Supporting Online Material for

The Incidence of Fire in Amazonian Forests with Implications for REDD

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1. INPE’s Fire Monitoring System data

For the current analysis we used the long-term record of thermal anomalies (or hot pixels) available from the Advanced Very High Resolution Radiometer (AVHRR) aboard the National Oceanic and Atmospheric Administration NOAA satellites. Hot pixel counts were derived from daily, night-time, 1 km spatial resolution, NOAA-12 database from the Brazilian Institute for Space Research (INPE) Queimadas project (1998–2006; freely available at http://www.cptec.inpe.br/queimadas/) (S1). The data product uses AVHRR channel 3 at 3.7 μm to quantify thermal anomalies and identify active fire (S2).

The night-time AVHRR fire product has an improved accuracy because of the minimization of spurious fire detections. Fire detections at night reduce the confusion of active fires with heated ground surfaces in deforested areas or sand patches. The AVHRR fire count product is highly correlated with similar product from MODIS (Moderate Resolution Imaging Spectroradiometer) and is therefore able to equally represent fire dynamics in Amazonia (S3, see section 5 of the SOM for more details). Hot pixels are indicators of fires and may well underestimate their occurrence owing to clouds and forest canopy cover, but hot pixel counts do allow the evaluation of patterns over time (S4), which is the aim of our analysis in this paper.

Clouds obstruct fire detections in Amazonia and may lead to underestimation of hot pixel counts. Temporal changes in cloudiness pattern are likely to influence fire incidence estimations.
However, clouds are also indicative of rain, when fire probability is very low, minimizing this effect. Dense forest canopy may also obstruct hot pixel detections leading to underestimation of understory fires. In the present analysis we are unable to quantify changes in understory fire patterns. AVHRR fire data are mainly representing the dynamics of deforestation fires with some contribution of high intensity fires in forest edges and degraded forests. The fire incidence values presented in our analysis are therefore likely to be an underestimation rather than an overestimation of fire occurrences.

The 1 km spatial resolution of the AVHRR pixel is expected to detect the presence of fires as small as 0.01 ha (S2, S5-S7). Validation work indicates that 80% of fire outbreaks are in a radius of 1 km of the coordinates given (S1). The coarse spatial resolution of the fire data though is coherent with the size of deforested areas in Amazonia. The majority (70%) of the monthly area detected as deforested by INPE’s DETER project (S8) is associated with polygons > 100 ha (Fig. S1). At an annual time scale the proportion of large polygons is likely to increase as small polygons may be grouped into larger polygons as deforestation advances.

For each year, the original fire data were aggregated by summing all hot pixels occurrence within each grid cell with 0.25° x 0.25° spatial resolution covering the Brazilian Amazon. This procedure allowed the production of nine annually-accumulated hot pixel surfaces, which were used subsequently to detect local trends in fire incidence.

The cumulative number of AVHRR fire detections used in our study is indicative of the amount of biomass burnt. There is a direct relation between fire counts and the deforestation area (S2, S4), as well as between fire counts and the mass of the emitted smoke particles (S6). Increasing the area deforested and consequently the amount of slashed vegetation available (fuel loads) the number of daily fire detections in the same location is expected to increase at a given year (S9).

### 2. INPE’s Deforestation Monitoring System data

For calculating deforestation trends in the Brazilian Amazon we used annual deforestation maps produced by the INPE’s PRODES program (S10) freely available in the World Wide Web at [http://www.obt.inpe.br/prodes/index.html](http://www.obt.inpe.br/prodes/index.html). Digital PRODES program uses a semi-automated procedure to perform the digital processing of TM/Landsat images in order to quantify deforested areas in tropical forest formations (S11-S12). The method consists in applying the spectral linear
mixing model \((S13)\), to decompose pixel information in the original bands 3 (0.63-0.69 μm), 4 (0.76-0.90 μm) and 5 (1.55-1.75 μm) into its fraction images of shade, vegetation and soil. Afterwards, taking into account the information condensed in the fraction images; a segmentation procedure is carried out followed by the classification of deforested areas. After visual inspection of the classified images by an expert, final step in the generation of deforestation surfaces, the product is released for users with a 60 m spatial resolution. Figure S2 shows the temporal pattern of deforestation in the Brazilian Amazon States from 1998 to 2008. Note that the 1998 and 1999 deforestation rates estimates are not available digitally.

