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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This work presents a model to estimate Gross Primary Production (GPP) globally from a carbon sink driven approach. In particular, the paper aims at improving previous modelling of GPP as a function of the vegetation optical depth (VOD; Teubner et al., 2019) by including the effect of temperature on the autotrophic respiration. Authors explain that the model is based on the fact that VOD is a good proxy of above-ground biomass (AGB). The link between residuals of the model and the drought index SPEI is also analysed. The results presented show an improvement of model performance in terms of temporal dynamics, especially in non-tropical regions. Interestingly, results also report that the presented model does not require complementary information from precipitation or drought indicators.

Despite that the results presented are consistent with previous works and show interesting contribution to GPP modelling, I have important concerns that have to be addressed before publication. The most relevant are related to the lack of penetration through the vegetation canopy of the X-band VOD (which is not a good proxy of biomass if compared to other frequency bands), and to the need of further explaining the modelling framework both in the introduction and the methods sections. These comments and other major and minor proposals for improving the paper are detailed hereafter:

Response: We thank David Chaparro for his detailed review of the manuscript and are happy to address his comments.

Major comments

1. Although the paper can be well understood if the reader knows previous literature on this topic published by the authors, it is necessary that the modelling approach (i.e., main ideas and equations from previous works) and the implementation in the current paper are explained in more detail. In particular:

a. I suggest that first paragraphs of the introduction provide a more detailed description of the framework explained in Teubner et al. (2019), including if necessary some equations (e.g., equations 4 to 6 in Teubner et al., 2019).

Response: Thank you for this suggestion. This was also suggested by the first referee. We will add this information in the revised manuscript.

b. Please, provide more detail on how you are computing and including into the model the different variables (Section 2.2). For instance, does the term "VOD" refer to VOD time-series? If so, how is the time-domain processed (raw data, smoothing, etc…)?

How is the variable computed?

In summary, please extend the text to provide enough information for readers that do not know your previous work.

Response: The term VOD refers to VOD time series. The VOD data were resampled to 8-daily values using the mean over 8 days and then used as input to the model, as stated in Lines 121-121 in Section 2.1. The temporal resolution of 8-daily values was chosen to match the resolution of FLUXCOM and MODIS. We will also include this information in Section 2.2 to make this clearer.

2. The basis of the work is the fact that VOD is a good proxy of AGB. Nevertheless, it is very important to note that X-band VOD (hereafter XVOD) has poor capacity to penetrate the vegetation canopy, and therefore it is very limited to accurately track AGB in regions with dense vegetation. While the AGB - L-band VOD relationship shows low saturation in tropical regions, X-band is not the most appropriate frequency to be used in these areas as a proxy of biomass (e.g., Brandt et al., 2018; Rodríguez-Fernández et al., 2018; Chaparro et al., 2019). Actually, even in low carbon density areas, XVOD is more representative of vegetation cover than it is for biomass, while lower frequencies (L-band VOD; hereafter LVOD) still have improved capacity to track AGB in these areas (e.g., see Fig. 9 in Chaparro et al., 2019).

Response: The reviewer is right: VOD from L-band has been demonstrated to be a suitable proxy for biomass which is less prone to saturate at high biomass than VOD from X-band (e.g., Chaparro et al., 2019; Li et al., 2021). This is well in line with theory, since L-band VOD is more sensitive to large plant parts while X-band VOD is more sensitive to small vegetation parts as leaves and twigs (Woodhouse, 2005). However, in our current study we do not estimate AGB but GPP and in a previous study we demonstrated that VOD from L-band (SMOS) yields the lowest correlation with GPP in vast areas of the world (Teubner et al., 2018).

It is very likely that this limitation explains the lack of improvement of the model in the tropical regions (Fig. 3b) and the low correlation between the model and the benchmark datasets in regions such as the Amazon (Fig. 3a).

