Detecting changes in essential ecosystem and biodiversity properties- towards a Biosphere Atmosphere Change Index: BACI

Deliverable 4.5: Global products of plant trait phenologies

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Summary

This deliverable describes the efforts to generate a global product of an plant trait phenology. We have explored different avenues and finally concluded that one should work at the ecosystem scale and use integrated trait estimates. We focussed on deriving the ecosystem level functional property "GPPsat" as target and produced a multi-year phenology based on the results of the upscaled half-hourly datasets (from the D4.4). However, an in-depth quality assessment of this data product did not provide convincing results as we explain here. Hence, we finally decided to work with a local maximal GPP estimate (GPP90) as phenology data set which is methodologically more robust to derive and still highly informative for assessing the development of ecosystem properties.

1. Introduction

In its original meaning, "Phenology" describes periodic events or states of development in the life of an organism or community. Phenology is considered a candidate "essential biodiversity variable" (EBV) by GEO-BON. However, by today this EBV is vaguely defined and it remains unclear what the underlying metrics should describe. Traditionally, direct observations of phonological states of different species had been considered. Since remotely sensed vegetation indices have become widely available, these data streams are also used to monitor vegetation phenology. However, defining phenology based on remote sensing indices only does not allow for an ecophysiological interpretation. Remote sensing indices rather indicate if the vegetation under scrutiny is "active" or "not" or one may identify e.g. senesce periods etc. However, phonological indicators of this kind are not so well interpretable in terms of "ecosystem functioning".

The goal of this deliverable was therefore to produce a "phenology" that offers a clear ecophysiological interpretation. We explored various avenues in this direction that are reported here: Firstly, we explored the potential of upscaling plant functional traits in space and time. While the spatial upscaling worked out well, we did not achieve a temporal description of the "active" traits. Secondly, we explored the possibility to derive a dynamical description of ecosystems photosynthetic capacity at light saturation (GPP_{sat}) by means of a model-data integration approach. This property is often named a key "ecosystem functional property", as it describes the potential of an ecosystem to take up CO_2 in a comparable way (i.e. at some reference condition). We found, however, that this approach suffers from severe limitations that are discussed here. Hence, we thirdly produced a robust metric on the temporally varying maximal GPP, i.e. the observed local maxima of GPP on a given time-horizon that can be interpreted as the realizable maximal ecosystem uptake of CO_2. This last data product is uncritical and can be well interpreted.

2. Potentials and limitations of extrapolating plant functional traits

We first investigated the potential and limitations of using plant functional trait observations from global databases (i.e. TRY, see data preparations as described in WP3). We followed two avenues: 1. Using geographical sampling information of plant traits. 2. Matching traits measured in-situ with traits inputted from a global database.

With respect to the first approach, we found that using geographical sampling information of plant traits we could, in practical terms, produce global maps by means of high-dimensional regression approaches (PLS). However, the prediction accuracy was only becoming accurate when we upscaling the traits first at a very course resolution, e.g. ecoregions sensu Olson et al. (2001).
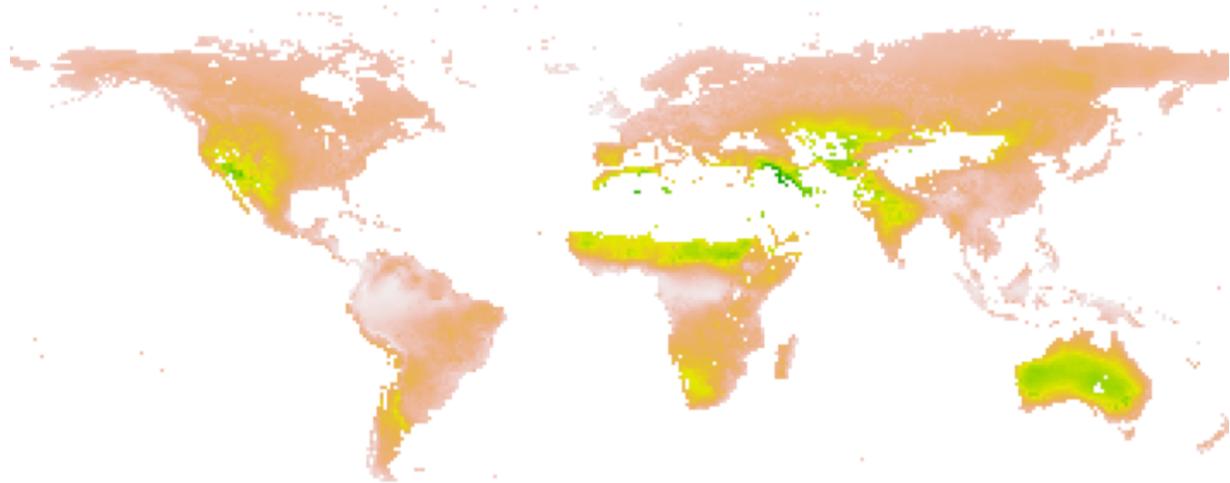
Figure 1 Predictions of leaf phosphorous (P) content per leaf dry mass predicted at 1° resolution. Predictions are based on single trait – climate (ERA-interim reanalysis) models (n=100) created by a variable selection (Competitive Adaptive Reweighted Sampling, CARS) in combination with a dimensionality reduction (Partial Least Squares, PLS) that accounts for collinear predictor variables. The encoded relationships have been learned at the level of ecoregions (Joswig et al. in prep.).

