*We thank the reviewers and editor for the time and effort they put in reviewing our manuscript. Based on their comments and advice, we have changed our methodology from an approach where the conversion of VOD to forest loss area was based on country-level statistics to a grid-cell level approach to estimate forest loss. This led to somewhat revised estimates and figures but overall our messages have not changed and the new approach allowed us to provide spatial estimates of errors. The spatial estimates resulted also in revised tables and figures.*

*The biggest changes are:*

- *Revised figure with the data that are excluded*
- *Revised estimates of forest loss on a country-level.*
- *Revised estimates of VOD forest loss on a state-level.*
- *A new figure with a spatial error map, which provides uncertainties on a grid-scale.*
- *A new figure which shows the relation between the error of VOD compared to GFC with the mean forest loss.*
- *A new table with the Root Mean Square Error and Coefficient of Variance on a grid-scale and a country-scale for the different bins.*
- *A new table with the average gridded error between GFC and VOD per on a Brazilian Amazon state-level*
- *The definition of net and gross forest loss and what GFC, VOD and PRODES exactly observe is described in more detail and used throughout the manuscript*
- *The introduction is extended with more information about other remote sensing techniques such as LiDAR and SAR deforestation products*
- *The conclusions include recommendations for future work with comparison to existing SAR and LiDAR based maps.*

*We will address the reviewers point by point, where we cross-reference to the marked-up manuscript version, at the bottom of this document.*

*Kind regards,*
*Margreet van Marle, on behalf of all co-authors*

Referee 1

In particular I am slightly concerned with a circularity of argument: VOD is presented as providing independent data on forest loss, but then the results are calibrated against the Hansen et al. forest loss product. This is understandable, as ground truth data on biomass loss are clearly not available at a quarter degree resolution. I would have liked to see this calibrated against biomass
change data, as might be available from SAR or LiDAR datasets in the future, but current data availability of that type of data in South America is very limited. However, more discussion of the results of using the Hansen data should be considered, and spatial maps showing where it agrees and where it disagrees with the Hansen dataset would be very useful. Equally, I think the correlation with the Hansen dataset in the Abstract, and to a lesser extent elsewhere, is overstated for two reasons. 1. the fact that the dataset is calibrated against the same Hansen dataset is not revealed in the Abstract, and 2. the comparisons are made as a total area of a country that is deforested, not its proportion - this inflates accuracy as area is on both axes. – Will/can be done

Major comments:
Introduction section is somewhat short. I think it should contain a wider discussion of what is actually detected by VOD, compared to active microwave and optical sensors (radar and lidar), and what is seen by optical sensors. A discussion of the different effects of seasonality, and differing definitions of deforestation in the different products and the effect of different forest definitions on the abilities of the different sensors. – *We agree with the reviewer and have revised part of the introduction for which the relevant section now reads as follows (starting with VOD seasonality):*

*Introduction, Page 29, Line 9:*
*In addition to the previously mentioned datasets mostly based on visible and infrared wavelengths, passive 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. VOD is primarily sensitive to the vegetation water content and also captures information about the vegetation structure (Jackson and Schmugge, 1991; Kerr and Njoku, 1990; Kirdiashev et al., 1979).*
*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 (Jones et al., 2011; Shi et al., 2008). VOD is shown to be highly correlated with aboveground biomass (Liu et al., 2011a; Owe et al., 2001) and thus yields information about the net forest loss; the balance between decreases in forest loss due to deforestation and degradation and increases in forest extend due to regrowth or thickening. Furthermore, the advantage of low frequency (<20 GHz) microwave remote sensing is that aerosols and clouds have a negligible effect on the observations, so even areas with regular cloud cover are observed frequently, which makes it suitable to use for global vegetation monitoring at daily time steps.*
*Comparing AVHRR NDVI and passive microwave based VOD datasets with a record longer than 20 years, Liu et al. (2011) showed that both datasets had similar seasonal cycles. VOD*

*however also shows interannual variations in regions with water stress, which corresponds for a large part to variations in precipitation. VOD was more sensitive to changes in woody vegetation compared to NDVI, whereas NDVI was more sensitive to herbaceous changes (Andela et al. 2013). This is the result of NDVI being more sensitive to canopy greenness (Myneni et al., 1995) and VOD being more sensitive to water content, relatively speaking. Thus, when forest is converted to large-scale cropland, the canopy greenness not necessarily drops, whereas the total water content of the aboveground biomass does show a drop (Liu et al., 2011a).*

*Added to Introduction, Page 28, Line 10:*
*'Other widely used satellite products for vegetation are the Normalized Difference Vegetation Index (NDVI), often derived from the Advanced Very High Resolution Radiometer (AVHRR). NDVI is sensitive to canopy greenness (Anyamba and Tucker, 2005; Tucker et al., 2005; Zhu et al., 2013).'*

*Other revised parts (mentioning LiDar and Radar):*
*Added to Introduction, Page 28, Line 15:*
*'Other vegetation datasets that can capture vegetation dynamics are for example the observations based on long-wavelength radar backscatter (Joshi et al., 2015), where deforestation, forest degradation and the follow-up vegetation cover could be captured, and those based on observations from the SeaWinds Ku-band scatterometer (Frolking et al., 2012), which have shown to capture gross forest loss in the tropics. Also LiDar data can be used to estimate forest biomass, and can thus capture vegetation dynamics (Mitchard et al., 2012). Data availability for Radar and LiDar datasets is usually from 1998 onwards.'*

*Added to Introduction, Page 30, Line 17:*
*'Guan et al. (2012) compared QuickScat Ku-band backscatter coefficients (dB) with VOD and NDVI and noted that the three datasets are comparable, but that dB shows abnormal high values when more bare soil is present in the pixel.'*

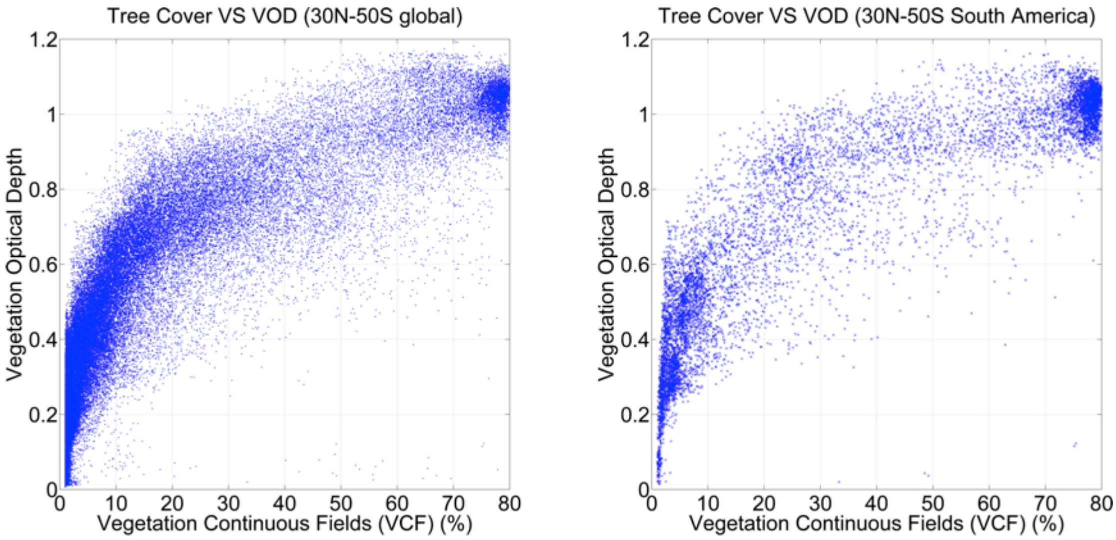
*Added to Section 2.1 Vegetation Optical Depth (VOD), Page 31, Line 21:*
*'VOD can be used as a measure for biomass (Liu et al., 2015) , which is in terms of forest loss, the net forest loss (equals the net sum of deforestation, degradation and regrowth) in a 0.25° grid cell.'*

*Added to Section 2.2 Global Forest Change (GFC), Page 32, Line 17*
*'Forest loss is defined in GFC as a change from forest to non-forest state, comprising deforestation and degradation. 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-meter values. While regrowth is detected and reported, we focused on the forest loss data when we used GFC for comparison; regrowth is thus not included in our analysis of GFC.'*

In the Methods section it would be useful to display a figure from one of the cited VOD papers showing the relationship between VOD and canopy cover based on real data. This would allow the reader to make more of an assessment of the validity to cut off at 0.6 and 1.2.

*We added at Page 33, Line 31:*

*'This value was based on the comparison between VOD and MODIS-based Vegetation Continuous Fields (VCF), which provides information about the fraction tree cover in a pixel. Our VOD threshold of 0.6 corresponds to 10% tree cover for two-third of the pixels, a number more often used to define forest (Saatchi et al., 2011; UNFCCC, 2006) although there is no consensus about this definition.'*




*Vegetation Continuous Fields (VCF) versus VOD averaged over 2001-2012 for 30N-30S globally (left) and the same latitude band over Central and South America (right).*

Either in the Methods, or Discussion, more should be made of the difference between what VOD and Hansen are actually detecting.

*We agree with the reviewer and added to Section 2.1 Vegetation Optical Depth (VOD), Page 31, Line 21:*

*'VOD can be used as a measure for biomass (Liu et al., 2015) , which is in terms of forest loss, the net forest loss (equals the net sum of deforestation, degradation and regrowth) in a 0.25° grid cell.'*

*Furthermore we changed in Section 2.2 Global Forest Change (GFC), Page 32, Line 17 to:*
*'Forest loss is defined in GFC as a change from forest to non-forest state, comprising deforestation and degradation. 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-meter values. While regrowth is detected and reported, we focused on the forest loss data when we used GFC for comparison; regrowth is thus not included in our analysis of GFC.'*

While the VOD changes have been calibrated against Hansen et al. data to give forest loss per 0.25 degree grid cell, that is just due to an empirical calibration, with error. I think more should be made of this error - e.g. I would love to see RMSE values at a grid scale, plotted on a map and with statistics given in a table. VOD is really seeing something similar to net biomass change - i.e. an integration of deforestation, degradation, and regrowth (both natural within forests, and after previous clearance - as well as artefacts due to for example moisture changes).
*We appreciate this comment and have modified our approach to switch from country-scale to grid-scale analysis, please see the revised Figures at the top of this reply. We also added a new Figure 4, which depicts the spatial difference between VOD and GFC forest loss area estimates on a grid-scale, where red indicates areas where VOD exceeds GFC and blue means VOD is lower than GFC. The relative errors are large, but that is mostly in grid cells with dense vegetation and little change, see Figure 5. However, we therefore recommend throughout the paper that our approach is most suitable for regional estimates.*

*Furthermore we calculated the RMSE for both the grid-scale and country-scale analysis and these results are shown in the revised Table 1. The main result is that the bin with the lowest average VOD values (0.6-0.7) has the highest error compared with GFC.*

Hansen et al. is just gross deforestation. In areas where deforestation is the dominant change, the correlation will work, but in areas where it isn't this is not necessarily because they're seeing different levels of deforestation, as reported, but because other processes may dominate. I don't think there is much that can be done about it, but this must be discussed.
*We have now included this in the Discussion at Page 42, Line 12:*
*'This could be caused by the difference in what both GFC and VOD measure. GFC measures gross forest loss while, due to our methodology, VOD yields net forest loss. In areas with much regrowth, VOD will therefore underestimate forest loss compared to GFC. This also has the consequence that VOD is most reliable in areas where deforestation is the dominant change. Another reason could be 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 meters and can capture more small-scale forest loss events, which will be missed in our dataset based on VOD with its much coarser 0.25° resolution.'*

I strongly feel a spatial map displaying, at a 0.25 degree grid scale, some metric of difference between PRODES, Hansen and VOD would be very useful in interpreting these datasets. Summing everything by country or by state is quite frustrating in this regard.
*We agree with the reviewer and we calculated the errors per grid-cell (Figure 4) and added to Section 4.1 Spatial Extent, Page 37, Line 8:*
*'The largest errors are found in the regions with dense vegetation and relatively little forest loss (Fig. 4, Fig. 5). The RMSE on a grid-cell scale shows that the bin with the lowest average VOD values (0.6-0.7) has the highest error compared to GFC (Table 1).'*

Figure 1 should be changed to display which pixels were cut off due to being above 1.2, and which cut off due to being below 0.6.
*This has been done. Please see the revised Figure 1 at Page 56. No pixels were excluded based on the combination of $VOD_{AVG}$ >1.2 and the presence of more than 50% according to the GLWD, therefore this class is not present in the legend.*

Figure 4 displays a somewhat spurious correlation. As it is in terms of gross forest loss, the area of each country is a significant factor on both axes. This increases the likelihood of a strong fit, even if there is little correlation between variables. I would like to see this reploted with forest loss in terms of proportion of country deforested per year. Only the area of the country considered by the analysis should be included in the area figure here, so it's somewhat similar to detectable forest area at the start of the period. It is okay for Figure 5 to be in terms of total area - though it would be interesting to see a deforestation rate figure like Figure 4 for PRODES vs VOD, separated by state.
*We replotted the forest loss in terms of proportion of the country deforested per year (See Figure below). The Pearson r=0.46, where the biggest proportion of forest is lost in Paraguay and the biggest differences are in Chile (-0.18% when VOD is compared to GFC), Suriname (0.22% difference) and Uruguay (0.65% difference). These areas correspond to the regions with the highest errors, see Figure 4. Although regionally the differences between GFC and VOD are large, the general trend between GFC and VOD forest loss (in dotted red) is almost the same (slope=1.005). We added the percentages to Table 2 and added a description at Section 4.2 Calibration with GFC.*

*The revised text at Page 37, Line 15 is as follows:*
*'In Fig. 6 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. As a percentage of the available area per country (Table 2) Uruguay (0.65%), Surinam (0.22%), French Guiana (0.14%) and Guyana (0.13%) also showed higher average forest losses over the overlapping time period based on VOD. Chile is on the other hand the country where VOD provides lower forest loss estimates for the overlapping time period (-0.18%) compared to GFC. The country with the largest relative forest losses is Paraguay for both VOD (1.05%) and GFC (0.98%). In Fig. 7 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 be different and thus yields new insights.'*

