |
| --- | --- |
|  | (2) |

The pure components GV, NPV and bare soil used to generate the SMA model were obtained from Souza Jr. *et al*. (2005) (generic pure components). The pure component of cloud was obtained afterwards and shade was calculated as a complement.

### Normalized Difference Fraction Index (NDFI)

Using fraction images obtained from SMA models, the NDFI (Souza Jr. *et al.*, 2005) was applied to the images to enhance the signal of forest degradation caused by logging and burning and can be computed by Equations (3) and (4):

|  |  |
| --- | --- |
|  | (3) |

for,

|  |  |
| --- | --- |
|  | (4) |

Where, *GVshade* is the shade-normalized vegetation fraction; *NPV* is the non-photosynthetic vegetation and *Soil* is the bare soils. This index is non-dimensional, ranging from -1 to +1 and the higher the value, the less degraded the forest is.

### Decision tree land cover classification

To perform the imagery processing steps - except georeferencing and atmospheric correction - a new software named ‘ImgTools’ was used. ImgTools is an intuitive software with a friendly user interface, developed in Interactive Data Language (IDL) platform and designed to automate the processing steps necessary to image classification (Souza Jr. and Siqueira, 2013).

Decision tree classification is a technique that uses a recursive partition of the data set, dividing it into smaller parts (Friedl and Brodley, 1997). The dividing process is performed by defining classification rules to each node in the tree. The basic elements that compose the tree are: rules, nodes, branches and classes. Additionally, the rules are composed of variable, operator and the optimal value to define the partitions. For this study the knowledge-based classification was performed, that is, the knowledge of the variables and the analyst interpretation were both used to classify images semi-automatically. The classification was performed to generate two main products: i) the distribution of forested and deforested areas for each year, and ii) a forest regeneration map. For the purposes of our analysis here, the class ‘forest’ encompassed undisturbed forests as well as degraded forests registered as having experienced some form of canopy disturbance (i.e. through logging or fire), but not outright deforestation.

The deforestation/degradation tree used NDFI and fraction images (GV, GVshade, NPV, bare soil, and cloud) as tree variables. The decision tree was firstly applied to the baseline (initial state of land cover, at the first year of analysis) to classify non-forest (deforestation and natural non-forest areas), undegraded forest, regeneration, degradation, water and cloud. Then, the same tree, with adjusted decision rules values, was applied to the time series to detect land cover change over years, using non-forest from the baseline and accumulated deforestation as a mask, in order not to map these areas in the following years. Figure S1 shows the tree structure, including default values for each rule in the tree. The final set of decision rules values were based on knowledge of the analyst and can be adjusted according to his data interpretation (Souza Jr. *et al.*, 2013b; Souza Jr. and Siqueira, 2013; Gardner *et al.*, 2013).

decision_tree_def.tif

Figure S1:Deforestation and degradation decision tree structure used to perform classification. *V* referes to variables, numbers are default values for each rule in the tree. Note: If the year of analysis is not the baseline, then the classes Non-forest and Regeneration are called Deforestation (Souza Jr. *et al.*, 2013b).

Changes in forest cover prior to 2010 were assessed both across the municipality as a whole, and also within 190 third or fourth order hydrological micro-catchments (selected to be of approximately equal size – c. 5000 ha) to quantify spatial variability in deforestation patterns. Catchments boundaries were obtained in the ArcSWAT software using TopoData digital elevation model (30 m resolution) and were distributed in Paragominas across a forest gradient (6 to 100%) (Gardner *et al.*, 2013).

