We thank the reviewers 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 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 start with showing the revised and new Figures and Tables and then address the reviewers point by point.

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

Table 1a. Slope and correlation (r^2) of annual GFC forest losses (km^2yr^{-1}) with IYD (yr^{-1}) for various VOD bins for all grid cells for the 2001-2010 overlapping time-period. In the fourth column 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	slope	r^2 (gridcell)	CV (%)	RMSE (km^2)
0.6-0.7	22.4	0.63	804	15.7
0.7-0.8	34.8	0.52	163	3.7
0.8-0.9	61.7	0.80	147	5.0
0.9-1.0	79.4	0.72	134	4.7
1.0-1.2	82.7	0.72	253	3.2

Table 1b. Country-level Pearson correlation coefficient (r^2) of annual GFC forest losses (km^2yr^{-1}) with IYD (yr^{-1}) for various VOD bins for the overlapping time period. In the third column 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	r^2 (country)	CV (%)	RMSE (km^2)
0.6-0.7	0.63	203	666
0.7-0.8	0.84	122	586
0.8-0.9	0.84	83	567
0.9-1.0	0.88	92	684
1.0-1.2	0.96	53	366

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

	Average forest loss 2001-2010						Slope 2001-2010			
	Absolute (km^2yr^{-1})		Percentage of total forest loss area (Absolute / Total)		Percentage of masked country [%]		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^2yr^{-2}	%	km^2yr^{-2}	%	km^2yr^{-2}	%	km^2yr^{-2}	%
Argentina	170***	4.58%	182**	6.47%	109*	2.37%	-73	-2.32%
Bolivia	49**	1.92%	92*	3.93%	72*	2.65%	-20	-0.16%
Brazil	-59*	-0.27%	1078*	4.85%	-765*	-3.65%	-1843	-16.74%
Chile	9**	5.23%	35***	21.39%	23**	12.11%	-12	-1.13%
Colombia	-36*	-1.88%	-197**	-9.98%	10*	0.58%	208	17.57%
Ecuador	-12*	-2.67%	-42**	-9.15%	-35*	-8.29%	6	2.27%
Fr. Guiana	0*	-0.31%	-8*	-6.13%	13***	11.60%	21	10.10%
Guyana	-8**	-2.72%	-16*	-4.98%	4*	1.58%	20	2.61%
Peru	-23*	-1.79%	-85*	-6.13%	45**	3.88%	130	6.94%
Paraguay	98**	3.99%	32*	1.76%	12*	0.39%	-21	-1.49%
Surinam	5*	2.25%	-21**	-10.38%	31***	12.09%	53	9.94%
Uruguay	60***	6.99%	130***	23.56%	-23*	-1.92%	-152	-13.99%
Venezuela	-50***	-3.97%	-57*	-3.91%	-80**	-7.79%	-23	-0.12%
Total	204*	0.55%	1122*	3.13%	-584*	-1.55%	-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*