We used all the data available on deforestation at the time of this study. Digital deforestation surfaces produced by INPE encompassed the period between 2000 and 2007 \((S10)\). To perform the trend analysis, we initially aggregated the 60 m spatial resolution into annual pixel fraction deforested at 0.25° x 0.25° \((774.35 \text{ km}^2)\) spatial resolution. We opted for calculating pixel fractions in the aggregation procedure in order to maintain the original area information while changing the surface resolution. We have produced a total of eight surfaces with information on the annual deforestation extent to perform the trend analysis.

It is important to note that INPE’s monitoring system (PRODES) only estimates the gross deforestation rates, without taking into account degradation (fires) and deforestation of regenerating secondary forests. Due to INPE’s approach of using fraction images to classify deforestation and subsequent visual inspection of classified images by experts using color composite images, confusion between fires and deforestation is unlikely. Burned forests are clearly identified in the shade fraction image \((S14)\), while clear cut areas have strong signal in the soil fraction images. Once the area is mapped as deforested, it is masked and not revisited. Despite being the best available system to monitor deforestation in tropical forests, the information provided by INPE does not encompass the full range of possible deforestation pathways and is limited to deforestation associated to the original forest area. Figure S3 exemplifies the method described above showing the construction of the deforestation mask according to the PRODES methodology. It also highlights processes happening after deforestation underneath the masked polygons.
3. Trend regression analysis

Trends in deforestation rates (2000-2007) and fires frequencies (1998-2006) across the Brazilian Amazon were quantified using a trend regression for each 0.25° x 0.25° pixel defined by its central latitude (i) and longitude (j). The confidence level of the trends observed in each grid cell was obtained according to the two-tailed student’s t distribution. The t-score for each grid cell \( t(i,j) \) was calculated dividing the slope \( b(i,j) \) of the regression line by its respective standard error \( SE(i,j) \) according to equation 1.

\[
t(i,j) = \frac{b(i,j)}{SE(i,j)}
\]

Equation (1)

The slope of the trend regression is defined as (Equation 2):

\[
b(i,j) = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sum(x - \bar{x})^2}
\]

Equation (2)

where \( x \) corresponds to the specific year (independent variable), \( \bar{x} \) is the average of all years, \( y \) is the number of hot pixels or deforested fraction (dependent variables) for the specific year \( x \) and \( \bar{y} \) is the average of hot pixels or deforested fraction between all years.

The standard error of the regression slope is defined as (Equation 3):

\[
SE(i,j) = \frac{\sqrt{\sum(y_o - \hat{y}_o)^2 / (n - 2)}}{\sqrt{\sum(x_o - \bar{x})^2}}
\]

Equation (3)

where \( y_o \) is the value of the dependent variable for the observation \( o \), \( \hat{y}_o \) is estimated value of the dependent variable for observation \( o \), \( x_o \) is the observed value of the independent variable (year), \( \bar{x} \) is the average of the independent variable, and \( n \) is the number of observations.

Figure S4 A and B shows the standard errors (according to Equation 3) associated to the trend estimations presented in Figure 1 of the main text.