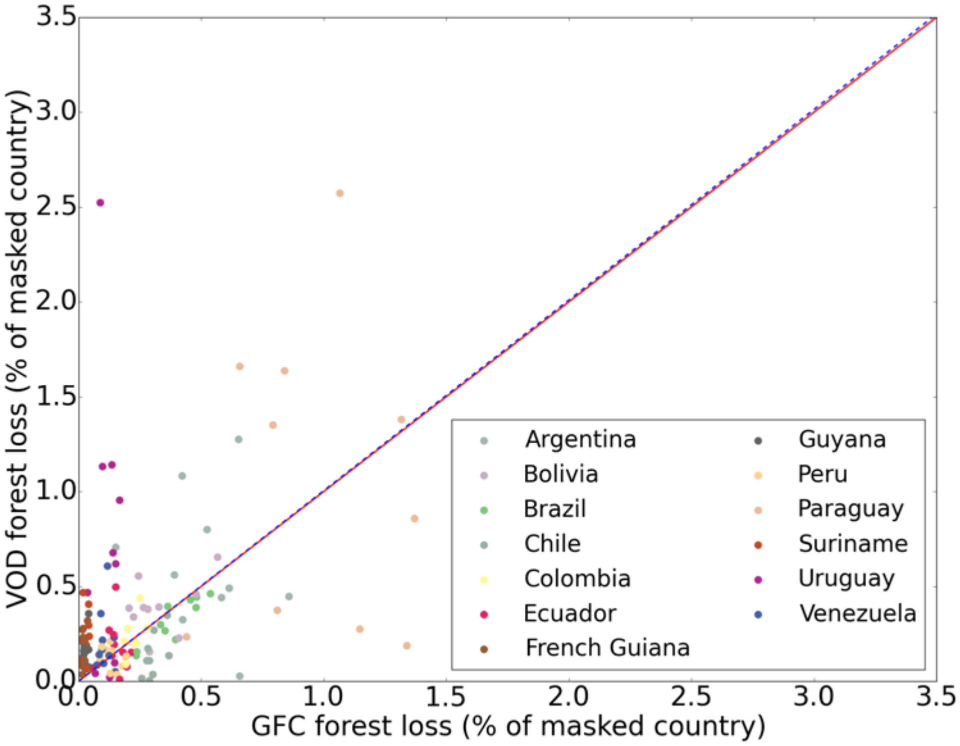
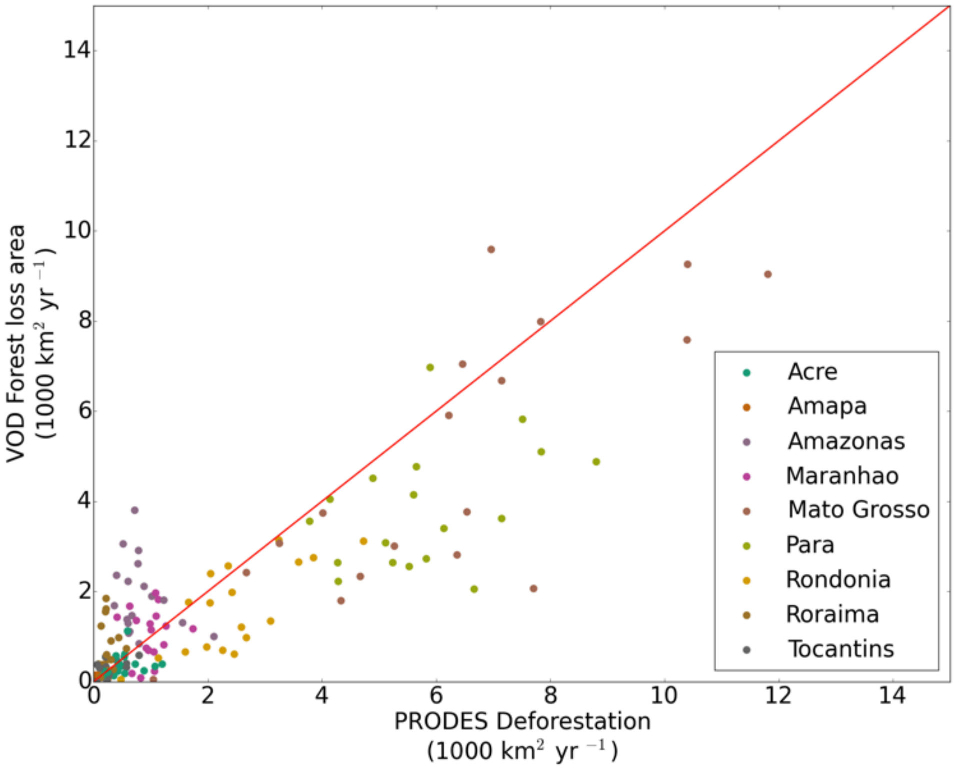



***Figure.*** *Country-level comparison of calibrated VOD and GFC forest losses based on annual totals as a percentage of the total country (2001 - 2010). The red lines depict the 1:1 line and the dotted red line shows the trend line based on Pearson linear regression (VOD=1.005 x GFC)*

*The same scatter plot as Figure 4 but with VOD forest loss area and PRODES deforestation on a state-level gives similar results as Figure 8; Amazonas and Roraima show higher forest losses compared to PRODES and the states with relatively high forest losses (Para and Mato Grosso) have lower estimates based on VOD compared to PRODES deforestation. In our opinion the scatter does not provide new insights compared Figure 8, therefore we prefer not to include this plot in the final manuscript.*



The conclusions could state more grounds for further work. It could cover ways in which VOD could be converted to net biomass change, rather than loosely correlated with gross deforestation which is a somewhat frustrating way to display these very interesting results. Maybe comparisons with LiDAR and SAR-based biomass change maps would be an interesting route for the future? VOD has great potential for largescale monitoring of whole-country net changes in carbon stocks, e.g. for REDD+: but that would

*We added to the Conclusions, Page 44, Line 17:*

*'This was a first approach towards a better forest loss dataset using VOD to better understand forest loss dynamics. The added value of our analysis is mostly providing new annual forest loss estimates during the 1990s, a period not covered by GFC, MODIS and other satellite datasets. Regarding future opportunities, more research is needed to know exactly what VOD represents, potentially comparing with existing LiDAR-based benchmark datasets (Baccini et al., 2012; Saatchi et al., 2011).'*

Minor points:

- Brazil - comparison to PRODES not just Hansen should be mentioned in the Abstract. This is very relevant because the calculations are not independent of the Hansen et al dataset, being calibrated again it.

*We changed the abstract and the relevant section at Page 26, Line 25 now reads:*

*'Our results compared reasonably well with the newly developed Landsat-based Global Forest Change (GFC) maps, available for the 2001 onwards period ($r^2$=0.90 when comparing annual country-level estimates). This allowed us to convert our identified changes in VOD to forest loss area and compute these from 1990 onwards. We also compared these calibrated results to PRODES ($r^2$=0.60 when comparing annual state-level estimates).'*

- Page 11501 Line 27 - erroneously suggests that Landsat has had 30 m data since 1972.

*We changed Page 28, Line 1 to: 'Landsat satellite imagery is the longest operative option for monitoring vegetation. Starting in 1972, through January 1999, the Landsat Multispectral Scanner (MSS) has continuous data on relatively high spatial resolution of 90 meter. From 1982 onwards the Landsat (Enhanced) Thematic Mapper ((E)TM) provides vegetation cover on a an even higher spatial resolution of 30 meter, with a 16 day revisit time.'*

- Page 11502 line 7 - I feel that MODIS should be mentioned here, as halfway between say AVHRR and Landsat. Products such as TerraI and the MODIS LCC product could be mentioned. Also spelling, coarser.

*We changed Page 28, line 23 to:*

*'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 thus increased substantially, often using Landsat and AVHRR data but also other data sources including the Moderate-resolution Imaging Spectroradiometer (MODIS, launched in 1999 on board of Terra and in 2002 on Aqua), Medium Resolution Imaging Spectrometer (MERIS, 2002-2012) and Satellite Pour l'Observation de la Terre Vegetation Program (SPOT VGT, from 1986 onboard different satellites) (Achard et al., 2014; Baccini et al., 2012; Broich et al., 2011; Ernst et al., 2013; Eva et al., 2012; 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; Morton*

*et al., 2005; Potapov et al., 2012; Saatchi et al., 2011; Verbesselt et al., 2012; Verhegghen et al., 2012; Wasige et al., 2012).'*

- line 18 - PRODES uses other datasets too to help with cloud cover, e.g. CBERS and DMC.

*We changed this part of the introduction, Page 29, Line 1, to:*

*'One of the regions most closely monitored is the Brazilian Legal Amazon, where the Brazilian National Institute for Space Research (INPE) developed the Program for Deforestation Assessment in the Brazilian Legal Amazon with Satellite Imagery (PRODES). PRODES estimates annual deforestation since 1988 based on a multi-data approach mostly based on Landsat data but also the China-Brazil Earth Resource Satellite (CBERS-2B) and UK-DCM2 from the Disaster Monitoring Constellation International Imaging (DMCii) (Shimabukuro et al., 1998).'*

- 11503 line 11-12: given actual resolution given for Landsat, for comparison suggest give actual resolution of VOD sensors.

*We added this to the Introduction, Page 30 Line 12, and changed the sentence to:*

*'The observations retrieved from the Advanced Microwave Scanning Radiometer (AMSR-E) and Special Sensor Microwave Imager (SSM/I) have been merged to one dataset on a spatial resolution of 0.25-degree, based on Cumulative Distribution Function (CDF) matching.'*

- 11505 section 2.2. I assume you did not filter the 'loss' dataset by the 2000 Canopy Cover layer as performed by Hansen et al. in their analysis? I do not think this is a problem, but it should be mentioned in 2.2. and discussed later, as some of the 'loss' changes thus compared to the VOD data will happen in pixels that were not forest in 2000.

*We added the following to Section 2.2 Global Forest Change (GFC), Page 32, Line 21:*

*'We did not include the 2000 forest cover map as mask for forested areas to avoid omitting areas that were deforested before 2000.'*

- 11516 - I do not agree with your argument particularly at the bottom of page 11516. This would be fine if VOD provided an independent metric of deforestation, but in fact it was calibrated by GFC, so biases due to differing scales should be corrected for in your dataset. The only possible difference could be due to Brazil having more small-scale deforestation than the rest of South America, but field experience suggests in fact the opposite is true. I think you need to at the least caveat this section more, or else think of some other possible explanations for this (interesting) discrepancy. I believe this could be due to the differences in gross deforestation (Hansen) vs gross forest biomass change (VOD), with there being extensive regrowth in some areas of Brazil.

*We have changed Page 42, Line 12 to:*

*'This could be caused by the difference in what both GFC and VOD measure. GFC measures gross forest loss while, due to our methodology, VOD yields net forest loss. In areas with much regrowth, VOD will therefore underestimate forest loss compared to GFC. This also has the consequence that VOD is most reliable in areas where deforestation is the dominant change. Another reason could be 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 meters and can capture more small-scale forest loss events, which will be missed in our dataset based on VOD with its much coarser 0.25° resolution.'*

- Somewhere in the general introduction might be good to mention active microwave remote sensing of vegetation change - mostly to avoid confusion among non-specialists.

*We added to Section 2.1 Vegetation Optical Depth (VOD), Page 31 Line 9, the following sentence:*

*'Passive microwave remote sensing differs from active microwave remote sensing (Radar) in the sense that radar transmits a long-wavelength microwave signal through the atmosphere and then records the amount of energy backscattered, whereas passive systems record electromagnetic energy that was reflected or emitted from the surface of the Earth.'*

Various papers exist giving change based on L-band satellites, especially ALOS PALSAR - a recent example in South America would be Joshi et al. 2015 (Environmental Research Letters). – *This paper is mentioned in the revised introduction including description of Radar and LiDAR efforts of detecting vegetation dynamics.*

Referee 2

General comments:

The method of estimating tropical forest loss on continental scale with passive microwave remote sensing data on continental scale is a new and interesting approach. The manuscript is well structured and well written. However, the authors should highlight what their new approach brings as new information with respect to existing datasets on forest loss, more specifically with respect to the Global Forest Change (GFC) dataset of Hansen et al. 2013, given that the VOD spatial resolution is much coarser than GFC's, and that a 'tuning' (calibration) of VOD data to GFC is performed (in order to produce forest loss area estimates from dimensionless VOD values). – In Abstract and Conclusions can be added. The authors must give an outlook on advantages and future potential use of this new method compared to existing methods. In general the authors should have put less emphasis on the detailed description of the forest loss area results per country but more on the reasons of the significant differences between the VOD-based forest loss area estimates and the corresponding PRODES and GFC estimates. In the conclusions the authors describe the three datasets (GFC, PRODES, VOD) as equally valid, each with their flaws and limitations. This view seems unfair (too positive) with regard to the VOD dataset which needs 'tuning' to another dataset (and is thus dependent on its quality), and, in addition, is missing a throughout analysis on its accuracy and on the factors that can influence the VOD signal (e.g. impact on "inter-annual scales by anomalous dry or wet conditions", volcanic eruptions, water bodies: : :).

Dear reviewer,

Major comments:

**Tuning**: The abstract should mention the comparison between the VOD-derived estimates and the PRODES data estimates and should clearly point out that the comparison with GFC estimates has limitations due to the interdependence of the two datasets (as the VOD-derived dataset was 'tuned' to GFC). This interdependence of the two datasets should also be pointed out more clearly in the sections where forest loss area estimates derived from of VOD and GFC are compared.

*We changed the relevant section at Page 26, Line 25 to:*

*'Our results compare reasonably well with 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 also compared these calibrated results to PRODES ($r^2$=0.60 when comparing annual state-level estimates).'*

**Early decade**: The fact that after 'tuning' VOD data from 2000-2010 to GFC data the two datasets show substantial differences in forest loss area estimates (Table 2, Figure 5) is questioning the validity of VOD forest loss area estimates for the 1990-2000 period. VOD forest loss area estimates are provided for this earlier decade, but how accurate are they?

*We agree with the reviewer that it is uncertain what the errors are over the 1990-2010 period, because no other datasets are available for such a long timeseries. Explanations for the differences are the different spatial resolutions of GFC and VOD and GFC measuring gross forest loss (deforestation and degradation), whereas VOD measures net forest loss (deforestation, degradation and net regrowth within a year).*

*However, based on the comparable results over the overlapping time period in combination with the average error over South America (Figure 7), we feel the trends over the 1990-2000 period are relatively robust, although we don't know the exact forest loss for that time period, especially on annual time steps.*

Moreover the comparison with PRODES estimates for the years 1990 to 2010 shows substantial differences in yearly forest loss area estimates over the Brazilian Amazon from the two datasets (VOD and PRODES).

*VOD and PRODES do show large differences, but this may be partly due to limitations in both datasets. PRODES measures only deforestation of primary forest and VOD shows large interannual variability and is sensitive to open water bodies. However, many patterns between PRODES and VOD are comparable as indicated by the* $r^2$ *of 0.60. Please keep in mind that for the overlapping period PRODES and GFC also deviate from each other, although they agree better with the Pearson* $r^2$ *of 0.92, see Figure X inserted below.*

*Most importantly, VOD is the only dataset available for annual forest loss for all of South America currently, so despite the limitations we mention throughout the manuscript it yields information for time periods and regions were we currently have none.*

*We do agree with the reviewer that in future work a thorough analysis should be done to know what VOD is exactly measuring and how PRODES and VOD can be compared more directly. Therefore we added the following recommendation to the Conclusions Section, Page 44, Line 17:*

*'This was a first approach towards a better forest loss dataset using VOD to better understand forest loss dynamics. The added value of our analysis is mostly providing new annual forest loss estimates during the 1990s, a period not covered by GFC, MODIS and other satellite datasets. Regarding future opportunities, more research is needed to know exactly what VOD represents, potentially comparing with existing LiDAR-based benchmark datasets (Baccini et al., 2012; Saatchi et al., 2011).'*

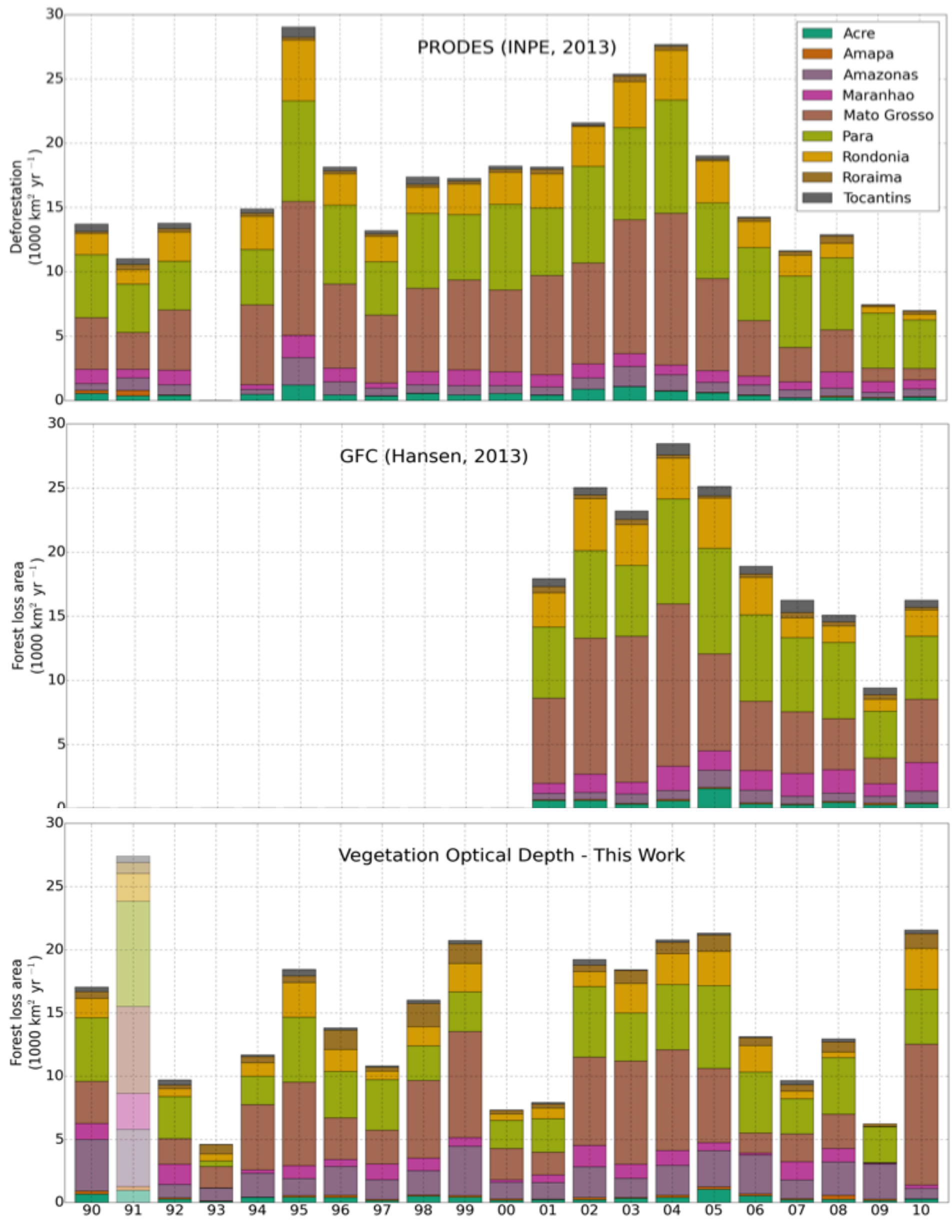



*Figure X. Time series of PRODES deforestation (top), GFC forest loss (middle) and VOD (bottom) for the Brazilian states in the Amazon (1990 – 2010). PRODES has no data for 1993 and the VOD values are unreliable in 1991 due to the volcanic eruption of Mt. Pinatubo.*

**Spatial comparison with other datasets**: In addition to the comparison of forest loss area estimates derived from VOD, GFC and PRODES (Figures 4, 5 and 6) the authors should also provide a spatial comparison with the GFC and PRODES datasets to show where the areas of forest loss coincide and where and how they differ. This can be very helpful in the discussion on the quality of the VOD-based forest loss data and on the factors that can influence VOD outlier values.

