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Annual South American forest loss estimates based on passive microwave remote sensing (1990–2010)

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Abstract

Consistent forest loss estimates are important to understand the role of forest loss and deforestation in the global carbon cycle, for biodiversity studies, and to estimate the mitigation potential of reducing deforestation. To date, most studies have relied on optical satellite data and new efforts have greatly improved our quantitative knowledge on forest dynamics. However, most of these studies yield results for only a relatively short time period or are limited to certain countries. We have quantified large-scale forest losses over a 21 year period (1990–2010) in the tropical biomes of South America using remotely sensed vegetation optical depth (VOD). This passive microwave satellite-based indicator of vegetation water content and vegetation density has a much coarser spatial resolution than optical but its temporal resolution is higher and VOD is not impacted by aerosols and cloud cover. We used the merged VOD product of the Advanced Microwave Scanning Radiometer (AMSR-E) and Special Sensor Microwave Imager (SSM/I) observations, and developed a change detection algorithm to quantify spatial and temporal variations in forest loss dynamics. Our results compared favorably to the newly developed Global Forest Change (GFC) maps based on Landsat data and available for the 2001 onwards period ($r^2 = 0.90$ when comparing annual country-level estimates), which allowed us to convert our results to forest loss area and compute these from 1990 onwards. We found that South American forest exhibited substantial interannual variability without a clear trend during the 1990s, but increased from 2000 until 2004. After 2004, forest loss decreased again, except for two smaller peaks in 2007 and 2010. For a large part, these trends were driven by changes in Brazil, which was responsible for 56 % of the total South American forest loss over our study period according to our results. One of the key findings of our study is that while forest losses decreased in Brazil after 2005, increases in other countries partly offset this trend suggesting that South American forest losses as a whole decreased much less than that in Brazil.

1 Introduction

There are large uncertainties in the spatial and temporal patterns of forest loss and associated fluxes of carbon in the tropical ecosystems (Grainger, 2008; Hansen et al., 2010; Malhi, 2010; Pan et al., 2011). Forest losses can be either natural, for example due to windthrow or natural fires, or anthropogenic, usually labeled deforestation. Deforestation carbon emissions are a significant but declining fraction of total anthropogenic CO_2 emissions (van der Werf et al., 2009). In Amazonia, tropical deforestation was the main source of carbon emissions (Morton et al., 2008), at least during their 2003 to 2007 study period. More than half of the total forest carbon is stored in tropical intact forests, from which 56 % is stored in living biomass and 32 % in the soil. The remaining 12 % is stored in dead wood and litter (Pan et al., 2011). Conversions of these forests to pasture or agriculture (deforestation) is an important source of carbon emissions, with South America being responsible for almost half of the tropical deforestation emissions (Harris et al., 2012; Pan et al., 2011). In South America, deforestation is mainly caused by expansion of agriculture and area used for cattle ranging (FAO, 2006; Fearnside, 2005; Geist and Lambin, 2002). Over the last 30 years soybean production has expanded rapidly in Amazonia, partly driven by improved yield-increasing and labor-saving technologies (Grau et al., 2005; Naylor et al., 2005).

Historically, widely used datasets for forest area changes and timber harvesting in the 80s and 90s are the forest resource assessments (FRAs), as reported by countries to the United Nations Food and Agriculture Organization (UN FAO) (FAO, 2006), but are known to suffer from issues regarding consistency (Grainger, 2008). Satellite observations overcome some of the issues found in earlier FAO datasets, because they systematically monitor in space and time. Over the last three decades several satellite-based deforestation datasets have been developed. Landsat satellite imagery is the longest operative option for monitoring vegetation, starting in 1972. Landsat provides vegetation cover on a relatively high spatial resolution of 30 m, with a 16 day revisit time. However, the temporal resolution of useful optical imagery is much lower though

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because of cloud cover issues, which often persists not only in the wet season but also during the dry season between June and November in the Amazon basin south of the equator (Costa and Foley, 1998). Therefore, these observations are mostly used in annual or multi-year analyses, but there is a need for alternative non-optical data techniques to provide time-series on a monthly or higher temporal resolution (Asner, 2001). Other widely used satellite products for vegetation mapping are derived from the Advanced Very High Resolution Radiometer (AVHRR) (Anyamba and Tucker, 2005; Tucker et al., 2005; Zhu et al., 2013). This dataset has a higher temporal, but courser spatial resolution than Landsat, and is also sensitive to aerosols and cloud cover.

Over the past years, the number of datasets quantifying vegetation dynamics, carbon stocks and other relevant vegetation quantities on both global and regional scale has increased substantially, often using Landsat data but also other data sources (Baccini et al., 2012; Broich et al., 2011; Céline et al., 2013; Frolking et al., 2012; Jones et al., 2011; de Jong et al., 2013; Kim et al., 2015; Koh et al., 2011; Mayaux et al., 1998; Potapov et al., 2012; Saatchi et al., 2011; Verbesselt et al., 2012; Wasige et al., 2012). One of the regions most closely monitored is the Brazilian Legal Amazon, where the Brazilian Space Agency (INPE) developed the Monitoring the Gross Deforestation in the Amazon Project (PRODES) yielding annual deforestation estimates since 1988 based on Landsat data (Shimabukuro et al., 1998). Other efforts include the recently published global maps of global forest gains and losses for the 2001–2012 period also using Landsat data (Hansen et al., 2013).

In addition to the previously mentioned datasets mostly based on visible and infrared wavelengths, microwave observations can also be used to characterize vegetation dynamics. Vegetation optical depth (VOD) is a vegetation attenuation parameter in the microwave domain. This parameter was first described by Kirdiashev et al. (1979) in a zero-order radiative transfer model for vegetation canopies. The VOD can be retrieved from all low-frequency microwave bands (< 20 GHz) and is shown to be proportional to aboveground biomass (Liu et al., 2011a; Owe et al., 2001). The advantage of low frequency microwave remote sensing is that aerosols and clouds have a negligible

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effect on the observations, so even areas with regular cloud cover are observed frequently, which makes it suitable to use for global vegetation monitoring on annual or even shorter time steps. Furthermore, the longer wavelengths of passive microwave enables sensitivity of VOD not only to the leafy part, but also to woody parts of vegetation (Andela et al., 2013). Therefore VOD yields information about both the photosynthetic and non-photosynthetic parts of aboveground vegetation, based on the water content of both wood and leaf components of vegetation (Jones et al., 2011; Shi et al., 2008).