Response: The poor agreement of our model in tropical regions may have several sources of uncertainty. First, our model can only be trained based on a few FLUXNET sites in tropical regions as most measurement sites are located in mid-latitudes. The same is also true for the FLUXCOM and MODIS GPP datasets. Second, the FLUXCOM and MODIS GPP products rely on optical satellite data which is highly affected by cloud cover in tropical regions (Zhao et al., 2005). Hence, correlation analyses with biophysical vegetation properties from optical sensors generally suffer from higher uncertainty of these datasets over tropical regions (Zhao et al., 2005).

In addition, this could also explain the saturation of the partial dependency plots (Fig. 1) at high VOD and T2M values (darkest lines in the first panel, probably representing vegetation-temperature conditions in the tropics) and at mdnVOD values above 0.4 (i.e., dense vegetation; third panel).

The application of XVOD is justified in the paper by the higher correlation between XVOD and GPP if compared to the LVOD-GPP correlation (Teubner et al., 2018). Nevertheless, it is important to note that the GPP benchmark datasets have an important contribution from visible-infrared (VIS-IR) indices (EVI, LAI, MIR, NDVI and NDWI, as stated in l. 96). I think it is expected that GPP datasets based on VIS-IR indices show a greater correlation with XVOD than with lower frequency VOD data, because both of them capture the same layer of vegetation (top of the canopy).

Response: Yes, this is true. As both VIS-IR-based indices or biophysical properties and XVOD are sensitive to the upper vegetation canopy, the layer where photosynthesis predominantly takes place, they can also well capture the temporal dynamic of GPP. This is exactly the motivation of using higher frequency microwave observations in our model. This has been further corroborated by correlation analyses carried out in Teubner et al. (2018). Despite the close agreement between optical indices and XVOD, we would like to note that our model still presents a sink-driven approach. This is demonstrated by the higher performance for the combination of VOD and ΔVOD compared to each input variable taken separately (Teubner et al., 2019).

In contrast, I would expect greater correlations with in situ GPP FluxNet data (Fig. 2a and Fig. 2b) if GPPvod and GPPvodtemp were computed using L-band VOD. Although it is not a global dataset, FluxNet in situ information is not conditioned by physical properties of remote sensing sensor measurements, so it is probably the most "independent" tool the authors have for evaluating the accuracy of the GPP estimates.

Response: During our previous analyses, LVOD consistently showed lower performance than higher microwave frequencies. At the global scale, among frequencies from L- to X-band, LVOD resulted in lowest correlations (Teubner et al., 2018). For in situ stations, a similar result, i.e., a closer agreement between GPP and XVOD than between GPP and LVOD, is obtained for the correlation of FLUXNET GPP with LVOD and XVOD (Figure AC1). A classification of the results into land cover classes shows that also a fair amount of forest stations is included in this analysis (~38%). In addition to the analysis of 8-daily values, we repeated the analysis also for monthly values. This was done in order to exclude the possibility that the low correlations for LVOD are caused by the relatively high temporal resolution of 8 days. However, a similar result as for 8-daily values is obtained.

Based on these results, we concluded that LVOD may not be a good proxy for estimating GPP and did not include LVOD in further analyses.