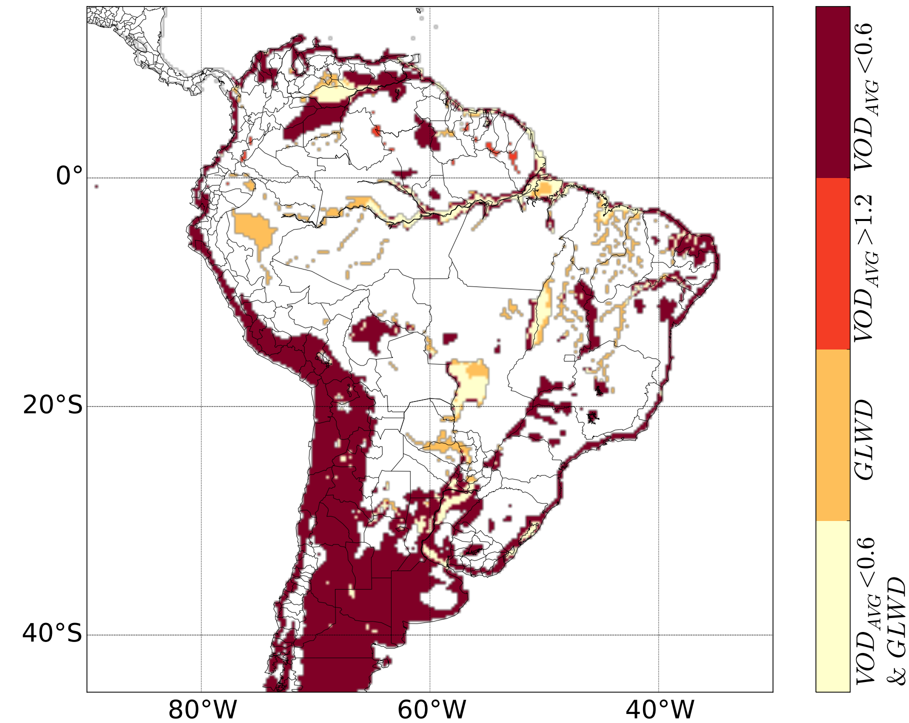


Figure 1. Grid cells that were excluded from our analysis: VOD avg: grid cells with an average VOD that is either above 1.2 or below 0.6 and thus outside the usable range for our study. GLWD: grid cells containing more than 50% open water, which leads to an unreliable VOD signal. Both: grid cells containing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