4. Integration of deforestation and fire trend surfaces

The results presented in the main text (Fig. 2A of the main text) was achieved by quantifying the number of grid cells with positive and negative fire trends (Fig. 1A of the main text) overlapping the grid cells with positive and negative deforestation trends (Fig. 1B of the main text). We used
a classification procedure based on a decision rule classifier where each grid cell was associated to one of the nine possible combinations of the trends (Table S1). Our decision rule classifier was built with eight nodes. Each node was fed with a Boolean operator. For each grid cell \((i, j)\) we computed the output class according to the example below:

**NODE 1**

If 
\[
FIRE_{SLOPE}(i,j) > 0 \text{ and DEFORESTATION}_{SLOPE}(i,j) > 0
\]

then 
\[
GRID\_CELL(i,j) = CLASS\ 1;
\]

else 
\[
GRID\_CELL(i,j) = NODE\ 2
\]

**NODE 8**

If 
\[
FIRE_{SLOPE}(i,j) = 0 \text{ and DEFORESTATION}_{SLOPE}(i,j) = 0
\]

then 
\[
GRID\_CELL(i,j) = CLASS\ 8;
\]

else 
\[
GRID\_CELL(i,j) = NODE\ 9
\]

After running the classifier for all grid cells we produced a map with nine classes (Fig. S5). For clarity, we only displayed classes that were relevant to our analysis in the final map (Fig. 2A of the main text).

5. **Influence of land use on fire patterns**

To generate our two land use surfaces, we used the one kilometre spatial resolution land cover information from the South America map (SAM; \(S15\)) produced by the European Commission's Joint Research Centre (JRC) as part of the Global Land Cover for the year 2000 project (GLC 2000, \(S16\)). The accuracy of the agriculture classes for the GLC-2000 Land Cover Map of South America is 89% in comparison to the reference data (\(S15\)).

We first merged all agricultural classes presented in the Brazilian Amazon into one class, in order to generate our “total agriculture” surface. This class in our analysis was an approximation of the current and most common land use in the Brazilian Amazon, where regions can have areas
planted with subsistence agriculture, more intensive agriculture for commercial purposes (e.g. soybeans and sugar-cane), abandoned areas with the presence of secondary forests and other vegetation types, and managed and unmanaged pastures. This procedure combined three classes from the SAM product: (i) cropland and other natural vegetation (non-forest), which is a mosaic of agriculture and degraded vegetation; (ii) cropland and tree cover, which is a mosaic of agriculture and degraded forest, including secondary forests; and (iii) intensive agriculture, which corresponds to areas with over 70% cultures or pastures, with regions of intensive cultivation and/or sown pasture falling into this class. In the SAM product, the mosaic of agriculture and non-forest vegetation is often a mixture of pasture, cultivation and degraded natural vegetation. On the other hand, the mosaic of agriculture and degraded forest corresponds to shifting cultivations, agro-forestry, fragmented forests and secondary forest and rural complex (S17). The second land use surface used in our analysis considered solely the SAM class “intensive agriculture”. This class in our analysis was used as a proxy for fire-free land management, as intensive (managed) agriculture is normally not accompanied by fire.

Subsequently, for each land use class, we aggregated the 1 km spatial resolution pixels into 0.25° x 0.25° spatial resolution grid cells containing information on the fraction of the area covered by the specific land use type, total agriculture (Fig. S6A) and intensive agriculture (Fig. S6B), respectively. Similarly to the method used in the processing of the deforestation surfaces, this aggregation procedure preserves the original area information while changing the surface resolution.

Finally, to quantify the relationship between land use type and fire incidence (Figure 3 in the main text), we extracted, for each grid cell containing land use information, the total number of fire occurrences during the year 2000 using each one of the two land use surfaces generated previously. The fire data was subsequently organized by agricultural fraction classes (divided in 20 intervals of 0.5 and varying between 0 and 1 when the grid cell is totally covered by agriculture). For each agricultural fraction class we then calculated the average number of hot pixels, considering all grid cells within that class, to account for differences in the number of grid cells in each class.

As stated above, the class total agriculture is a proxy of the most common land use in Amazonia where there are mosaics of degraded vegetation, subsistence agriculture and pastures. However, the fact that this class contain forest does not necessarily mean that it is more susceptible to burn. Naturally, fire is a very rare event in tropical forests (S18). If humans do not set fire intentionally to the land, even areas
exposed to strong drought would not burn \((S19)\). Therefore, the main driver of fire is not fuel availability but human ignition, which reflects the land management type. Areas with low fuel availability, such as pastures, would burn because people use intentional fire as a management practice. This type of fire will show up in the satellite data \((S20)\).