**Accuracy**: An independent assessment of the accuracy of the VOD-based forest loss area estimates is missing. Although such accuracy assessment can represent a large amount of work, it can be very useful to build confidence in such a dataset.

*We appreciate this comment and have modified our approach to switch from country-scale to grid-scale analysis, please see the revised figures at the top of this document. We also added a new Figure 7, which depicts the spatial difference between VOD and GFC forest loss area estimates. The relative errors are large, but that is mostly on grid cells with dense vegetation and little change, see Figure 8. Because of this, we recommend throughout the paper that our approach is most suitable for regional estimates.*

*Furthermore we calculated the RMSE for both the grid-scale and country-scale analysis and these results are shown in the revised Table 1. The main result is that the bin with the lowest average VOD values (0.6-0.7) has the highest error compared with GFC.*

*An independent assessment is difficult, because no other dataset exists with continuous data over the whole time period for such a large region. We think PRODES is the dataset that comes closest and provides valuable estimates. However, PRODES and VOD do not measure the same, so a spatial comparison with this dataset does in our opinion not add so much to the already existing Figure 8. We did calculate the Root Mean Square Error with PRODES on a state-level.*

*Therefore we changed Page 39 Line 22 in Section 4.4 to:*
*'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 0.60 ($p<0.001$) with a RMSE of 1.6E3 $km^2 yr^{-1}$ on a state-level.'*

**PRODES comparison**: The comparison with the PRODES forest loss dataset is definitely an independent one, but is not discussed in depth and rather regarded as of minor significance ("apples and oranges"), because of the "differences in methodology and spatial resolution: : : but also potential inconsistencies: : :". For the Brazilian Legal Amazon region, the PRODES dataset is one of the most relevant existing datasets, and should be fully taken into consideration. While certainly some technical issues need to be taken into account for such comparison (minimum mapping unit, cloud compensation, the exclusion of forest regrowth from the forest cover), a more in-depth comparison should be carried out and could be used as partial accuracy assessment over this region.

*We agree with the reviewer that PRODES is a dataset with significant value for the scientific community, but this dataset does not provide the same information as VOD. VOD measures the change in net forest loss (the net result of deforestation, degradation and regrowth within a year), whereas PRODES measures deforestation only once in primary forest. Furthermore VOD is based on consistent daily observations and PRODES measures deforestation once per year.*

*We do agree we could discuss this more including the new insights from error estimates from Figure 4 and the new Table 4 containing average errors per state based on Figure 4.*

*We replaced Section 4.4, Page 39, Line 31 to:*
*'While there are substantial differences in the temporal variability in the VOD and PRODES datasets, they do agree on where most forest losses 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).'*

*Added to Section 4.4 Page 40, Line 6:*
*'The states with largest relative differences between VOD forest loss and PRODES deforestation are Amazonas and Roraima, with 1307 $km^2yr^{-1}$ and 499 $km^2yr^{-1}$ respectively. These regions have little forest loss. The gridded errors for these states for VOD compared with GFC for the overlapping time period are relatively large: 705% and 399 % for Amazonas and Roraima respectively (Fig. 4, Table 4).'*

*Added to Discussion at Page 43, Line 11:*
*'On a state-level VOD overestimates forest loss area in the states of Amazonas and Roraima, which is mostly related to the relatively low and small-scale forest losses in these states (Fig. 4, Table 4).'*

**Difference in forest loss area estimates between PRODES and GFC**: Part of the considerable differences of forest loss area estimates between PRODES and GFC for the year 2010 can be explained, as the authors state, by the limitation of the PRODES method which does not take into account re-clearing or forest regrowth. However, when comparing yearly estimates of gross forest loss from the two datasets, a relatively stable offset appears between the two datasets (systematic higher values in GFC data), thus leaving the GFC peak for 2010 unexplained.

*We agree with the reviewer that in most of the years there is a relative stable offset between GFC and PRODES (Fanin and van der Werf, 2015, Figure 3a). However, the years 2010 (and in their research also 2012) show an increase in forest loss in GFC. Those years were years with elevated fire activity in secondary forests, thus masked out and not registered by PRODES.*

**Usage of monthly VOD values**: The authors mention that one of the advantages of the VOD is the possibility to use monthly data. However, these monthly datasets (calculated through a 19-month moving average) are used to produce the "Interyearly Difference (IYD)", of which the negative IYD values only are used for further analysis by calculating yearly and 5-year accumulation of IYD values. The monthly VOD signal as such is not used directly for analysis but only indirectly to produce yearly IYDs, and no conclusions are based directly on the monthly values. In this respect, the monthly VOD values are not used in a very different way compared to the bi-monthly image acquisitions of Landsat 7, which are mosaicked and analysed in order to produce the GFC yearly forest loss area dataset. The potential of producing monthly VOD estimates should be described and further discussed.

*The reason why we used the 19-month moving average is to filter for seasonal variations in the signal. With using this averaged signal the interannual variability in the start of the dry season is minimalized and therefore we hope to prevent false detections during the dry season. We agree that GFC based on Landsat 7 is for now the best dataset available for forest loss and it does produce bi monthly data, but is only available from 1999 onwards, whereas earlier Landsat images do not provide clear images on such a high temporal resolution.*

*To clarify this we changed in the Discussion, Page 42 Line 27 to:*

*'While we would in general favour GFC over VOD during the overlapping periods for reasons mentioned above, the temporal resolution of VOD is superior to any other dataset for our study period from 1990-2010. 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 over the 90s.'*

**Forest Plantations**: The authors do not mention the issue of forest plantation harvesting which has a high impact on the VOD values. In many areas (e.g. Southern and Central Brazil, Uruguay) forest cover changes in forest plantations are the main sources of (temporary) forest cover loss. The high forest losses e.g. in the Amazon (land use change) has different implications compared to the high forest losses in e.g. Southern Brazil (mainly land cover change). This should be pointed out in the manuscript.
*We agree and changed at the Discussion, Page 42, Line 23 to:*
*'In Uruguay many forest plantations occur (Suppl. Figure 1, Achard et al., 2014) and the result of these plantations is that forest losses are often of small scale. This in combination with the overestimation of VOD with smaller scale forest losses, could explain why Uruguay shows so much higher values on a country scale, although additional research is required to better understand these differences.'*

**False VOD-based forest loss**: The manuscript discusses in detail the forest losses in the Amazon rainforest and the Chaco forest, where the VOD approach seems to work reasonably well. However, the discussion addresses only shortly the issue that for countries like Chile, Uruguay, and Surinam the VOD approach provides very different estimates compared to GFC (the paper mentions only the different spatial resolutions of the two datasets as the probable main reason). This discussion is essential and should be held in more depth. In fact, the VOD results show relatively high forest loss values in areas where the forest cover is very small (e.g. Uruguay). This issue of overestimation of forest loss arises also within Brazil outside the Amazon and Chaco regions: e.g. high forest loss is estimated for Southern Brazil (Rio Grande do Sul, Santa Catarina and Parana States) for the period of 2000-2004 (with 5-year VOD outlier values comparable to those within the arc of deforestation) which does not seem to correspond to reality. Another example would be Southern Bahia (South of Salvador) where, according to VOD data, high forest loss occurs throughout the 20 year period – while not much evidence is found for this loss in the satellite imagery. –
*We agree with the reviewer and we hope to cover this point by doing the grid cell analysis including error estimates described in the new Figures 4 and 5. We tried to correct for this by taking different VOD classes (e.g. 0.6-0.7,0.7-0.8, etc.) as a measure for tree cover percentage per grid cell. This however, will not correct for size of the forest loss.*

**Country level statistics:** Under point 4.2 (Calibration with GFC) the authors describe the 'tuning' of the VOD outliers to the GFC forest losses and state for some years considerable differences in forest loss estimates. A throughout discussion on these differences is missing, as well as information (as mentioned before) on their spatial distribution (apart from country-specific information).
*We hope to have answered this comment by performing the per-grid cell analysis and spatial error estimation, see Figures 4 and 5.*

Technical corrections:

Section 11500, Line 24 (Abstract): "One of the key findings" mentioned in the abstract is the decrease of forest loss in Brazil after year 2005, but this decrease has already been reported by many sources, e.g. by FAO in the FRA 2010 report. The sentence should thus be changed in "the analysis of VOD-based forest loss estimates are in agreement with other studies that state : : :", or similar.

*We changed this in the Discussion, Page 41, Line 11, and refer to the FRA 2010 report: 'Our results agree with earlier work showing that forest loss area, and probably also carbon emissions, declined after peaking in the year 2004 (Food and Agriculture Organization of the United Nations, 2010; Macedo et al., 2012; Malhi et al., 2008; Nepstad et al., 2009).'*

Section 11501, Line 27: Starting in 1972, Landsat MSS had a spatial resolution of 80 m (but was often resampled to 60 m), this should be added to the mentioned resolution of Landsat (E)TM spatial resolution of 30m

*We changed Page 28, Line 1 to: 'Landsat satellite imagery is the longest operative option for monitoring vegetation. Starting in 1972, through January 1999, the Landsat Multispectral Scanner (MSS) has continuous data on relatively high spatial resolution of 90 meter. From 1982 onwards the Landsat (Enhanced) Thematic Mapper ((E)TM) provides vegetation cover on a an even higher spatial resolution of 30 meter, with a 16 day revisit time.'*

Section 11502, Line 8: "coarser" spatial resolution instead of "courser: : :"

*We changed this.*

Section 11502, Line 12 ff.: Achard et al. 2014 (global), Eva et al. 2012 (regional, for tropical South and Central America) and Verhegghen et al. 2012 (regional approach with MERIS and SPOT VGT data) should be added to the list of publications mentioned here. The reference "Céline et al. 2013" should be "Ernst et al. 2013", the first name and last name of the author was reversed – which is the case for all other names in this reference (Section 11519). –

*We changed this part, Page 28, Line 23, of the Introduction to:*

*'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 thus increased substantially, often using Landsat and AVHRR data but also other data sources including the Moderate-resolution Imaging Spectroradiometer (MODIS, launched in 1999 on board of Terra and in 2002 on Aqua), Medium Resolution Imaging Spectrometer (MERIS, 2002-2012) and Satellite Pour l'Observation de la Terre Vegetation Program (SPOT VGT, from 1986 onboard different satellites) (Achard et al., 2014; Baccini et al., 2012; Broich et al., 2011; Ernst et al., 2013; Eva et al., 2012; 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; Morton et al., 2005; Potapov et al., 2012; Saatchi et al., 2011; Verbesselt et al., 2012; Verhegghen et al., 2012; Wasige et al., 2012).'*

Section 11502, Line 17 (and Section 11506, Line 2): INPE is not the Brazilian Space Agency, but the Brazilian National Institute for Space Research

Section 11502, Line 18: the project called PRODES is not called the "Monitoring the Gross Deforestation in the Amazon Project", but "Program for Deforestation Assessment in the Brazilian Legal Amazon with Satellite Imagery"
*We changed this part, Page 29, Line 1, of the Introduction to: 'One of the regions most closely monitored is the Brazilian Legal Amazon, where the Brazilian National Institute for Space Research (INPE) developed the Program for Deforestation Assessment in the Brazilian Legal Amazon with Satellite Imagery (PRODES). PRODES estimates annual deforestation since 1988 based on a multi-data approach mostly based on Landsat data but also the China-Brazil Earth Resource Satellite (CBERS-2B) and UK-DCM2 from the Disaster Monitoring Constellation International Imaging (DMCii) (Shimabukuro et al., 1998).'*

Section 11503, Line 27: ": : :to Landsat-derived datasets including: : :" should be ": : :to the Landsat-derived datasets of PRODES: : :"
*We changed this at Page 30, Line 24, to: 'We detail how we translated the VOD signal to forest loss area by calibrating our results to the Global Forest Change maps of Hansen et al. (2013), which are subsequently compared to the Landsat-derived PRODES-dataset.*

Section 11505, Line 20: "with" or "at" instead of "on a 30 m resolution, the 30 m can then be dropped in the next sentence
*We changed this at Page 32, Line 14, to: '…at a 30-meter resolution.'*

Section 11506, Line 10: "Landsat 5/TM" should be "Landsat 5 and Landsat 7"
*We changed this at Page 33, Line 3.*

Section 11506, Line 14: "shadefractioned images" should be "images of soil, shade and vegetation fractions"
*We changed this at Page 33, Line 5 to: 'After 2002, PRODES started to use digital image processing and visual interpretation of Landsat bands 3, 4 and 5 creating and interpreting images of soil, shade and vegetation fractions (INPE, 2013; Shimabukuro et al., 1998).'*

Section 11506, Line 16: the method described does not yield 'gross forest loss', it yields 'net forest loss', for areas where the forest loss exceeds forest gain (as only negative VOD outliers were considered) –
*We changed Section 3.3, Page 35, Line 27, to:*
*'In general, our method yields net forest loss per gridcell within one year, because we considered decreases in VOD, which is the net result of deforestation, forest degradation and regrowth within a gridcell per year.'*

Section 11510, Line 5 ff.: In Figure 3 the arc of deforestation is not a 'dominant' feature, it is rather a well-known feature which is thus recognized easily, but in all four parts of the figure it is one among various areas which show high absolute "Summed IYD values (-)".
*We changed this at Page 36, Line 13, to: 'The largest 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 in every period.'*

The interpretation of figure 3 is too short and too fuzzy with respect to the importance of the figure that shows the main results (summed IYD values (-) indicating forest loss) in their spatial distribution.
*We included a spatial error analysis on a gridcell-scale and added the following text to Section 4.1 Spatial Extent, Page 37, Line 8:*
*'The largest errors are found in the regions with dense vegetation and relatively little forest loss (Fig. 4, Fig. 5). The RMSE on a grid-cell scale shows that the bin with the lowest average VOD values (0.6-0.7) has the highest error compared to GFC (Table 1).'*

Section 11511, Line 5: Equation (4) is either missing or not numbered correctly. *We changed this at Page 37, Line 5, to: 'We converted the summed* $VOD_{outliers}$ *to a forest loss area according to Eq. 3, where the slopes varied between the 5 different bins (Table 1).'*

Section 11516, Line 12: 'strict regulations' is an imprecise term, it should be "strict forest law and effective forest law enforcement" or similar.
*We changed this at Page 41, Line 28, to: 'One explanation could be relocation of agricultural hotspots because of the strict forest law and effective forest law enforcement within Brazil (Dobrovolski and Rattis, 2014).'*

Section 11518, Line 7: ": : : partly because it was related to secondary forest degradation" should be ": : :partly because of the deforestation of secondary forest" or similar. –
*PRODES does not capture changes in degradation nor deforestation of secondary forest. Therefore we changed this sentence at Page 43, Line 27, to:*
*'PRODES did not show this peak, partly because it was related to secondary forest degradation and deforestation, which is not captured by PRODES (Fanin and van der Werf, 2015).'*

Section 11532, Figure 3: The caption of the figure is not correct, as the figure does not show forest loss extend, but the "Summed IYD values (-)".
*In the new and revised figures, Figure 3 is replaced with spatial maps of forest loss area.*

## References

Achard, F., Beuchle, R., Mayaux, P., Stibig, H.-J., Bodart, C., Brink, A., Carboni, S., Desclée, B., Donnay, F., Eva, H. D., Lupi, A., Raši, R., Seliger, R. and Simonetti, D.: Determination of tropical deforestation rates and related carbon losses from 1990 to 2010, Glob. Chang. Biol., 20, 2540–2554, doi:10.1111/gcb.12605, 2014.

