Reviewer comments
Reply to comments

Interactive comment on "Impact of temperature and water availability on microwave-derived gross primary production" by Irene E. Teubner et al.

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Impact of temperature and water availability on microwave-derived gross primary production

by Irene E. Teubner

This study evaluates the capabilities of VOD to provide new information on the changes in vegetation productivity at a global scale. Specific improvements obtained by accounting for temperature effects on autotrophic respiration are analyzed.

I found that interesting results are presented. However, I think significant improvements should be made. As I am not familiar with the studies by the authors on this topic, I found it is difficult to understand many points in this manuscript, unless, maybe, I read in detail all papers published before. Basic elements of the modeling approach published before should be given here, so that the paper is "more autonomous". I present below many points to be improved, so that readers who are not familiar with the papers published by the authors, may understand the results and the discussion

Response: Dear Jean-Pierre Wigneron,

many thanks for your detailed and very constructive review. We agree with you that the manuscript is hard to understand without knowledge about our previous publications. Therefore, we will include the main equations and assumptions from Teubner et al. (2019) in the revised version of the manuscript.

I have 4 main comments which should be accounted for before publication

1) I think, the lack of improvement in the tropics could be related to the low sensitivity of X-VOD to biomass changes, which was found in many regions of the world but particularly in the tropics. This should be better discussed and accounted for throughout the manuscript.

Response: We agree that X-band VOD is less sensitive to changes in total biomass in the tropical forests, since L-band VOD has been shown to be less prone to saturation at high biomass values (e.g., Chaparro et al., 2019; Li et al., 2021). This may thus suggest that the use of L-band VOD would yield better results in estimating GPP than X-band VOD. However, various studies show that X-band VOD generally yields a higher agreement with GPP (Teubner et al., 2018) or proxies for productivity like NDVI (Li et al., 2021) than L-band VOD. This finding that L-band VOD agrees less with GPP than X-band VOD was also observed for the land cover classes with higher biomass, i.e., forest land cover classes (Teubner et al., 2018). The reason for the general higher suitability of X-band VOD for the estimation of GPP in forests and other land cover types with a large woody component can be explained by differences in metabolic activity of various plant parts. Plant parts with a higher metabolic activity, like leaves and roots, are a better proxy for GPP than large structural components like branches and trunks

(Litton et al., 2007). For further details, see discussion section 6.2 in Teubner et al. (2019). In addition, our approach is based on the change in biomass between two successive time steps (mostly a few days). At this short time interval, leaf biomass - to which higher frequency microwaves are more sensitive (Woodhouse, 2005) - is expected to potentially show changes, while woody above-ground components - to which lower frequency microwaves like L-band are more sensitive (Woodhouse, 2005) - may not.

However, in general the correlations between all VOD bands and existing global GPP products are low in evergreen broad-leaved tropical forests (Teubner et al., 2018). This disagreement can be due to multiple reasons. First, also data-driven large-scale products of GPP like FLUXCOM are based on only few station observations in tropical forests and thus have large uncertainty in this region (Jung et al., 2020). Second, the optical remote sensing input data to produce these datasets are highly affected by cloud cover (Zhao et al., 2005).

To make the choice of X-band in our approach clearer, we will add the issue of high- vs low-frequency VOD in the discussion.

For instance, many references discussing the capabilities of VOD to monitor biomass are missing. Cf below references on this topic including applications on biomass changes / productivity monitoring, to better account for and reflect the published literature on this topic (Brandt et al., 2018, Fan et al., 2019; Al -Yaari et al., 2020; Lei et al., 2020; Frappart et al., 2020).

Response: Thank you for these suggestions and we are well aware about these publications. However, some of the papers that you co-authored (Frappart et al., 2020; Lei et al., 2020) were published just before or after the submission of our manuscript and hence we could not include it. We will incorporate these references where appropriate.

line 14: “regions outside the tropics”, many studies have shown that X-band and Cband VOD present saturation vs biomass (close to 200 t/ha). So, how do you expect to monitor GPP from VOD indices that saturate over dense vegetation forests, which represent a large fraction of the vegetation cover in those regions.

Response: See our reply above about our previous findings on the correlation between VOD bands and GPP.

line 72-74, I did not review these previous papers, but I think it is quite surprising that XVOD provide best agreement with GPP by considering “sink terms” related to biomass changes. X-VOD is better related to LAI/NDVI (and thus to photosynthesis and “source terms”), while L-VOD is better related to biomass changes (see Li et al., 2020).

