Anonymous Referee #1

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Review for "A global spatially Continuous Solar Induced Fluorescence (CSIF) dataset using neural networks" by Yao Zhang et al.

In this work the authors produce three datasets of CSIF by filling spatial and temporal gaps of SIF soundings by OCO2 using MODIS surface reflectances and machine learning. The resulting datasets in 0.05deg and 4-day resolution represent gap-filled instantaneous SIF under cloud-free conditions, cloud-free SIF integrated to a daily value and daily SIF under all-sky conditions. To illustrate the advantages and the usefulness of these high-resolution datasets they compare to another downscaled fluorescence product (RSIF, based on GOME2 and different MODIS reflectance datasets), GOME2 SIF, EC GPP and OCO2-SIF itself based on drought occurrences.

The authors convincingly argue why a new down-scaled SIF product - based on OCO2 as a new factor – is needed. At several points I do see, however, need for clarification (where the authors partly contradict themselves in my opinion), further discussion and analysis.

Response: Thanks for your nice summary. We address your concerns point-by-point below.

The main points are:

1) Does CSIF represent SIF or APARgreen (p. 3 l. 30)? At several occasions in the manuscript (e.g. p.8 l.14, p.11 l.26) the authors state that based on the reflectances SIFyield cannot be reproduced by NN. They base the drought event analysis on this assumption by comparing CSIF to OCO2 SIF (p.10 l.5). At other moments, however, they stress the close relationship of CSIF to SIF (p.8 l. 18, p.11 l. 31) and call it CSIF.

Response: As we discussed in the introduction, $APAR_{chl}$ (or $APAR_{green}$) is the primary driver of the SIF variation at subdaily or seasonal scales (Du et al., 2017). The SIF_{yield}, on the other hand, can be relatively stable at monthly or seasonal scales although diurnal variations exist. A recent study using canopy SIF observations at a paddy rice site also showed that SIF is strongly correlated with APAR more so than with GPP at both half-hourly (R^2=0.82) and daily (R^2=0.85) scale (Yang et al., 2018). However, this only holds when no strong environmental stress is present. When environmental stress exists, the SIF_{yield} should play a more important role and decrease SIF from its normal conditions (Liu et al., 2018).

We call this dataset CSIF since it reproduces most of the SIF variations retrieved by the OCO-2 satellite. The drought may happen for a limited space and time and deviate CSIF from OCO-2 SIF, but the overall relationship between CSIF and OCO-2 SIF is still very close.

Liu, L., Yang, X., Zhou, H., Liu, S., Zhou, L., Li, X., Yang, J., Han, X. and Wu, J.: Evaluating the utility of solar-induced chlorophyll fluorescence for drought monitoring by comparison with NDVI derived from wheat canopy, Science of The Total Environment, 625, 1208–1217, doi:10.1016/j.scitotenv.2017.12.268, 2018.

Yang, K., Ryu, Y., Dechant, B., Berry, J. A., Hwang, Y., Jiang, C., Kang, M., Kim, J., Kimm, H., Kornfeld, A. and Yang, X.: Sun-induced chlorophyll fluorescence is more strongly related to absorbed light than to photosynthesis at half-hourly resolution in a rice paddy, Remote Sensing of Environment, 216, 658–673, doi:10.1016/j.rse.2018.07.008, 2018.

2) Related to point 1, why not compare CSIF to other estimates of APAR? Greenness index * PAR?

Response: Thanks for your suggestion, the comparison between SIF and APAR has been carried out by several other studies both at regional scale (Zhang et al., 2016) and at site level (Yang et al., 2015; Yang et al., 2018). However, accurate acquisition of $APAR_{chl}$ (rather than APAR) that drives the SIF and GPP is problematic. When using $APAR_{canopy}$ observations, the difference between $APAR_{chl}$ and $APAR_{canopy}$ (mostly related to chlorophyll concentration in the canopy) will be mistakenly interpreted as fluorescence yield or light use efficiency (Zhang et al., 2018).