Andela, N., Liu, Y. Y., van Dijk, A. I. J. M., de Jeu, R. A. M. and McVicar, T. R.: Global changes in dryland vegetation dynamics (1988-2008) assessed by satellite remote sensing: Comparing a new passive microwave vegetation density record with reflective greenness data, Biogeosciences, 10, 6657–6676, doi:10.5194/bg-10-6657-2013, 2013.

Anyamba, A. and Tucker, C. J.: Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003, in Journal of Arid Environments, vol. 63, pp. 596–614., 2005.

Baccini, A., Goetz, S. J., Walker, W. S., Laporte, N. T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P. S. A., Dubayah, R., Friedl, M. A., Samanta, S. and Houghton, R. A.: Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps, Nat. Clim. Chang., 2, 182–185, doi:10.1038/nclimate1354, 2012.

Broich, M., Hansen, M., Stolle, F., Potapov, P., Margono, B. A. and Adusei, B.: Remotely sensed forest cover loss shows high spatial and temporal variation across Sumatera and Kalimantan, Indonesia 2000–2008, Environ. Res. Lett., 6, 014010, doi:10.1088/1748-9326/6/1/014010, 2011.

Dobrovolski, R. and Rattis, L.: Brazil should help developing nations to foster agriculture and environmental protection, Front. Ecol. Environ., 12, 376–376, doi:10.1890/14.WB.010, 2014.

Ernst, C., Mayaux, P., Verhegghen, A., Bodart, C., Christophe, M. and Defourny, P.: National forest cover change in Congo Basin: Deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005, Glob. Chang. Biol., 19, 1173–1187, doi:10.1111/gcb.12092, 2013.

Eva, H. D., Achard, F., Beuchle, R., de Miranda, E., Carboni, S., Seliger, R., Vollmar, M., Holler, W. a., Oshiro, O. T., Arroyo, V. B. and Gallego, J.: Forest cover changes in tropical south and Central America from 1990 to 2005 and related carbon emissions and removals, Remote Sens., 4, 1369–1391, doi:10.3390/rs4051369, 2012.

Fanin, T. and van der Werf, G. R.: Relationships between burned area, forest cover loss, and land cover change in the Brazilian Amazon based on satellite data, Biogeosciences, 12, 6033–6043, doi:10.5194/bg-12-6033-2015, 2015.

Food and Agriculture Organization of the United Nations: Global forest resources assessments main report, FAO For. Pap., 163 [online] Available from: http://www.fao.org/docrep/013/i1757e/i1757e00.htm (Accessed 10 September 2014), 2010.

Frolking, S., Hagen, S., Milliman, T., Palace, M., Shimbo, J. Z. and Fahnestock, M.: Detection of Large-Scale Forest Canopy Change in Pan-Tropical Humid Forests 2000–2009 With the SeaWinds Ku-Band Scatterometer, IEEE Trans. Geosci. Remote Sens., 50, 2603–2617, doi:10.1109/TGRS.2011.2182516, 2012.

Guan, K., Wood, E. F. and Caylor, K. K.: Multi-sensor derivation of regional vegetation fractional cover in Africa, Remote Sens. Environ., 124, 653–665, doi:10.1016/j.rse.2012.06.005, 2012.

INPE: PRODES - Metodologia para o Cálculo da Taxa Anual de Desmatamento na Amazônia Legal. [online] Available from: http://www.obt.inpe.br/prodes/metodologia_TaxaProdes.pdf, 2013.

Jackson, T. J. and Schmugge, T. J.: Vegetation effects on the microwave emission of soils, Remote Sens. Environ., 36, 203–212, doi:10.1016/0034-4257(91)90057-D, 1991.

Jones, M. O., Jones, L. A., Kimball, J. S. and McDonald, K. C.: Satellite passive microwave remote sensing for monitoring global land surface phenology, Remote Sens. Environ., 115, 1102–1114, doi:10.1016/j.rse.2010.12.015, 2011.

de Jong, R., Verbesselt, J., Zeileis, A. and Schaepman, M. E.: Shifts in global vegetation activity trends, Remote Sens., 5, 1117–1133, doi:10.3390/rs5031117, 2013.

Joshi, N., Mitchard, E. T., Woo, N., Torres, J., Moll-Rocek, J., Ehammer, A., Collins, M., Jepsen, M. R. and Fensholt, R.: Mapping dynamics of deforestation and forest degradation in tropical forests using radar satellite data, Environ. Res. Lett., 10, 034014, doi:10.1088/1748-9326/10/3/034014, 2015.

Kerr, Y. H. and Njoku, E. G.: Semiempirical model for interpreting microwave emission from semiarid land surfaces as seen from space, IEEE Trans. Geosci. Remote Sens., 28, 384–393, doi:10.1109/36.54364, 1990.

Kim, D.-H., Sexton, J. O. and Townshend, J. R.: Accelerated deforestation in the humid tropics from the 1990s to the 2000s, Geophys. Res. Lett., 42, 3495–3501, doi:10.1002/2014GL062777, 2015.

Kirdiashev, K. P., Chukhlantsev, A. A. and Shutko, A. M.: Microwave radiation of the earth’s surface in the presence of vegetation cover, Radio Eng. Electron. Phys., 24, 256–264, 1979.

Koh, L. P., Miettinen, J., Liew, S. C. and Ghazoul, J.: Remotely sensed evidence of tropical peatland conversion to oil palm., Proc. Natl. Acad. Sci. U. S. A., 108, 5127–32, doi:10.1073/pnas.1018776108, 2011.

Liu, Y. Y., van Dijk, A. I. J. M., de Jeu, R. A. M., Canadell, J. G., McCabe, M. F., Evans, J. P. and Wang, G.: Recent reversal in loss of global terrestrial biomass, Nat. Clim. Chang., 5, 470–474, doi:10.1038/nclimate2581, 2015.

Liu, Y. Y., de Jeu, R. A. M., McCabe, M. F., Evans, J. P. and van Dijk, A. I. J. M.: Global long-term passive microwave satellite-based retrievals of vegetation optical depth, Geophys. Res. Lett., 38, L18402, doi:10.1029/2011GL048684, 2011.

Macedo, M. N., DeFries, R. S., Morton, D. C., Stickler, C. M., Galford, G. L. and Shimabukuro, Y. E.: Decoupling of deforestation and soy production in the southern Amazon during the late 2000s, Proc. Natl. Acad. Sci. U. S. A., 109, 1341–1346, doi:10.1073/pnas.1111374109, 2012.

Malhi, Y., Roberts, J. T., Betts, R. A., Killeen, T. J., Li, W. and Nobre, C. A.: Climate change, deforestation, and the fate of the Amazon., Science, 319, 169–172, doi:10.3832/efor0516-005, 2008.

Mayaux, P., Achard, F. and Malingreau, J.-P.: Global tropical forest area measurements derived from coarse resolution satellite imagery: a comparison with other approaches, Environ. Conserv., 25, 37–52, doi:10.1017/S0376892998000083, 1998.

Mitchard, E. T. A., Saatchi, S. S., White, L. J. T., Abernethy, K. A., Jeffery, K. J., Lewis, S. L., Collins, M., Lefsky, M. A., Leal, M. E., Woodhouse, I. H. and Meir, P.: Mapping tropical forest biomass with radar and spaceborne LiDAR in Lopé National Park, Gabon: overcoming problems of high biomass and persistent cloud, Biogeosciences, 9, 179–191, doi:10.5194/bg-9-179-2012, 2012.

Morton, D. C., DeFries, R. S., Shimabukuro, Y. E., Anderson, L. O., Del Bon Espírito-Santo, F., Hansen, M. and Carroll, M.: Rapid Assessment of Annual Deforestation in the Brazilian Amazon Using MODIS Data, Earth Interact., 9, 1–22, doi:10.1175/EI139.1, 2005.

Myneni, R. B., Hall, F. G., Sellers, P. J. and Marshak, A. L.: The interpretation of spectral vegetation indexes, IEEE Trans. Geosci. Remote Sens., 33, 481–486, doi:10.1109/36.377948, 1995.

Nepstad, D., Soares-Filho, B. S., Merry, F., Lima, A., Moutinho, P., Carter, J., Bowman, M., Cattaneo, A., Rodrigues, H., Schwartzman, S., McGrath, D. G., Stickler, C. M., Lubowski, R., Piris-Cabezas, P., Rivero, S., Alencar, A., Almeida, O. and Stella, O.: Environment. The end of deforestation in the Brazilian Amazon., Science, 326, 1350–1351, doi:10.1126/science.1182108, 2009.

Owe, M., de Jeu, R. A. M. and Walker, J. P.: A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index, IEEE Trans. Geosci. Remote Sens., 39, 1643–1654, doi:10.1109/36.942542, 2001.

Potapov, P. V., Turubanova, S. A., Hansen, M. C., Adusei, B., Broich, M., Altstatt, A., Mane, L. and Justice, C. O.: Quantifying forest cover loss in Democratic Republic of the Congo, 2000-2010, with Landsat ETM+ data, Remote Sens. Environ., 122, 106–116, doi:10.1016/j.rse.2011.08.027, 2012.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T. A., Salas, W., Zutta, B. R., Buermann, W., Lewis, S. L., Hagen, S., Petrova, S., White, L., Silman, M. and Morel, A.: Benchmark map of forest carbon stocks in tropical regions across three continents., Proc. Natl. Acad. Sci. U. S. A., 108, 9899–9904, doi:10.1073/pnas.1019576108, 2011.

Shi, J., Jackson, T., Tao, J., Du, J., Bindlish, R., Lu, L. and Chen, K. S.: Microwave vegetation indices for short vegetation covers from satellite passive microwave sensor AMSR-E, Remote Sens. Environ., 112, 4285–4300, doi:10.1016/j.rse.2008.07.015, 2008.

Shimabukuro, Y. E., Batista, G. T., Mello, E. M. K., Moreira, J. C. and Duarte, V.: Using shade fraction image segmentation to evaluate deforestation in Landsat Thematic Mapper images of the Amazon Region, Int. J. Remote Sens., 19, 535–541, doi:10.1080/014311698216152, 1998.

Tucker, C., Pinzon, J., Brown, M., Slayback, D., Pak, E., Mahoney, R., Vermote, E. and El Saleous, N.: An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data, Int. J. Remote Sens., 26, 4485–4498, doi:10.1080/01431160500168686, 2005.

UNFCCC: Annex to UNFCCC decision 16/CMP.1 Land use, land-use change and forestry, Rep. Conf. Parties Serv. as Meet. Parties to Kyoto Protoc. its first Sess. held Montr. from 28 Novemb. to 10 December 2005, FCCC/KP/CM, 3, 2006.

Verbesselt, J., Zeileis, A. and Herold, M.: Near real-time disturbance detection using satellite image time series, Remote Sens. Environ., 123, 98–108, doi:10.1016/j.rse.2012.02.022, 2012.

Verhegghen, A., Mayaux, P., de Wasseige, C. and Defourny, P.: Mapping Congo Basin vegetation types from 300 m and 1 km multi-sensor time series for carbon stocks and forest areas estimation, Biogeosciences, 9, 5061–5079, doi:10.5194/bg-9-5061-2012, 2012.

Wasige, J. E., Groen, T. A., Smaling, E. and Jetten, V.: Monitoring basin-scale land cover changes in Kagera Basin of Lake Victoria using: Ancillary data and remote sensing, Int. J. Appl. Earth Obs. Geoinf., 21, 32–42, doi:10.1016/j.jag.2012.08.005, 2012.

Zhu, Z., Bi, J., Pan, Y., Ganguly, S., Anav, A., Xu, L., Samanta, A., Piao, S., Nemani, R. R. and Myneni, R. B.: Global data sets of vegetation leaf area index (LAI)3g and fraction of photosynthetically active radiation (FPAR)3g derived from global inventory modeling and mapping studies (GIMMS) normalized difference vegetation index (NDVI3G) for the period 1981 to 2, Remote Sens., 5, 927–948, doi:10.3390/rs5020927, 2013.

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

**M. J. E. van Marle[1], G. R. van der Werf[1], R. A. M. de Jeu[1,2] and Y. Y. Liu[3]**

[1]{Faculty of Earth and Life Sciences, Vrije Universiteit Amsterdam, Amsterdam, the Netherlands}

[2]{now at Transmissivity B.V. , Space Technology Centre, Noordwijk, the Netherlands}

[3]{ARC Centre of Excellence for Climate System Science & Climate Change Research Centre, University of New South Wales, Sydney, Australia}

Correspondence to: M. J. E. van Marle (m.j.e.van.marle@vu.nl)

## 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 data 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 reasonably well with the newly developed Landsat-based Global Forest Change (GFC) maps, available for the 2001 onwards period ($r^2$=0.90 when comparing annual country-level estimates). This allowed us to convert our identified changes in VOD to forest loss area and compute these from 1990 onwards. We also compared these calibrated results to

PRODES ($r^2$=0.60 when comparing annual state-level estimates). 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 area 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). 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), and the continent is responsible for almost half of the tropical deforestation emissions (Harris et al., 2012; Pan et al., 2011). 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 which 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, through January 1999, the Landsat Multispectral Scanner (MSS) has continuous data on relatively high spatial resolution of 90 meter. From 1982 onwards the Landsat (Enhanced) Thematic Mapper ((E)TM) provides vegetation cover on a an even higher spatial resolution of 30 meter, with a 16 day revisit time. However, the effective temporal resolution is much lower 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 are the Normalized Difference Vegetation Index (NDVI), often derived from the Advanced Very High Resolution Radiometer (AVHRR). NDVI is sensitive to canopy greenness (Anyamba and Tucker, 2005; Tucker et al., 2005; Zhu et al., 2013). This dataset has a higher temporal, but coarser spatial resolution than Landsat, and is also sensitive to aerosols and cloud cover. Other vegetation datasets that can capture vegetation dynamics are for example the observations based on long-wavelength radar backscatter (Joshi et al., 2015), where deforestation, forest degradation and the follow-up vegetation cover could be captured, and those based on observations from the SeaWinds Ku-band scatterometer (Frolking et al., 2012), which have shown to capture gross forest loss in the tropics. Also LiDar data can be used to estimate forest biomass, and can thus capture vegetation dynamics (Mitchard et al., 2012). Data availability for Radar and LiDar datasets is usually from 1998 onwards.

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 thus increased substantially, often using Landsat and AVHRR data but also other data sources including the Moderate-resolution Imaging Spectroradiometer (MODIS, launched in 1999 on board of Terra and in 2002 on Aqua), Medium Resolution Imaging Spectrometer (MERIS, 2002-2012) and Satellite Pour l'Observation de la Terre Vegetation Program (SPOT VGT, from 1986 onboard different satellites) (Achard et al., 2014; Baccini et al., 2012; Broich et al., 2011; Ernst et al., 2013; Eva et al., 2012; 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; Morton et al., 2005; Potapov et al., 2012; Saatchi et al., 2011; Verbesselt et al., 2012; Verhegghen et al., 2012; Wasige et al., 2012).

One of the regions most closely monitored is the Brazilian Legal Amazon, where the Brazilian National Institute for Space Research (INPE) developed the Program for Deforestation Assessment in the Brazilian Legal Amazon with Satellite Imagery (PRODES). PRODES estimates annual deforestation since 1988 based on a multi-data approach mostly based on Landsat data but also the China-Brazil Earth Resource Satellite (CBERS-2B) and UK-DCM2 from the Disaster Monitoring Constellation International Imaging (DMCii) (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, passive 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. VOD is primarily sensitive to the vegetation water content and also captures information about the vegetation structure (Jackson and Schmugge, 1991; Kerr and Njoku, 1990; Kirdiashev et al., 1979).