Response: X-band VOD is indeed more similar to LAI/NDVI which represent commonly used inputs for source-driven approaches. Although high-frequency VOD is closely related to small vegetation parts like leaves and twigs (Woodhouse, 2005) and therefore closely related to LAI or NDVI, the method can still be regarded as a sink-driven approach. If X-band VOD was better suited for a source-driven approach, the use of VOD alone should be enough for estimating GPP. However, Teubner et al. (2019) could demonstrate that the combination of VOD and change in VOD (computed as the change over consecutive time steps) outperforms the use of each VOD variable taken separately. We think that this performance is related to allometric relationships between the biomass in canopies and biomass in stems. A certain long-term increase in canopy biomass should correspond to an increase in stem diameter and tree height. Hence, we assume that the sensitivity of X-band VOD to the canopy serves also as proxy for changes in total above-ground biomass. The sensitivity of high-frequency VOD to allometric patterns in vegetation is also supported by the overall medium to high correlation between VOD and canopy height which is partly higher for X-band than for L-band (Li et al., 2020). Hence, we assume that our sink-driven approach is even valid if the used VOD band is not directly sensitive to the changes in total above-ground biomass.

Still based on L-VOD, Tian et al., 2018, found a decoupling between seasonal changes in VOD and in the leafy/biomass component in dry tropical forests. This should explain some errors too in the tropics, when attempting to relate VOD changes to vegetation productivity (?)

Response: Such temporal shifts between VOD and LAI (or GPP) based on optical data may occur and may result in negative correlations between VOD and GPP (Teubner et al., 2018). A potential reason could be that water availability and photosynthesis are negatively correlated in tropical forests (Green et al., 2020), although the hypothesis of increasing photosynthesis under drought conditions in the Amazon is highly controversial (Koren et al., 2018; Huete et al., 2006; Morton et al., 2014). Hence the sensitivity of VOD to the vegetation water content might explain why VOD is negatively correlated to GPP in tropical forests. As we do not specifically account for this, it will have an effect on our estimates of GPP in tropical forests as also discussed before in Teubner et al. (2019).

2) I found it is very difficult to understand section 2.2, except if you are an expert in this specific modelling approach Temperature is an important parameter in Ra but also in other key processes such as photosynthesis. How can you be sure that only the Ra(T) dependence was accounted for here? Because I cannot see any deterministic equations relating Ra to temperature: in Eq 1 and 2, is it fully a machine learning approach that you used, isn't it?

Response: Although our approach is based on a machine learning method, we make use of knowledge about the relationships between VOD and biomass and between biomass and GPP. Equations 1 and 2 present the machine learning formulas. For the temperature dependency of Ra, we did not present a formula per se since it is difficult to express a formula which combines both the instantaneous temperature response (which may not necessarily apply to 8-daily values) and the acclimation effect; an issue which we addressed in the introduction. As described in the methods section, this was also the reason for choosing Generalized Additive Models as modelling approach, since the relationship is not required to be known a piori but instead estimated from the input data (Hastie and Tibshirani, 1987). We will improve the description of our method in the revised version of the manuscript by including the formulas for GPP, on which our approach is based on.

As I'm not expert of this kind of regressions and many terms are unclear to me. Maybe, it is very specific to me, but maybe it will apply to many other readers: Better explain what is "VOD time series", "delta VOD", "mdn VOD": over which time step? Considering daily , monthly or yearly values? do you compute mean of delta VOD, etc: : :? What is the time step of Eq 1 & 2: daily? "spline terms for representing 2-dim functions": what do you mean? which 2-dim parameters are considered here? "smoothing factor"?, etc.

Response: Following our approach described in Teubner et al. (2019), the VOD time series are the VOD values that were aggregated to 8-daily time steps, ΔVOD is the change of VOD over consecutive time steps of the smoothed 8-daily VOD time series and mdnVOD is the median of the VOD time series computed over all time steps of the grid cell. The term "2-dimensional" refers to fact that the partial dependency for the spline-terms describe a 2-dimensional function between input and response variable. In contrast, the partial dependency for the tensor-term (with two input variables) is represented by a surface in the 3-dimensional space; the three dimensions being the two input variables and one response variable. In Generalized Additive Models, a number of spline functions are fitted between the input data of the respective term and the response variable; and the resulting partial dependency function is further smoothed (Hastie and Tibshirani, 1987; Servén and Brummitt, 2018). The strength of the smoothing is controlled via the smoothing factor lambda. We will add more details for the mentioned terms in the revised version.