Another problem with greenness index * PAR is that the greenness indices do not align with fPAR at 0. Several studies use different factors to correct for this misalignment, ranging from 0.02 (Ruimy et al., 1994) to 0.28 (Lind and Fensholt, 1999) for NDVI. In essence, this correction factor is affected by the soil (or snow) background and no universal value may be used. CSIF may be able to better capture the soil background information since it is directly trained on OCO-2 SIF, the soil background information can be correctly picked up by the NN and the resulting CSIF can be more closely related to SIF than greenness index * PAR.

Ruimy, A., Saugier, B., & Dedieu, G. (1994). Methodology for the estimation of terrestrial net primary production from remotely sensed data. *Journal of Geophysical Research: Atmospheres*, *99*(D3), 5263-5283.

Lind, M., & Fensholt, R. (1999). The spatio-temporal relationship between rainfall and vegetation development in Burkina Faso. *Geografisk Tidsskrift*, *2*.

Yang, K., Ryu, Y., Dechant, B., Berry, J. A., Hwang, Y., Jiang, C., Kang, M., Kim, J., Kimm, H., Kornfeld, A. and Yang, X.: Sun-induced chlorophyll fluorescence is more strongly related to absorbed light than to photosynthesis at half-hourly resolution in a rice paddy, Remote Sensing of Environment, 216, 658–673, doi:10.1016/j.rse.2018.07.008, 2018.

Yang, X., Tang, J., Mustard, J. F., Lee, J., Rossini, M., Joiner, J., Munger, J. W., Kornfeld, A. and Richardson, A. D.: Solar-induced chlorophyll fluorescence that correlates with canopy photosynthesis on diurnal and seasonal scales in a temperate deciduous forest, Geophysical Research Letters, 42(8), 2977–2987, doi:10.1002/2015GL063201, 2015.

Zhang, Y., Xiao, X., Jin, C., Dong, J., Zhou, S., Wagle, P., Joiner, J., Guanter, L., Zhang, Y., Zhang, G., Qin, Y., Wang, J. and Moore, B.: Consistency between sun-induced chlorophyll fluorescence and gross primary production of vegetation in North America, Remote Sensing of Environment, 183, 154–169, doi:10.1016/j.rse.2016.05.015, 2016.

Zhang, Y., Xiao, X., Wolf, S., Wu, J., Wu, X., Gioli, B., Cescatti, A., Van Der Tol, C., Zhou, S., Gough, C., Gentine, P., Zhang, Y., Steinbrecher, R. and Ardö, J.: Spatio-temporal convergence of maximum daily light-use efficiency based on radiation absorption by canopy chlorophyll, Geophysical Research Letters, (45), 3508–3519, doi:10.1029/2017GL076354, 2018.

3) Temporal resolution: The final data sets are claimed to have 4day temporal resolution. What is left unmentioned in the manuscript is that the MCD43C4 reflectance data have daily sampling, but each value for a given day still represents a 16-day period (weighted to the central date). So the 4-daily temporal resolution might in reality represent periods of 19days length and potentially affect the downscaling and all comparisons. Please consider this in your evaluations and discussion.

Response: Thanks for your suggestion, we also realized that the MCD43C4 dataset uses 16 days of data as input and the day of interest is emphasized. This may cause potential temporal inconsistency in the dates it represents. However, we think this would have limited effect due to the following reasons: (1) the vegetation growth is continuous in time, the optical properties that will be obtained by satellite would not change abruptly. (2) although MCD43C4 uses 16-day worth of inputs, it also emphasizes the day of interest. Nevertheless, we agree this should be made clear in the revised manuscript and we added the discussions of this issue in the Method section 2.2.

4) Although data processing is described in detail, at points clarification is necessary (e.g. regarding temporal aggregation for training, quality filters of reflectance and EC GPP data, see below).

Response: We tried to resolve your concerns and clarify the data filtering issues.