Similarly, an intensive sugar-cane plantation, which is currently expanding in the Brazilian Amazon, would be intentionally burnt as a traditional way of cleaning the area before harvesting manually \((S21)\). However, this is not the dominant intensive culture in the region yet. On the other hand, the dominant intensive agriculture in the Brazilian Amazon is soybeans, which is not followed by fire. An intensive forest plantation, despite the large fuel availability would also very rarely burn without intentional fire. Therefore, this analysis is an indicative of land management rather than differences in fuel availability in the two classes used.

6. Uncertainties

6.1. Effect of the time-series on the trend analysis results

The difference in the data periods used in the analysis presented in the manuscript does not have any specific reason, but only due to the availability of the dataset used. We used the most complete time-series at the time of the analysis. Complete fire time-series from AVHRR/NOAA-12 is available from 1998-2006 \((S1)\), the NOAA-12 satellite was decommissioned in August 2007 after 16 years of continuous operation. The PRODES deforestation data in its digital format is available from 2000-2007 at the time of this analysis \((S10)\). As we were interested in showing temporal trends, and the temporal coverage of the dataset is limited, we opted for using the longest time-series available for each one of the dataset. Differences in the length of the time-series used in our analysis could introduce bias in the results. Therefore, in this section we tested the effect of using the 2000 to 2006 datasets for both time-series in our trend calculations.

To carry out the analysis, we used equivalent datasets for fire and deforestation to those described in sections 1 and 2 of the SOM, but restricted for the period 2000 to 2006 for both datasets. We first calculated the pixel-based trend regression slopes for each surface \((SOM\ section\ 3)\) and then combined the results using the decision rule classifier used for the analysis presented in the main text and described in the SOM section 4.
The trend analysis on the deforestation data using the 2000-2006 time-series revealed a similar pattern as the one obtained using the 2000-2007 time-series. Using the 2000-2007 time-series, we showed that 54% of the grid cells have negative deforestation slopes and only 17% have positive deforestation slopes. Evaluating the data from 2000-2006 the proportion of grid cells with negative deforestation slopes (66%) is also more than 30% higher than the proportion of grid cells with positive slopes (31%). Similarly, the results of the trend analysis on fire data using the 1998-2006 time-series was replicated by the analysis using the 2000-2006 time-series. Using the 1998-2006 time-series we showed that the number of grid cells with positive slopes is 1.7-fold higher than the number of grid cells with negative slopes. Using the 2000-2006 time-series we found that the number of grid cells with positive fire trend (1,949 or 42% of the total) was 1.5 times greater than the number of grid cells with negative fire trend (1,339 or 29% of the total), confirming the patterns observed in the analysis used in the paper.

In addition, the combined trends in deforestation and fires using the time-series from 2000-2006 for both datasets have similar spatial patterns as the analysis carried out with different time-series length (Fig. S7). Areas with decreased deforestation trends and increased fire trends are similar in both maps as well as areas with increased deforestation trends and increased fire trends, corroborating our results. The frequency distribution of the trend slopes observed using the different time-series as presented in the manuscript is also corroborated by the 2000-2006 analysis (Fig. S8). The histogram is skewed to the right indicating a higher frequency of grid cells with positive fire trends in either areas with positive (71% of grid cells in contrast to 81% presented in the paper) and negative (56% of grid cells in contrast to 59% presented in the paper) deforestation trends.