Despite of this apparent progress, we found that the explanatory power of environmental variables is limited if we use only climate data as predictors for plant traits. Figure 1 is showing the predicted "leaf phosphorous content" as an example where only 40% of the trait variability was explained with climate variables using the partial least square regression (PLS) method. To understand this pattern better, i.e. why we only achieve moderate prediction powers, we performed a PCA of the plant traits. We reduced the dimensionality of the trait space into two dimensions. Visualizing the leading two axes against latitudes (see Fig. 2) shows that one can hardly see any pattern. There is hardly any distinction of plants between trait assemblies across latitudes. However, when we aggregate the components to a 1° latitudinal band we would find an excellent agreement of latitude vs. PC1 of the traits (r2 = 0.84) (Fig 2). This analysis leads us to one insight: Plant traits are very heterogeneous in space, and therefore a straight forward upscaling approach, as it has proven to be successful for land-surface fluxes of CO_2 (see D4.1),

cannot be achieved. Nevertheless, this study has nourished our hypothesis that we may find clear environmental signals when aggregating plant traits to scales that are of sufficient coarseness to not be confounded by local environmental conditions. In fact, this is an avenue that we are currently exploring in a separate study under the lead of Julia Joswig in close collaboration with the iDiv.
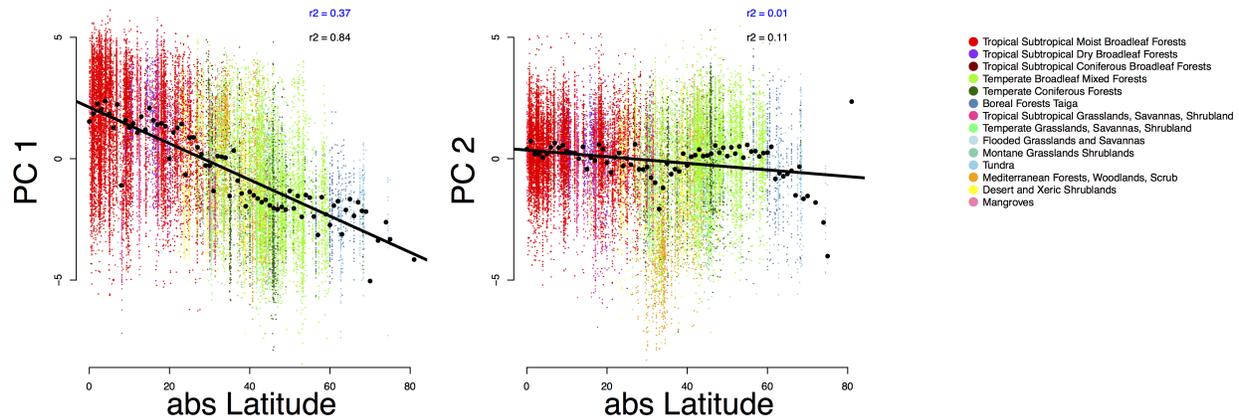
Figure 2 Dimensionality reduced (PCA) gap-filled traits (bHPMF, Shan et al. 2012, Fazayeli et al. 201x, Schrodt et al. 2015) on single plant observation scale along the absolute latitude. Point colour according to biome (a) First PCA axis of observation level traits along absolute latitude, points in black refer to binned PC 1 values to 1° of absolute latitude (b) Second PCA axis of observation level traits along absolute latitude, points in black refer to binned PC 1 values to 1° of absolute latitude.

With respect to the second approach, we investigated to which extent we can benefit from global plant trait databases to explain ecosystem photosynthetic capacity at the local scale. As these are entirely independent measures, we have an independent source for exploring the potential to upscale plant traits. We carried out a study where we compared the explanatory power of locally sampled trait data versus data aggregated from the global database TRY (see in-situ data curating efforts in WP3). In order to have an independent reference, we explored how local traits correspond to ecosystem functional properties (EFPs, see Del. 4.2). We carried out a full study to investigate this issue: The paper by Musavi et al. (2016) used ecosystem photosynthetic capacity as an example EFP. The study first provides an objective approach to derive robust EFP estimates from gross primary productivity (GPP) as obtained from eddy covariance flux measurements. This is similar to the approach provided in Del. 4.2, but more elaborated as it based on a conceptually well-founded model-data integration approach.