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 (Jones et al., 2011; Shi et al., 2008). VOD is shown to be highly correlated with aboveground biomass (Liu et al., 2011a; Owe et al., 2001) and thus yields information about the net forest loss; the balance between decreases in forest loss due to deforestation and degradation and increases in forest extend due to regrowth or thickening. Furthermore, the advantage of low frequency (<20 GHz) microwave remote sensing is that aerosols and clouds have a negligible effect on the observations, so even areas with regular cloud cover are observed frequently, which makes it suitable to use for global vegetation monitoring at daily time steps.

Comparing AVHRR NDVI and passive microwave based VOD datasets with a record longer than 20 years, Liu et al. (2011) showed that both datasets had similar seasonal cycles. VOD however also shows interannual variations in regions with water stress, which corresponds for a large part to variations in precipitation. VOD was more sensitive to changes in woody vegetation compared to NDVI, whereas NDVI was more sensitive to herbaceous changes (Andela et al. 2013). This is the result of NDVI being more sensitive to canopy greenness

(Myneni et al., 1995) and VOD being more sensitive to water content, relatively speaking. Thus, when forest is converted to large-scale cropland, the canopy greenness not necessarily drops, whereas the total water content of the aboveground biomass does show a drop (Liu et al., 2011a).

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 retrievals therefore have a relatively coarse resolution, compared to observations in the visible and near infrared spectra. 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 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 with a spatial resolution of 0.25°, 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). Guan et al. (2012) compared QuickScat Ku-band backscatter coefficients (dB) with VOD and NDVI and noted that the three datasets are comparable, but that dB shows abnormal high values when more bare soil is present in the pixel.

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 area by calibrating our results to the Global Forest Change maps of Hansen et al. (2013), which are subsequently compared to the Landsat-derived PRODES-dataset. We then provide a country-level analysis of the newly derived maps, and zoom in on Brazil to 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), which besides being used for comparing the spatio-temporal variability is also used to translate our results to area estimates, 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. Passive microwave remote sensing differs from active microwave remote sensing (Radar) in the sense that radar transmits a long-wavelength microwave signal through the atmosphere and then records the amount of energy backscattered, whereas passive systems record electromagnetic energy that was reflected or emitted from the surface of the Earth. 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) already 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). VOD can be used as a measure for biomass (Liu et al., 2015) , which is in terms of forest loss, the net forest loss (equals the net sum of deforestation, degradation and regrowth) in a 0.25° grid cell.

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 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, 2011b). 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 at a 30-meter resolution. The maps are based on the 30-meter 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 in GFC as a change from forest to non-forest state, comprising deforestation and degradation. 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-meter values. While regrowth is detected and reported, we focused on the forest loss data when we used GFC for comparison; regrowth is thus not included in our analysis of GFC. We did not include the 2000 forest cover map as mask for forested areas to avoid omitting areas that were deforested before 2000.

## 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 and Landsat 7 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 images of soil, shade and vegetation fractions (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 the data (Sect. 3.1), followed by explaining the methodology used 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. This

value was based on the comparison between VOD and MODIS-based Vegetation Continuous Fields (VCF), which provides information about the fraction tree cover in a pixel. Our VOD threshold of 0.6 corresponds to 10% tree cover for two-third of the pixels, a number more often used to define forest (Saatchi et al., 2011; UNFCCC, 2006) although there is no consensus about this definition.

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, which also gives an indication of our underestimation due to masking out of these grid cells.

## 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):

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

where *lat,lon,m* is the latitude (*lat*), longitude (*lon*) and month (*m*). With *m-9:m+9* we refer to all data points 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 (Fig. 2a).

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):

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

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 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 meter 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 net forest loss per gridcell within one year, because we considered decreases in VOD, which is the net result of deforestation, forest degradation and regrowth within a gridcell per year.

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 year related to the same GFC values. Based on the linear regression, we obtained a slope for each VOD bin, which was used to convert $VOD_{outliers}$ to gross forest loss area per 0.25° grid cell (Eq. 3).

$$VOD_{areaforestloss}(year) = \sum_{bin=1}^{5} VOD_{outliers}(year, bin) \text{ x } slope(bin) \qquad (3)$$

# 4 Results

## 4.1 Spatial extent

The largest 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 in every period. 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 00s. During the 2005-2009 time window some 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. 3, where the slopes varied between the 5 different bins (Table 1). The Pearson correlation on a grid-scale was lowest ($r^2$=0.52) for the bin with the average VOD from 0.6-0.7. The other 4 bins had correlations ranging from $r^2$=0.63 to 0.80 (Table 1). The largest errors are found in the regions with dense vegetation and relatively little forest loss (Fig. 4, Fig. 5). The RMSE on a grid-cell scale shows that the bin with the lowest average VOD values (0.6-0.7) has the highest error compared to GFC (Table 1).

On a country-scale the correlations per bin were higher with the lowest ($r^2$=0.63) for the bin with the lowest average VOD (0.6-0.7) and the 4 other bins with increasing correlations from $r^2$=0.84 to 0.96 (Table 1). 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. 6 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. As a percentage of the available area per country (Table 2) Uruguay (0.65%), Surinam (0.22%), French Guiana (0.14%) and Guyana (0.13%) also showed higher average forest losses over the overlapping time period based on VOD. Chile is on the other hand the country where VOD provides lower forest loss estimates for the overlapping time period (-0.18%) compared to GFC. The country with the largest relative forest losses is Paraguay for both VOD (1.05%) and GFC (0.98%). In Fig. 7 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 be different and thus yields new insights.

The main differences between VOD and GFC are thus 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 (Fig. 7, 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 -2.9 and -1.4 % $yr^{-2}$, for VOD and GFC respectively, which in absolute terms corresponds to -1121 $km^2 yr^{-2}$ and -568 $km^2 yr^{-2}$. For individual countries in general both datasets agreed and these trends were highly variable (Table 2).

### 4.3.2 1990-2010

Focusing on the full time series, Fig. 7 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 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. 7).

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 60 $km^2 yr^{-2}$). Over the same time period also Argentina, Chile, Paraguay and Venezuela showed substantial in- or decreasing trends larger than 3% $yr^{-2}$. 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 5% $yr^{-2}$. During the 2000s, Brazil, Ecuador and Surinam showed trends below -5% $yr^{-2}$. The strongest differences per decade were found in Brazil (where the forest loss trend changed from +9.8% $yr^{-2}$ in the 1990s to -7% $yr^{-2}$ in the 2000s) Colombia (-16.7% $yr^{-2}$ to 0.88% $yr^{-2}$) and in Uruguay (+11.9% $yr^{-2}$ to -2.1% $yr^{-2}$) (Table 3). Other countries with substantial different trends between the two periods were Argentina 5.8% $yr^{-2}$ to 3.4% $yr^{-2}$), French Guiana (-3.8% $yr^{-2}$ to 6.3% $yr^{-2}$), Peru (-4.6% $yr^{-2}$ to 2.4% $yr^{-2}$) and Surinam (-4% $yr^{-2}$ to 5.9% $yr^{-2}$).

### 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. 8). 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 0.60 ($p<0.001$) with a RMSE of 1.6E3 $km^2 yr^{-1}$ on a state-level.

Our results show for the Brazilian states a highly dynamic pattern with no steadily in- or decreasing trend (Fig. 8). 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 losses 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 16.6E3 $km^2yr^{-1}$ and 15.2E3 $km^2yr^{-1}$ for PRODES and VOD respectively. The states with largest relative differences between VOD forest loss and PRODES deforestation are Amazonas and Roraima, with 1307 $km^2yr^{-1}$ and 499 $km^2yr^{-1}$ respectively. These regions have little forest loss. The gridded errors for these states for VOD compared with GFC for the overlapping time period are relatively large: 705% and 399 % for Amazonas and Roraima respectively (Fig. 4, Table 4).

### 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.

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 (Food and Agriculture Organization of the United Nations, 2010; 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).

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 metres tall) with closed canopy is converted to shorter (<10 metres) 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 7, 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 forest law and effective forest law enforcement 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. 7), 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 $km^2yr^{-1}$ or 7.6% $yr^{-1}$ 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 difference in what both GFC and VOD measure. GFC measures gross forest loss while, due to our methodology, VOD yields net forest loss. In areas with much regrowth, VOD will therefore underestimate forest loss compared to GFC. This also has the consequence that VOD is most reliable in areas where deforestation is the dominant change. Another reason could be 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 meters and can capture more small-scale forest loss events, which will be missed in 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. 6). In Uruguay many forest plantations occur (Suppl. Figure 1, Achard et al., 2014) and the result of these plantations is that forest losses are often of small scale. This in combination with the overestimation of VOD with smaller scale forest losses, could explain why Uruguay shows so much higher values on a country scale, although additional research is required to better understand these differences. While we would in general favour GFC over VOD during the overlapping periods for reasons mentioned above, the temporal resolution of VOD is superior to any other dataset for our study period from 1990-2010. 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 over the 90s.

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 and regrowth, PRODES shows on average over the whole time period 1451 $km^2 yr^{-1}$ (9.6% $yr^{-1}$ 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. On a state-level VOD overestimates forest loss area in the states of Amazonas and Roraima, which is mostly related to the relatively low and small-scale forest losses in these states (Fig. 4, Table 4).

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 the state of Amazonas. During 1999 heavy floodings occurred in this region (Chen et al., 2010). Since VOD is 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 and deforestation, 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 improve on characterizing 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, partly offsetting the reductions in forest loss in Brazil.

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. This was a first approach towards a better forest loss dataset using VOD to better understand forest loss dynamics. The added value of our analysis is mostly providing new annual forest loss estimates during the 1990s, a period not covered by GFC, MODIS and other satellite datasets. Regarding future opportunities, more research is needed to know exactly what VOD represents, potentially comparing with existing LiDAR-based benchmark datasets (Baccini et al., 2012; Saatchi et al., 2011).

## Acknowledgements

We thank Douglas Morton, Jan Verbesselt and Niels Andela for useful discussions. Furthermore we acknowledge INPE and Matthew Hansen for making their data publicly available. This research was supported by the European Research Council grant number 280061.

# References


Achard, F., Beuchle, R., Mayaux, P., Stibig, H.-J., Bodart, C., Brink, A., Carboni, S., Desclée, B., Donnay, F., Eva, H. D., Lupi, A., Raši, R., Seliger, R. and Simonetti, D.: Determination of tropical deforestation rates and related carbon losses from 1990 to 2010, Glob. Chang. Biol., 20, 2540–2554, doi:10.1111/gcb.12605, 2014.

Andela, N., Liu, Y. Y., van Dijk, A. I. J. M., de Jeu, R. A. M. and McVicar, T. R.: Global changes in dryland vegetation dynamics (1988-2008) assessed by satellite remote sensing: Comparing a new passive microwave vegetation density record with reflective greenness data, Biogeosciences, 10, 6657–6676, doi:10.5194/bg-10-6657-2013, 2013.

Anyamba, A. and Tucker, C. J.: Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003, in Journal of Arid Environments, vol. 63, pp. 596–614., 2005.

Asner, G. P.: Cloud cover in Landsat observations of the Brazilian Amazon, Int. J. Remote Sens., 22, 3855–3862, doi:10.1080/01431160010006926, 2001.

Baccini, A., Goetz, S. J., Walker, W. S., Laporte, N. T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P. S. A., Dubayah, R., Friedl, M. A., Samanta, S. and Houghton, R. A.: Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps, Nat. Clim. Chang., 2, 182–185, doi:10.1038/nclimate1354, 2012.

Barbosa, R. I. and Fearnside, P. M.: Incêndios na Amazônia Brasileira: estimativa da emissão de gases do efeito estufa pela queima de diferentes ecossistemas de Roraima na passagem do evento "El Niño" (1997/1998), Acta Amaz., 29, 513–534, 1999.

Boletta, P. E., Ravelo, A. C., Planchuelo, A. M. and Grilli, M.: Assessing deforestation in the Argentine Chaco, For. Ecol. Manage., 228, 108–114, doi:10.1016/j.foreco.2006.02.045, 2006.

Broich, M., Hansen, M., Stolle, F., Potapov, P., Margono, B. A. and Adusei, B.: Remotely sensed forest cover loss shows high spatial and temporal variation across Sumatera and Kalimantan, Indonesia 2000–2008, Environ. Res. Lett., 6, 014010, doi:10.1088/1748-9326/6/1/014010, 2011.

Chen, J. L., Wilson, C. R. and Tapley, B. D.: The 2009 exceptional Amazon flood and interannual terrestrial water storage change observed by GRACE, Water Resour. Res., 46, 1–10, doi:10.1029/2010WR009383, 2010.

Chen, Y., Morton, D. C., Jin, Y., Collatz, G. J., Kasibhatla, P. S., van der Werf, G. R., DeFries, R. S. and Randerson, J. T.: Long-term trends and interannual variability of forest, savanna and agricultural fires in South America, Carbon Manag., 4, 617–638, doi:10.4155/cmt.13.61, 2013.

Costa, M. H. and Foley, J. A.: A comparison of precipitation datasets for the Amazon Basin, Geophys. Res. Lett., 25, 155, doi:10.1029/97GL03502, 1998.

Dobrovolski, R. and Rattis, L.: Brazil should help developing nations to foster agriculture and environmental protection, Front. Ecol. Environ., 12, 376–376, doi:10.1890/14.WB.010, 2014.

Ernst, C., Mayaux, P., Verhegghen, A., Bodart, C., Christophe, M. and Defourny, P.: National forest cover change in Congo Basin: Deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005, Glob. Chang. Biol., 19, 1173–1187, doi:10.1111/gcb.12092, 2013.

Eva, H. D., Achard, F., Beuchle, R., de Miranda, E., Carboni, S., Seliger, R., Vollmar, M., Holler, W. a., Oshiro, O. T., Arroyo, V. B. and Gallego, J.: Forest cover changes in tropical south and Central America from 1990 to 2005 and related carbon emissions and removals, Remote Sens., 4, 1369–1391, doi:10.3390/rs4051369, 2012.

Fanin, T. and van der Werf, G. R.: Relationships between burned area, forest cover loss, and land cover change in the Brazilian Amazon based on satellite data, Biogeosciences, 12, 6033–6043, doi:10.5194/bg-12-6033-2015, 2015.

FAO: Global Forest Resources Assessment 2005: Progress towards sustainable forest management, Food and Agricultural Organization of the United Nations, Rome., 2006.

Fearnside, P. M.: Global Warming and Tropical Land-Use Change: Greenhouse Gas Emissions from Biomass Burning, Decomposition and Soils in Forest Conversion, Shifting Cultivation and Secondary Vegetation, Clim. Change, 46, 115–158, doi:10.1023/A:1005569915357, 2000.

Fearnside, P. M.: Deforestation in Brazilian Amazonia: History, Rates, and Consequences, Conserv. Biol., 19, 680–688, doi:10.1111/j.1523-1739.2005.00697.x, 2005.

Food and Agriculture Organization of the United Nations: Global forest resources assessments main report, FAO For. Pap., 163 [online] Available from: http://www.fao.org/docrep/013/i1757e/i1757e00.htm (Accessed 10 September 2014), 2010.

Frolking, S., Hagen, S., Milliman, T., Palace, M., Shimbo, J. Z. and Fahnestock, M.: Detection of Large-Scale Forest Canopy Change in Pan-Tropical Humid Forests 2000–2009 With the SeaWinds Ku-Band Scatterometer, IEEE Trans. Geosci. Remote Sens., 50, 2603–2617, doi:10.1109/TGRS.2011.2182516, 2012.

Gasparri, N. I. and Grau, H. R.: Deforestation and fragmentation of Chaco dry forest in NW Argentina (1972-2007), For. Ecol. Manage., 258, 913–921, doi:10.1016/j.foreco.2009.02.024, 2009.

Geist, H. J. and Lambin, E. F.: Proximate Causes and Underlying Driving Forces of Tropical Deforestation, Bioscience, 52, 143, doi:10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2, 2002.

Grainger, A.: Difficulties in tracking the long-term global trend in tropical forest area., Proc. Natl. Acad. Sci. U. S. A., 105, 818–23, doi:10.1073/pnas.0703015105, 2008.

Grau, H. R., Gasparri, N. I. and Aide, T. M.: Agriculture expansion and deforestation in seasonally dry forests of north-west Argentina, Environ. Conserv., 32, 140, doi:10.1017/S0376892905002092, 2005.

Guan, K., Wood, E. F. and Caylor, K. K.: Multi-sensor derivation of regional vegetation fractional cover in Africa, Remote Sens. Environ., 124, 653–665, doi:10.1016/j.rse.2012.06.005, 2012.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V, Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O. and Townshend, J. R. G.: High-resolution global maps of 21st-century forest cover change., Science, 342, 850–3, doi:10.1126/science.1244693, 2013.