The main disadvantage of these low-frequency passive observations is that a large footprint is needed to yield an observable signal, making this dataset most suitable for large regional and continental-scale studies. These datasets therefore have a relatively coarse resolution, compared to the visible and near infrared sensors. Furthermore the presence of open water regions affects the signal. This, in combination with the large footprint of the gridded product, may lead to underestimation of VOD when the grid cells are close to large open waters (Jones et al., 2011). VOD is retrieved from several satellite sensors. The observations retrieved from the Advanced Microwave Scanning Radiometer (AMSR-E) and Special Sensor Microwave Imager (SSM/I) have been merged to one dataset, based on Cumulative Distribution Function (CDF) matching. This merged VOD dataset has been used to study vegetation dynamics in different ecosystems on both global and regional scales (Andela et al., 2013; Liu et al., 2012, 2013, 2015; Poulter et al., 2014; Zhou et al., 2014).

This paper aims to estimate large-scale forest losses in South America. We show how the merged VOD product can be used to estimate forest loss for South America on a country-level scale, but we also point towards limitations of our approach and the dataset. The main novelty of our approach is the relatively long (1988–2011) time series based on a consistent data stream. We detail how we translated the VOD signal to forest loss and compare these results to Landsat-derived datasets including PRODES and the Global Forest Change maps of Hansen et al. (2013). We then provide a country-level analysis of the newly derived maps, and zoom in on Brazil to

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present a state-level analysis of forest loss over the 1990–2010 period. This time period is somewhat shorter than the time span of the VOD dataset due to the requirements of the change detection algorithm we developed.

2 Datasets

In this section we describe the datasets we used in our analysis. First, we give more information on the VOD dataset that is used for our estimation of forest losses (Sect. 2.1), followed by describing the two datasets we used for comparison: the Global Forest Change (GFC, Sect. 2.2) and the PRODES dataset (Sect. 2.3).

2.1 Vegetation Optical Depth (VOD)

Forest loss estimates in this article are based on VOD, which is derived from passive microwave remote sensing. VOD was first introduced by Kirdiashev et al. (1979), and then modified to be used in the well-known omega-tau model (Mo et al., 1982). Kirdiashev et al. (1979) also described the relationship between VOD and vegetation water content. This relationship was further simplified by Jackson and Schmugge (1991) where the vegetation water content was directly related to VOD. The algorithm of the VOD dataset we used here is based on the land parameter retrieval model (LPRM) (Meesters et al., 2005; Owe et al., 2001, 2008). LPRM is based on a radiative transfer model and solves simultaneously for soil moisture and VOD. It can be applied to passive microwave sensors and has been used in numerous studies (see de Jeu et al., 2014).

The VOD time series used here is based on merging observations from two sensors (Liu et al., 2011a). The different observations come from SSM/I (1988–2007) and AMSR-E (July 2002–September 2011). These two sensors have different specifications regarding wavelength, viewing angle and spatial footprint and therefore the absolute values of the retrieved VOD values differ. Their relative dynamics, however, are similar (Liu et al., 2011a). In the merging procedure the AMSR-E retrievals were used as a reference, because this product has the higher accuracy due to its relatively low microwave frequency. The cumulative distribution frequency (CDF) matching technique was used for rescaling SSM/I to match AMSR-E. For the period July 2002 through September 2011 AMSR-E data are used. Before July 2002, SSM/I observations are used. Full details on the merging process can be found in Liu et al. (2011a, b). In this study, we used monthly values, which were derived from the merged VOD dataset (version January 2015) by averaging the daily data fields, and were resampled to 0.25°.

VOD observations are dimensionless and their values range from 0 to 1.5. At a certain point, when VOD values exceed 0.8, the vegetation becomes so dense that the soil component in the radiative transfer becomes very small. This is a gradual process and when VOD values are higher than 0.8 additional checks are necessary before using the values in vegetation studies. When VOD exceeds 1.2 smaller scale variations in the vegetation canopy cannot be captured anymore (Owe et al., 2001).

2.2 Global Forest Change (GFC)

Hansen et al. (2013) released early 2014 the Global Forest Change (GFC) project gridded dataset, which is probably the most data rich and computer intensive production of global forest change maps. It contains annual maps over the time period 2001–2013 on a 30 m resolution. The maps are based on the 30 m Landsat 7 Enhanced Thematic Mapper Plus (ETM+) scenes, which were resampled and normalized to create a gridded dataset of cloud-free image observations. Forest loss is defined as a change from forest to non-forest state. In our analysis, we used the annual forest loss dataset and reprocessed these to the 0.25° resolution of our analysis by summing the 30 m values.

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2.3 PRODES deforestation

The Brazilian space agency INPE provides annual gross deforestation maps of the Brazilian Legal Amazon within the Program for Deforestation Assessment in the Brazilian Legal Amazonia (PRODES). INPE defines deforestation as the gross deforestation rate of the conversion of intact forests (old growth forest) to a different land use such as agro-pasture, wood exploration areas and silviculture. Degradation and deforestation of regenerating secondary forests are not monitored by PRODES (INPE, 2013).

Although PRODES covers a relatively long time period, the method of detection of deforestation has changed over time. For the time period 1988–2002 the detection of deforestation polygons was done by visual interpretation of Landsat 5/TM scenes. More recently these polygons were manually digitized in the PRODES Analog project (INPE, 2013). After 2002, PRODES started to use digital image processing and visual interpretation of Landsat bands 3, 4 and 5 creating and interpreting segmented shade-fractioned images (INPE, 2013; Shimabukuro et al., 1998). Deforestation is reported once per year in August based on changes over the previous 12 month period. Deforestation within PRODES is defined as clear-cut areas of primary forests exceeding 6.25 ha. Because of this threshold in detection omitting deforestation smaller than 6.25 ha, INPE reports that underestimation of deforestation occurs. Furthermore there may be unobserved areas due to cloud cover in the Landsat images during the time period of visual interpretation until 2005 (INPE, 2013).