The study then investigates how well EFPs and plant functional traits are related in time and space. The relationships between foliar nitrogen concentration and ecosystem photosynthetic capacity are tighter when both of the measurements are synchronized in space and time. In addition, we found that when using multiple plant traits simultaneously as predictors for ecosystem photosynthetic capacity variation, the combination of leaf carbon to nitrogen ratio with leaf phosphorus content explains the variance of ecosystem photosynthetic capacity best (adjusted R^2 = 0.55) (Fig. 3).
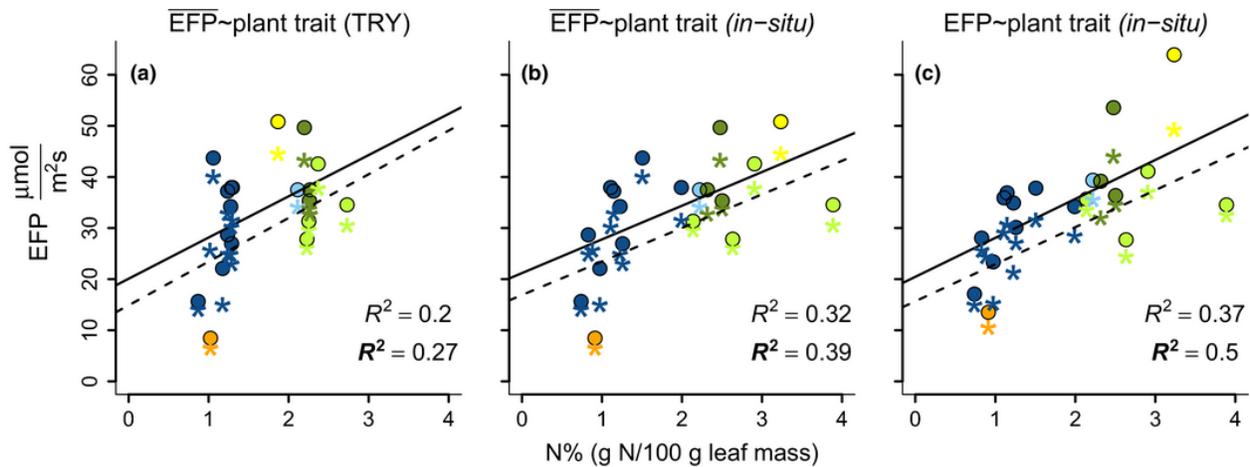
Figure 3 Relationship between photosynthetic capacity at 1000 Wm^{-2} global radiation GPP_{sat} (star symbols: ecosystem photosynthetic capacity estimates using PAR), photosynthetic capacity at 2000 $\mu mol.m^{-2}s^{-1}$ absorbed photosynthetic active radiation (APAR) or $GPP_{sat.structure}$ (round points are for the relationship with ecosystem photosynthetic capacity estimates using APAR) and a) and N% from TRY, b) N% in situ, and c) GPP_{sat} and $GPP_{sat.structure}$ derived from the same year of the trait sampling and N% in situ. Bold Bold R^2 quantify relationships GPP_{sat} and nonbold R^2 quantify relationship with $GPP_{sat.structure}$. Y-axes are ecosystem photosynthetic capacity as an example of an EFP, and x-axes are community weighted N%. The Macro accent on the EFP indicates that the GPP_{sat} and $GPP_{sat.structure}$ are the multiyear averages for each site. The colors dark blue, light blue, dark green, light green, orange and yellow represent evergreen needle leaf forest, evergreen broad leaf forest, deciduous broad leaf forest, grassland, closed shrub-land, and cropland as the plant functional types of the sites, respectively.

Overall, this study identified a clear link between leaf level traits and canopy level processes and highlights the relevance of the temporal dynamic nature of ecosystems. However, a key finding is that synchronizing measurements of eddy covariance fluxes and plant traits in time and space is shown to be highly relevant to better understand the importance of intra- and interspecific trait variation on ecosystem functioning. Following up on this, in a later study we investigated the interannual stability of the very same type of EFP. We found that ecosystem photosynthetic capacity (GPPsat) exhibits a strong link to stand age and biodiversity (Musavi et al., 2017). In this paper, Musavi et al., (2017) investigated the differences between sites for the stability in GPPsat and shows that it is best explained by the stand age and biodiversity differences between sites. Overall, these different studies revealed that 1) there is too much spatial variation in plant traits so that any relationship with climate/soil predictors at high resolutions (below 0.5°) unfeasible to derive accurately given our methods, and 2) that only space and time local measurements would allow to relate plant functional traits well with ecosystem functioning in time. Hence, we decided to explore different avenues in this deliverable.

3. Phenologies of ecosystem functional properties

Although we found that a direct extrapolation of traits intersected e.g. with species distributions and their phenologies (as it was the original plan) is not defendable we identified alternative ways forward. For instance, Musavi et al. (2016 and 2017) showed that leaf N% is tightly related to GPPsat and that the stability of GPPsat is linked to stand age and biodiversity. GPPsat is a property that has a direct physiological interpretation. It is very closely linked to plant traits at one hand and at the other hand is also maintained stable at the sites through the synergy

between stand age and local biodiversity of the sites. More importantly, given that BACI has provided the first global product of half-hourly GPP data (see Del. 4.4) we expected to be able to produce phenologies of the EFP (here i.e. GPPsat) everywhere on the globe for a period of ten years.

At each grid cell, we extracted the upscaled GPP half hourly products as provided by WP4 (see D4.4). For extracting the EFPs we followed the exact methodology as reported in the BACI paper by Musavi et al. (2017). For every grid cell, the estimates of photosynthetic capacity (GPPsat) were determined from upscaled half-hourly GPP estimates and absorbed photosynthetic active radiation (APAR). We fitted a non-rectangular hyperbolic light response curve function (NHLRC) to GPP and APAR data (sensu Gilmanov et al., 2003). The NHLRC is fitted to 5 days of data selected with a moving window approach. The parameters of the NHLRC were estimated (Amax, intercept, slope, and curvature) and we computed the expected GPP at 1,500 of $\mu molm^{-2}s^{-1}$ APAR (GPPsat), which represents the GPP at saturating light (that is, ecosystem photosynthetic capacity in the selected 5-day window). The estimated parameters and the GPPsat values were assigned to the day in the middle of the 5-day window. And so one could obtain a time series of GPPsat. Only parameters estimated with a model efficiency above a certain threshold (e.g. 0.5) would be accepted. For the estimation of GPPsat we not only relied on upscaled GPP (at half-hourly time-steps) but also needed a half hourly product of APAR. So far no APAR product is available at half hour time scales. In order to produce the data, we used a procedure using global solar radiation (Rg), potential radiation (Rpot) and fraction of photosynthetic absorbed radiation (fapar).