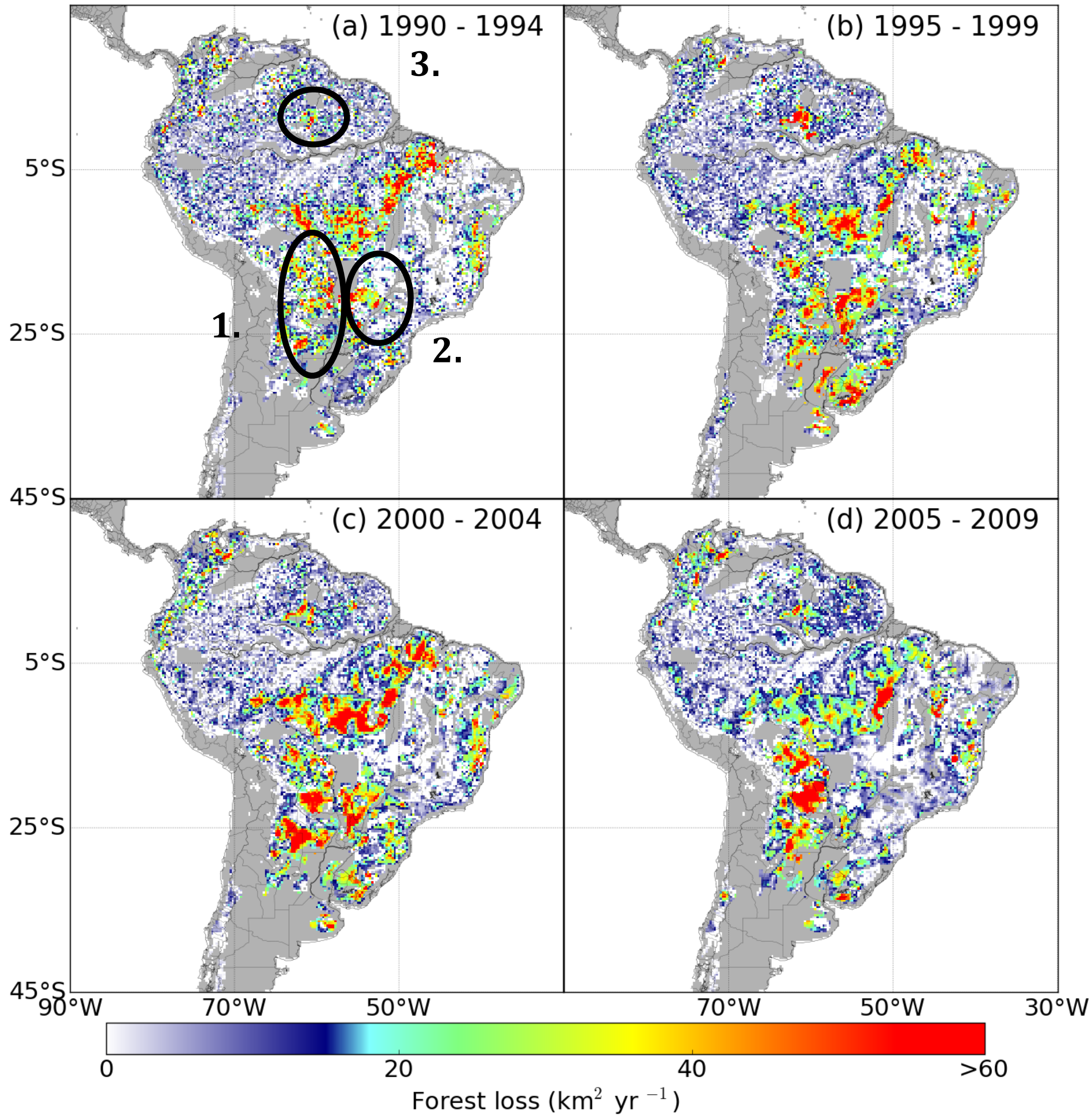


Figure 3. Forest loss extent based on the $VOD_{outliers}$ for 5-year epochs. Grey areas correspond to masked out grid cells.

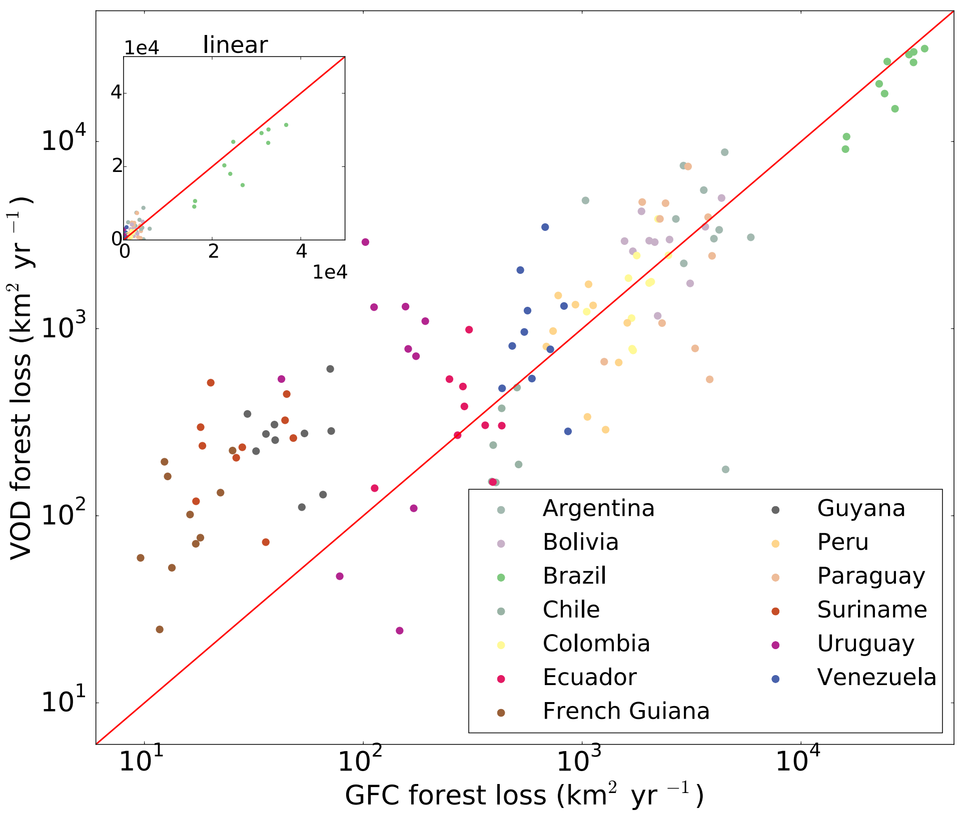


Figure 4. Country-level comparison of calibrated VOD and GFC forest losses based on annual totals (2001 - 2010). The inset shows the same data on a linear scale. The red lines depict the 1:1 line.