3 Methods

In this section we will first explain the pre-processing of our data (Sect. 3.1), followed by our methodology to detect forest losses (Sect. 3.2). Finally we will explain how the detected changes were converted to forest loss area (Sect. 3.3)

3.1 Data selection

We aimed to estimate gross forest loss for each 0.25° pixel on an annual basis, which will be explained in Sect. 3.2. We first filtered the available data to circumvent false detections related to the use of microwave data. The excluded grid cells are shown in Fig. 1, and the data exclusion was based on two criteria:

1. Average VOD values should be below 1.2. This is to prevent false detection in densely vegetated areas without clear forest loss. The value was based on Owe et al. (2001), who stated that VOD values larger than 1.2 cannot be used to detect significant vegetation changes. When vegetation is very dense, the VOD signal becomes noisy and potential changes in forest cover cannot be detected anymore. These pixels are mainly found in the middle of the Amazon forest, where forest loss rates are low. In addition, we excluded grid cells where VOD values were on average below 0.6 to maintain a focus on forested grid cells. Also when forest loss occurs in the early stages of the time series, the average VOD value will not be below this limit of 0.6.

2. Large open water should be avoided. Open water affects microwave emissions and can lead to underestimation of VOD (Jones et al., 2011). Therefore 0.25° grid cells, which contain more than 50 % open water based on the Global Lakes and Wetlands Database (GLWD, Lehner and Döll, 2004), were masked out.

We excluded these grid cells also from GFC and PRODES data when we compared the results. Therefore, total South American forest losses over 2001–2010 for GFC reported here are on average 4 % lower than without the data exclusion.

3.2 Detection of forest losses

Our method is a change detection method based on the principle that VOD is directly related to the above ground living biomass. Therefore persistent changes in VOD over time are related to changes in biomass (Liu et al., 2015), for example when forest is converted to non-forest. Basically we track the full time series and inspect whether there are sudden drops in the signal that could be the result of forest loss. Our approach is based on 4 steps and explained using an example grid cell located in the Brazilian state of Mato Grosso, where forest losses have been high during the 2000–2005 interval according to Hansen et al. (2010).

As a first step we deseasonalized the time series based on a 19 month moving average of VOD ($VOD_{MovingAVG}$, Fig. 2a):

$$VOD_{MovingAVG}(lat, lon, m) = Average(VOD_{obs}(lat, lon, m-9 : m+9)) \quad (1)$$

where lat, lon, m is the latitude (lat), longitude (lon) and month (m). $m-9 : m+9$ are all values 9 months before until 9 months after the specific month. This approach was preferred over taking out the seasonal cycle based on the average of all cycles because the seasonal cycle from forest and non-forest is different. In addition, a longer moving average masks part of the signal due to droughts or anomalous wet periods which also influence VOD. We also tested longer averaging windows (see Sect. 4.5 for details about the tested windows), but the results were relatively insensitive to this and it decreased the numbers of years over which we could report. In the example grid cell $VOD_{MovingAVG}$ decreased most strongly during 2002–2005.

To estimate where forest loss potentially occurred and how this was partitioned over different year(s), in the second step we calculated the difference of $VOD_{MovingAVG}$ with the same variable 12 months earlier, and label this the inter-yearly-difference (IYD, Fig. 2b):

$$IYD(lat, lon, m) = VOD_{MovingAVG}(lat, lon, m) - VOD_{MovingAVG}(lat, lon, m-12) \quad (2)$$

When the IYD was below 0, this specific month was detected as possible moment for forest loss. In the third step, we tested using a two-sided t test whether IYD was negative because of forest losses, or because of other reasons, for example due to natural interannual variability related to rainfall. The first group of the t test consisted of all VOD observations preceding the month where IYD was negative. The second

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group consisted of all other VOD observations from that moment until the end of the time series. When the p value was smaller than 0.05, we flagged the grid cell and month as forest loss (Fig. 2b). These three steps were done for every grid cell and month from October 1989 until January 2011.

In the fourth and final step, we calculated the sum of the absolute IYD values to which we will refer to as $VOD_{outliers}$ in the rest of this paper. This was done from 1990 through 2010 to get annual values (Fig. 2b).

3.3 Conversion to area forest loss

Our method yields the number of $VOD_{outliers}$ per year for each grid cell, which is related qualitatively to the amount of forest loss and may thus yield insight into the spatial and temporal dynamics of forest loss. However, to go one step further and convert our results to the area of forest loss we calibrated our results to the gross forest loss estimates of GFC. Because of the large differences in spatial resolution (30 m for GFC and 0.25° for VOD) and because our dataset is most useful for large-scale assessments, we calibrated the conversion of the $VOD_{outliers}$ to area based on a country-level approach for the overlapping time period (2001–2010). In general, our method yields gross forest loss, because we only considered decreases in VOD. However, if forest loss and forest gain occur simultaneously within a grid cell then our approach yields net forest loss.

Because VOD and biomass are not linearly related, we binned VOD in 5 groups comprising the average VOD values between 0.6 and 1.2 (0.6–0.7, 0.7–0.8, 0.8–0.9, 0.9–1.0 and 1.0–1.2). The last bin was larger to arrive at more robust regression outcomes, because there are fewer grid cells with VOD above 1.0. For every bin we performed a Pearson regression (Pearson performed preferably, compared to Spearman) forced through the origin, with all $VOD_{outliers}$ per country and year related to the same GFC values. Based on the linear regression, we obtained a slope for each VOD bin, which

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was used to convert $VOD_{outliers}$ to an area gross forest loss per 0.25° grid cell (Eq. 3).

$$VOD_{areaforestloss}(country, year) = \sum_{bin=1}^{5} VOD_{outliers}(country, year, bin) \times slope(bin) \quad (3)$$

4 Results

4.1 Spatial extent

The dominant feature over our study period is the well-known arc of deforestation along the Southern edge of the Amazon basin (Fig. 3), showing high forest loss. Highest forest losses were observed in the Brazilian states Mato Grosso, Pará and Maranhão. However, forest loss rates were not uniform in space and time, Fig. 3 shows that forest loss rates have fluctuated with lowest forest loss observed during the 1995–1999 period and the highest forest loss observed over 2000–2004 period.