Another source of uncertainty in our analysis is the potential bias in our fire trends due to the degradation through time of AVHRR band 3 used for detecting fire hot spots. We opted for using the AVHRR dataset because it had a longer time-series available (1998-2006) than the MODIS-Terra (2001-2007) and MODIS-Aqua (2002-2007), despite the later being a newer sensor and therefore potentially less affected by detector degradation. Other authors have already reported that AVHRR and MODIS hot pixel data are strongly correlated and trends over time (S3, S22) and space (S23) are consistent in Amazonia. However, to confirm the validity of our analysis, we
evaluated if there was any bias introduced by AVHRR degradation in the fire trend analysis by carrying out a set of comparisons between AVHRR and MODIS dataset. We first evaluated the correlation between the two datasets using the 2001-2006 time-series (Fig. S9). This analysis showed that the two datasets are strongly correlated temporally (p<0.01), despite an offset. The offset is likely to be mainly due to differences in satellites overpass time (MODIS-Terra ~10:30 am and AVHRR-NOAA-12 ~19:30 pm). The lower number of fires detected with MODIS reflects in part the daily fire pattern, with most of the deforestation fires starting in the afternoon and evening time (personal observation). The observed differences in the absolute values do not have any implications for our results as we are interested in quantifying changes over time. By using the linear equation established from the relationship between AVHRR and MODIS (Fig. S9) we calibrated the data from both sensors for the subsequent analysis. To evaluate trends over time we carried out three analyses: First, we show that AVHRR is as stable as MODIS in reproducing fire evolution over time (2001-2006) in the Brazilian Amazon (Fig. S10). Second, we show that the normalized number of fire counts per unit deforested area (fire counts divided by deforestation rates) is significantly increasing in the Brazilian Amazon independently of the sensor used to estimate hot pixel incidence or time-series length (Fig. S11). Finally, we calculated the pixel-based trend slopes using the MODIS and AVHRR fire data (2001-2006) in order to evaluate the spatial consistence between the datasets. The two surfaces: AVHRR (Fig. S12A) and MODIS (Fig. S12B) trend slopes showed similar spatial patterns. Our comparison showed 63% agreement between the trend slopes in both surfaces (Fig. S12C). Both datasets were able to identify similar regions with increase of fire in Amazonia, despite some differences. Different overpass time for MODIS-Terra (~10:30 am) and AVHRR-NOAA-12 (~19:30 pm), may be the prime source of uncertainty between the two surfaces. Also differences in spatial patterns of law enforcement through time may lead to changes in the time of the burnings to avoid problems with the authorities and consequently influencing the spatial patterns of fire detections.
**Problems in reporting emissions from deforestation and forest degradation in Amazonia**

Carbon emissions from forest fires and the recovery potential of these forests as well as carbon emissions and recovery of secondary forests are arguably the most uncertain components of Amazonia’s net biome productivity (NBP). First because we do not have basic information and an operational monitoring system capable of quantifying the area, the recurrence time and the intensity of forest fire events in Amazonia. Similarly, the area and age of secondary forests growing in already deforested areas is not monitored. Second because long-term studies of productivity and carbon fluxes in disturbed forest are very rare. Therefore, little information exists about how these systems recover from disturbance and how long does it takes to completely restore its carbon stocks and functioning. The impact of disturbed forests and secondary forests on the NBP may be larger than expected and unreported emissions from these components may lead to unrealistic calculations of emission reductions.

Three key points should be highlighted: First, cryptic processes in Amazonia such as selective logging may add \( \sim 0.1 \text{ Gt C yr}^{-1} \) to the gross carbon emission (S24), almost the double of the amount used in previous estimates (S25-S26). Second, carbon emissions from forest fires are estimated to be around \( 0.01 \text{ Gt C yr}^{-1} \) in normal years or between \( 0.1-0.2 \text{ Gt C yr}^{-1} \) (S27 and S25, respectively) during drought years, therefore total gross emissions from unmonitored processes may be significant. Moreover, recovery time for carbon stocks and productivity in these areas are unknown. There is evidence of long term effects of forest fires on tree mortality. Increase in large tree mortality three years after fire can potentially double current estimates of biomass loss and committed carbon emissions from low-intensity fires in tropical forests (S28). Third, even if forests can recover quickly after a disturbance event and slash-and-burn of secondary forests may appear carbon neutral, the use of fire induces emissions of other greenhouse gases such as \( \text{CH}_4 \) and \( \text{N}_2\text{O} \) which have a much higher warming potential and account for around 10% (in terms of \( \text{CO}_2 \) equivalent) of the total \( \text{CO}_2 \) emission from burning (S29). Therefore, in terms of radiative forcing these areas will have a positive Global Warming Potential.