5) Spatial splitting for training-validation in addition to the temporal one, as extrapolation is not only done in time but also in space. I put it here as a recommendation.

Response: Since the largest variation in vegetation activity are the spatial and seasonal variability, splitting samples by years will maximize the spatial and seasonal coverage in the training and validation samples. In addition, since we need to randomize all the samples prior training the NN, using samples from entire years tend to get more randomly distributed samples in the space-season domain. If we separate the samples by latitude, there may be ecosystems/areas that only occur in the validation but not the training dataset, and the model may be biased.

6) I miss plots of time series throughout the manuscript both regarding training/validation as well as comparisons to other datasets. Such plots could contribute to supporting CSIF as a very useful dataset.

Response: We agree that such time series plots would be helpful to get a sense of seasonal variations. We therefore added a figure for the training and validation dataset (see Figure R1 below). We also revised the figure for the RSIF and SIF* comparison and added the time-series comparison in addition to the regression analysis.

7) Related to point 2: An interesting comparison next to the one to RSIF and GOME2

SIF v27 would also be the one to SIF* by Duveiller and Cescatti 2016 that you cite several times.

Response: Thanks for your suggestions, we added this comparison in the revised manuscript and a paragraph of discussion is also added to Section 3.3.

ad 4)

a) Which period exactly do the OCO2 SIF data cover? It was launched only in Septem- ber 2014, so only a few months of this year are available. Do you use the full year of 2017?

Response: We used the data between September 2014 to December 2017. This has been clarified in the revised manuscript. It is normal to have less samples for validation than for training.

b) Aggregation of OCO2 SIF (p.4 l. 29-p.5 l.18): How do you aggregate in time? Daily, 4-daily?

Response: The aggregation is conducted for each OCO-2 SIF files (daily), since the revisit cycle of OCO-2 SIF is 16 days, and only nadir view SIF observations were used, using daily or 4-day aggregation should not change the value of the samples.

c) Figure 1 nicely shows the spatial distribution of the training and validation data. What does the temporal distribution and representativeness look like? A lat-time plot might be useful here. Why are there no data for validation in Alaska and eastern Siberia?

Response: In Figure 1 (a,b), the color of the dots represents the observations' day of year. Although these dots overlapped in the lower latitude, most of the lower latitude have training and validation samples throughout the year. The boreal regions only have samples during the summer where sun zenith angle is relatively low and no snow or ice cover.

Since the OCO-2 satellite was launched in July 2014 and starting to obtaining data after September that year, limited observations is acquired in boreal regions that year. In 2017, the satellite also experienced malfunctioning in August and early September, making limited observations in the boreal growing season.

d) You might consider removing barren areas in Sahara and central Asia from the analysis to potentially obtain clearer signals as many data points are obtained from these areas (Fig.1) and might affect the relationships in Fig.2-4.

Response: We agree that using the non-barren samples to train the dataset may yield slightly better performance. However, in this study, we aim to generate a global spatially continuous dataset. The SIF dynamic in these sparsely vegetated may be potentially of interest to future studies. Therefore, using the training samples from these regions are necessary.

e) p.5 ll. 12-17: If you first aggregate several soundings to 0.05deg and only afterwards integrate to a daily value, which SZA of the measurement do you use?

Response: If we call a 0.05-degree aggregated pixel a training sample, all the retrievals to generate this sample are from the consecutive observations within a very short period of time, usually within several seconds. The SZA during this period have little change and the average SZA from these retrievals is used as the SZA of this aggregated sample.

f) p.5 l. 21 and at several other occasions in the manuscript: which is the period covered? 2000-2017 or 2001-2016 (abstract) for CSIF?

Response: The clear-sky instantaneous/daily CSIF only requires surface reflectances and calculated SZA as input, therefore, these two datasets span from 2000 to 2017. Limited by the availability of BESS PAR (2000-2016), the all-sky daily CSIF only span from 2000-2016. We have corrected the data coverage throughout the manuscript.

g) Processing of reflectance data: Do you apply any quality filters? You mention the 'best atmospheric conditions' (p. 6 l. 7), what did you do? I am wondering how can you obtain 'more realistic prediction of SIF during winter' if the reflectances do not represent vegetation but snow? MCD43C4 is sampled daily but values represent 16 days worth of data.