While forest loss in South America is most often associated with this arc of deforestation, also other regions experienced forest loss. One is the region extending from Northern Argentina to Bolivia via Paraguay (Fig. 3a, label 1), also known as the Chaco region, showing high forest loss over the full time period. Forest losses in this region are expanding and increasing in intensity over time.

Another region extends from the southeastern part of Paraguay into Brazil along the border of the Brazilian state Mato Grosso do Sul (Fig. 3a, label 2). During the 1995–1999 period forest loss was on the rise here and increased to a maximum during the 2000–2004 period, but decreased during the 2005–2009 epoch.

Finally, the region north of Manaus in the Brazilian states of Roraima and Amazonas (Fig. 3a, label 3) which partly consists of wooded savanna, also showed high forest loss. Here the forest losses increased and expanded during the 1990s with the biggest change between the first and second half of the 1990s. Forest losses stayed relatively stable during the first half of the 2000s. During the 2005–2009 time window some

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intense forest losses disappeared. Besides these three large regions, several smaller fluctuations occurred. These can mostly be seen in the southeastern Brazilian state Minas Gerais.

4.2 Calibration with GFC

We converted the summed $VOD_{outliers}$ to a forest loss area according to Eq. (4), where the slopes varied between the 5 different bins (Table 1). The Pearson correlation was lowest ($r^2 = 0.62$) for the bin with the lowest average VOD (0.6–0.7). The other 4 bins had increasing correlations ranging from $r^2 = 0.84$ to 0.96 (Table 1). For every country the converted annual area per bin was summed to get total country-level values of forest losses per year. The country-level comparison of our $VOD_{outliers}$ with GFC forest losses had a Pearson linear agreement of $r^2 = 0.90$ ($p < 0.001$).

In Fig. 4 the country-level VOD and GFC forest loss area estimates are plotted against each other along with the 1 : 1 line. Most data points were reasonably close to this line, although VOD overpredicted forest loss towards the lower end of the spectrum. Especially in the countries with the lowest forest loss, including Surinam, Uruguay, French Guiana and Guyana, our method yielded more forest loss than GFC. In Fig. 5 we show these derived annual forest losses from VOD for the full time period, along with GFC for 2001 trough 2010. Obviously the average forest loss area for the overlapping period agrees between both datasets because our approach was tuned to match GFC, but the spatial and temporal variability can still yield differences and new insights.

The main differences are that VOD estimates higher forest losses for the countries Uruguay, Paraguay and Chile compared to GFC. Furthermore, although VOD and GFC agreed on Brazil being the main driver of South American forest losses (54 % for VOD and 68 % for GFC), VOD estimates higher interannual variability in this. This is mainly the case in 2001, 2006 and 2009, where VOD estimated 36–41 % less Brazilian forest loss compared to GFC (Table 2).

The main feature in the GFC time series is the peak in 2004 (with values of 49 and 58 thousand $km^2\,yr^{-1}$ for GFC and VOD respectively). VOD also shows this peak, but indicates that the two preceding years were high as well, making for a broader peak (2002–2004) with comparable values. The higher VOD values in 2002 and 2003 than GFC were mainly the result from higher estimated forest losses in Argentina and Paraguay. From 2005 onwards both datasets agreed on the decreasing forest loss rates and the interruptions in 2007, 2008 and 2010, although the exact patterns differed.

Following Brazil, the countries with the highest forest losses were Argentina, Bolivia, Colombia and Paraguay, each responsible for 5–8 % of total South American forest losses. The difference between VOD and GFC in relative contribution of each country to the total South American forest losses is on average 2 % with the maximum difference of 13 % for Brazil (All absolute differences, see Table 2).

4.3 Country-level trends

4.3.1 2001–2010

To further compare VOD with GFC, we also calculated the trends per country, based on linear regression, over the 2001–2010 period in absolute values and as a percentage relative to their average forest loss over that time period (Table 2). It should be noted that not all the trends are statistically significant, partly because of the large interannual variability (Table 2). The overall trend for all South American forest losses over the overlapping time period is negative for both datasets with a relative slope of −3.3 and $-1.5\,\%\,\mathrm{yr}^{-2}$, for VOD and GFC respectively, which in absolute terms corresponds to −1384 and $-587\,\mathrm{km}^2\,\mathrm{yr}^{-2}$. For individual countries in general both datasets agreed and were highly variable (Table 2).

4.3.2 1990–2010

Focusing on the full time series, Fig. 5 indicates that total forest losses in South America were not stable or monotonically in- or decreasing. Instead, they appear to be highly dynamic – at least from a VOD perspective –, especially during the first few years of

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our study period (1990–1994). After that, forest losses were fluctuating without a clear trend until about 2001, with 1991, 1995 and 1999 being high forest loss years. After this fluctuating period a period with relatively high forest losses started, with 2002–2005 being 4 subsequent years with high forest losses. After 2005 forest losses decreased, with interruptions in 2007 and 2010 (Fig. 5).

We calculated the linear trends over the whole time period and the two decades 1990–2000 and 2000–2010 separately (Table 3). Over 1990–2010 Uruguay showed a clear relative increasing trend of almost 7 % yr^{-2} (in absolute values 76 $km^2\,yr^{-2}$). Over the same time period also Argentina, Chile, Paraguay and Venezuela showed substantial in- or decreasing trends larger than 3 % yr^{-2} (or more than 36 $km^2\,yr^{-2}$). When investigating the decades 1990–2000 and 2000–2010 separately, additional patterns emerged. During the 1990s Argentina, Brazil, Colombia, Ecuador and Uruguay had trends exceeding 6 % yr^{-2}. During the 2000s, Brazil and Ecuador showed trends below −6 % yr^{-2}. The strongest differences per decade were found in Brazil (where the forest loss trend changed from +13.2 % yr^{-2} in the 1990s to −8.4 % yr^{-2} in the 2000s) and in Uruguay (+13.7 to −2.2 % yr^{-2}) (Table 3). Other countries with substantial difference between the two periods were Argentina (−3.7 % yr^{-2}, −142 $km^2\,yr^{-2}$) French Guiana (3.7 % yr^{-2}, +5 $km^2\,yr^{-2}$), Peru (3.7 % yr^{-1}, +75 $km^2\,yr^{-2}$) and Surinam (3 % yr^{-2}, −188 $km^2\,yr^{-2}$).

