

Title: Global Datasets of Leaf Photosynthetic Capacity for Ecological and Earth System Research

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Answer to Reviewer #2: Dennis Baldocchi

If we accept the Farquhar-von Caemmerer-Berry photosynthetic model as the dominant paradigm for computing leaf and ecosystem photosynthesis and to apply it to the challenge of assessing photosynthesis everywhere and all the time, we will need to assess such key parameters as  $V_{cmax}$ , at a reference temperature. Chen and colleagues have been leading the way in developing a means to do this and here is their global dataset. It profits from the sharing of data by many through the TRY plant traits dataset (>3700 datasets) and use of optimization theory by many of the coauthors and inferences with information from satellite remote sensing to upscale information.

**Answer:** Thank you for pointing out the merits of this paper and the conditions that made this work possible. These  $V_{cmax}$  datasets presented in this paper are obtained through in-depth collaboration with a large number of individuals in different institutions who contributed in various ways. It would have not been possible to produce and validate these datasets without this collaboration.  $V_{cmax}$  is an indispensable parameter for the FvCB model. Although there are on-going attempts to modify or even replace the model,  $V_{cmax}$  that sets the limit on the carboxylation rate in the dark reaction would still be an essential parameter in any new photosynthetic models.

For the upscaling the authors use two multiple constraints and plausible means, SIF and leaf chlorophyll information deduced from plant reflected spectra. These are useful and defensible. Though I do worry about SIF as the signal is small and many show that it represents absorbed light more. But I don't see this as a fatal flaw and it is worth exploring.

Dechant, B., et al. (2020). "Canopy structure explains the relationship between photosynthesis and sun-induced chlorophyll fluorescence in crops." *Remote Sensing of Environment* **241**: 111733.

Your concern on the SIF signal is valid, similar to the comment of the other reviewer (Yao Zhang). SIF signals are about 1-5% of the reflected radiation in the near infrared wavelengths. However, at the Fraunhofer lines the signals are much stronger because the reflected radiation is much reduced, giving rise to accurate retrieval of SIF from satellite spectral measurements with high spectral resolutions (better than 0.2 micrometers). We therefore believe that satellite SIF measurements are reliable for the purpose of assessing canopy photosynthesis (many studies showed this) and  $V_{cmax}$  (our studies starting from He et al., 2019). In response to your and Zhang's concern, we have modified some lines (Lines101-104) in Methods and cited Dechant et al., 2020) for angular effects on SIF.

My other words of wisdom, having spent time with books on the ground assessing  $V_{cmax}$  is that we know there is lots of seasonality in this parameter, with changes in leaf allocation of N and effects of soil moisture deficits. But this request may be beyond the scope of this work. But I strongly argue for future efforts to create seasonal maps of  $V_{cmax}$ . My other experience is to find vertical variations in  $V_{cmax}$  with depth in deciduous forests, as there is much light acclimation and strong vertical gradients in leaf N that affect  $V_{cmax}$ . This complication, too, is beyond the scope of this work.

Our current study leads to the production of reliable growing season mean  $V_{cmax}$  maps. Although our remote sensing algorithms allow production of  $V_{cmax}$  maps series with seasonal variation, they are not yet ready for distribution for the following reasons: (1) ground-based data used in this study do not have seasonal variation, although there are a limited number of data points with seasonal variation but they are insufficient for validation purposes; (2) the ecological optimality theory can so far be used to derive the mean  $V_{cmax}$  values over the growing season; (3) SIF data are often not reliable over non-growing seasons; and (4) annual patterns of retrieved LCC have irregularities in some places because of inaccuracies of input LAI. In fact, some progress has been made recently to resolve all these issues, and it is possible to produce a multi-decadal times series of  $V_{cmax}$  with seasonal variations in the near future. We have added a paragraph in Discussion to address this concern (Lines 340-350).

However, the growing season mean  $V_{cmax}$  products are already a large step forward from the current state of the art of using PTF specific constants for  $V_{cmax}$ . The remote sensing products represent the average values of leaves at the top of the canopy, and to obtain the canopy mean  $V_{cmax}$  for sunlit and shaded leaves, we have already developed a vertical integration scheme to consider the vertical gradient of leaf nitrogen content (Chen et al., 2012, Global Biogeochemical Cycles). A paragraph is added in Discussion to ease this common concern (Lines 333-339).