Response: The MCD43C4 dataset has filtered out bad estimates (cloud affected) during the pre-processing for the model inversion (Schaaf et al., 2002), therefore no additional quality check is applied in this study. However, the MCD43C4 also suffers from spatial gaps caused by failing to implement the inversion model and predict the NBAR. To fill the gaps in the MCD43C4 dataset, we used the algorithm (Zhang et al., 2017) for each band to reconstruct the 4-day observations.

Since the RossThick/LiSparse-Reciprocal BRDF model used to generate MCD43C4 dataset may fail under contaminated atmospheric conditions, the observations obtained at bad atmospheric conditions is likely to be filter out during the model inversion and aggregation processes. We realized that this statement is not accurate and we have revised this to:

"Since this processing does not involve any extra information and only uses the reflectance observations from the successful model inversion, it should be comparable to the reflectance used for NN training."

We deliberately included the snow affected pixels in the training and prediction, so that if the pixel is covered by snow (usually have quite different surface reflectances than vegetated surface), its SIF values can be correctly predicted. If the vegetation is covered by snow, it is likely to have minimum APAR and little SIF, both spectral observation (reflectance) from MODIS and SIF from OCO-2 would contain little vegetation signal. This enables us to get consistent SIF values with the satellite retrievals.

We added some discussion about the temporal representation of MCD43C4 in Section 2.2

Zhang, Y., Xiao, X., Wu, X., Zhou, S., Zhang, G., Qin, Y. and Dong, J.: A global moderate resolution dataset of gross primary production of vegetation for 2000–2016, Scientific Data, 4, 170165, doi:10.1038/sdata.2017.165, 2017.

Schaaf, C. B., Gao, F., Strahler, A. H., Lucht, W., Li, X., Tsang, T., Strugnell, N. C., Zhang, X., Jin, Y., Muller, J.-P., Lewis, P., Barnsley, M., Hobson, P., Disney, M., Roberts, G., Dunderdale, M., Doll, C., d'Entremont, R. P., Hu, B., Liang, S., Privette, J. L. and Roy, D.: First operational BRDF, albedo nadir reflectance products from MODIS, Remote Sensing of Environment, 83(1–2), 135–148, doi:10.1016/S0034-4257(02)00091-3, 2002.

h) You might consider adding a few sentences on BESS PAR in addition to citing Ryu et al. 2018. The quality of BESS PAR is not discussed in the discussion part.

Response: We have now added several sentences in Section 4.4 to discuss the quality of BESS PAR dataset and its effect on CSIF.

i) In the comparisons to GOME2 SIF v27 and RSIF, is there any accounting for over- pass time and wavelength necessary between GOME2 and OCO2? A comparison to SIF* by Duveiller and Cescatti would complete the suite of products.

Response: We did not consider the differences of SIF emission at 757nm and 740nm. Since the regression is conducted at the temporal domain for each pixel, the temporal variation of ratio between SIF at 757nm to SIF at 740nm is thought to be limited and does not affect the coefficient of determination. Since all the comparisons uses the daily averaged SIF, there is no need to consider the overpass time differences.

We did not add the SIF* dataset into comparison in the first version of the manuscript since it is not open to the public. In this revised version, we added the comparison between CSIF and SIF* together with the RSIF dataset. We also added a paragraph to describe this results in Section 3.3

j) EC GPP: Please add a bit more information: Did you use FLUXNET 2015 or the LaThuile data set? Is there any reason for choosing nighttime partitioning? l. 28-30: I would think you retain those data?

Response: We used the FLUXNET2015 dataset. This is made clearer in the revised manuscript. The nighttime partitioning method is now better described and can be regarded as more independent estimate of GPP. The daytime method assumes a hyperbolic dependence of PAR which also affect SIF. However, the difference between these two is minor (see the detailed comparison in Zhang et al., 2018).