4.4 Brazilian state-level comparison with PRODES

In addition to a comparison on country scale, we also compared our results for the Brazilian states within the legal Amazon using the PRODES dataset (Fig. 6). PRODES covers a longer period than GFC, but provides only data for the Legal Amazon. We do not expect PRODES and our dataset to compare perfectly given that PRODES detects only deforestation of primary forests and VOD detects both deforestation and degradation including forest loss of secondary forest. Nevertheless, the Pearson's r^2 over the full 21 year time period between these two datasets was 0.66 ($p < 0.001$) (Table 3).

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Our results show for the Brazilian states a highly dynamic pattern with no steadily in- or decreasing trend (Fig. 6). The most notable difference between both datasets is that VOD suggest that 1991, 1999, 2002 and 2010 were high forest loss years, which PRODES did not show. Furthermore PRODES showed increasing deforestation from 2002 until a peak in 2004, whereas VOD peaked in 2005. While there are substantial differences in the temporal variability in the VOD and PRODES datasets, they do agree on where most forest loss occurred: Pará and Mato Grosso. Combined, these two states were responsible for 69 and 61 %, for PRODES and VOD respectively, of all Brazilian Legal Amazon deforestation (PRODES) and forest loss (VOD). The total average forest loss in the Legal Amazon from 1990 through 2010 (excluding 1993, which is missing in PRODES) was 16.6×10^3 and 15.2×10^3 $km^2\,yr^{-1}$ for PRODES and VOD respectively.

4.5 Sensitivity analysis

Our forest loss detection approach was based on several assumptions, and we tested how sensitive our results are to two main assumptions. First we tested whether the way we used the *t* test (i.e. group 1 consists of all data until IYD is negative and group 2 consists of all data after this moment) is valid, or whether a fixed or smaller time period would capture forest losses better. The main reason to test this is that based on our method, group sizes in the *t* test are not equal and group 2 could become so large, that recovery of vegetation could have taken place. Therefore we performed the same detection method, but now with the *t* test group sizes fixed to 12, 24 or 36 months. This implies that the detectable time period changed to 1990–2010, 1991–2009 and 1992–2008 for the three different group sizes. The results showed for both the country-level analysis and the state-level analysis that our original method (without a fixed time period) yielded the highest correlations with GFC and PRODES. In general we found that correlation decreased with decreasing group sizes.

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Besides the t test group sizes, we also tested whether excluding grid cells that were not normally distributed would make a difference. This was done because a t test requires normally distributed data. We tested three scenarios.

1. The standard scenario, where we excluded grid cells where the total average VOD was either larger than 1.2 or below 0.6, and GLWD was larger than 50 %.
2. As 1., but we also excluded grid cells that were not normally distributed ($p = 0.10$).
3. As 1., but we also excluded grid cells that were not normally distributed ($p = 0.05$)

Excluding these not-normally distributed grid cells in scenario 2 and 3 implied that respectively 25 and 32 % of the total South American forest losses based on GFC would be missed. However, the Pearson's r^2 for all three scenarios stayed 0.90. Based on these results we assumed that excluding the not-normally distributed points did not have an effect on the large-scale country-level analysis and we used all grid cells based on scenario 1 in our analysis.

5 Discussion

Our results indicated that the patterns of forest losses change over both space and time, although the well-known arc of deforestation remained the single largest feature in South America over our full study period. Our results agree with earlier work showing that forest loss area, and probably also carbon emissions, declined after peaking in the year 2004 (Macedo et al., 2012; Malhi et al., 2008; Nepstad et al., 2009). This decrease in forest losses is observed mainly because Brazil reduced forest loss through a combination of conservation policies (law enforcement, expansion of the governmental protection of the Amazon area and strict control of these enforcement by suspension of credit to landowners violating the rules) and because of changes in prices of agricultural outputs from 2005 onwards (Nepstad et al., 2009).

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While forest losses in the arc of deforestation, the region around the southern border of Mato Grosso do Sul (Fig. 3a, label 2) and the region around Manaus (Fig. 3a, label 3) declined after 2004, in the Gran Chaco region (Fig. 3a, label 1) it increased over the time, as shown earlier by Chen et al. (2013). In this region the observed forest losses are in areas where deciduous broadleaf forest (> 10 m tall) with closed canopy is converted to shorter (< 10 m) Chacoan woodlands and agricultural areas (Steininger et al., 2001) and could be related to soy bean production in this region (Boletta et al., 2006; Gasparri and Grau, 2009; Zak et al., 2004). This is in line with our trends and time series (Fig. 5, Table 2) where both VOD and GFC show an increasing trend for Argentina over 2001–2010, whereas a decreasing trend over that time period occurred in Brazil (Table 2). One explanation could be relocation of agricultural hotspots because of the strict regulations within Brazil (Dobrovolski and Rattis, 2014).

The spatial pattern of forest losses in Northern Brazil in the states of Amazonas and Roraima (Fig. 3, label 3) can partly be explained by forest fires (Fearnside, 2000); the peak during the 1995–2000 time period for example could be caused by the El Niño drought fire events during 1997 and 1998 (Barbosa and Fearnside, 1999). This is supported by fire emissions estimates for this region derived from the Global Fire Emissions Database (van der Werf et al., 2010). During these droughts, man-made fires destroyed millions of hectares of fragmented and natural forest (Laurance, 1998). This increase that continued during the 2000s in Amazonas and Roraima is not seen anymore in the country-level time series (Fig. 5), because these changes are relatively small compared to the changes in the arc of deforestation.