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

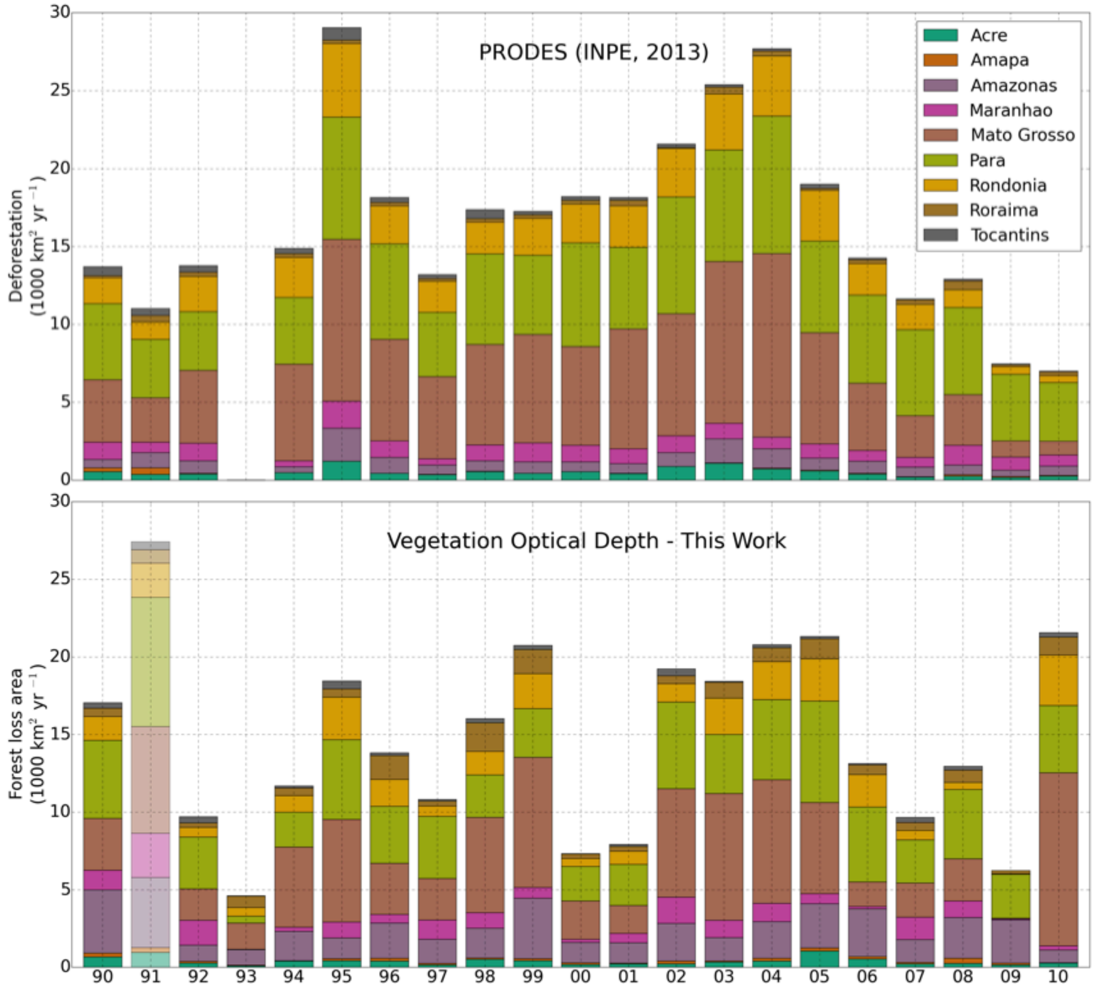


Figure 6. Time series of deforestation (a, PRODES) and forest loss area (b, VOD) for the Brazilian states in the Amazon (1990 – 2010). PRODES has no data for 1993 and the VOD values in 1991 are unreliable due to the volcanic eruption of Mt. Pinatubo.