For forest regeneration analysis, a different classification tree was performed to detect regeneration process after deforestation events, regeneration detected in the baseline and new deforestation mapped over the time series (Figure S2). The regeneration tree used fraction images (GV, NPV, bare soil, and cloud) as rule variables. An algorithm written in IDL was used to calculate the age of regeneration detected in 2010 (Siqueira, 2012). As a result, we had five classes, as it follows:

(i) regeneration - secondary forest younger than baseline (1988);

(ii) old-regeneration-regeneration: areas classified as secondary forest in the baseline and also mapped as secondary forest in the year of analysis, although they may have been mapped as deforestation between the baseline and year of analysis;

(iii) old-regeneration-deforestation: deforestation of secondary forests identified in the baseline;

(iv) non-forest: deforestation detected over years before the year of analysis plus natural non-forest areas;

(v) cloud.

decision_tree_reg.tif

Figure S2: Regeneration decision tree structure used to perform classification. Where, *V* refers to variable; *Vprevious*is the classification before year of analysis; *NF+D* is the non-forest detected in the baseline + the accumulated deforestation detected until the year before analysis and *RegBL* is the regeneration detected in the baseline. Numbers are default values for each rule in the tree (Gardner *et al.*, 2013).

A spatial filter was used in order to eliminate classification errors (small groups of misclassified isolated pixels), reclassifying those pixels to the more abundant class in a 3x3 pixel neighborhood window. A temporal filter was also used to avoid some ‘disallowed transitions’ (Souza Jr. and Siqueira, 2013). For example, clouds detected in the year of analysis can be removed if mapped as forest in the year before and in the following year. Other combinations have also been implemented in order to reduce classification errors (Souza Jr. and Siqueira, 2013). To achieve a regular time interval data from 1988 to 2010, the deforestation from 1991, 1999 and 2003 was counted in the following year.

### Accuracy assessment of land cover mapping

In order to validate the Landsat classification described in the previous section, we performed an accuracy assessment of Paragominas land cover map for 2010, using 55 RapidEye high-resolution images (5 metres - Table S2) as reference data. Whilst it would be ideal to validate land cover map for all years, extrapolating an accuracy assessment for one focal year to the full time-series being assessed in a given study is generally accepted as standard procedure in the remote sensing community, since we used a normalized time-series of Landsat imagery and applied the same image classification algorithm to entire data set. For this purpose, we applied the methodology developed by (Powell *et al.*, 2004) with adaptations for this study.

The pixels distribution followed the cluster sampling method, in which a pivot pixel is randomly positioned and four companion pixels are systematically positioned around the first one, creating the cluster. Each pixel of the cluster was treated as an independent sample. A total of 260 pivot pixels were randomly distributed in the study area to ensure that the samples were representative of the municipality and each land cover class. Thus, considering the cluster sampling, a total of 1300 pixels sample were evaluated to validate land cover map from 2010: 200 for forest, 400 for degradation, 250 for deforestation and 450 for regeneration class. In order to reduce uncertainties and confusion among classes, forest and degradation were evaluated as a single class called ‘forest’ – which was the class used for the main analyses in the paper. Clouds, shade, water, mixed and no data pixels were excluded from the analysis. We used stratified sampling to ensure that our results were representative both inside and outside RAPPs.

Two trained analysts evaluated each selected pixel to determine whether the result of the classification corresponds to the same land cover class observed in the high resolution image. The final decision about the land cover for each pixel is made considering the highest number of votes at the end of the evaluation between the two analysts. This final decision is used as reference value in the accuracy assessment. The final sample used to calculate overall accuracy was obtained after corrections of the reference data (geocorrections, edges and different dates between reference and map, called change pixels) to eliminate errors in the processing. The accuracy of the classifier was assessed using a confusion matrix (Story and Congalton, 1986) (see Results below).

### Riparian areas of permanent preservation (RAPP) mapping

We used a procedure to map water courses based on a Digital elevation model (DEM) product refined with 5-metre RapidEye images and a knowledge-based classification to map land cover changes in eastern Amazon, using a software designed to automate the processing steps necessary to image classification (Souza Jr. and Siqueira, 2013). Both products were combined in order to assess RAPPs loss over time.