In the country-level analysis between VOD and GFC the latter indicates higher average South American forest losses, with a difference of 3126 $km^2 yr^{-2}$ or 7.6 % yr^{-2} of average VOD forest loss. The country with the largest absolute contribution in both datasets is Brazil. In GFC Brazil had a 10 % larger contribution to the South American total forest loss than in VOD. This could be caused by the different spatial resolutions of both satellite products where both datasets are based on. GFC is based on Landsat, which has a spatial resolution of 30 m and will probably capture more small-scale forest

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loss events than our dataset based on VOD with its much coarser 0.25° resolution. The difference in spatial resolution could also be the reason why other countries, such as Chile, show less forest losses and higher interannual variability in VOD than in GFC, and why countries with relatively little forest losses, such as Uruguay, Surinam, French Guiana and Guyana had more forest losses based on VOD (Fig. 4), although additional research is required to better understand these differences. While we would in general favor GFC over VOD during the overlapping periods for reasons mentioned above, the temporal resolution of VOD is superior to any other product. For areas with frequent cloud cover where Landsat may have difficulties in acquiring reliable data, VOD may be in a better position to map forest loss.

We also compared our results for the whole time period from 1990 through 2010 with PRODES data in a state-level comparison and they had a Pearson r^2 of 0.66. As mentioned earlier, to some degree the comparison is one of apples and oranges because PRODES provides annual estimates of deforestation in pixels where no deforestation has occurred before, whereas the VOD dataset will give information about deforestation and degradation and potentially regrowth. Although forest loss based on VOD includes degradation, PRODES shows on average over the whole time period 1451 $km^2\,yr^{-2}$ (9.6 % yr^{-2} of the total average legal Amazon forest loss according to VOD) more deforestation than VOD. This could be caused by the differences in methodology and spatial resolution of both datasets we mentioned before, but also potential inconsistencies in PRODES could play a role; until 2002 PRODES is based on visual interpretation, after which PRODES digital was used.

One of the most striking differences between VOD and PRODES were the years 1991, 1999 and 2010 when VOD was much higher than PRODES. The underlying reasons may not be directly related to forest loss. In 1991 this difference could be explained by the eruption of Mount Pinatubo, which had the result that over the whole tropics the average VOD was higher than before (Kobayashi and Dye, 2005; Liu et al., 2011a). The peak in 1999 in VOD was mainly caused by an increase in Amazonas. During 1999 heavy floodings occurred in this region (Chen et al., 2010). Since VOD is

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sensitive to large waters, the VOD signal could have been influenced by this event. Finally the peak in 2010 could be caused by drought that hit the Amazon that year (Lewis et al., 2011). Amazon forests are sensitive to increasing moisture stress and this could affect above ground biomass (Phillips et al., 2009). This supports the findings of Liu et al. (2012), who noticed that VOD responded to interannual variability in precipitation for tropical regions. However, this 2010 peak in forest loss was also detected by GFC. PRODES did not show this peak, partly because it was related to secondary forest degradation, which is not captured by PRODES (Fanin and van der Werf, 2015). This indicates the need to better reconcile the differences between these various estimates and not rely on one single dataset.

6 Conclusions

We have used a new satellite-based dataset using microwave observations to estimate forest losses in South America for the 1990–2010 period in a consistent manner. Our approach may have difficulties in capturing small-scale forest loss and may be impacted on interannual scales by anomalous dry or wet conditions, and is therefore most useful for regional, long-term assessments. The long study period of our study enables us to better characterize than before the spatiotemporal dynamic nature of forest loss. Our results confirm the well-known decrease of forest loss in the Brazilian Amazon since 2005, but indicate no trend over the full time period. In the regions south of the arc of deforestation, forest loss has increased over the full time period. This includes Argentina, Bolivia, Chile, and Paraguay where trends up to 4 $\%\,yr^{-2}$ were observed over 1990–2010.

Each of the datasets used here has limitations for mapping forest loss including length of time period (GFC), limited spatial domain and focus on detecting only pristine forest loss (PRODES), and coarse resolution and influence of droughts and wet periods on the detected signal (VOD). This indicates that better understanding the differences between those, and other, forest loss datasets requires more scrutiny and that uncertainties are large when relying on one single dataset.

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Table 1. Slope and correlation (r^2) of GFC forest losses ($km^2 yr^{-1}$) vs. $VOD_{outliers}$ (yr^{-1}) based on summed values for each country and year over 2001–2010.

VOD bin	Slope	r^2
0.6–0.7	36.0	0.60
0.7–0.8	52.5	0.84
0.8–0.9	71.8	0.84
0.9–1.0	96.9	0.86
1.0–1.2	105.6	0.96

Table 2. Country-level forest loss estimates (total area, contribution to total South American forest loss, as well as absolute and relative trends) for VOD and GFC for the overlapping time period (2001–2010). Asterisks indicate the significance, where [a] = $p > 0.25$, [b] = $p < 0.25$, [c] = $p < 0.05$

	Average forest loss 2001–2010				Slope 2001–2010			
	Absolute ($km^2 yr^{-1}$)		Percentage of total (Absolute/Total)		Absolute ($km^2 yr^{-2}$)		Relative (Absolute/Average)	
	VOD	GFC	VOD	GFC	VOD	GFC	VOD	GFC
Argentina	5455	3329	13.08 %	8.43 %	81[a]	358[b]	1.42 %	11.00 %
Bolivia	3484	2300	8.44 %	5.89 %	19[a]	166[c]	0.59 %	7.96 %
Brazil	23 725	26 917	54.47 %	67.88 %	−1660[b]	−1539[c]	−7.20 %	−5.66 %
Chile	245	408	0.64 %	1.05 %	42[c]	17[c]	16.04 %	4.19 %
Colombia	2005	1796	4.80 %	4.66 %	−2[a]	63[b]	−0.09 %	3.50 %
Ecuador	428	286	1.08 %	0.76 %	−60[c]	18[b]	−13.95 %	6.37 %
Fr. Guiana	49	11	0.13 %	0.03 %	4[b]	1[a]	8.95 %	5.07 %
Guyana	190	40	0.46 %	0.11 %	−5[a]	−2[a]	−2.83 %	−4.43 %
Peru	1041	969	2.67 %	2.53 %	26[a]	77[c]	2.29 %	8.17 %
Paraguay	3420	2556	8.00 %	6.60 %	144[a]	213[c]	4.31 %	8.78 %
Surinam	125	25	0.33 %	0.07 %	16[b]	2[b]	12.32 %	9.73 %
Uruguay	1136	122	2.76 %	0.32 %	156[a]	18[c]	12.41 %	15.43 %
Venezuela	1316	644	3.14 %	1.70 %	−145[c]	20[a]	−13.28 %	3.11 %
Total	42 620	39 404	100.00 %	100.00 %	−1384[a]	−587[a]	−3.31 %	−1.50 %

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Table 3. Trends in forest losses based on VOD for the whole time period (1990–2010) and the decades 1990–2000 and 2000–2010. Absolute values indicate the slope based on Pearson linear regression and the relative values are the absolute values relative to the average forest loss for that country over the full 21 year time period. Asterisks indicate the significance, where [a] = $p > 0.25$, [b] = $p < 0.25$, [c] = $p < 0.05$.