For testing this method further, we used the fast track sites as they have been selected by the validation workpackage (WP6) – see Del. 6.1:

Fast track site	Latitude	Longitude
Central Romania	46	25
Viterbo Province	42.5	12
North Somalia	9	48
South Somalia	2	43
Kafa, South-west Ethiophia	7	35
Krueger National Park (South Africa)	-24	32

The images of the time series clearly show the shifted phonological properties of e.g. the two sites in Somalia with two very distinct growing seasons (Fig. 6). The time series of GPPsat will be used to study its phenology e.g. periods of time when it is the highest during the year.
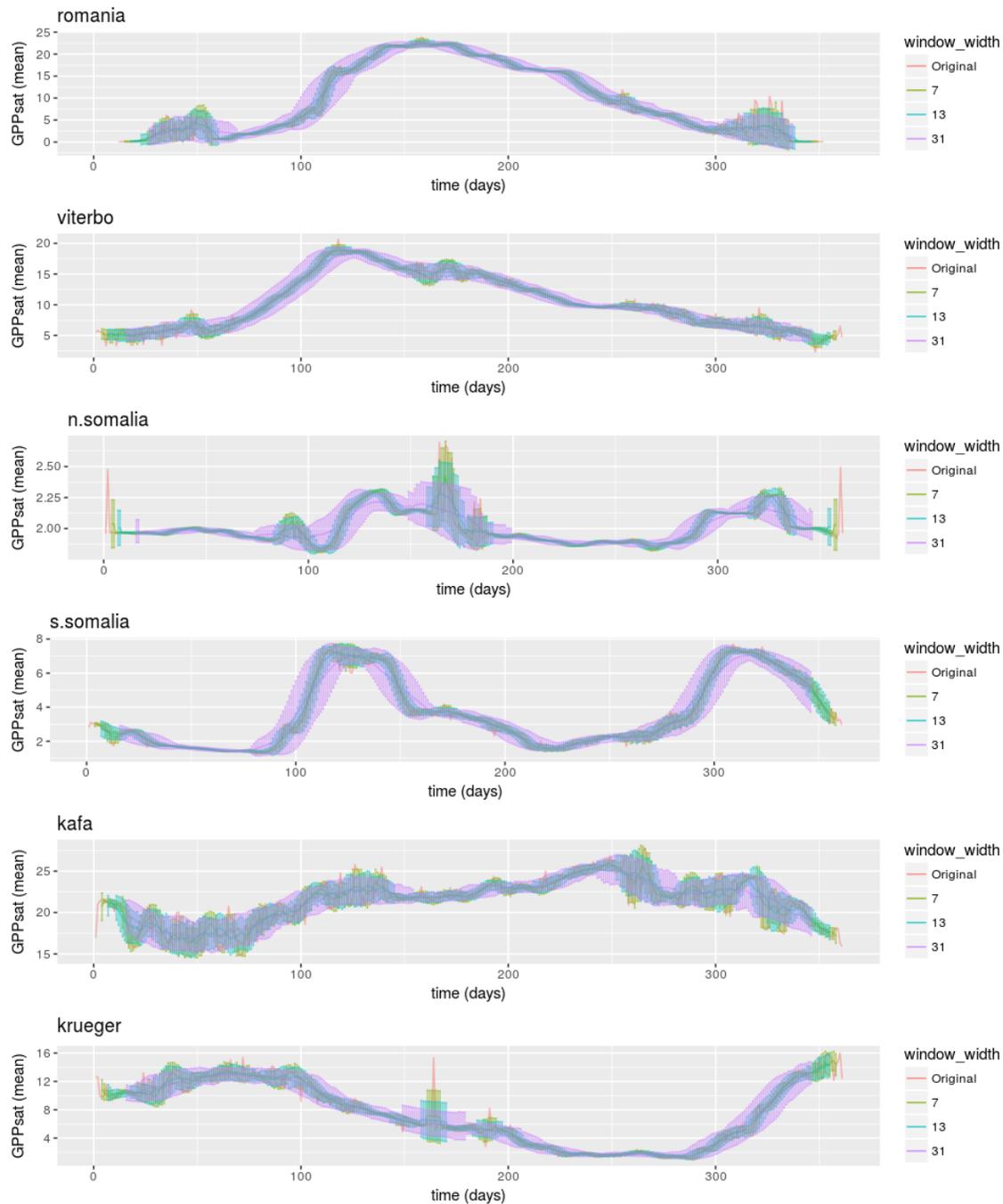
Fig 5 The phenology of the photosynthetic capacity at the BACI fast-track sites.