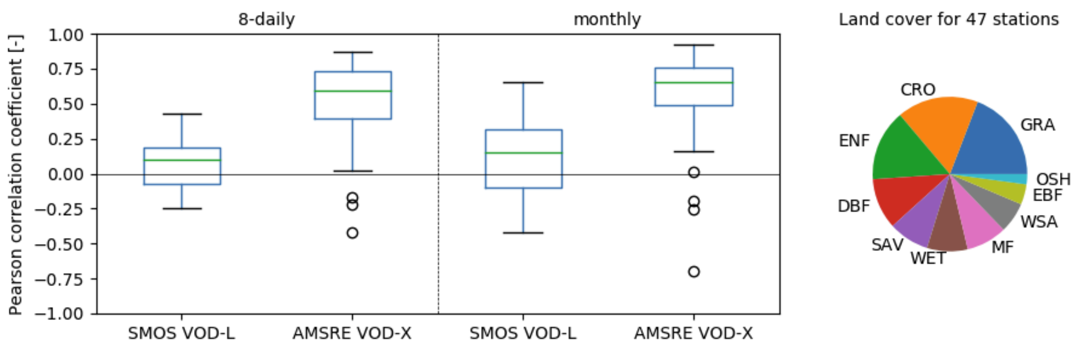

Figure AC1: Left: Correlation between FLUXNET GPP (mean of GPP_DT_VUT_REF and GPP_NT_VUT_REF) and VOD from two different frequencies, L-band VOD (SMOS VOD-L, 7/2010–12/2014) and X-band VOD (AMSR-E VOD-X, 1/2007–9/2011). Data were resampled to 8-daily or monthly values. The analysis was conducted only for stations where both of the VOD data set were available (47 stations). Right: Composition of land cover classes for the stations used in the analysis. Abbreviations: GRA (Grasslands), CRO (Croplands), ENF (Evergreen Needleleaf Forests), DBF (Deciduous Broadleaf Forests), EBF (Evergreen Broadleaf Forests), SAV (Savannas), MF (Mixed Forests), WET (Permanent Wetlands), WSA (Woody Savannas) and OSH (Open Shrublands).

For all these reasons, it would be very interesting if the authors include new GPPvod and GPPvodtemp models based on L-band VOD and validate their accuracy using in situ FluxNet data (i.e., including them in Fig. 2). They could show (and compare) the resulting GPP estimates between different frequencies and, importantly to preserve the scope of the paper, between GPPvod and GPPvodtemp models. However, I am aware that this could move the work slightly beyond its initial scope, as it adds another factor (i.e., frequencies) in the comparisons. I encourage the authors to work on this possibility, although it is up to them to finally incorporate this change or to keep only XVOD in the paper. In any case, they must discuss all the possible implications of using XVOD.

Response: Thank you for your suggestion. However, based on our above analysis results that show a poor performance of LVOD in predicting GPP, we will not add LVOD to the paper to not further complicate the paper. But we follow the suggestion of the referee and will improve our discussion with respect to the use of XVOD vs. LVOD data.

Within the discussion, they should address at least the following points/questions:

- It is stated that "the VOD-GPP model relies on estimating carbon sink terms, […], based on VOD as a proxy of aboveground living biomass" (l. 35-37). To what point is this true, according to the facts that XVOD is more representative of vegetation cover than of biomass, and that lower VOD frequencies have enhanced capacities to capture biomass? Please clearly explain the possible limitations of the approach.

Response: Indeed, the use of VOD from X-band may appear counterintuitive and the use of LVOD might seem more appropriate. However, as LVOD cannot capture well the intra-annual temporal dynamics of canopies, it cannot serve as a good proxy for the high-frequency temporal dynamics in GPP. In addition, the reason for using X-band VOD (and not L-band VOD) for the estimation of GPP might be explained with differences in metabolic activity of various plant parts. Litton et al. (2007) showed that leaves and roots may present a better proxy for GPP than large structural components with a lower metabolic activity. For further details, see discussion section 6.2 in Teubner et al. (2019). On the other hand, LVOD might be a better predictor for the annual-integrated total carbon allocation (net primary production) as this is closely related to the annual increment in biomass. However, testing this hypothesis is beyond the scope of our study.

We will expand our discussion for using X-band VOD to make this clearer.

- Please, discuss about the saturation effects in Fig. 1 (first and third panel; see my comment above). Are they likely to be linked to XVOD saturation in the tropics? If so, which are the implications?

Response: Although we cannot rule out a saturation effect of VOD with regard to GPP, the partial dependency plots should, in this case, resemble an exponential curve and not the optimum curve, which we observed. The plots rather suggest that the in situ GPP estimates are limited at around 10 gC m-2 d-1.