	Slope 1990–2010		Slope 1990–2000		Slope 2000–2010		Difference 2000s-1990s	
	$km^2 yr^{-2}$	%	$km^2 yr^{-2}$	%	$km^2 yr^{-2}$	%	$km^2 yr^{-2}$	%
Argentina	192[c]	4.17 %	244[a]	6.40 %	102[a]	2.68 %	−142	−3.72 %
Bolivia	54[b]	1.81 %	134[a]	0.99 %	77[a]	0.57 %	−57	−0.42 %
Brazil	−59[a]	−0.25 %	1591[b]	13.20 %	−1009[a]	−8.37 %	−2600	−21.57 %
Chile	12[c]	4.55 %	49[c]	4.31 %	28[b]	2.44 %	−21	−1.87 %
Colombia	−29[a]	−1.43 %	−153[b]	−12.48 %	7[a]	0.58 %	161	13.07 %
Ecuador	−13[b]	−2.90 %	−35[b]	−14.29 %	−34[b]	−13.97 %	1	0.32 %
Fr. Guiana	0[a]	−0.30 %	−1[a]	−0.62 %	4[b]	3.10 %	5	3.72 %
Guyana	−4[a]	−2.27 %	−6[a]	−0.92 %	1[a]	0.14 %	7	1.05 %
Peru	−18[a]	−1.49 %	−55[a]	−2.74 %	20[a]	0.98 %	75	3.71 %
Paraguay	106[b]	3.76 %	45[a]	3.01 %	31[a]	2.10 %	−14	−0.91 %
Surinam	3[a]	2.73 %	−7[b]	−1.21 %	13[b]	2.24 %	20	3.45 %
Uruguay	76[c]	6.76 %	162[c]	13.68 %	−26[a]	−2.18 %	−188	−15.86 %
Venezuela	−36[b]	−3.00 %	−28[a]	−0.13 %	−82[b]	−0.39 %	−54	−0.25 %
Total	283[a]	0.70 %	1940[a]	4.73 %	−867[a]	−2.12 %	−2807	−6.85 %

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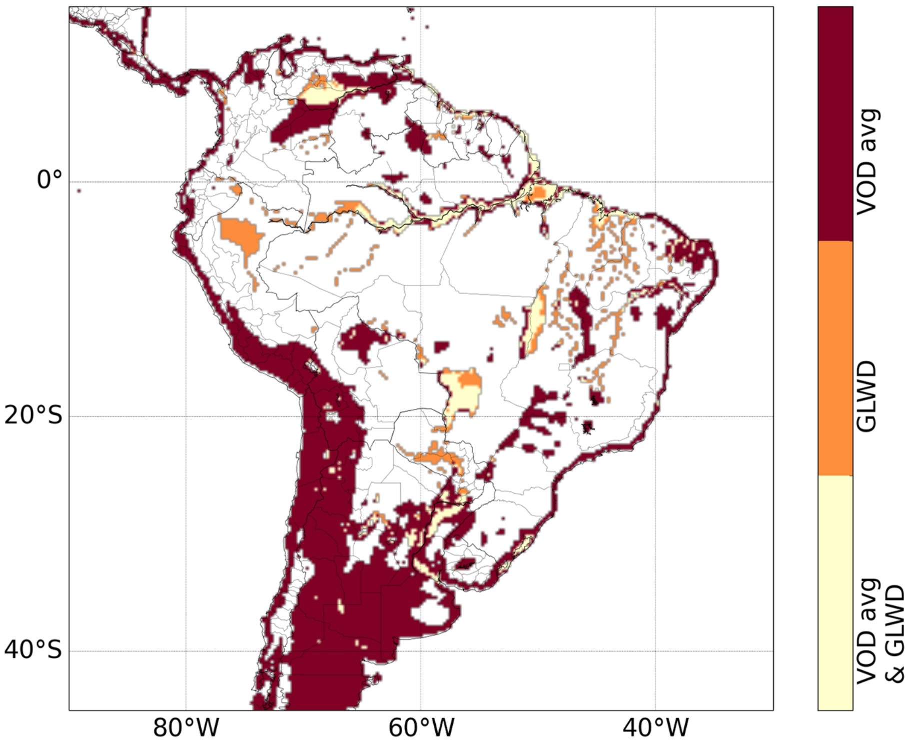

Figure 1. Grid cells that were excluded from our analysis: VOD avg: grid cells with an average VOD that is either above 1.2 or below 0.6 and thus outside the usable range for our study. GLWD: grid cells containing more than 50 % open water, which impact the VOD signal too much. Both: grid cells containing more than 50 % open water and where VOD is outside the usable range.

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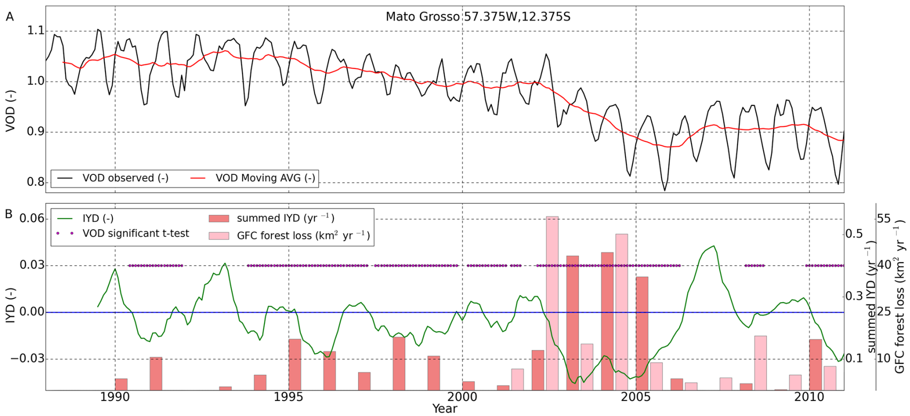

Figure 2. Example 0.25° grid cell in the Brazilian state of Mato Grosso. **(a)** Observed monthly VOD signal and 19 month moving average ($VOD_{MovingAVG}$). **(b)** Interyearly difference (IYD), whether it met the *t* test criteria, and annually summed IYD values taking only negative values into account. For comparison the corresponding GFC values are also given.