3) Did GPP-VOD-temp showed improvements vs GPP-VOD, when considering correlation of residuals with SPEI? Since the present study focuses on analyzing possible improvement of the new GPP-VOD-temp, intercomparing residuals vs SPEI with GPPVOD is key and should be added in this manuscript. The present description of results is a bit lengthy and should be reduced to the profit of the above inter-comparison.

Response: We will conduct the suggested analysis for the revised manuscript and place it (where appropriate) either in the results or the supplement.

4) I found that conclusions are much more nuanced considering the relative improvement obtained with the new GPP-VOD-temp product. This should be better reflected in the abstract which I found too optimistic.

Response: We will revise the abstract accordingly.

Minor

line 16- 20; it seems to me the two sentences are a bit contradictory

Response: Thank you for this comment. It was meant that the analysis reveals that the residuals largely do not correlate with SPEI, which indicates that the relationship largely is reliable with respect to variations in water availability. Exceptions from this rule are found in some areas which may point towards specific plant properties. We will clarify this in the revised version.

line 25-30, Cf above remarks on C- and X-VOD saturation, many papers were published based on SMOS L-VOD and none is mentioned in this short review. This short review should be more “opened”

Response: As the focus of our study is the estimation of GPP, we did not specially include papers on the relation between VOD and biomass. But we are open to add references in order to improve the argumentation.

line 35: “VOD as a proxy of AGB”: I guess very few FLUXNET sites are available in relatively dense vegetation sites, and more generally in the tropics. The VOD-derived GPP is manly calibrated based on data in temperate climate?

Response: The spatial distribution of in situ stations may indeed be an issue which we therefore already addressed in the discussion (Lines 305-307). However, we will revise these lines to make it clearer.

Line 43: “ as a necessity”: what do you mean here; not so convincing as a scientific term.

Response: It is meant that dry cells, which do not contain water, will not contribute to the estimation of respiration, since these cells are not living. We will make this clearer in the revised version.

Lien 50 define what is Q10?

Response: The definition of Q10 is given in Lines 51-52.

Line 94: why not using FLUXCOM RS + Meteo , which has more input and could be more reliable. I do not understand the reason given here "our approach is mainly based on RS..". This is a not a good reason to me (?)

Response: In contrast to the FLUXCOM RS setup, the RS + Meteo setup includes only the mean seasonal cycle of remote sensing data as input but does not use any information from remote sensing data that could be sensitive to inter-annual changes such as under dry conditions. Our approach mainly relies on remote sensing data, namely VOD estimates. For a fair comparison, we thus choose the FLUXCOM RS setup.

Please provide more information on Fluxnet sites used here (maps of locations, main vegetation types, etc.)

Response: A map of FLUXNET stations is already given in the Appendix (Figure A2). We will add information on the vegetation type in the overview of the FLUXNET stations (Table A1).

Fig. 1 saturation for VOD > 0.6, can this be related to the saturation of the VOD / Biomass relationship? (0.6 corresponds very well to the saturation level of X-band)

Response: This is an interesting point; however, if saturation had a strong impact here, the relationship should yield more an exponential-like behavior rather than the optimum curve-like behavior, which we observed in the partial dependency plots for VOD and T2M.

Line 179, add that you consider 8-daily values.

Response: We will add this in the revised version.

Line 218 "increase of" ?

Response: Thank you, we will revise this.

– check grammar in line 223-225.

Response: We will revise these lines.

– Figure 3 and 4: is this based on the whole study period (please add the information caption and check throuhout)?

Response: The analyses in both figures are based the whole study period. We will add this information to the captions.

– Figure 4, the overestimation in the tropics seems to be much more significant than the very small decrease outside -35_, +60_. Can we really consider this is "improvement"?

Response: At first glance, it might appear contradictory that this result may be considered an improvement. However, when looking at the relative latitudinal distribution in Figure A1, the setup with temperature shows closer agreement with the other two data sets.

- add site for Fig 5 in the Fluxnet map. Why selecting this site: is it representative of more general results (specific canopy types, climate?)?

Response: The area was selected as an example of a region where the residuals between GPPvodtemp and GPPfluxcom/GPPmodis are not correlated with SPEI. We will add this information and the information about the location used in Figure 5.

– line 239; “holds true” is too strong; here you only find no contradiction on a specific point; mathematically it is not right at all to say that the hypothesis is validated. It is only one indication you go the right way …

Response: We will rephrase it.

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