- In l. 197, it is mentioned (referring to tropical regions) that "[in these regions] sensitivity to temperature is also low, which makes the interaction term mainly controlled by VOD."

If I correctly understood plots in Fig. 1, would it be more precise to affirm that it is mostly controlled by , as other dependencies (VOD, mdnVOD) saturate in tropical regions?

Response: Our statement is referring to the lack of a strong seasonality in the tropics, which might explain why the improvement in temporal correlation is absent or lower than in temperate regions because these regions do not experience large temperature differences.

3. The GPP estimates (GPPvod and GPPvodtemp) are calibrated using FluxNet in situ data. Also, both FluxNet and FLUXCOM data (an upscaling of FluxNet) are used as reference datasets for evaluating GPP estimates. I think that, consequently, reference datasets may not be fully independent from GPP estimates. To what extent? Which is the contribution of FluxNet data in the reference datasets and in the estimates? This has to be acknowledged and possible implications discussed.

Response: Yes, the FLUXCOM product has been trained against the FLUXNET station data (Tramontana et al., 2016; Jung et al., 2020). In comparison to the FLUXCOM product, we could use much fewer station data (only Tier 1 data). Also, the MOD17 GPP product has been partly calibrated to some FLUXNET stations (Running et al., 1999). At large/global scales, there is no alternative to constrain absolute estimates of GPP than using FLUXNET data. We will add this point to the discussion.

In addition, authors should try to guarantee at least one year of "fully independent" comparison between estimates and FluxNet/FLUXCOM data. I suggest they could calibrate the model by leaving one year of data apart (e.g., use 2004-2014 for calibration) and apply the remaining data (2003) for fully independent comparisons. They can show these new comparisons in supplementary materials and refer to them to show consistency/inconsistency with the full-period comparisons of Figures 2 to 6.

Response: As a common approach (that was also used in FLUXCOM), we performed leave-site out cross-validation and we will add these cross-validation results for GPPvod and GPPvodtemp in the supplement.

Minor comments

- Lines 5-6: "VOD-GPP model generally showed good agreement" → Please quantify (e.g. correlation coefficient).

Response: A quantification of the previous correlation coefficient would imply that the results can be directly compared. However, different aspects of the model have changed. In the current study, we are using a merged VOD (VODCA X-band), while we previously only considered single sensor VOD (AMSRE or AMSR2 X-band). In addition, we analyzed a longer period, which also makes the training dataset different from the previous studies. Therefore, we would not add information of correlation coefficients from previous studies in the abstract.

For the direct comparison of previous (GPPvod) and current (GPPvodtemp) model results under similar conditions, we would like to refer to our results presented in section 3.3.

- L. 6: "tended to overestimate" → By how much? Please quantify.

Response: The overestimation was not quantified in the previous study; therefore, we cannot provide a specific number here.

- L. 13: "Our results reveal an improvement" → Please quantify this improvement (e.g., increase on the average correlation).

Response: Thank you for this suggestion, we will add the increase in correlation coefficient from the results section also in the abstract.

- L. 14: "This increase in temporal dynamic" → "This improvement in temporal dynamics."

Response: We will revise this.

- L. 19: can you mention which are these regions?

Response: We will add this information.

- L. 19: "between […] with" → "between […] and"

Response: We will revise this.

- L. 25: provide → provides

Response: We will revise this.

- L. 25 to 30: you may want to include other references which are explicitly linked to water content: e.g., Feldman et al., 2018; Tian et al., 2018.

Response: Thank you for this suggestion, we will add these references.

- L. 28: Chaparro et al., 2019→Chaparro et al., 2018 (this is different from the "carbonstocks work" in Chaparro et al., 2019). Add the new reference to the references list if you want to keep it in the text.

Response: Thank you, we will revise it.

- L. 70: maybe saying "only a few years" is a bit excessive (e.g., SMOS spans >10 years). Try using another expression, please.