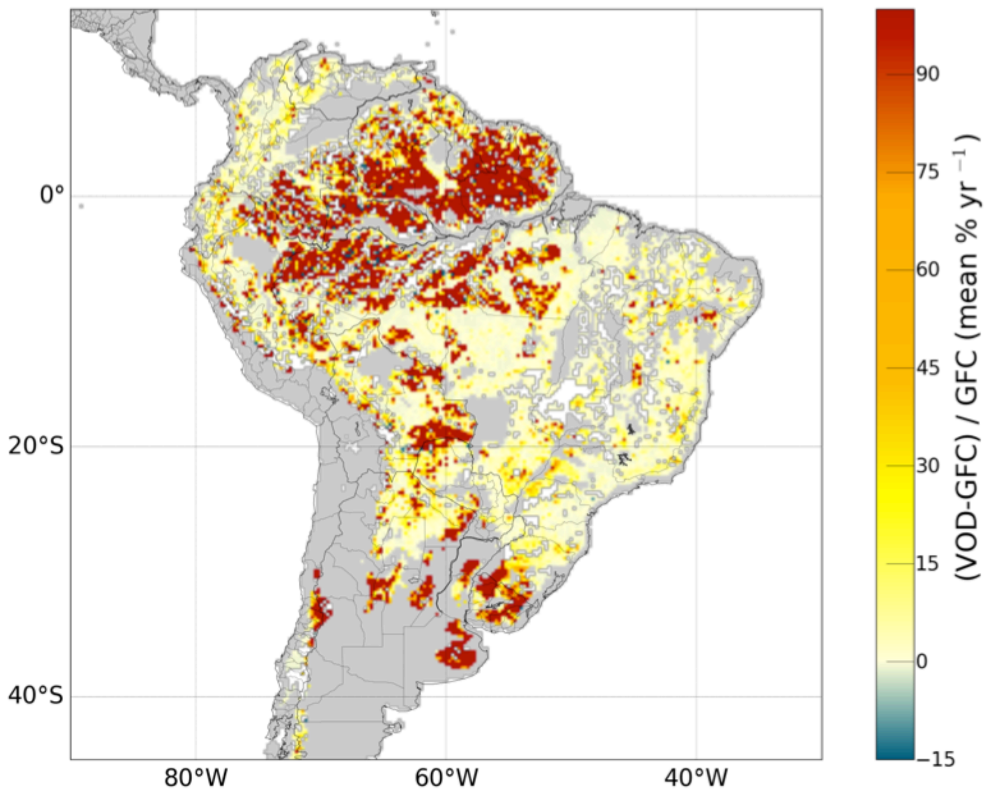


Figure 7: Error estimates for each grid cell. The error is defined as VOD minus GFC forest loss area as a percentage of GFC for the overlapping time period. White means no forest loss is observed in both datasets.