In the methods, I am glad to see the authors consider clumping and sun and shade leaves. This is an effort I would insist upon if one is working on a specific canopy. Though for global assessments I worry that by doing so it may introduce error in  $V_{cmax}$  as we may not now these other factors with enough precision.

This is also a valid concern. In our remote sensing algorithms, we used a global clumping index map at 500 m resolution derived from MODIS data (He et al., 2012) to aid the separation of sunlit and shaded leaves. In our assessment of the CI product against ground data, the error is less than  $\pm 0.1$  while the mean values of conifer and broadleaf forests are about 0.53 and 0.66, respectively. Since these mean values are much smaller than unity (the random case), the signal from the CI product is 3-4 times larger than the noise, suggesting that it is highly worthwhile to use the product. Otherwise, the estimation of sunlit and shaded leaf fractions would be in much error, cascading it to  $V_{cmax}$  derivation.

With regards to inverting information derived from leaf chlorophyll I am satisfied to see them using a state of art radiative transfer model, PROSPECT, for this inversion. It is the best way to proceed in my mind. Yes, one may use simple empirical algorithms instead, but are they good enough? Nor may they be mechanistic enough.

This is an excellent insight. In the leaf-level inversion implemented on remote sensing images, we in fact used PTF-specific empirical relationships between LCC and one of two vegetation indices using MERIS red edge bands. The relationships were simulated using the PROSPECT model, in order to attain the necessary computational efficiency (Croft et al., 2020). Considering the differences in input parameters to PROSPECT among PTFs, it was necessary to make the empirical relationships applicable at the global scale.

As noted above using 3700 datasets on  $A/C_i$  brings the remote sensing inversion to reality. Can't ask for a better way to do this.

We are fortunate to have this dataset compiled by previous scientists for validation of these new  $V_{cmax}$  products.

Temperature normalization is always the trickiest as we see lots of temperature acclimation in the field. But don't know what else to suggest. Better than nothing.

Since we have only conducted a short period of  $V_{cmax}$  inversion, temperature acclimation is not considered in our temperature normalization. The ecological optimality theory may be adjusted for this purpose if a long-term time series of  $V_{cmax}$  is produced in the future.

## Results

While it is nice to see computations compared with ground based measurements, realize that the model is fitted with information from the ground. So a bit circular. Would be better to reserve a subset of data for model testing. It probably won't change things because with 3700 data points there is over sampling, especially given the scaling work of Reich and others showing that 80% of variances in leaf photosynthesis scales with only a few factors, leaf N, specific leaf weight and age. Maybe comparing your results to this economic leaf scaling result may be a reasonable alternative.

The  $V_{cmax}$  values derived from SIF and LCC are totally independent of the ground-based data used for validation, so it is unnecessary to separate the dataset into training and validation subsets. Scaling  $V_{cmax}$  against other leaf traits (N, SLA, age) is a good idea and would help interpret and evaluate the remote sensing products. There are global leaf economics spectrum datasets used by various studies (Wright et al., 2004; Sack et al., 2013; Osnas et al., 2013; Reich 2014). However, these datasets are collected over a long period of time with different techniques and often without sufficient details of geographical locations for temporal and spatial matching with our remote sensing data over a short period of time. It is possible to do this leaf economic scaling study partially

with our dataset at hand, but we feel that this is an issue for exploring the usefulness of the dataset while the main purpose of this present paper is to show the derivation and information content of this dataset. We have added a paragraph to discuss the possible use of our Vcmax products for leaf economic studies (Lines 266-279).

Wright, I. J., P. B. Reich et al., 2004. The worldwide leaf economics spectrum. *Nature*, 428, 821-827.

Osnas, J. L. D., J. W. Lichstein, P. B. Reich, and S. W. Pacala, 2013. Global leaf trait relationships: mass, area, and the leaf economics spectrum. *Science*, 340, 741-744.