Yes, we do mean those data are retained. This has been corrected in the revised manuscript.

Zhang, Y., Xiao, X., Zhang, Y., Wolf, S., Zhou, S., Joiner, J., Guanter, L., Verma, M., Sun, Y., Yang, X., Paul-Limoges, E., Gough, C. M., Wohlfahrt, G., Gioli, B., van der Tol, C., Yann, N., Lund, M. and de Grandcourt, A.: On the relationship between sub-daily instantaneous and daily total gross primary production: Implications for interpreting satellite-based SIF retrievals, Remote Sensing of Environment, 205, 276–289, doi:10.1016/j.rse.2017.12.009, 2018.

Training and validation (p. 8 ll. 1-26):

-Time series of the CSIF during validation would be nice to see, with validation points overlaid, for example to illustrate the point of SIFyield in SV and GRA.

Response: We agree that the time series validation of the CSIF data would be a great complimentary to the scatter plot and the boxplot, here we select 12 2°×2° gridboxes, and plot their time-series for the SIF retrieval from OCO-2, and CSIF predicted values for the corresponding pixels and date. The CSIF generally showed minimum differences from the original OCO-2 SIF, except slight underestimation during the peak growing season for cropland and deciduous broadleaf forest for some years. Since the SIF_{yield} may only have significant effect during strong environmental stress period, which will be further shown and discussed in Section 3.4 and 4.2, we did not deliberately select samples that are affected by the drought.