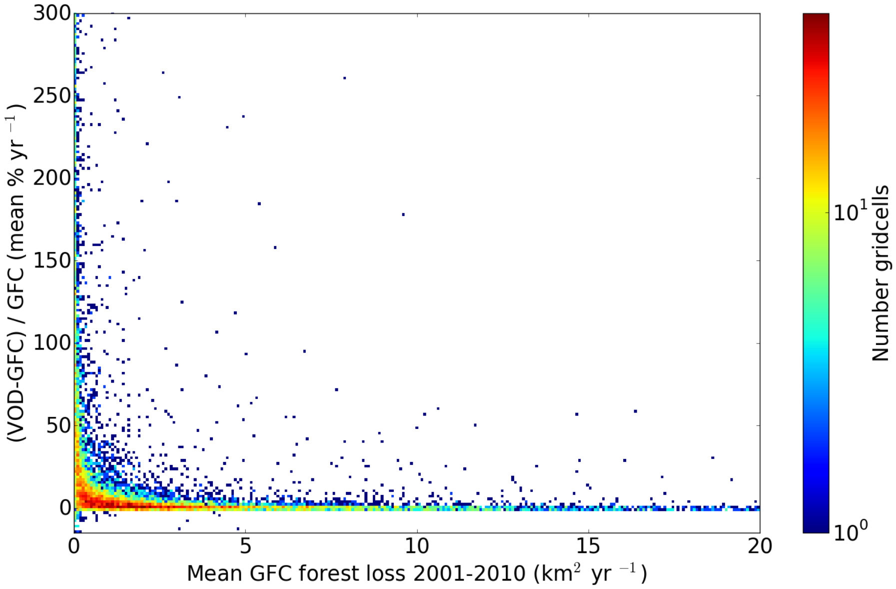


Figure 8. Error between GFC and VOD versus mean GFC forest loss, where the error is defined as VOD minus GFC forest loss area as a percentage of GFC for the overlapping time period.

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):

Page 11502, line 22:
'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). The VOD is shown to be highly correlated with aboveground biomass (Liu et al., 2011, 2015; Owe et al., 2001), and thus gives us information about the net forest loss; the balance between decreases in forest loss due to deforestation and forest 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 the 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. 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., 2011).'

Add to Page 11502 line 6:
'Other widely used satellite products for vegetation mapping are derived from the Advanced Very High Resolution Radiometer (AVHRR), where the NDVI derived from AVHRR 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 at Page 11502, Line 9:
'Other vegetation datasets that can capture vegetation dynamics are for example the observations based on long-wavelength radar backscatter (Joshi et al., 2015) and observations from the SeaWinds Ku-band scatterometer (Frolking et al., 2012), where deforestation, forest degradation and the follow-up vegetation cover could be captured 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 at Page 11503, Line 22:
'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.'

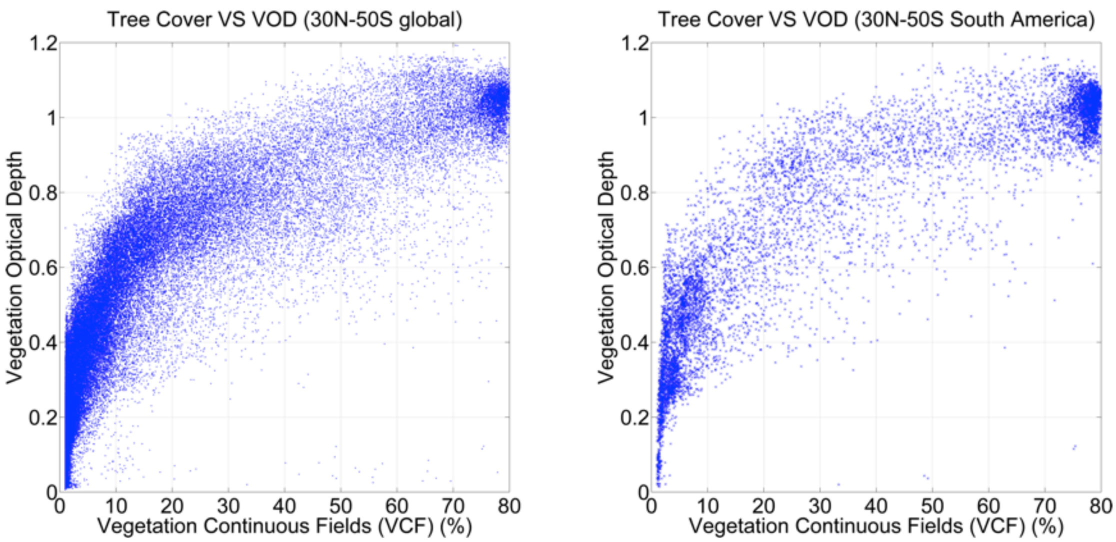
Added at Section 2,1 Vegetation Optical Depth (VOD)
'VOD can be used as a measure for biomass (Liu et al., 2015) , which is in terms of forest loss, the net forest loss (equals the net sum of deforestation, degradation and regrowth) in a 0.25 degree grid cell.'