Response: It was meant it in the sense that the use of single sensor VOD may hamper the comparison of longer time periods. We will rephrase it.

- L. 83-85: "During data processing…" → Please move these lines to the methods section.

Response: We will move this sentence to section 2.1 Data processing.

- L. 118: "T2M was used in our analysis, since this parameter is most common for describing the temperature dependency" → Please add some references to show the common use of this variable.

Response: We will add references regarding the use of T2M for describing the temperature dependency of autotrophic respiration.

- L. 121-122: "aggregated to 8-daily estimates" → Please, specify that this is done to match MODIS time-steps in case it was your intention.

Response: We will add this information.

- L. 162: "savitzky-golay" → "Savitzky-Golay."

Response: We will revise this.

- L. 170: "are consistent the previous" → "Are consistent with the previous."

Response: We will revise it.

- Figure 1: Please add marginal distribution rug plots to each panel. Name the panels as "a" to "d" and complete the figure caption with explanation of each panel.

Response: Thank you for this suggestion. We will add rug plots and include the information about each panel in the caption. Panel names are already included in the bottom of each panel.

- Figure 2: add GPPvod as another panel for comparison with GPPvodtemp and benchmark data. Also, I find that the blue to yellow colorbar shows very low contrasts. To me, it is difficult to appreciate color gradients in the figure. You could use other colors (e.g., blue to red?) or saturate the colorbar at the (e.g., 95th, 99th) percentile to improve contrast.

Response: We will add GPPvod and adjust the color bar.

- L. 218: "For a region in Europe" → Please add coordinates also here, as well as the general situation (e.g., "Central Europe") to help the reader.

Response: We will include the information about the location given in the caption of Figure 5 also in the text.

- L. 218: "increase" → "increase in".

Response: We will revise this.

- L. 227-229: there is no a verb in this sentence, please rephrase.

Response: We will revise this.

- L. 233: "between […] with" → "between […] and".

Response: We will revise this

- Figures 4 and 6: please define in the text what are "zonal means".

Response: We will include this information.

- Figures 5 and 8: please, could you make each panel wider? Then there is more place for seeing interannual variability in the figures.

Response: We will update the figure layout.

- Figure 6: Add GPPvod as another panel for comparison with GPPvodtemp and benchmark data.

Response: Although this would be possible in general, we would rather keep the main part as it is. The reason for this is that we narrowed the two setups down to one setup (i.e. GPPvodtemp) based on the results in the preceding section. But in order to provide the information, we will put the figure for GPPvod in the appendix.

- L. 236: "given that correlations in these regions are high" → Authors probably mean correlations between GPPvodtemp and benchmark data. Please specify this, because as you explained correlations of residuals in the previous sentence, it can be confusing.

Response: We will clarify this.

- Figure 7: to improve the boxes for regions, you could use colors different than those from the colorbar (e.g., light green instead of blue?).

Response: We will adjust the color.

- L. 282: “increase” → Do you mean “improvement”?

Response: We will revise it.

- L. 338: "between with" → "with".

Response: We will revise this.

- Figure A1: please add GPPvod as well as a map of the median differences between GPPvod and GPPvodtemp. Also, note that the contrast in the blue to yellow colorbar could be improved, or colors changed to a blue-red scale.

Response: We will add GPPvod and a difference map between GPPvod and GPPvodtemp.

- Figure A3: please add GPPvod.

Response: Consistent with the scatter plots, we will add GPPvod to this figure.

- Figure A4: this seems an interesting result, but I do not fully understand what do you mean by “scaled latitudinal” distribution. Could you please explain this?

Response: The scaled latitudinal distribution is obtained by dividing the data by the maximum of the latitudinal distribution. We will rephrase it to make it clearer.

- Table A1: it could be useful to detail the dominant land cover in each station. Then, the reader will be able to see which vegetation types have been included in calibration of GPP estimates.

Response: We will include the information about land cover in the table.

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