Forest burnings that are directly induced by humans and are followed by subsequent complete conversion of the forest canopy will have emissions accounted simply using the PRODES
system. However, forest fires (from accidental burning – indirectly induced by humans) that do not lead to complete land cover conversion, are growing in size and frequency in the tropics, and may significantly contribute to the global net CO₂ emissions (S18). This type of fire that usually affects large extents of Amazonian forests during drought periods (S19, S27, S30) may not lead to complete conversion of the forest cover and may go unreported if we rely on the existing operational systems and the existing IPCC rules (S31).

It is expected that Brazil would have to account for burned forests in a REDD system. However, there is no system currently in place capable of performing this task. Brazil is the most advanced tropical forest nation regarding monitoring of its forests, therefore, it is important to recognise that problems highlighted here are certainly much more critical in other tropical regions of Africa and Asia, which may hold back the REDD effectiveness as a global climate change mitigation initiative.

Brazil has several funding programs including the Plano Nacional de Mudança do Clima and the Fundo Amazônia in order to promote actions on REDD, conservation and sustainability (S32). Brazil also has several monitoring programs led by either governmental institutions (S33) or independent NGOs (S34) aiming to quantify land cover change. However, even the recent programs that estimate degraded areas, such as the DEGRAD system from INPE (S35), do not have a distinction between fire and logging; do not quantify secondary forest conversion; and probably, well underestimate low impact forest fires. Moreover, the quantification of natural disturbances in the IPCC guidelines is in most of the cases not suitable for the Amazonian reality.

The Good Practice Guidance for Land use, Land use Change and Forestry (GPG-LULUCF) is the Intergovernmental Panel on Climate Change (IPCC) response to the decision on LULUCF adopted by the Conference of the Parties (COP7) at the United Nations Framework Convention on Climate Change (UNFCCC) in the Marrakesh Accords (paragraph 3(c)) (S31). The GPG-LULUCF assists countries in producing inventories for the land use, land use change and forestry sector (S31). In this guide they state that the issues related to degradation (which they include in a class called “other categories”) are often complex and agreed methodologies were not available at the time the IPCC Guidelines were being prepared. The issue is not only that emissions from fires represent a contribution to greenhouse gases (GHGs) emission that may not be tackled by REDD efforts, but also that they may go unreported if the monitoring, reporting
and verification (MRV) processes mirror those on LULCF used by Annex I countries. The first critical problem is that the guidelines used by Annex I countries covers disturbance in managed forests and therefore disturbance emissions from unmanaged forests may go unreported. Second, that according to the IPCC guidelines on Definitions and Methodological Options to Inventory Emissions from Direct Human-induced Degradation of Forests and Devegetation of Other Vegetation Types (S36) any disturbance relates only to direct human-induced changes in carbon stocks, and emissions from fire as a “natural” or “not directly induced by human” do not need to be reported. In another case, if secondary or a forest plantation is replacing cleared natural forest with no intervening period of agriculture it is possible that under the IPCC rules there would be no change in land use.

The leakage of deforestation and degradation to the outside of monitored boundaries may be another problem for REDD implementation and reporting. However, considering that Brazil has a wall-to-wall monitoring system for the whole Brazilian Amazon, leakage, at least for deforestation, would not be a problem. This is because changes in geographical location of deforestation would be accounted for in the national estimations. This would be a problem however in the case that land cover change is displaced to other vegetation types that are not currently monitored, such as the Cerrado or other neighborhood countries such as Bolivia.