Added at Section 2.2 Global Forest Change (GFC)
'Forest loss is defined as a change from forest to non-forest state, comprising deforestation and degradation. This means regrowth is 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 11507, line 15:

'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 (Figure below). 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 at page 11504, line 20:

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

Furthermore we changed page 11505, line 22 to:

'Forest loss is defined as a change from forest to non-forest state, comprising deforestation and degradation. This means regrowth is 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 7, 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 8. 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 1a (grid-scale) and Table 1b (country-scale). 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 a section in the discussion at page 11516, line 26: '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 more 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 7 above).

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 below. 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. 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 7. 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 these percentages to Table 2 and added a description at Section 4.2 Calibration with GFC.

The revised text is as follows:

'In Fig. 4 the country-level VOD and GFC forest loss area estimates are plotted against each other along with the 1:1 line. Most data points were reasonably close to this line, although VOD overpredicted forest loss towards the lower end of the spectrum. Especially in the countries with the lowest forest loss, including Surinam, Uruguay, French Guiana and Guyana, our method yielded more forest loss than GFC. As a percentage of the available area per country (Table 2) Uruguay (0.65%), Suriname (0.22%), French Guiana (0.14%) and Guyana (0.13%) also show higher forest losses based on VOD. Chile is on the other hand the country where VOD provides lower estimates (-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. 5 we show these derived annual forest losses from VOD for the full time period, along with GFC for 2001 trough 2010. Obviously the average forest loss area for the overlapping period agrees between both datasets because our approach was tuned to match GFC, but the spatial and temporal variability can still yield differences and new insights.'