For this study, we considered only RAPPs from streams, rivers and water bodies (lakes and dams), excluding the other types of APPs (e.g. headwaters, mangrove, sand dune vegetation, high declivity areas - > 45°). First, we used the 90m-resolution Digital Elevation Model (DEM) of Space Shuttle Topographic Mission (SRTM) in order to map rivers automatically, based on the SRTM elevation data, using ArcGIS 10.0.

Second, we performed a fusion between the SRTM and the 5-metre RapidEye images from 2009 and 2010 to create an anaglyph product using the software ERDAS Anaglyph tool. RapidEye images satisfy the mapping scale required by law (1:50.000) (Souza Jr. *et al.*, 2013a). In order to correct possible mistakes found in the linear features mapped automatically (streams and rivers), we combined the features to the anaglyph product and performed a visual analysis using ArcGIS. The visual analysis was facilitated by using 3D glasses to have a better perception of the three dimensional relief (Souza Jr. *et al.*, 2013a). Lakes and dams were manually mapped using Landsat images from 2010, at a 1:50.000 scale.

The third step was to map the RAPPs around the streams, rivers, lakes and dams, according to Brazilian environmental law. RAPPs around streams and rivers were calculated under the previous Brazilian Forest Code requirements (Brazilian Federal Law Nº 4.771, from 15th September 1965), since our goal is to assess how legislation affected riparian forest protection in the past two decades (1988 to 2010) (Table S3). All streams and rivers mapped in this study were considered to be subject to enforcement as defined by Brazilian law. However, there remains considerable uncertainty as to what regulating authorities actually define as a RAPP in practice and for a given place, particularly in areas where water flows may have been altered due to historical land-use change and in areas where water flow may temporarily cease (perhaps naturally) during particularly dry periods. The variable width along the same water course was not taken into account in this study.

Table S3: Buffers radius around rivers, streams, lakes and dams used to map RAPP in Paragominas, based on Brazilian legislation (Law Nº 4.771, from 15th September 1965).

|  |  |  |
| --- | --- | --- |
| **Water courses** | **Water course width** | **RAPP width** |
| Rivers and streams | < 10 m wide | 30 m |
| 10-50 m wide | 50 m |
| 50-200 m wide | 100 m |
| Lakes | < 1 ha | - |
| 1-20 ha | 50 m |
| > 20 ha | 100 m |
| Dams | < 1 ha | - |
| 1-20 ha | 15 m |

Approximately 95% of the water courses mapped were less than 10m in width; 3% were 10 to 50m in width and 2% were 50 to 200m. RAPPs from streams, rivers, lakes and dams were joined into a single shape file, which was then combined with the classification products (deforestation and regeneration), using ArcGIS 10.0, in order to describe patterns of RAPP loss over time and the history of regeneration. The class ‘water’ detected in RAPPs was removed from the analysis, since protection area includes only the marginal area of the water courses and water bodies.

### Current RAPP environmental liabilities by land tenure

The first step to obtain the environmental license for economic activities is for land owners to provide the state government a digital geodatabase (CAR) of their properties. This register must inform the land cover, including APP (Guimarães *et al.*, 2011). In order to calculate RAPP environmental liabilities, we used Landsat classification from 2010 and divided Paragominas into four main categories of land tenure: CAR from February 2013 (small, medium and large private properties – 74% of the municipality) provided by The State Secretary for the Environment (SEMA), agrarian settlements (agricultural families placed in rural lands by the Brazilian Colonization and Land Reform Agency – 6%), indigenous land (5%) and unregistered private lands (private untitled lands - 15%) (Figure 1c, in main manuscript).

According to the new Brazilian Forest code areas deforested up to 22nd July 2008 are termed ‘consolidated rural areas’, and RAPPs do not need to be fully restored. The RAPP width to be restored depends on the private property sizes and the water course types (Table S4). In order to estimate environmental liabilities in RAPPs, we considered all the deforestation in RAPPs detected in smallholder properties (<= 220 ha) and agrarian settlements as being from ‘consolidated areas’ (areas deforested before 22nd July 2008) – meaning that the landowner would not need to recover the entire RAPP according to Brazilian environmental law. By contrast, it was assumed that RAPPs from medium and large properties (> 220 ha), unregistered private lands and indigenous lands would need to be fully restored (Table S4).