Hansen, M. C., Stehman, S. V. and Potapov, P. V.: Quantification of global gross forest cover loss., Proc. Natl. Acad. Sci. U. S. A., 107, 8650–8655, doi:10.1073/pnas.0912668107, 2010.

Harris, N. L., Brown, S., Hagen, S. C., Saatchi, S. S., Petrova, S., Salas, W., Hansen, M. C., Potapov, P. V and Lotsch, A.: Baseline map of carbon emissions from deforestation in tropical regions., Science, 336, 1573–6, doi:10.1126/science.1217962, 2012.

INPE: PRODES - Metodologia para o Cálculo da Taxa Anual de Desmatamento na Amazônia Legal. [online] Available from: http://www.obt.inpe.br/prodes/metodologia_TaxaProdes.pdf, 2013.

Jackson, T. J. and Schmugge, T. J.: Vegetation effects on the microwave emission of soils, Remote Sens. Environ., 36, 203–212, doi:10.1016/0034-4257(91)90057-D, 1991.

de Jeu, R. A. M., Holmes, T. R. H., Parinussa, R. M. and Owe, M.: A spatially coherent global soil moisture product with improved temporal resolution, J. Hydrol., 516, 284–296, doi:10.1016/j.jhydrol.2014.02.015, 2014.

Jones, M. O., Jones, L. A., Kimball, J. S. and McDonald, K. C.: Satellite passive microwave remote sensing for monitoring global land surface phenology, Remote Sens. Environ., 115, 1102–1114, doi:10.1016/j.rse.2010.12.015, 2011.

de Jong, R., Verbesselt, J., Zeileis, A. and Schaepman, M. E.: Shifts in global vegetation activity trends, Remote Sens., 5, 1117–1133, doi:10.3390/rs5031117, 2013.

Joshi, N., Mitchard, E. T., Woo, N., Torres, J., Moll-Rocek, J., Ehammer, A., Collins, M., Jepsen, M. R. and Fensholt, R.: Mapping dynamics of deforestation and forest degradation in tropical forests using radar satellite data, Environ. Res. Lett., 10, 034014, doi:10.1088/1748-9326/10/3/034014, 2015.

Kerr, Y. H. and Njoku, E. G.: Semiempirical model for interpreting microwave emission from semiarid land surfaces as seen from space, IEEE Trans. Geosci. Remote Sens., 28, 384–393, doi:10.1109/36.54364, 1990.

Kim, D.-H., Sexton, J. O. and Townshend, J. R.: Accelerated deforestation in the humid tropics from the 1990s to the 2000s, Geophys. Res. Lett., 42, 3495–3501, doi:10.1002/2014GL062777, 2015.

Kirdiashev, K. P., Chukhlantsev, A. A. and Shutko, A. M.: Microwave radiation of the earth's surface in the presence of vegetation cover, Radio Eng. Electron. Phys., 24, 256–264, 1979.

Kobayashi, H. and Dye, D. G.: Atmospheric conditions for monitoring the long-term vegetation dynamics in the Amazon using normalized difference vegetation index, Remote Sens. Environ., 97, 519–525, doi:10.1016/j.rse.2005.06.007, 2005.

Koh, L. P., Miettinen, J., Liew, S. C. and Ghazoul, J.: Remotely sensed evidence of tropical peatland conversion to oil palm., Proc. Natl. Acad. Sci. U. S. A., 108, 5127–32, doi:10.1073/pnas.1018776108, 2011.

Laurance, W. F.: A crisis in the making: Responses of Amazonian forests to land use and climate change, Trends Ecol. Evol., 13, 411–415, doi:10.1016/S0169-5347(98)01433-5, 1998.

Lehner, B. and Döll, P.: Development and validation of a global database of lakes, reservoirs and wetlands, J. Hydrol., 296, 1–22, doi:10.1016/j.jhydrol.2004.03.028, 2004.

Lewis, S. L., Brando, P. M., Phillips, O. L., van der Heijden, G. M. F. and Nepstad, D.: The 2010 Amazon drought., Science, 331, 554, doi:10.1126/science.1200807, 2011.

Liu, Y. Y., van Dijk, A. I. J. M., de Jeu, R. A. M., Canadell, J. G., McCabe, M. F., Evans, J. P. and Wang, G.: Recent reversal in loss of global terrestrial biomass, Nat. Clim. Chang., 5, 470–474, doi:10.1038/nclimate2581, 2015.

Liu, Y. Y., van Dijk, A. I. J. M., McCabe, M. F., Evans, J. P. and de Jeu, R. A. M.: Global vegetation biomass change (1988-2008) and attribution to environmental and human drivers, Glob. Ecol. Biogeogr., 22, 692–705, doi:10.1111/geb.12024, 2012.

Liu, Y. Y., Evans, J. P., McCabe, M. F., de Jeu, R. A. M., van Dijk, A. I. J. M., Dolman, A. J. and Saizen, I.: Changing climate and overgrazing are decimating Mongolian steppes., PLoS One, 8, e57599, doi:10.1371/journal.pone.0057599, 2013.

Liu, Y. Y., de Jeu, R. A. M., McCabe, M. F., Evans, J. P. and van Dijk, A. I. J. M.: Global long-term passive microwave satellite-based retrievals of vegetation optical depth, Geophys. Res. Lett., 38, L18402, doi:10.1029/2011GL048684, 2011a.

Liu, Y. Y., Parinussa, R. M., Dorigo, W. A., de Jeu, R. A. M., Wagner, W., M. van Dijk, A. I. J., McCabe, M. F. and Evans, J. P.: Developing an improved soil moisture dataset by blending passive and active microwave satellite-based retrievals, Hydrol. Earth Syst. Sci., 15, 425–436, doi:10.5194/hess-15-425-2011, 2011b.

Macedo, M. N., DeFries, R. S., Morton, D. C., Stickler, C. M., Galford, G. L. and Shimabukuro, Y. E.: Decoupling of deforestation and soy production in the southern Amazon during the late 2000s, Proc. Natl. Acad. Sci. U. S. A., 109, 1341–1346, doi:10.1073/pnas.1111374109, 2012.

Malhi, Y.: The carbon balance of tropical forest regions, 1990–2005, Curr. Opin. Environ. Sustain., 2, 237–244, doi:10.1016/j.cosust.2010.08.002, 2010.

Malhi, Y., Roberts, J. T., Betts, R. A., Killeen, T. J., Li, W. and Nobre, C. A.: Climate change, deforestation, and the fate of the Amazon., Science, 319, 169–172, doi:10.3832/efor0516-005, 2008.

Mayaux, P., Achard, F. and Malingreau, J.-P.: Global tropical forest area measurements derived from coarse resolution satellite imagery: a comparison with other approaches, Environ. Conserv., 25, 37–52, doi:10.1017/S0376892998000083, 1998.

Meesters, A. G. C. A., De Jeu, R. A. M. and Owe, M.: Analytical derivation of the vegetation optical depth from the microwave polarization difference index, IEEE Geosci. Remote Sens. Lett., 2, 121–123, doi:10.1109/LGRS.2005.843983, 2005.

Mitchard, E. T. A., Saatchi, S. S., White, L. J. T., Abernethy, K. A., Jeffery, K. J., Lewis, S. L., Collins, M., Lefsky, M. A., Leal, M. E., Woodhouse, I. H. and Meir, P.: Mapping tropical forest biomass with radar and spaceborne LiDAR in Lopé National Park, Gabon: overcoming problems of high biomass and persistent cloud, Biogeosciences, 9, 179–191, doi:10.5194/bg-9-179-2012, 2012.

Mo, T., Choudhury, B. J., Schmugge, T. J., Wang, J. R. and Jackson, T. J.: A model for microwave emission from vegetation-covered fields, J. Geophys. Res., 87, 11229, doi:10.1029/JC087iC13p11229, 1982.

Morton, D. C., Defries, R. S., Randerson, J. T., Giglio, L., Schroeder, W. and van der Werf, G. R.: Agricultural intensification increases deforestation fire activity in Amazonia, Glob. Chang. Biol., 14, 2262–2275, doi:10.1111/j.1365-2486.2008.01652.x, 2008.

Morton, D. C., DeFries, R. S., Shimabukuro, Y. E., Anderson, L. O., Del Bon Espírito-Santo, F., Hansen, M. and Carroll, M.: Rapid Assessment of Annual Deforestation in the Brazilian Amazon Using MODIS Data, Earth Interact., 9, 1–22, doi:10.1175/EI139.1, 2005.

Myneni, R. B., Hall, F. G., Sellers, P. J. and Marshak, A. L.: The interpretation of spectral vegetation indexes, IEEE Trans. Geosci. Remote Sens., 33, 481–486, doi:10.1109/36.377948, 1995.

Naylor, R., Steinfeld, H., Falcon, W., Galloway, J., Smil, V., Bradford, E., Alder, J. and Mooney, H.: Agriculture. Losing the links between livestock and land., Science, 310, 1621–2, doi:10.1126/science.1117856, 2005.

Nepstad, D., Soares-Filho, B. S., Merry, F., Lima, A., Moutinho, P., Carter, J., Bowman, M., Cattaneo, A., Rodrigues, H., Schwartzman, S., McGrath, D. G., Stickler, C. M., Lubowski, R., Piris-Cabezas, P., Rivero, S., Alencar, A., Almeida, O. and Stella, O.: Environment. The end of deforestation in the Brazilian Amazon., Science, 326, 1350–1351, doi:10.1126/science.1182108, 2009.

Owe, M., de Jeu, R. A. M. and Holmes, T.: Multisensor historical climatology of satellite-derived global land surface moisture, J. Geophys. Res., 113, F01002, doi:10.1029/2007JF000769, 2008.

Owe, M., de Jeu, R. A. M. and Walker, J. P.: A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index, IEEE Trans. Geosci. Remote Sens., 39, 1643–1654, doi:10.1109/36.942542, 2001.

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautiainen, A., Sitch, S. and Hayes, D.: A large and persistent carbon sink in the world’s forests., Science, 333, 988–993, doi:10.1126/science.1201609, 2011.

Phillips, O. L., Aragão, L. E. O. C., Lewis, S. L., Fisher, J. B., Lloyd, J., López-González, G., Malhi, Y., Monteagudo, A., Peacock, J., Quesada, C. A., van der Heijden, G., Almeida, S., Amaral, I., Arroyo, L., Aymard, G., Baker, T. R., Bánki, O., Blanc, L., Bonal, D., Brando, P., Chave, J., de Oliveira, A. C. A., Cardozo, N. D., Czimczik, C. I., Feldpausch, T. R., Freitas, M. A., Gloor, E., Higuchi, N., Jiménez, E., Lloyd, G., Meir, P., Mendoza, C., Morel, A., Neill, D. A., Nepstad, D., Patiño, S., Peñuela, M. C., Prieto, A., Ramírez, F., Schwarz, M., Silva, J., Silveira, M., Thomas, A. S., Steege, H. Ter, Stropp, J., Vásquez, R., Zelazowski, P., Alvarez Dávila, E., Andelman, S., Andrade, A., Chao, K., Erwin, T., Di Fiore, A., Honorio C, E., Keeling, H., Killeen, T. J., Laurance, W. F., Peña Cruz, A., Pitman, N. C. A., Núñez Vargas, P., Ramírez-Angulo, H., Rudas, A., Salamão, R., Silva, N., Terborgh, J. and Torres-Lezama, A.: Drought sensitivity of the Amazon rainforest., Science, 323, 1344–1347, doi:10.1126/science.1164033, 2009.

Potapov, P. V., Turubanova, S. A., Hansen, M. C., Adusei, B., Broich, M., Altstatt, A., Mane, L. and Justice, C. O.: Quantifying forest cover loss in Democratic Republic of the Congo, 2000-2010, with Landsat ETM+ data, Remote Sens. Environ., 122, 106–116, doi:10.1016/j.rse.2011.08.027, 2012.

Poulter, B., Frank, D., Ciais, P., Myneni, R. B., Andela, N., Bi, J., Broquet, G., Canadell, J. G., Chevallier, F., Liu, Y. Y., Running, S. W., Sitch, S. and van der Werf, G. R.: Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle., Nature, 509, 600–3, doi:10.1038/nature13376, 2014.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T. A., Salas, W., Zutta, B. R., Buermann, W., Lewis, S. L., Hagen, S., Petrova, S., White, L., Silman, M. and Morel, A.: Benchmark map of forest carbon stocks in tropical regions across three continents., Proc.

Natl. Acad. Sci. U. S. A., 108, 9899–9904, doi:10.1073/pnas.1019576108, 2011.

Shi, J., Jackson, T., Tao, J., Du, J., Bindlish, R., Lu, L. and Chen, K. S.: Microwave vegetation indices for short vegetation covers from satellite passive microwave sensor AMSR-E, Remote Sens. Environ., 112, 4285–4300, doi:10.1016/j.rse.2008.07.015, 2008.

Shimabukuro, Y. E., Batista, G. T., Mello, E. M. K., Moreira, J. C. and Duarte, V.: Using shade fraction image segmentation to evaluate deforestation in Landsat Thematic Mapper images of the Amazon Region, Int. J. Remote Sens., 19, 535–541, doi:10.1080/014311698216152, 1998.

Steininger, M. K., Tucker, C. J., Townshend, J. R. G., Killeen, T. J., Desch, A., Bell, V. and Ersts, P.: Tropical deforestation in the Bolivian Amazon, Environ. Conserv., doi:10.1017/S0376892901000133, 2001.

Tucker, C., Pinzon, J., Brown, M., Slayback, D., Pak, E., Mahoney, R., Vermote, E. and El Saleous, N.: An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data, Int. J. Remote Sens., 26, 4485–4498, doi:10.1080/01431160500168686, 2005.

UNFCCC: Annex to UNFCCC decision 16/CMP.1 Land use, land-use change and forestry, Rep. Conf. Parties Serv. as Meet. Parties to Kyoto Protoc. its first Sess. held Montr. from 28 Novemb. to 10 December 2005, FCCC/KP/CM, 3 [online] Available from: http://unfccc.int/resource/docs/2005/cmp1/eng/08a03.pdf#page=3, 2006.

Verbesselt, J., Zeileis, A. and Herold, M.: Near real-time disturbance detection using satellite image time series, Remote Sens. Environ., 123, 98–108, doi:10.1016/j.rse.2012.02.022, 2012.

Verhegghen, A., Mayaux, P., de Wasseige, C. and Defourny, P.: Mapping Congo Basin vegetation types from 300 m and 1 km multi-sensor time series for carbon stocks and forest areas estimation, Biogeosciences, 9, 5061–5079, doi:10.5194/bg-9-5061-2012, 2012.

Wasige, J. E., Groen, T. A., Smaling, E. and Jetten, V.: Monitoring basin-scale land cover changes in Kagera Basin of Lake Victoria using: Ancillary data and remote sensing, Int. J. Appl. Earth Obs. Geoinf., 21, 32–42, doi:10.1016/j.jag.2012.08.005, 2012.

van der Werf, G. R., Morton, D. C., DeFries, R. S., Giglio, L., Randerson, J. T., Collatz, G. J. and Kasibhatla, P. S.: Estimates of fire emissions from an active deforestation region in the southern Amazon based on satellite data and biogeochemical modelling, Biogeosciences, 6, 235–249, doi:10.5194/bg-6-235-2009, 2009.

van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G. J., Mu, M., Kasibhatla, P. S., Morton, D. C., Defries, R. S., Jin, Y. and Van Leeuwen, T. T.: Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997-2009), Atmos. Chem. Phys., 10, 11707–11735, doi:10.5194/acp-10-11707-2010, 2010.

Zak, M. R., Cabido, M. and Hodgson, J. G.: Do subtropical seasonal forests in the Gran Chaco, Argentina, have a future?, Biol. Conserv., 120, 589–598, doi:10.1016/j.biocon.2004.03.034, 2004.

Zhou, L., Tian, Y., Myneni, R. B., Ciais, P., Saatchi, S., Liu, Y. Y., Piao, S., Chen, H., Vermote, E. F., Song, C. and Hwang, T.: Widespread decline of Congo rainforest greenness in the past decade., Nature, 509, 86–90, doi:10.1038/nature13265, 2014.