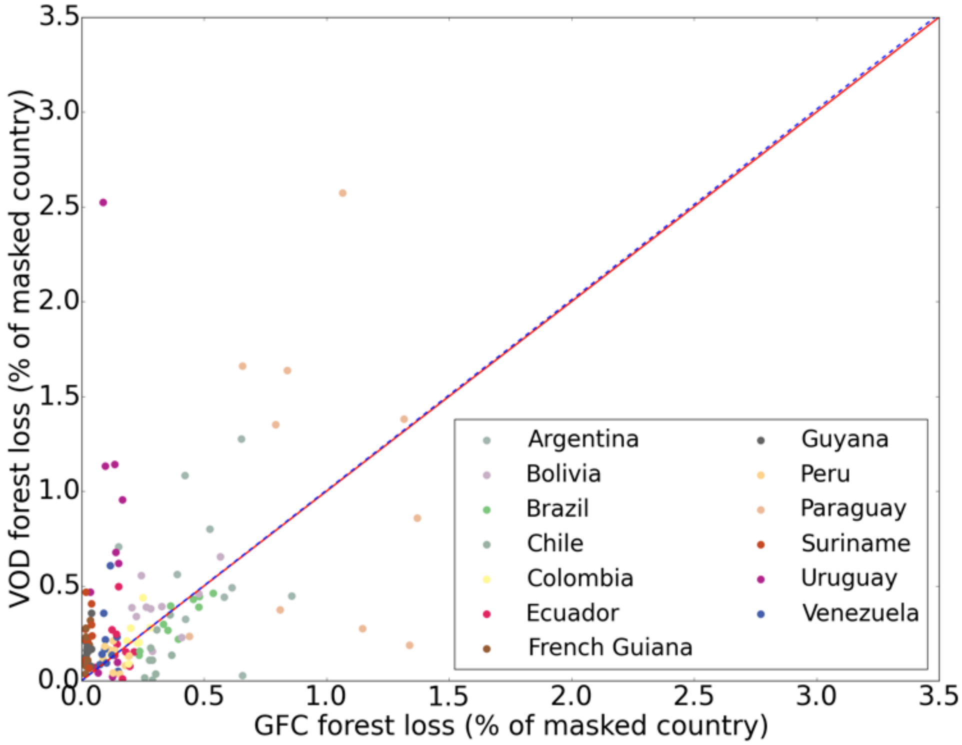
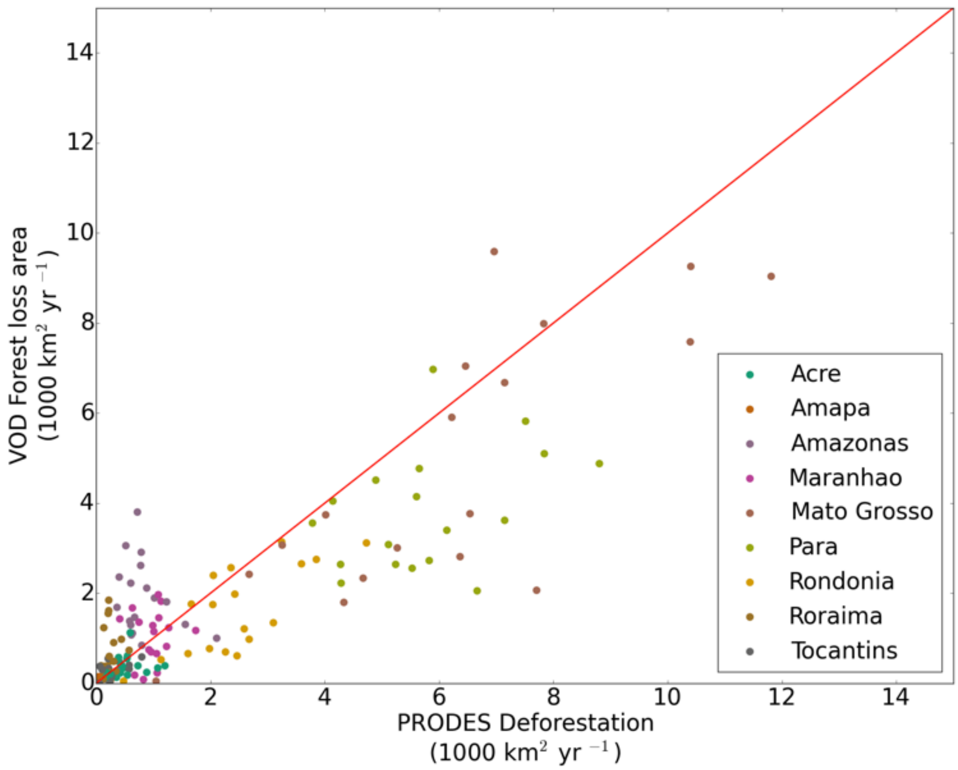


Figure. *Country-level comparison of calibrated VOD and GFC forest losses based on annual totals as a percentage of the total country (2001 - 2010). The red lines depict the 1:1 line and the dotted red line shows the trend line based on Pearson linear regression (VOD=1.005 x GFC)*

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 6; 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 6, 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:

'This was a first approach towards a better forest loss product 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 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 now reads:

'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).'

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

We changed this 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 1972 the Landsat (Enhanced) Thematic Mapper ((E)TM) provides vegetation cover from 1982 onwards 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 this 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 increased substantially, often using Landsat data but also other data sources including datasets based on 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 to:
'One of the regions most closely monitored is the Brazilian Legal Amazon, where the Brazilian Space Agency (INPE) developed the Monitoring the Gross Deforestation in the Amazon Project (PRODES) yielding annual deforestation estimates since 1988 based on a multi-data approach using mostly Landsat data aided by the China-Brazil Earth Resource Satellite (CBERS-2B) and UK-DCM2 from the Disaster Monitoring Constellation International Imaging (DMCii) satellites to help with detecting cloud cover in order to identify cloud-free pixels (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 line 16-18 on page 11503 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, page 11505, line 24:
'We did not include the 2000 forest cover map to avoid missing 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 this 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 thus underestimate forest loss compared to GFC. This also has the consequence that the regions where VOD is most reliable are 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 page 11504 line 11 the following sentence:
'Passive microwave remote sensing differs from active microwave remote sensing (Radar) in the sense radar transmits a long-wavelength microwave 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.*

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