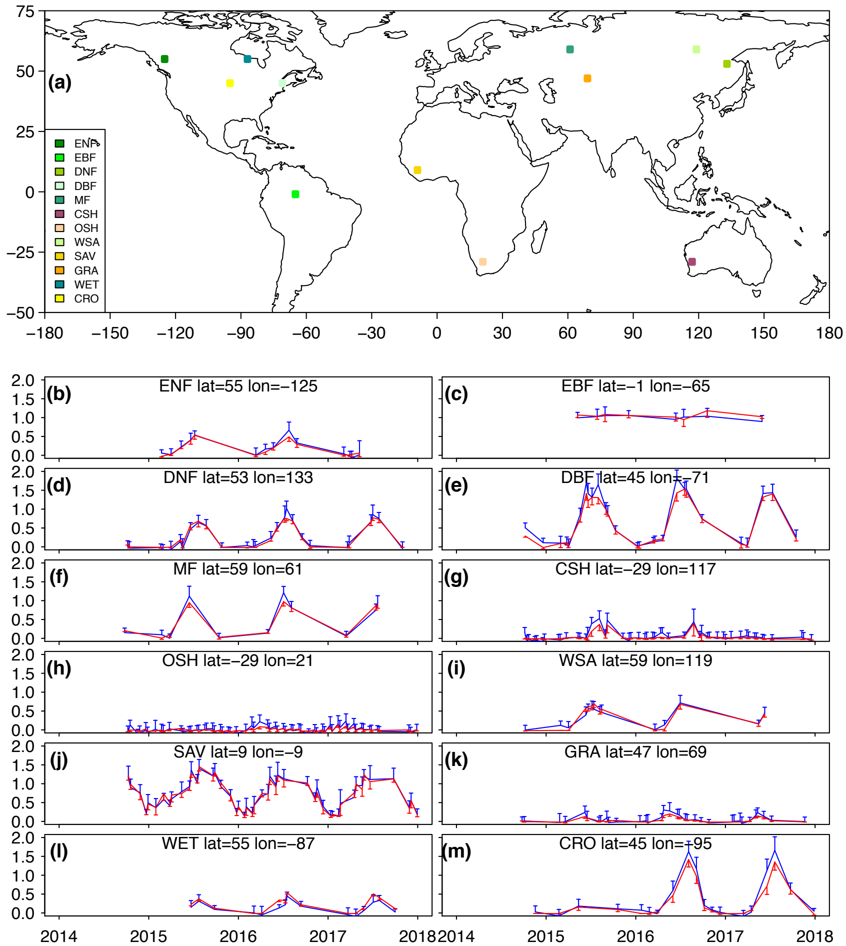

Figure R1. Comparison of predicted SIF by NN and OCO-2 observed SIF for 12 samples (2° ×2°) of major vegetated land cover types during 2014 to 2017. All samples in the training and validation are used. The blue color represents the observed SIF by OCO-2 and the red color represent the SIF prediction by NN. The error bars represent the standard deviation of all 0.05° ×0.05° samples used to generate the 2° ×2° gridboxes. MODIS MOD12C1 V6 land cover dataset is used to select these sample gridboxes.

-Also crops are strongly biased.

Response: Thanks for pointing out, we also described and discussed this in the revised manuscript.

-l.17-19: At other points it is argued that CSIF cannot accurately reproduce SIFyield effects based only on reflectances. Please clarify and discuss.

Response: Through a sensitivity test using the SCOPE model, the fluorescence yield variations under unstressed conditions are small, especially compare to the variation of APAR. This is also supported by a recent study carried out at a paddy rice cropland, suggesting that SIF contains most information of APAR than GPP (Yang et al., 2018). The short-term variations of fluorescence yield may be significant and become important when strong stress presents (Frankenberg et al., 2017), which is not prevalent for the training samples. The long-term (seasonal) or cross-biome changes in fluorescence yield may be related to leaf nitrogen content or carboxylation rate that may be in embedded in the surface reflectance and implicitly picked up by the Neural Network.

We highlighted the differences between the mean fluorescence yield and stress induced fluorescence yield changes in the revised manuscript.

Frankenberg, C. and Berry, J. A.: Solar Induced Chlorophyll Fluorescence: Origins, Relation to Photosynthesis and Retrieval, in Comprehensive Remote Sensing, pp. 143–162, Elsevier., 2017.

Drought monitoring application:

-Please consider the different temporal information in instantaneous OCO2 SIF versus CSIF based on 19 days worth of data and take it into account and/or discuss it.

Response: Thanks for your suggestion. Since during the drought period, the atmospheric conditions are less likely to be contaminated and the MCD43C4 dataset tends to give the best estimate using the full model inversion with the day of interest highlighted. This reduced the possibility of using observations far from the day of interest.

We agree this could be an important issue for the drought monitoring using CSIF. We therefore added some discussion in Section 4.2 about this issue.

"MCD43C4 dataset uses 16 days of inputs for the model inversion, although this may lead to temporal inconsistency for the comparison between CSIF and OCO-2 SIF, it may have limited effect due to the higher data quality during drought with less cloud coverage."

-It would also be interesting to see here a comparison (although I see that the different temporal resolutions would mean more work) also to an estimate of APAR, RSIF, OCO2 SIF/ APAR and SIF* by Duveiller & Cescatti 2016.

Response: Thanks for your suggestion. For the drought monitoring, as we discussed later in the Section 4.2, we would like to highlight the different basis for two drought monitoring methods, the VI based ones use interannual anomalies and detect drought only at later stage. The CSIF based method focuses more on the physiological stress on fluorescence yield. Adding additional APAR dataset would introduce uncertainties related to both PAR and fPAR ($fPAR_{chl}$ and $fPAR_{canopy}$, see our response to comments related Sims et al., 2005). In addition, the SIF* dataset does not have coverage for the period of interest.

A few questions when reading the Discussion:

4.1. What is the advantage of CSIF compared to using vegetation index * PAR?

Response: please refer to our responses to the first two comments about the difference between CSIF and vegetation index*PAR

Is there a trend in RSIF?

Response: Since RSIF starts from January 15th 2007, we only have 9 full years to calculate the trend for the RSIF, which is much shorter than CSIF dataset. The spatial patterns are somewhat similar, for example a positive trend in Europe, southeast China, North India, and a negative trend in East Brazil. Since RSIF is not the focus of this study and the comparison is during different period of time, we did not include this figure in the paper.