Zhu, Z., Bi, J., Pan, Y., Ganguly, S., Anav, A., Xu, L., Samanta, A., Piao, S., Nemani, R. R. and Myneni, R. B.: Global data sets of vegetation leaf area index (LAI)3g and fraction of photosynthetically active radiation (FPAR)3g derived from global inventory modeling and mapping studies (GIMMS) normalized difference vegetation index (NDVI3G) for the period 1981 to 2, Remote Sens., 5, 927–948, doi:10.3390/rs5020927, 2013.

Table 1. Grid-cell level slope and Pearson correlation ($r^2$) for both grid-cell and country-level between annual GFC forest losses ($km^2yr^{-1}$) and IYD ($yr^{-1}$) per different VOD bin for the overlapping time-period. Furthermore the corresponding Coefficient of Variation (CV in %), which is based on the Root Mean Square Error (RMSE in $km^2$) between both datasets.

| VOD bin | Gridcell-scale | | | | Country-scale | | |
|---|---|---|---|---|---|---|---|
| | slope | $r^2$ | CV (%) | RMSE ($km^2$) | $r^2$ | CV (%) | RMSE ($km^2$) |
| 0.6-0.7 | 22.4 | 0.63 | 804 | 15.7 | 0.63 | 203 | 666 |
| 0.7-0.8 | 34.8 | 0.52 | 163 | 3.7 | 0.84 | 122 | 586 |
| 0.8-0.9 | 61.7 | 0.80 | 147 | 5.0 | 0.84 | 83 | 567 |
| 0.9-1.0 | 79.4 | 0.72 | 134 | 4.7 | 0.88 | 92 | 684 |
| 1.0-1.2 | 82.7 | 0.72 | 253 | 3.2 | 0.96 | 53 | 366 |

Table 2. Country-level forest loss estimates (total area, contribution to total South American forest loss, contribution of forest loss as a percentage of the masked-country area, as well as absolute and relative trends) for VOD and GFC for the overlapping time period (2001-2010). Asterisks indicate the significance, where $^{*}=p>0.25$ $^{**}=p<0.25$ $^{***}=p<0.05$

| | Average forest loss 2001-2010 | | | | | | Slope 2001-2010 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Absolute ($km^2yr^{-1}$) | | Percentage of total forest loss area (Absolute / Total) | | Percentage of masked country area (%) | | Absolute ($km^2yr^{-2}$) | | Relative (Absolute/Average) | |
| | VOD | GFC | VOD | GFC | VOD | GFC | VOD | GFC | VOD | GFC |
| Argentina | 4517 | 3329 | 11.73% | 8.29% | 0.61% | 0.53% | $79^{*}$ | $358^{**}$ | 1.68% | 11.00% |
| Bolivia | 3045 | 2338 | 8.07% | 5.89% | 0.39% | 0.33% | $21^{*}$ | $166^{***}$ | 0.75% | 7.84% |
| Brazil | 21926 | 27317 | 55.18% | 67.81% | 0.32% | 0.39% | $-1385^{**}$ | $-1530^{**}$ | -6.47% | -5.55% |
| Chile | 173 | 408 | 0.50% | 1.04% | 0.12% | 0.30% | $35^{**}$ | $17^{***}$ | 18.62% | 4.19% |
| Colombia | 1899 | 1861 | 4.95% | 4.75% | 0.20% | 0.21% | $-2^{*}$ | $65^{**}$ | -0.13% | 3.46% |
| Ecuador | 450 | 305 | 1.24% | 0.79% | 0.18% | 0.15% | $-63^{**}$ | $19^{**}$ | -14.19% | 6.21% |
| Fr. Guiana | 115 | 17 | 0.33% | 0.04% | 0.16% | 0.02% | $13^{**}$ | $0^{*}$ | 11.08% | 1.18% |
| Guyana | 288 | 50 | 0.75% | 0.13% | 0.16% | 0.03% | $-3^{*}$ | $0^{*}$ | -1.24% | -0.61% |
| Peru | 1077 | 1047 | 3.06% | 2.69% | 0.12% | 0.13% | $52^{*}$ | $84^{***}$ | 4.46% | 8.24% |
| Paraguay | 3030 | 2556 | 7.68% | 6.49% | 1.05% | 0.98% | $115^{*}$ | $213^{***}$ | 3.93% | 8.78% |
| Surinam | 276 | 29 | 0.75% | 0.08% | 0.25% | 0.03% | $34^{***}$ | $2^{**}$ | 12.57% | 8.69% |
| Uruguay | 868 | 122 | 2.28% | 0.31% | 0.77% | 0.12% | $131^{*}$ | $18^{***}$ | 13.61% | 15.43% |
| Venezuela | 1322 | 658 | 3.46% | 1.70% | 0.21% | 0.11% | $-148^{***}$ | $20^{*}$ | -13.65% | 3.12% |
| ***Total*** | 38987 | 40038 | 100.00% | 100.00% | | | $-1121^{*}$ | $-568^{*}$ | -2.94% | -1.42% |

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 $^{*}$=$p$>0.25 $^{**}$=$p$<0.25 $^{***}$=$p$<0.05

| | Slope 1990-2010 | | Slope 1990-2000 | | Slope 2000-2010 | | Difference 00s-90s | |
|---|---|---|---|---|---|---|---|---|
| | km$^2$yr$^{-2}$ | % | km$^2$yr$^{-2}$ | % | km$^2$yr$^{-2}$ | % | km$^2$yr$^{-2}$ | % |
| Argentina | 170$^{***}$ | 4.58% | 182$^{**}$ | 5.76% | 109$^{*}$ | 3.43% | -73 | -2.32% |
| Bolivia | 49$^{**}$ | 1.92% | 92$^{*}$ | 0.75% | 72$^{*}$ | 0.59% | -20 | -0.16% |
| Brazil | -59$^{*}$ | -0.27% | 1078$^{*}$ | 9.79% | -765$^{*}$ | -6.95% | -1843 | -16.74% |
| Chile | 9$^{**}$ | 5.23% | 35$^{***}$ | 3.34% | 23$^{**}$ | 2.21% | -12 | -1.13% |
| Colombia | -36$^{*}$ | -1.88% | -197$^{**}$ | -16.69% | 10$^{*}$ | 0.88% | 208 | 17.57% |
| Ecuador | -12$^{*}$ | -2.67% | -42$^{**}$ | -14.85% | -35$^{*}$ | -12.58% | 6 | 2.27% |
| Fr. Guiana | 0$^{*}$ | -0.31% | -8$^{*}$ | -3.76% | 13$^{***}$ | 6.34% | 21 | 10.10% |
| Guyana | -8$^{**}$ | -2.72% | -16$^{*}$ | -2.12% | 4$^{*}$ | 0.50% | 20 | 2.61% |
| Peru | -23$^{*}$ | -1.79% | -85$^{*}$ | -4.55% | 45$^{**}$ | 2.39% | 130 | 6.94% |
| Paraguay | 98$^{**}$ | 3.99% | 32$^{*}$ | 2.35% | 12$^{*}$ | 0.86% | -21 | -1.49% |
| Surinam | 5$^{*}$ | 2.25% | -21$^{**}$ | -4.03% | 31$^{***}$ | 5.91% | 53 | 9.94% |
| Uruguay | 60$^{***}$ | 6.99% | 130$^{***}$ | 11.91% | -23$^{*}$ | -2.08% | -152 | -13.99% |
| Venezuela | -50$^{***}$ | -3.97% | -57$^{*}$ | -0.30% | -80$^{**}$ | -0.42% | -23 | -0.12% |
| **Total** | 204$^{*}$ | 0.55% | 1122$^{*}$ | 3.01% | -584$^{*}$ | -1.57% | -1706 | -4.58% |

Table 4. Average error on a state-level. The error is defined as the VOD minus GFC forest loss area as a percentage of GFC forest loss for the overlapping time period per state in the Legal Amazon.

| State | (VOD-GFC) / GFC (mean % $yr^{-1}$) |
|---|---|
| Acre | 17 |
| Amapá | 50 |
| Amazonas | 399 |
| Maranhâo | 17 |
| Mato Grosso | 35 |
| Pará | 94 |
| Rondônia | 37 |
| Roraima | 705 |
| Tocantins | 2 |

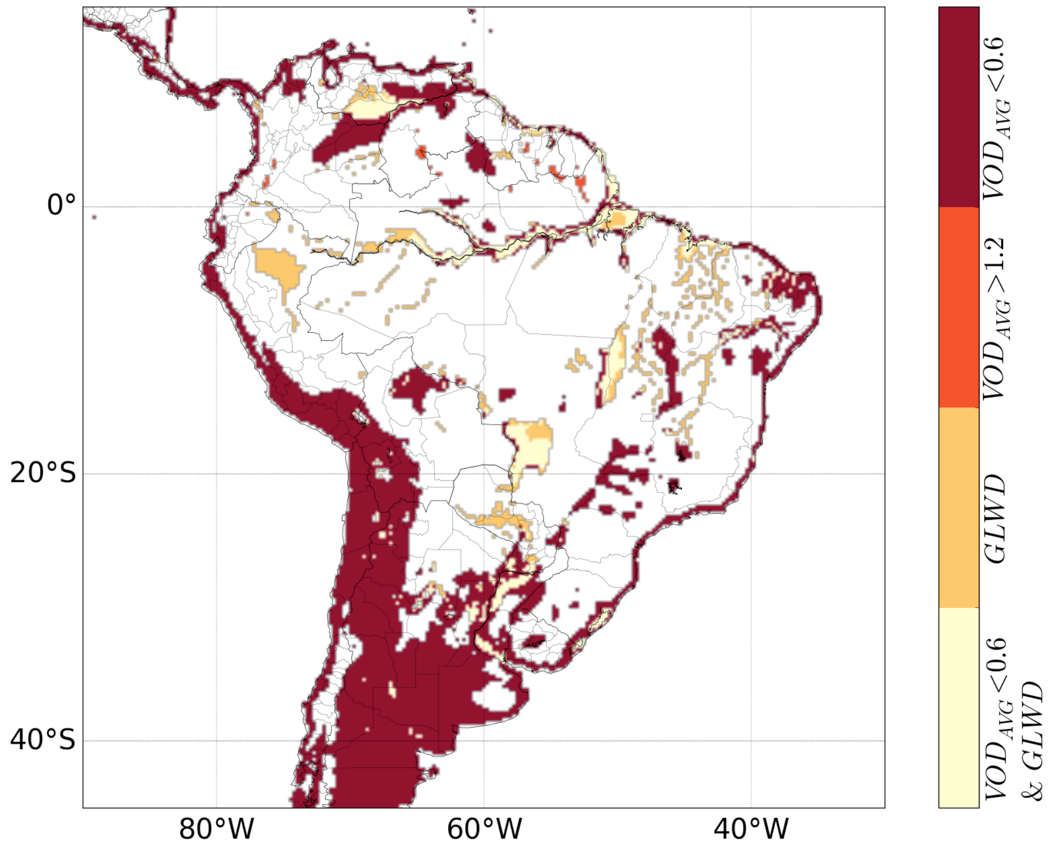



Figure 1. Grid cells that were excluded from our analysis: VOD avg: grid cells with an average VOD that is either above 1.2 or below 0.6 and thus outside the usable range for our study. GLWD: grid cells containing more than 50% open water, which makes the VOD signal to become unreliable. Both: grid cells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

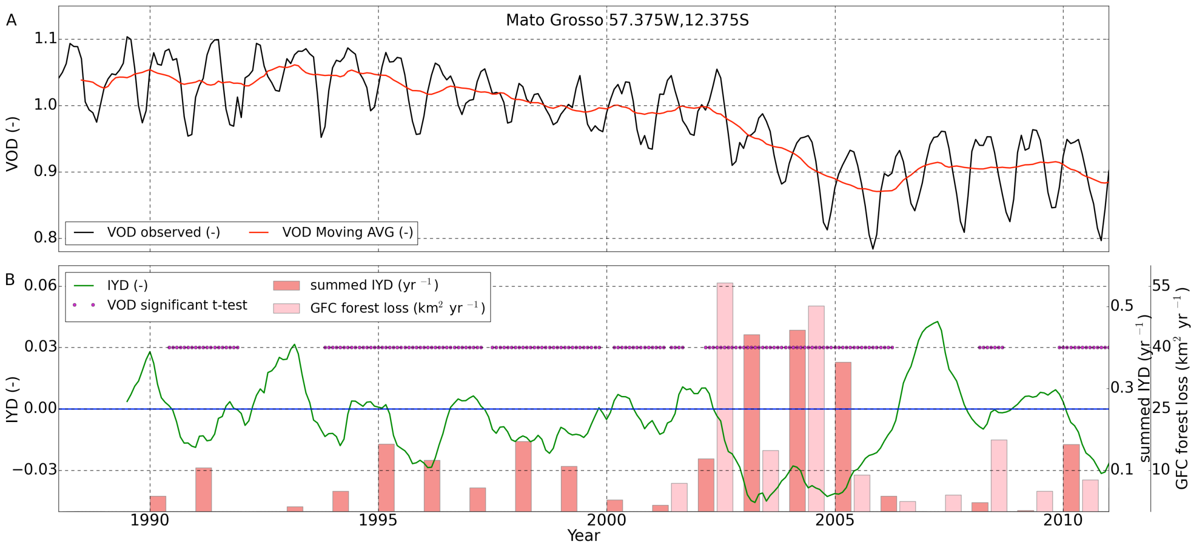



Figure 2. Example 0.25° grid cell in the Brazilian state of Mato Grosso. A: Observed monthly VOD signal and 19-month moving average ($VOD_{MovingAVG}$). B: Interyearly difference (*IYD)*, whether it met the t-test criteria, and annually summed *IYD* values taking only negative values into account. For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

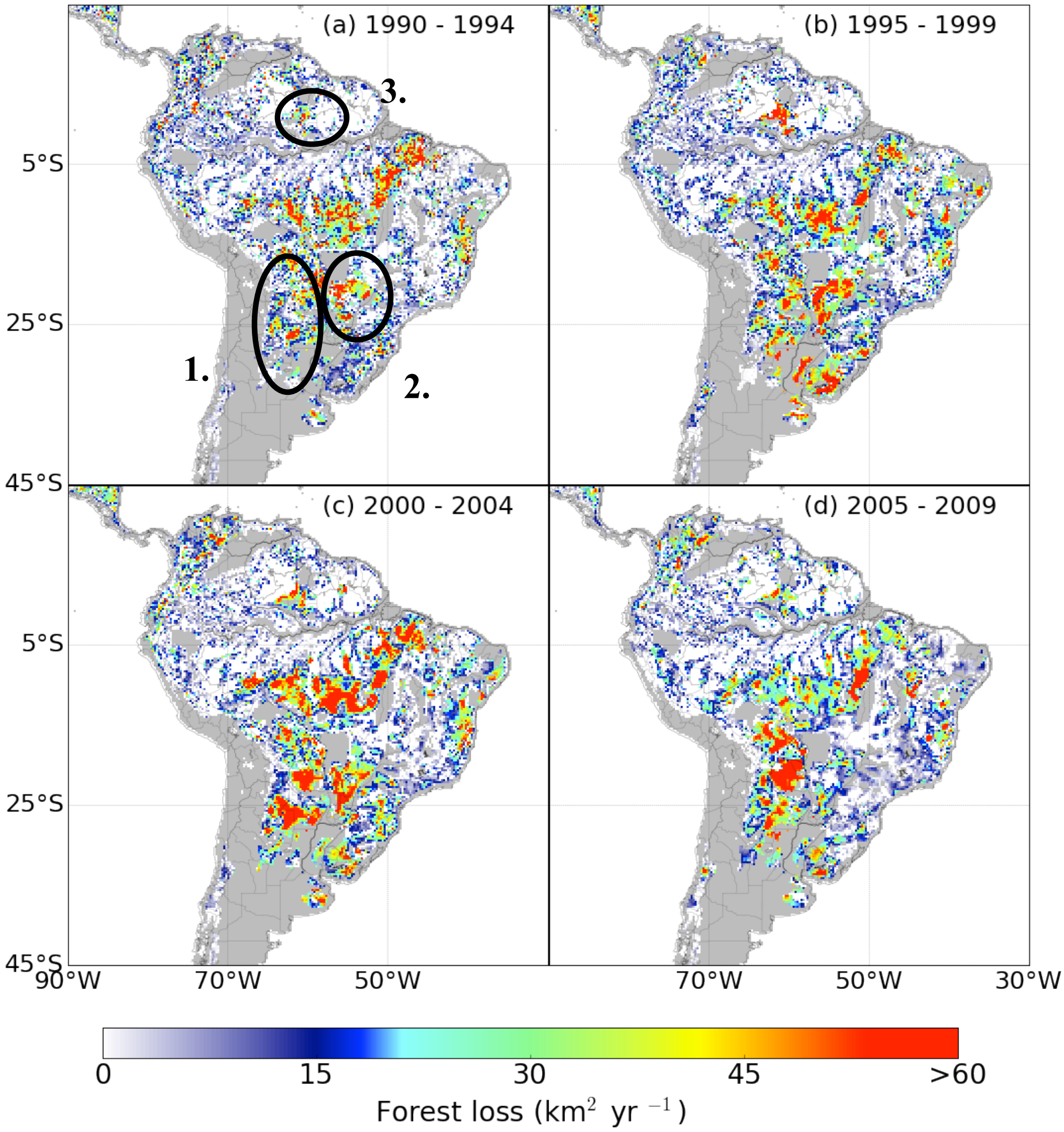



Figure 3. Forest loss extent based on the $VOD_{outliers}$ for the 5-year epochs. Grey means no data.