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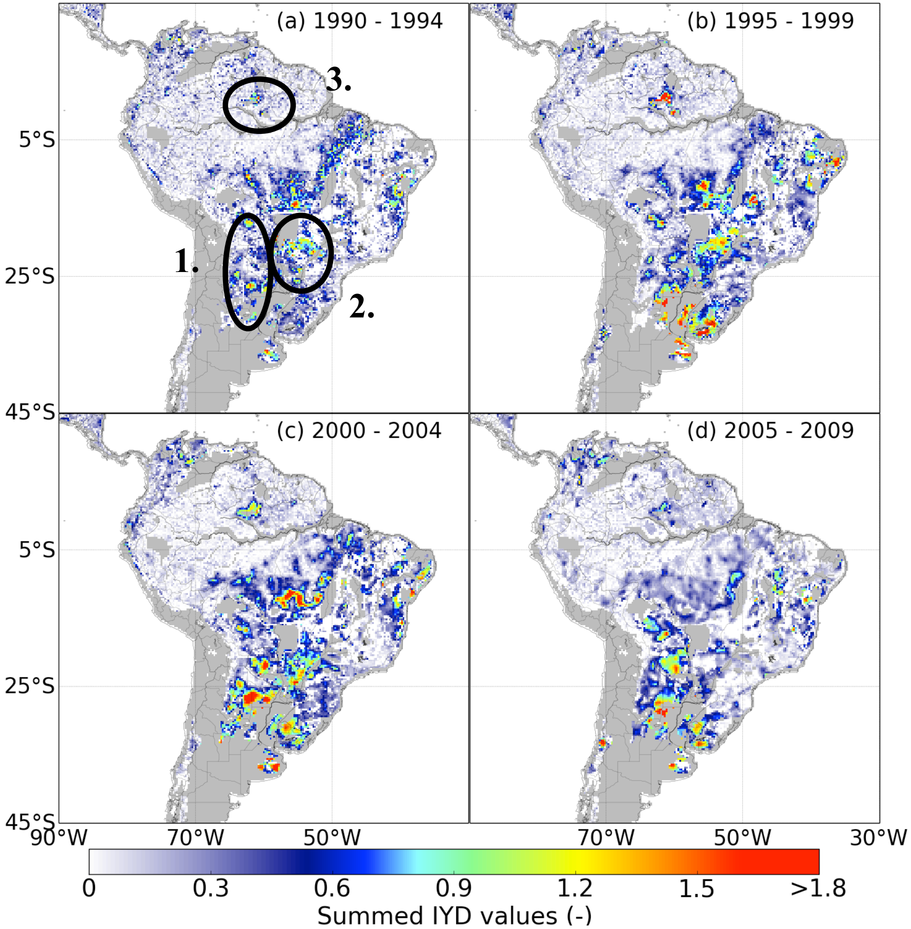

Figure 3. Forest loss extent based on the $VOD_{outliers}$ for the 5 year epochs. Grey means no data.

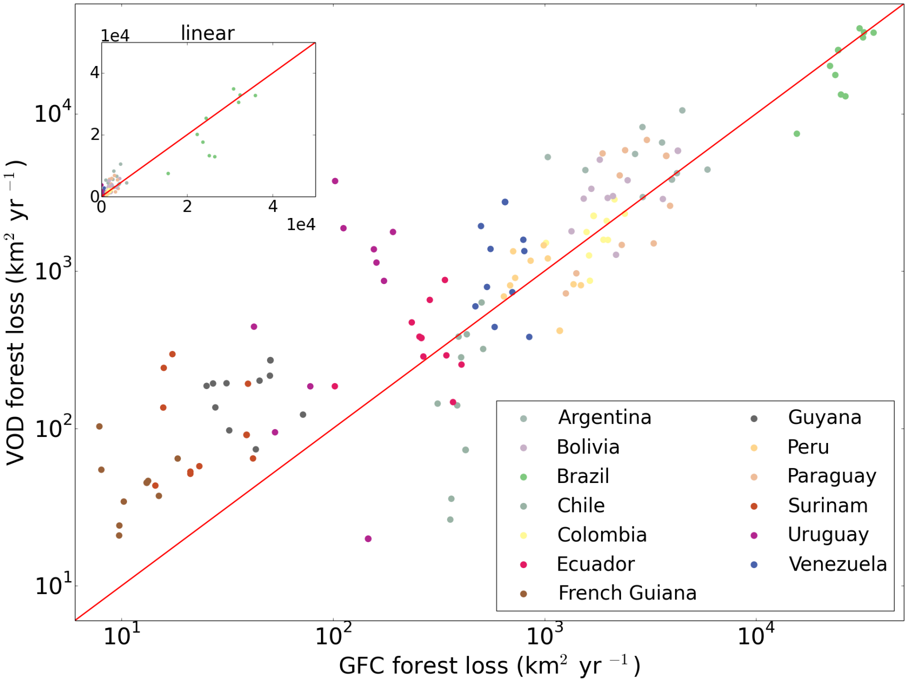

Figure 4. Country-level comparison of calibrated VOD and GFC forest losses based on annual totals (2001–2010). The inset shows the same data on a linear scale. The red lines depict the 1 : 1 line.

Figure 5. Country-level time series of annual totals of forest loss according to GFC (2001–2010) and VOD (1990–2010).

Figure 6. Time series of deforestation (PRODES) and forest loss area (VOD) for the Brazilian states in the Amazon (1990–2010). PRODES deforestation data is missing for 1993.

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