The phenology can, of course, be produced at multiannual scales and across space as shown e.g. in Fig. 6. In fact we estimated the time series of GPPsat for 10 years between 2001 and 2010. The mean annual GPPsat is shown in Fig. 7.
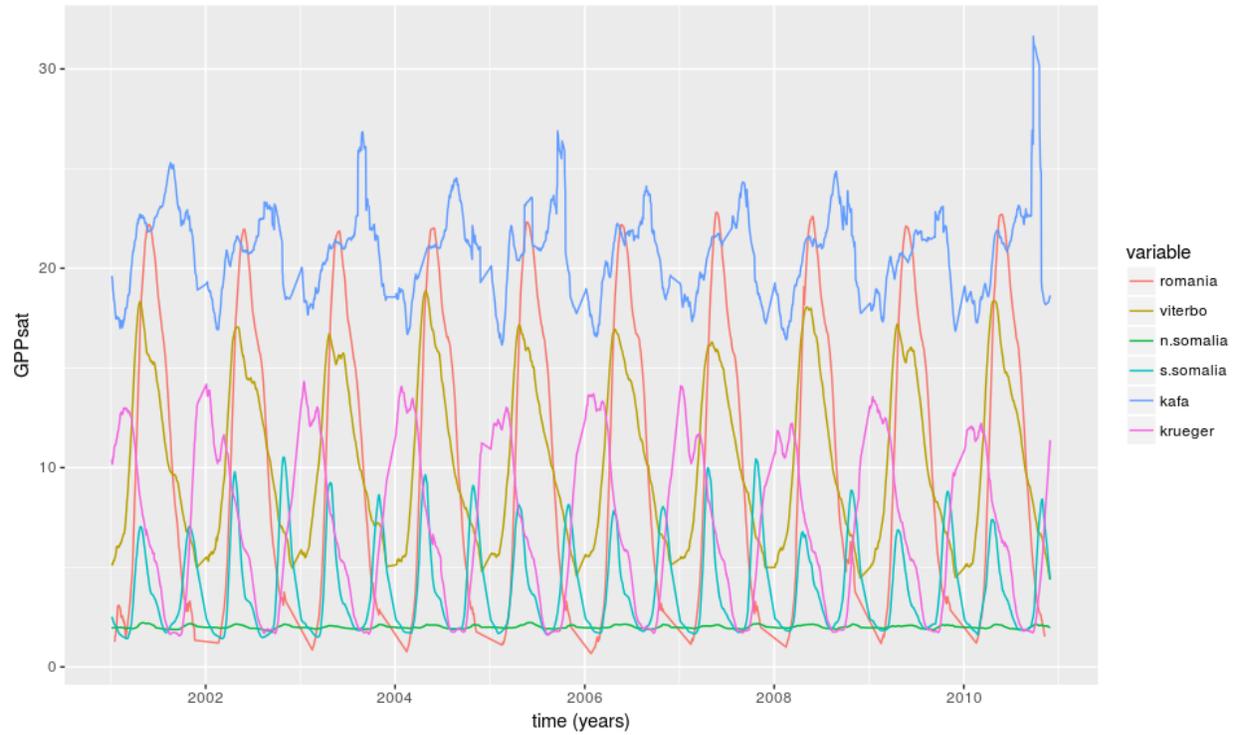
Fig 6 The multiyear phenology of the photosynthetic capacity at the BACI fast-track sites.
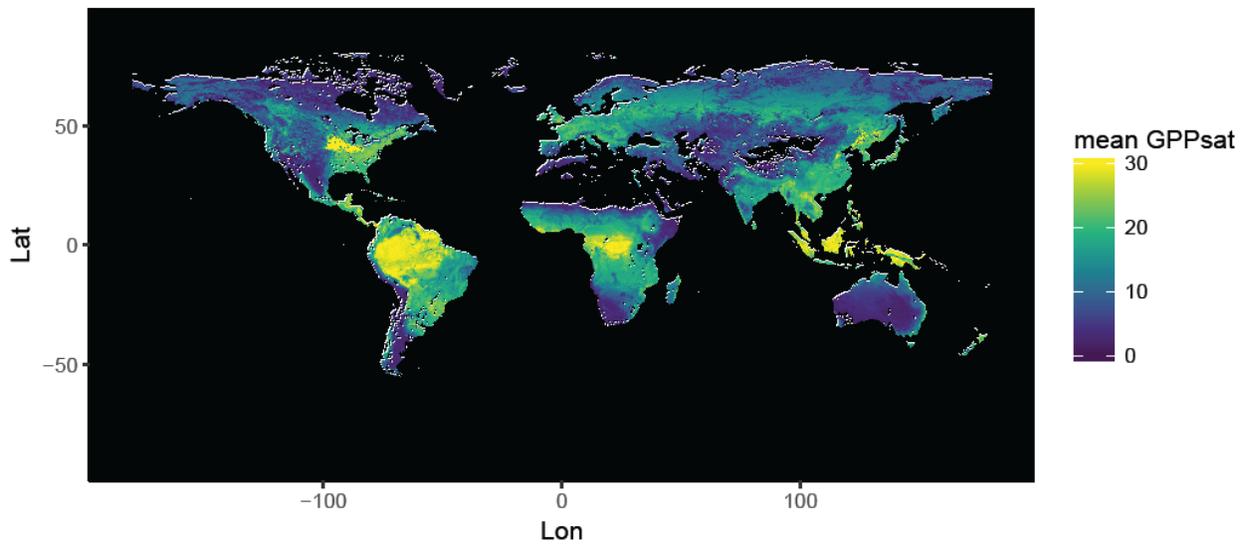
Figure 7 Mean annual GPPsat for the years 2001 to 2010. The statistics are as following; minimum 0.07, 1st quantile 0.11, mean 12.53, 3rd quantile 17.97 and maximum 54.52 µmolm-2s-1 of GPPsat.

Figures 5-7 show that we were technically capable to derive a data product of GPPsat that would allow us, theoretically, to describe the phenology of ecosystem functioning. However, in order to assess the quality of this data product we performed some further quality assessments:

- In order to reduce the number of outliers in the time series of GPPsat we attempted to use the parameter estimation of the previous moving window to have a better first parameter guess to use in model optimization. The results were then compared to the previous method when the first parameters guess was more fixed and not influenced by the previous moving window. However, unlike our expectation the outcome did not improve.
- We also examined the moving windows in different gridcells, which revealed two issues regarding the use of NHLRC with our data: Firstly, the APAR values estimated using downscaling of Rpot by Rg and remote sensed retrievals of FAPAR values showed a very low range of values (see Fig. 8), which implies that the model could not fit the saturation well (see Fig. 9). Secondly, inspecting the relationships between the GPP and Rg shows that there is a strong linear relationship between the two which makes model efficiency (EF) to be high because the NHLRC model finds a very good fit only in the first part of the response curve, where the relationship is almost linear and GPP increases with APAR, but it does not saturate (Fig. 9). It seems like the GPP and Rg relationship in our data is more linear than a saturating one.
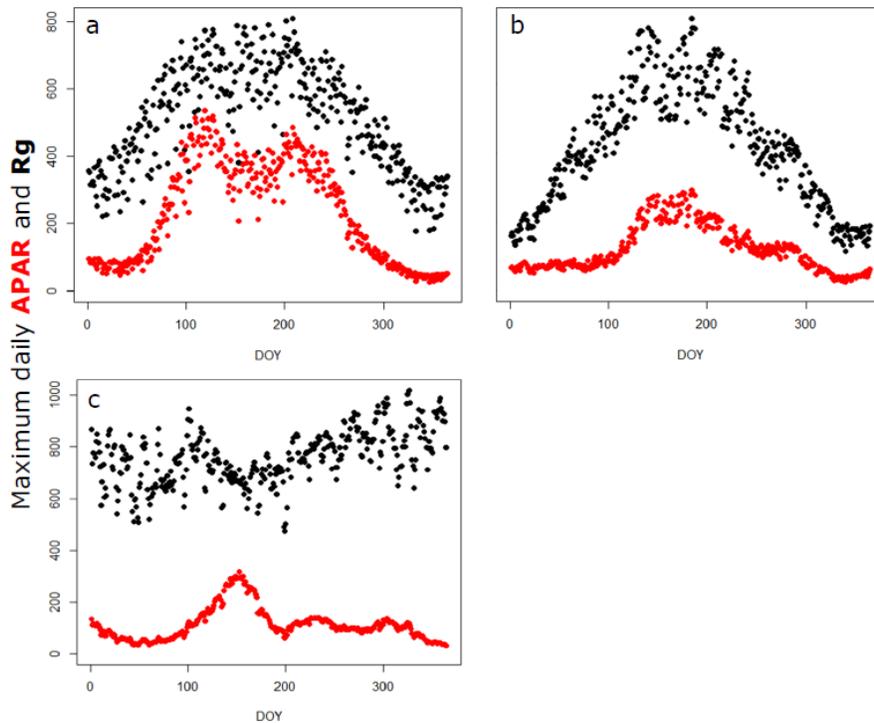
Figure 8 Example of the global radiation (Rg –black points) and absorbed photosynthetic active radiation (APAR – red points) time series of three grid cells in 2001. a) grid cell located in Harward forest with latitude of 42.75 and longitude -72.25. b) grid cell located in central Germany with latitude 50.75 and longitude 10.25. c) grid cell located north of Australia with latitude -17.25 and longitude 133.25. (DOY: day of the year)
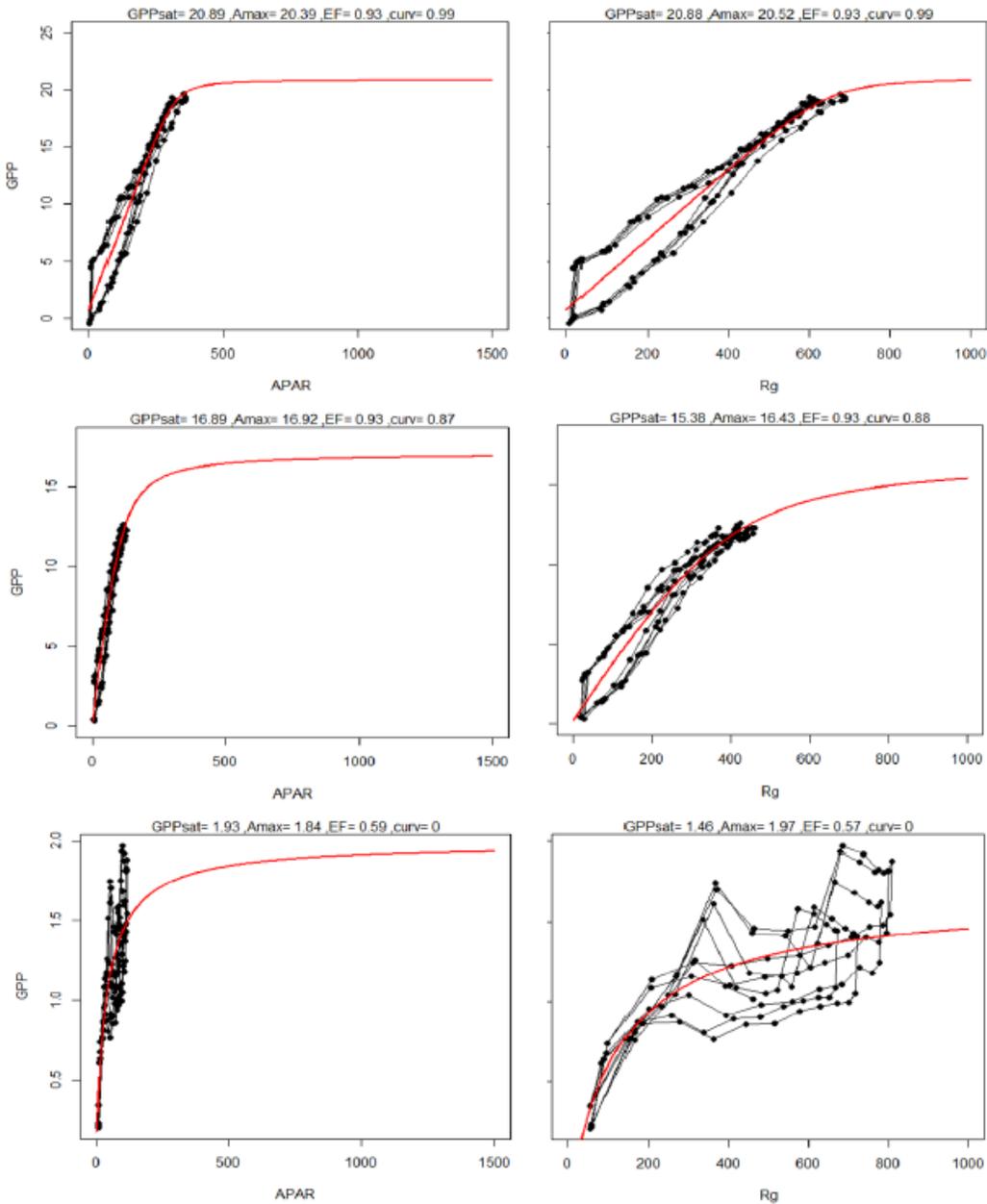
Figure 9 A 5 day moving window example of the NHLRC fit for GPP in response to APAR (left panel) and Rg (right panel) with the central day being the 250 day of the year (DOY), which is in September (data from 2001). For three different gird cells from up to down, located in Harward forest with latitude of 42.75 and longitude -72.25, located in central Germany with latitude 50.75 and longitude 10.25 and located north of Australia with latitude -17.25 and longitude 133.25.