The reality is that rules are imperfect and not inclusive for all plausible situations. However, by highlighting the impact of fires on the tropical forests even with decrease deforestation rates it is possible to underpin the need for proactive actions in order to solve this problem with or without top-down rules.
SOM Figures

Fig. S1 Area of polygons detected monthly as deforestation by the DETER system from 2004-2008 and its relative contribution to the total area deforested.

Fig. S2 Annual deforestation rates accumulated by States for the Brazilian Amazon from 2000 to 2008 calculated according to the PRODES methodology. Note the increase in deforestation rates from 2000 to 2004 and the subsequent decrease from 2005 to 2008.
Figure S3. False colour composite (RGB) of Landsat TM images (226/069) from Mato Grosso State using bands 3 (Blue), 4 (Green) and 5 (Red). (A) is the 2006 image used for classification of the deforestation polygons. (B) is the same image as (A) overlaid by the 2006 PRODES deforestation mask (purple). (C) is the 2007 image and (D) is the same as (C) overlaid by the 2007 classified polygons (yellow). (E) is the 2008 image and (F) is the same as (E) overlaid by the 2008 classified polygons (blue). Note that some areas (in magenta tones) are not masked in this example because they are degradation or fire, which are not accounted by PRODES. Arrows with the same colour indicates a specific process occurring in the selected polygons. Interesting to note deforestation and burning of secondary forests that happens in the already deforested areas and are not detected by INPE’s monitoring system.
Fig. S4 Standard error estimates for (A) the deforestation trend slopes and for (B) the fire trend slopes presented in the main text Figure 1A and B respectively. Note that the scales in A and B are different. White areas are grid cells with no trend or outside the geographic boundaries of our analysis.
Fig. S5 Result of the decision rule classification showing the nine possible combinations of trend slopes for each grid cell considering the trends in fire and deforestation.
Figure S6. (A) Proportion of total agriculture and (B) intensive agriculture for each 0.25° spatial resolution grid cell derived from the Global Land Cover for the year 2000 project (GLC 2000) map of South America (SAM) produced by the European Commission's Joint Research Centre (JRC).
Fig. S7 (A) Figure 2A of the main text and (B) the combined trends in deforestation and fires using the time-series from 2000-2006 for both datasets. Blue circles indicate areas with decreased deforestation and increased fire trends in both images and yellow circles highlight areas with increased fire and deforestation trends. Note that patterns in both surfaces are similar and independent of the time-series period used.

Fig. S8. Frequency distribution of trend slopes calculated for each grid cell using deforestation and fire from 2000-2006 for both datasets. Note the pattern here reproduces well the pattern presented in Figure 2B of the main text.
Fig. S9 Relationship between AVHRR/NOAA-12 night time fire detections and MODIS/Terra before and after calibration.

Fig. S10 Temporal evolution of fire incidence in the Brazilian Amazon according to AVHRR and MODIS (Calibrated for better visualization). Grey bars indicate the annual deforestation rates from PRODES.
Fig. S11 Linear trends of the normalized fire incidence (fire counts/deforestation rates) for the Brazilian Amazon. Horizontal bars and circle indicate the fire counts per unit of deforested area for each year. Grey vertical bars are the annual rates of deforestation. Note that trends are reproduced using different time-series period for the AVHRR dataset as well as using a time-series from a different sensor (MODIS).
Fig. S12 Pixel-based trend slopes calculated using the time period between 2001-2006 of (A) AVHRR and (B) MODIS dataset. (C) Shows the percent of agreement between the two surfaces. Green bars indicate similar trend detected for AVHRR and MODIS. Red bars indicate different trend.
**SOM Table**

Table S1. The nine possible combinations for the trends in fire and deforestation presented in (Fig. 2A and Fig. S5).

<table>
<thead>
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<th>Class</th>
<th>FIRE</th>
<th>DEFORESTATION</th>
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<td>invalid</td>
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<td>1</td>
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</table>
SOM References

S1. Instituto Nacional de Pesquisas Espaciais (INPE) Queimadas project. See http://www.cptec.inpe.br/queimadas/ (2006).