Table S4: RAPP forest restoration requirements under the new Brazilian Forest Code (Law N° 12,651, from 25th March 2012), for private properties in Paragominas.

|  |  |  |
| --- | --- | --- |
| **Water courses** | **Private property sizes** | **RAPP width to be restored** |
| Rivers and lakes | ≤ 55 ha | 5 m |
| > 55 ha and ≤ 110 ha | 8 m |
| > 110 ha and ≤ 220 ha | 15 m |
| > 220 | min. 20 m to max. 100 m1 |
| Lakes | > 220 | 30 m |
| Dams | - | 15m |

1 Depending on the Environmental Regulation Program (PRA, in Portuguese) of the property.

Property sizes registered in CAR were defined according to the Federal Law n° 8.629, from 25th February, 1993, as small (≤ 220 ha), medium (> 220 ha and ≤ 825 ha) and large properties (> 825 ha).

## Results

### Accuracy assessment of land cover mapping

The overall accuracy for mapping forest (under varying levels of degradation), deforestation and regeneration was 0.89 using RapidEye 5-metre resolution imagery as reference data. The user's accuracy for forest, regeneration and deforestation was 0.84, 0.92 and 0.96, respectively (Table S5). The overall accuracy ranged from 0.78 with no correction to 0.89 when all reference data corrections were applied (Table S6). The total of number of excluded samples pixels, including correction, water, cloud/shade and mixed pixels, was 249 (Table S7). The lower accuracy for the forest class can be explained by the fact that degraded and un-degraded forest were evaluated as a single class. However, the estimates of degradation and deforestation are susceptible to significant uncertainty, since severe forest degradation can commonly be confused with deforestation during classification processes (Souza Jr. *et al.*, 2013b). That said, both ‘undegraded’ and ‘degraded’ forest were pooled for the purposes of our analysis into ‘forest’ so this uncertainty does not affect our results.

Table S5: Accuracy assessment of the Landsat classification results using high spatial resolution RapidEye data as a reference.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Land cover classes** | **Reference data** | | | **Row total** | **User's Accuracy** |
| Forest (forest + degradation) | Regeneration | Deforestation |
| Forest (forest + degradation) | 424 | 10 | 72 | 506 | 0.84 |
| Regeneration | 15 | 188 | 2 | 205 | 0.92 |
| Deforestation | 6 | 6 | 328 | 340 | 0.96 |
| Columm total | 445 | 204 | 402 | 1051 | - |
| Producer's Accuracy | 0.95 | 0.92 | 0.82 | - | - |
| **Overall accuracy = 0.89** |  |  |  |  |  |

Table S6: The impact of applying corrections to the reference data on the accuracy assessment of the Landsat classification results.

|  |  |  |  |
| --- | --- | --- | --- |
| **Version** | **Correction to reference data set** | **Number of samples** | **% Overall agreement** |
| 1 | None | 1199 | 0.78 |
| 2 | Geocorrection | 1167 | 0.81 |
| 3 | Map edge | 1143 | 0.82 |
| 5 | Change pixel | 1051 | 0.89 |

Table S7: Total number of excluded sample pixels from the accuracy assessment of the Landsat classification.

|  |  |  |
| --- | --- | --- |
| **Reason for exclusion** | **# of samples** | **%** |
| No data | 2 | 0,8 |
| Geocorrection | 32 | 12,9 |
| Map edge | 24 | 9,6 |
| Mixed pixel | 3 | 1,2 |
| Change pixel | 92 | 36,9 |
| Cloud/shade | 81 | 32,5 |
| Water | 15 | 6,0 |
| Total | 249 | 100,0 |

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