We then tested whether a linear model would be better for the fit rather than using a NHLRC model. We compared the Akaike Information Criterion (AIC) of the NHLRC model with the one of a simple linear regression model. The AIC as used here (sensu Burnham and Anderson 2002) corrects for the number of parameters used in a models, i.e. is not biased by the unequal number of parameters in the two models:

$$AICc = nlog\sigma^2 + 2p + \frac{2p(p+1)}{n-p-1}$$

The model with the lower value would be the one considered more suitable for the data.
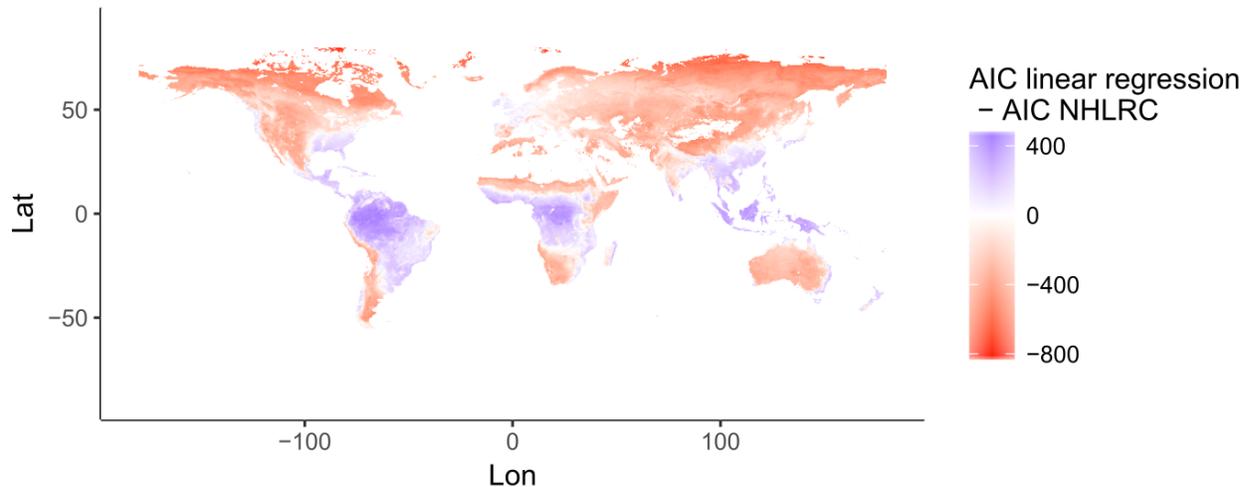
Figure 10 The difference between the AIC of the linear regression model and AIC of the nonlinear light response curve model (NHLRC). Positive values indicate the advantage of using NHLRC in comparison to the linear model. Negative values indicate the advantage of the linear model over the NHLRC. Zero values are when both models are equally good. For 74.4% of the land area the linear model would be a better choice over the NHLRC (negative values showed in red). The data used in the models are GPP and global solar radiation (Rg).