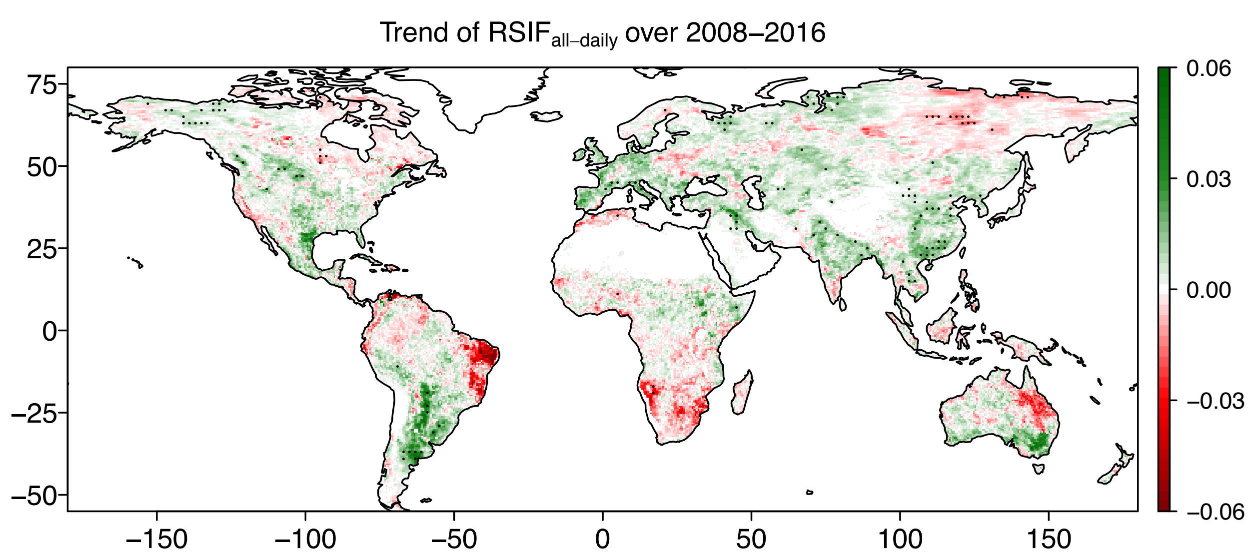

Figure R2. The trend of RSIF during 2008 to 2016. Black dots represent trend is significant at $P<0.05$ through the Mann-Kendall test. The trend is estimated by the Sen's slope estimator.

4.2. Although I fully agree, vegetation indices might not be completely blind. Sims et al. 2006 (RSE, 10.1016/j.rse.2005.01.020) argue that for some ecosystems vegetation indices can contain information on photosynthetic yields.

Response: We agree that several studies including Sims et al., 2006; Wu et al., 2010 suggested that the vegetation indices (VI) have positive correlation with the light use efficiency and a VI model is further developed. However, we argue that these positive correlations may be caused by different definitions of light use efficiency (Gitelson and Gamon, 2015; Zhang et al., 2018). The fraction of light absorbed by the canopy chlorophyll ($fPAR_{chl}$) is what drives the photosynthesis, but it is only a proportion of the total light absorbed by canopy ($fPAR_{canopy}$). There may be positive correlations between the ratio of these two FPAR definitions ($fPAR_{chl}$/ $fPAR_{canopy}$) and the VI, but the correlation between these two does not support the usage of VI for plant physiological stress, which is also suggested by Sims et al., 2005, as the correlation break down during drought. In other words, the VIs may correlate with the seasonal changes of chlorophyll concentration, but the yield information is only related to the energy partitioning after absorption by photosystems by its definition, and should be independent from the canopy characteristics.