Sack, L., C. Scoffoni et al., 2013. How do leaf veins influence the worldwide leaf economic spectrum? Review and synthesis. *Journal of Experimental Botany*, 64: 4053-4080.

Reich, P. B., 2014, The world-wide “fast-slow” plant economics spectrum: a traits manifesto. *Journal of Ecology*, 102: 275-301.

Glad to see a section on response to drivers. Useful. The issue on irrigation is interesting and could be a scale emergent property from this work. Remember irrigated fields are also fertilized so they will stand out compared to native vegetation.

We agree. Irrigation was used as a surrogate of cropland and grassland management. A limited number of studies showed that crop and grassland water stress decreased Vcmax (Reed and Loik, 2016; Chen et al., 2019; Song et al., 2021). Leaf economics spectrum datasets also show that for natural ecosystems, leaf photosynthetic capacity increases with mean annual precipitation (Wright et al., 2004; Osnas et al., 2013), suggesting that increased water availability in grassland would increase its leaf Vcmax. These could explain partly the positive correlation between Vcmax and irrigation for crops and grassland found in this study. These positive effects could also be associated to fertilization that often co-occurs with irrigation. We have added some discussion on this issue (Lines 237-240).

Chen, B., J. M. Chen, D. D. Baldocchi, Y. Liu, T. Zheng, T. A. Black, and H. Croft. 2019. A new way to include soil water stress in terrestrial ecosystem models. *Agricultural and Forest Meteorology*, 276, 107649, <https://doi.org/10.1016/j.agrformet.2019.107649>.

Reed, C. C. and M. E. Loik, 2016. Water relations and photosynthesis along an elevation gradient for *Artemisia tridentata* during and historic drought. *Oecologia*, doi: 10.1007/s00442-015-3528-7.

Song X., G. Zhou, Q. He, and H. Zhou, 2021. Quantitative response of maize Vcmax25 to persistent drought stress at different growth stages. *Water*, 13, <https://doi.org/10.3390/w13141971>.

## Discussion

Looking at your maps I see high  $V_{cmax}$  in desert and semiarid areas (Africa, India, Australia and the Cerrado of Brazil). In my early work on stress, I looked a lot at Park Nobel's work on desert species and indeed did see among the higher  $V_{cmax}$  values. Thinking about Prentice optimization theory I think it makes sense. They need to acquire enough carbon to outpace respiration. But they have a short growing season due to low water supply and high demand. The only way they can make the economics work is to achieve very high rates of photosynthesis, which comes at the cost of high  $V_{cmax}$  and N. I find this interesting and the authors may want to discuss this a bit.

This is an excellent observation and useful suggestion. From the leaf economics perspective, your point of the cost of high  $V_{cmax}$  and N for short growing seasons seems logical. However, the available leaf economics spectrum data (Wright et al., 2004; Osnas et al., 2013) all show that leaf mass per area (LMA) decreases with mean annual rainfall (MAR), leading to higher photosynthetic capacity. It means  $V_{cmax}$  increases with MAR or is lower at drier places. This seems to be opposite to what you expected. The higher  $V_{cmax}$  values in India and southeast Brazil are mostly located in agricultural areas where irrigation might have positive influence on  $V_{cmax}$ . In the areas near the southern border of the Sahara desert, the high  $V_{cmax}$  area is also mostly associated with cropland, and the latitudinal radiation gradient may explain the  $V_{cmax}$  north-south gradient. In Australia, the  $V_{cmax}$  spatial pattern is compatible with precipitation distribution, i.e. low  $V_{cmax}$  in central Australia is associated with low precipitation, while higher  $V_{cmax}$  values in northern Savanah areas are related to higher precipitation. The latitudinal gradient of radiation also enhances the north-south gradient of  $V_{cmax}$ . These  $V_{cmax}$  maps provide a lot of new information for leaf economics studies. We have added a paragraph to discuss the  $V_{cmax}$  distribution patterns in these regions (Lines 266-279).

The quality of the figures is good enough. Looks like they are generated by Matlab and have nice color gradients.

These figures are indeed generated in Matlab!