The result shows that in large parts of the world a linear model will lead to a better fit than the NHLRC (Fig. 10). Considering these severe spatial limitations we cannot recommend using the GPPsat approach based on the NHLRC model for deriving a global phenology of ecosystem functioning. A more robust approach would be to estimate the 0.9 quantile of GPP (GPP90) in each moving window and to use the time series of GPP90 in future studies. The maximum GPP (GPP90) should be comparable to GPPsat and we have showed that the two estimates are highly correlated (Musavi et al., 2016) The advantage of a more simple approach of this kind is that the latter is not plagued by the methodological issues described for GPPsat. For each grid cell we used a moving window of 5 days and estimate GPP90 based on the GPP half hourly data, which are then assigned to the center day. In addition, we estimate the integral of half hourly GPP (GPPcum) for each day using the 5 day moving window approach. The comparison of the two products GPP90 and GPPcum would be beneficial when ecosystems with different seasonal cycle are compared (e.g. ever green vs. deciduous). In both cases we also use a bootstrapping of 500 repetitions and a sample size of 50 with replacement to estimate the mean and standard deviation of GPP90 and GPPcum. In Fig. 11 the mean GPP90 for the year 2001 is shown as an example. The data are made available on the BACI portal.
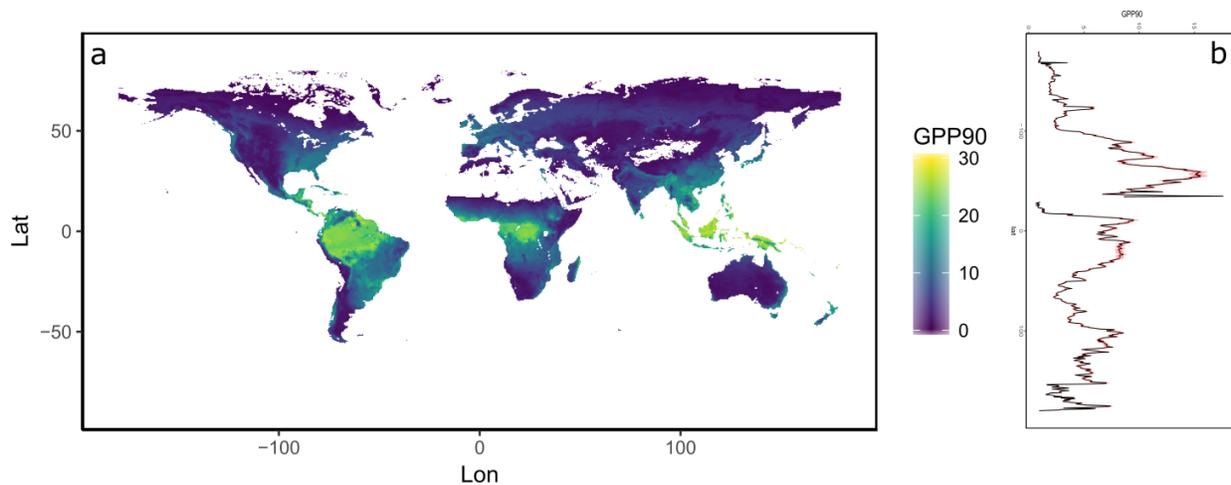
Figure 11 a) The average GPP90 for the year 2001, b) latitudinal pattern of average GPP90 in year 2001. Red band around the line is the standard deviation of the GPP90 from the bootstrapping.

4. Conclusions

The original intention of task 4.4 and this very deliverable was to investigate novel ways to generate phenologies that can be computed globally and are of ecophysiological relevance. We have been exploring various avenues to achieve this goal. Initially we had assumed that the following workflow could be realized without major problems: 1) Intersecting various sources of species occurrence information and building species distribution estimates for all species for which we have plant functional traits. 2) Intersecting these results with phenological data to prune the species information back to timings when species are non-dormant and, via intersection of plant functional traits, a phenology of plant traits. However, our first analyses in this direction revealed that this approach was not tenable. This has to do with the problem that the spatial heterogeneity of plant traits is so large that it is hard to generalize directly. We followed various avenues in this direction, but considered that using ecosystem-scale values of GPPsat can be interpreted as an integrated surrogate for physiological traits. However, multiple methodological issues detected in a quality control step showed that we should better focus on local maxima of GPP (i.e. GPP90). The resulting time series can be of relevance for monitoring changes in ecosystem properties and will be analyzed in the remaining time of the project.

5. References

- Burnham, K. P. and Anderson, D. E.: Model selection and mul-timodel inference: A practical information-theoretic approach, 2nd Edn., Springer-Verlag, New York, 2002.
- Britton, C M, and J D Dodd. 1976. "Relationships of photosynthetically active radiation and shortwave irradiance." *Agricultural Meteorology* 17 (1): 1–7. doi:https://doi.org/10.1016/0002-1571(76)90080-7.
- Musavi, T., M. Migliavacca, M. J. van de Weg, J. Kattge, G. Wohlfahrt, P. M. van Bodegom, M. Reichstein, et al. 2016. "Potential and limitations of inferring ecosystem photosynthetic capacity from leaf functional traits." *Ecology and Evolution* 6 (20): 7352–66. doi:10.1002/ece3.2479.
- F. Fazayeli, A. Banerjee, J. Kattge, F. Schrodt, P.B. Reich (2014) Uncertainty quantified matrix completion using Bayesian Hierarchical Matrix factorization. *International Conference on Machine Learning and Applications (ICMLA).*
- F. Schrodt, J. Kattge, H. Shan, F. Fazayeli, A. Karpatne, A. Banerjee, M. Reichstein, M. Boenisch, S. Diaz, J. Dickie, A. Gillison, V. Kumar, S. Lavorel, P.W. Leadley, C. Wirth, I. Wright, S.J. Wright, P.B. Reich (2015) "BHPMF - a hierarchical Bayesian approach to gap-filling and trait prediction for macroecology and functional biogeography." *Global Ecology and Biogeography* 24, 1510–1521.
- H. Shan, J. Kattge, P. B. Reich, A. Banerjee, F. Schrodt, and M. Reichstein. (2012) Gap Filling in the Plant Kingdom – Trait Prediction Using Hierarchical Probabilistic Matrix Factorization . *International Conference on Machine Learning (ICML)*.
- Olson, David M., Dinerstein, Eric , Wikramanayake, Eric D., et al., (2001) "Terrestrial Ecoregions of the World: A New Map of Life on Earth", Vol. 51 No. 11, *BioScience* 933.
- Gilmanov, T. G. *et al.* (2003) "Gross primary production and light response parameters of four Southern Plains ecosystems estimated using long-term CO2-flux tower measurements." *Global Biogeochemical Cycles* **17**, 1071.