Wu, C., Niu, Z. and Gao, S.: Gross primary production estimation from MODIS data with vegetation index and photosynthetically active radiation in maize, Journal of Geophysical Research Atmospheres, 115(12), 1–11, doi:10.1029/2009JD013023, 2010.

Gitelson, A. A. and Gamon, J. A.: The need for a common basis for defining light-use efficiency: Implications for productivity estimation, Remote Sensing of Environment, 156, 196–201, doi:10.1016/j.rse.2014.09.017, 2015.

Zhang, Y., Xiao, X., Wolf, S., Wu, J., Wu, X., Gioli, B., Cescatti, A., Van Der Tol, C., Zhou, S., Gough, C., Gentine, P., Zhang, Y., Steinbrecher, R. and Ardö, J.: Spatio-temporal convergence of maximum daily light-use efficiency based on radiation absorption by canopy chlorophyll, Geophysical Research Letters, (45), 3508–3519, doi:10.1029/2017GL076354, 2018.

4.3. In far-red SIF reabsorption should play a very minor role compared to scattering.

Response: Thanks for your suggestion, we agree that the reabsorptions are relatively small at far-red SIF and recent studies suggest scattering is important for SIF at far-red wavelength (Yang et al., 2018). We revised these sentences to make them accurate.

I am afraid I do not understand the last paragraph (specifically p.14 ll. 12-15). Please rephrase.

Response: We rewrote this paragraph in the revised version of the manuscript. It should be clearer now.

Minor:
P.6 l. 3: In the end four bands are used, not seven.

Response: revised as suggested.

Fig.6a) There are also low values in 2007 and 2010 and high values in 2011 compared to 2010 and 2012 during La Nina in Australia at 40S.

Response: Thanks for pointing out, since the austral summer is between the two years, we revised this sentence to accurately describe the dry and wet years.

"Low SIF values can be found in dry years (2006-2007, 2009-2010) while high values were observed in wet or normal years (2010-2011, 2012-2015)."

Fig.9 Maybe exclude SAA from the plot as GOME2 v27 will be affected by it. p.10 l. 27: somehow there are too many numbers.

Response: Thanks for your suggestions, we agree that GOME-2 SIF in parts of South America is affected by the SAA. SIF retrievals from these areas has high uncertainty, and the correlation between CSIF and GOME-2 SIF is much lower than other regions that have similar seasonal variability. We decided to keep the comparison in this region since it is interesting when comparing with the RSIF for the same region. We added additional sentences describing this phenomenon and its causes.

We also corrected the slope range issues for the $CSIF_{site}$.

Fig. 10: I recommend a clearer white for the zero values, the gray is difficult to distinguish from the red and blue for small values.

Response: We revised this figure as suggested. However, to make these white points distinguishable, we changed the background to dark grey.

Discussion of uncertainties in BESS PAR is missing.

Response: Thanks for pointing out, we added the discussion about BESS PAR performance in Section 4.4

Conclusion:
MCD43C4 is based not only on Aqua.

Response: We have removed Aqua in this sentence.

p. 15 l. 19: 0.5 deg or 0.05deg?

Response: The 0.5-degree dataset is provided through Figshare. The raw 0.05-degree dataset exceeded the storage limit and can be obtained upon request. We added this information in the revised text.

p. 15 l. 27: beam radiation
subscripts sb and sd are sometimes incorrect/the same

Response: two misuses of sb are corrected.

For me, calling the SIF multiplied by a daily correction factor 'daily average SIF' is confusing. It is rather an integration over the day, 'daily integrated SIF'.

Response: We followed the OCO-2 SIF user guide (https://docserver.gesdisc.eosdis.nasa.gov/public/project/OCO/OCO2_SIF_B7000_Product_Description_090215.pdf) and name it daily average SIF. It makes sense calling it daily average since the output represents average SIF over 24 hours, although SIF values are 0 during the night.

Are there any applications or areas for which you would not recommend the use of CSIF?

Response: As we have discussed, the CSIF dataset uses only the spectral information and is not suitable to extract plant physiological information by using it alone.