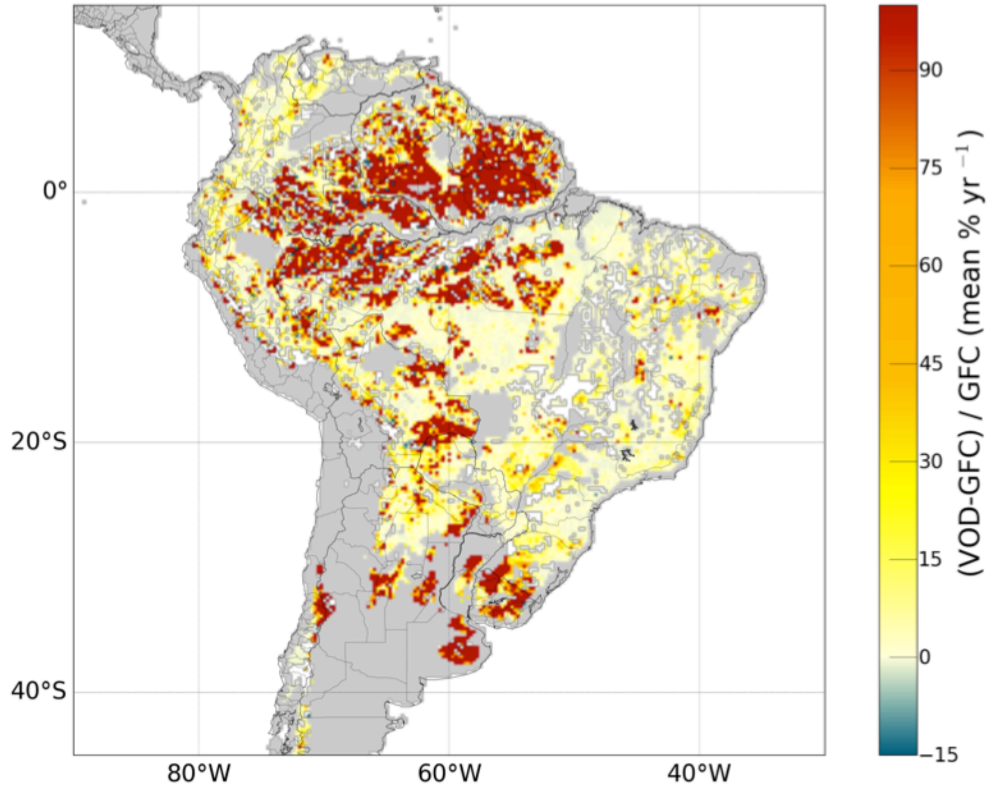



Figure 4. Error estimates for each grid cell. The error is defined as VOD minus GFC forest loss area as a percentage of GFC for the overlapping time period. White means no forest loss is observed in both datasets.

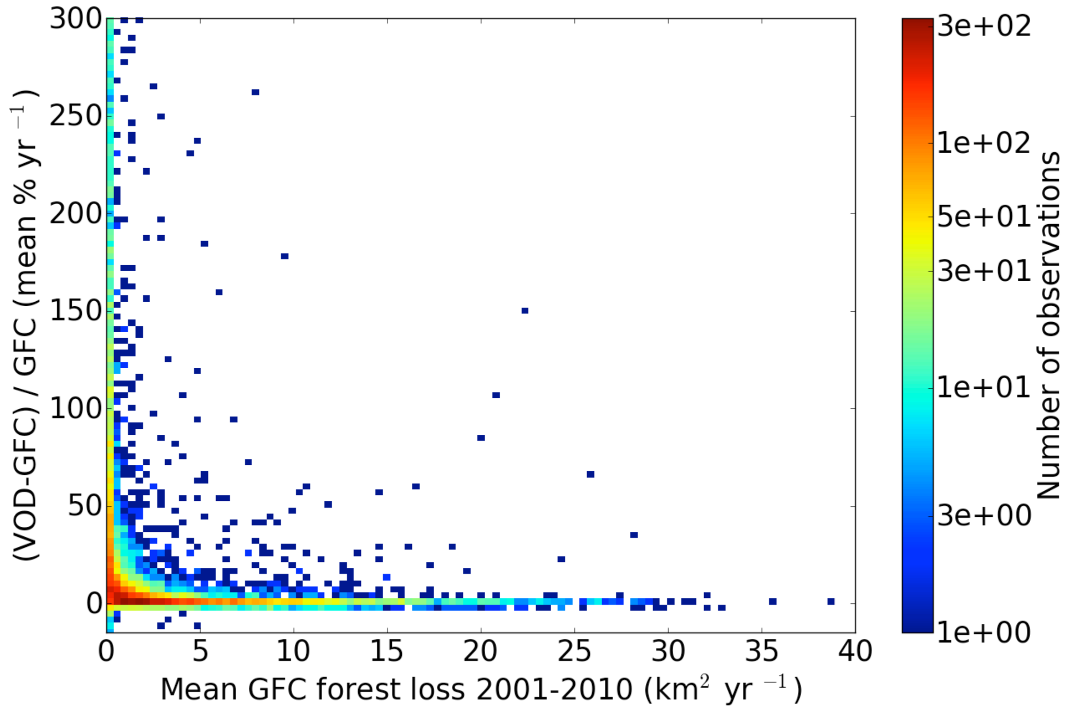



Figure 5. Error between GFC and VOD versus mean GFC forest loss, where the error is defined as VOD minus GFC forest loss area as a percentage of GFC for the overlapping time period.

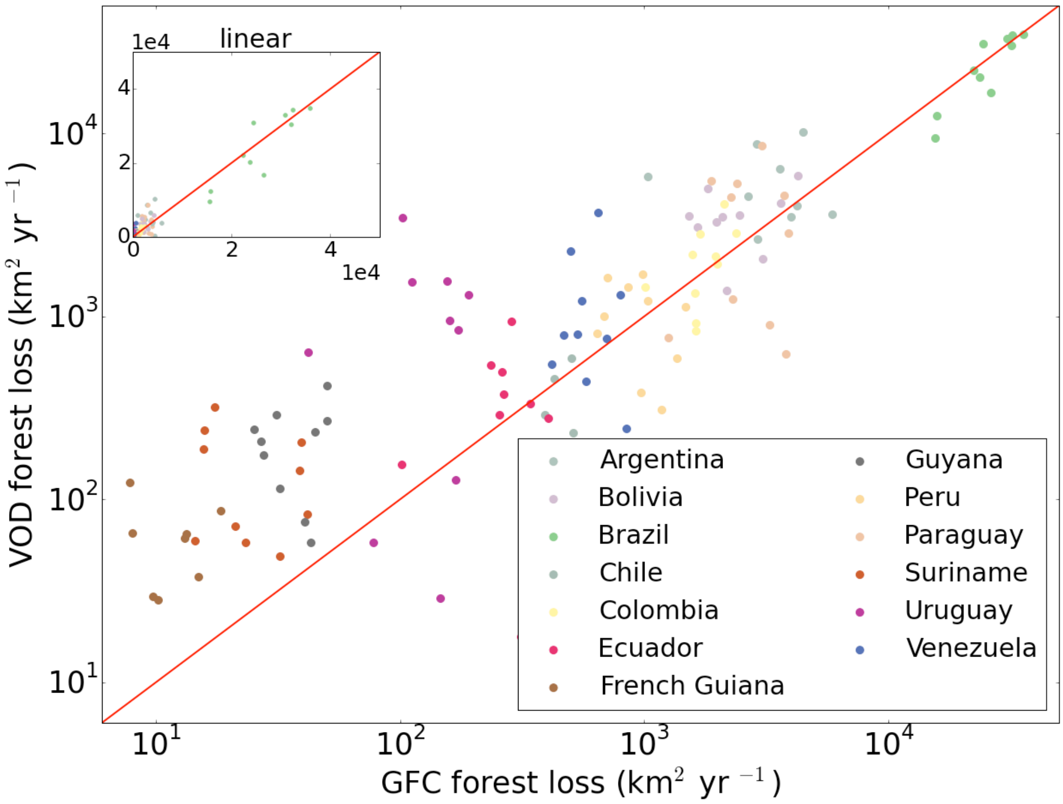



Figure 6. Country-level comparison of calibrated VOD and GFC forest losses based on annual totals (2001 - 2010). The inset shows the same data on a linear scale. The red lines depict the 1:1 line.

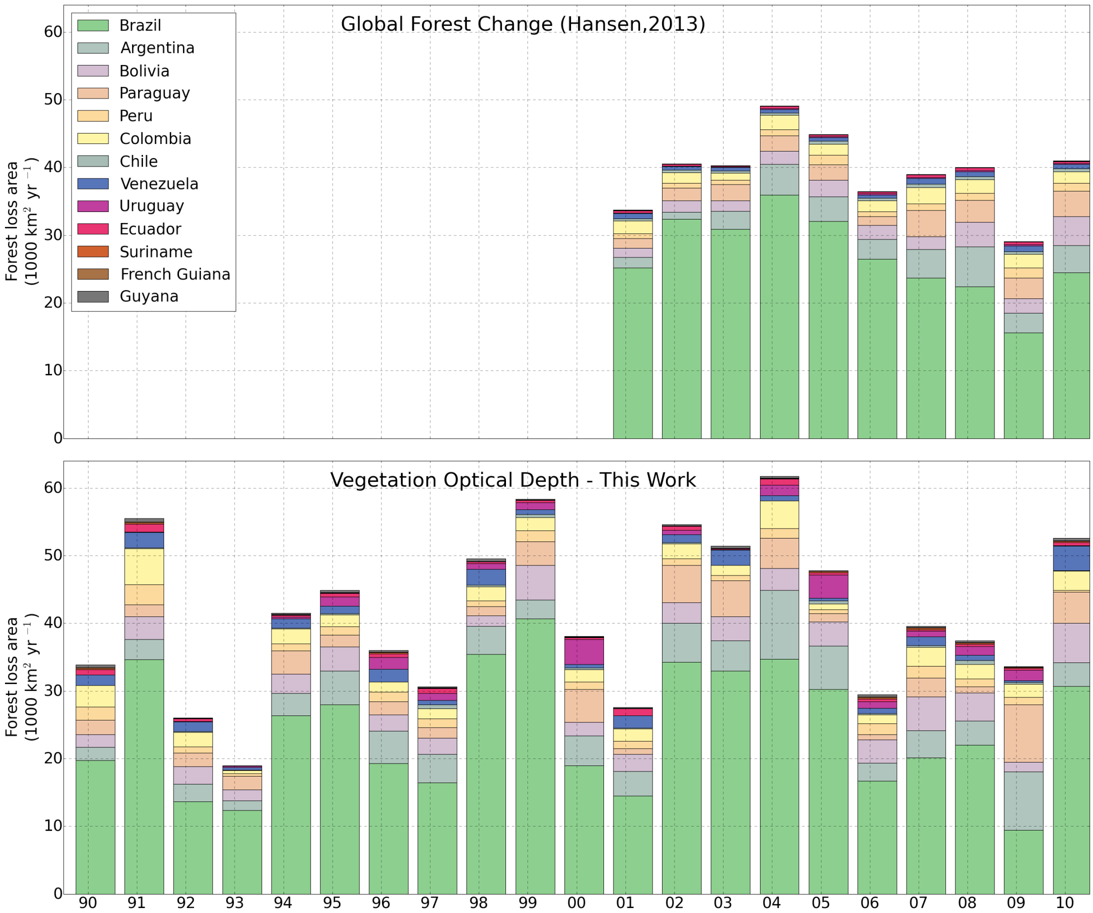



Figure 7. Country-level time series of annual totals of forest loss according to GFC (2001 - 2010) and VOD (1990 - 2010).

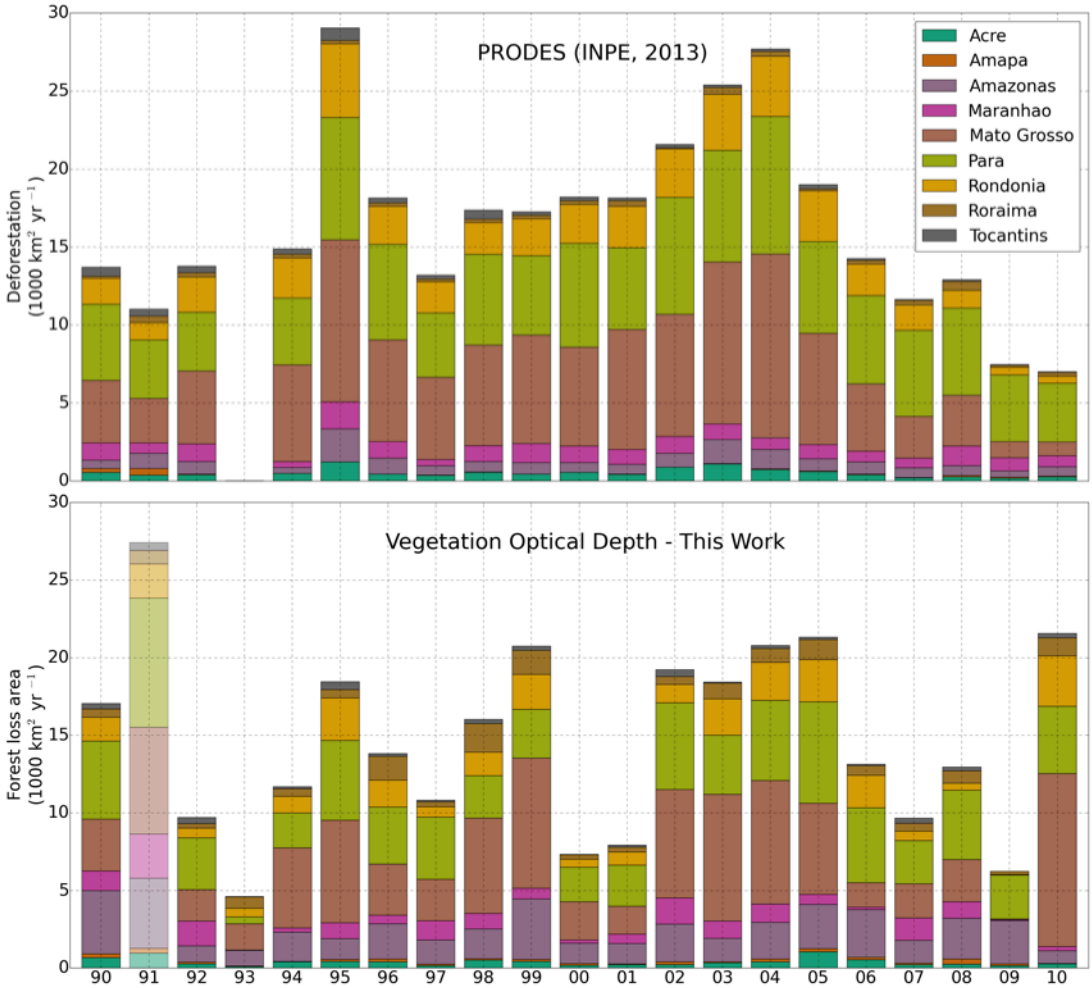



Figure 8. Time series of deforestation (PRODES) and forest loss area (VOD) for the Brazilian states in the Amazon (1990 – 2010). PRODES deforestation data is missing for 1993. VOD data is unreliable for 1991 as a result of the eruption of Mount Pinatubo.