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Interactive comment on "Identifying environmental controls on vegetation greenness phenology through model-data integration" *by* M. Forkel et al.

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We are grateful to the anonymous Referee 2 for the very valuable comments (Biogeosciences Discuss., 11, C4434–C4436, 2014).

1 Length of the manuscript and selection of figures

"This is a very comprehensive and detailed study, and overwhelmingly provides evidence towards the main conclusion that the GSI model performs better than the original phenology scheme. The paper is well-written and structured, and the aims, methods and conclusions are very clear. There are possibly too many figures in this paper however, especially for the model evaluation, which I fear could prevent some from reading the manuscript thoroughly. The number of figures could be reduced by focusing on fewer features of the temporal and spatial analysis, such as choosing between the mean seasonal cycle, monthly time series and annual time series. This choice could be guided and justified by which scales the authors think are most important in terms of getting a correct representation of phenology in DGVMs."

We will consider this suggestion in the revised version of our manuscript. Specifically, we will shorten text with corresponding figures for the evaluation of spatial patterns and temporal dynamics of FAPAR (Figures 7-11). We will remove Figures 7, 8, and 10 from the main text. Additionally, we will combine and shorten the chapters 3.2.2 to 3.2.4 into a single chapter about model evaluation of FAPAR dynamics. This will provide more room to discuss remaining limitations and potential applications of the LPJmL-GSI phenology model.

2 Model deficiencies and impacts on carbon and water cycles

"The weight given to benchmarking the model, although useful, precludes more discussion on remaining model deficiencies and what further work could be done to improve the phenology schemes. It also leaves less room to discuss the wider impact of the improved phenology on other variables and feedbacks between the phenology and the carbon, water and energy cycles. These two points are discussed at various points, but the balance between this type of discussion and the results of the benchmarking could be slightly more even."

We will follow the referee's suggestion and use the gained room to summarize and discuss remaining model deficiencies in a separate chapter. We already have shown the impact of the improved phenology model on mean annual spatial patterns and mean seasonal cycles of gross primary production and evapotranspiration (Fig. 6 of the main text) and on global total carbon stocks and fluxes (Table E1 of the main text). As the focus of our manuscript is on model development, optimization and evaluation to finally identify controlling factors for phenology, a more detailed analysis of couplings between phenology and carbon, water and energy cycles will be addressed in future studies. In order to better understand these couplings it will be of benefit to use site-level FLUXNET eddy covariance data in ecosystem-scale optimization experiments if future studies (Kuppel et al., 2012; Williams et al., 2009).

"For example, the relative lack of impact of the new GSIbased model on ET is clearly stated but the significance of this in terms of using this new model, and what further work might be needed to improve this situation, is not discussed further."

We are thankful for the referee's comment on ET. Motivated by this comment we checked again the computation of ET. Thereby we found a mistake in the post-processing of our global LPJmL model results. ET from LPJmL consists of three components: transpiration, evaporation and interception loss (Gerten et al., 2004). We forgot to consider the interception loss in our previous computations of ET. This is the reason why ET was too low in comparison with the MTE estimate in most regions (especially tropical forests) in our previous results (Fig. 6 of the main text). We updated this figure (Figure 1 a). Nevertheless, the interpretation remains the same that LPJmL-GSI did not affect much mean annual ET. ET increased in LPJmL-GSI and LPJmL-OP-gc in comparison to LPJmL-OP-prior only in tropical rainforests around the Equator. This is due to the increased GPP in these regions. In other regions ET remained almost unchanged. But this does not imply that LPJmL-GSI does not affect transpiration processes (Figure 1 b-d). Indeed, LPJmL-GSI had lower interception losses than LPJmL-OP in boreal forests because of the reduced tree cover. On the other hand this implies that soil evaporation was increased. As a consequence of decreased interception and increased soil evaporation in LPJmL-GSI in comparison to LPJmL-OP in boreal regions, the total evapotranspiration remained unchanged. LPJmL-GSI resulted also in a different seasonality of soil evaporation, interception and transpiration than

LPJmL-OP (Figure 2).

3 Transferability to other DGVMs

"The authors stop short of making recommendations to other modelers. The results show, and they state clearly, that the GSI-based model performs better, even before optimization. Both implementing new models and optimizing existing ones takes considerable time and effort (which is one reason why this exhaustive study is so impressive), so what can they suggest to other modeling groups. Would they suggest that in order to improve the phenology, researchers working with other models might want to consider implementing some version of the GSI model, even without optimization? This discussion would be a further contribution, given the GSI model is a significant shift from the typical type of phenology models used in many other DGVMs."

Our results demonstrate the improved performance of LPJmL-GSI. Consequently, we suggest considering besides temperature, effects of light and water availability in phenology modules of other DGVMs. We believe that similar approaches like the LPJmL-GSI phenology module can be adapted in other models. Nevertheless, this has to be done with care. A 1:1 adaptation to other models is risky because of several reasons: (1) LPJmL-GSI is an empirical model with PFT-dependent parameters that need to be estimated. (2) Models do not use the same definition and set of PFTs. (3) Models use different hydrology routines. (4) Our posterior parameters for phenology were also constrained by using albedo and GPP data. Thus LPJmL-GSI model parameters cannot be easily transferred to other models. It might be possible to use the parameters of the temperature and light limiting functions in other models because these functions depend on forcing data. On the other hand, the parameters for the water availability limiting function might need to be re-optimized because of differences in soil moisture computations. Consequently, other modelling groups need to be aware about the potential need to optimize parameters of the LPJmL-GSI phenology model in order to obtain plausible model results. We think that the LPJmL-GSI phenology model can be probably easy applied to other models of the LPJ “family” (Prentice et al., 2011; Smith et al., 2001) that are using the hydrology routines of Gerten et al. (2004) while probably a higher effort including parameter optimization is needed to adapt the model to other types of DGVMs or ecosystem models.

4 Correlations between parameters, dataset differences and posterior uncertainties

“One final remark, the authors emphasize that water can be limiting in all ecosystems, but in the boreal tundra regions for example water may be limiting because the permafrost has not thawed, but this surely this is ultimately controlled by temperature? Light also seems to be limiting in all ecosystems.”

We agree with the referee that seasonal water availability in boreal and arctic regions is too a large extent driven by air temperatures. Nevertheless, besides air temperature, variations in snow or vegetation cover affect soil temperature and moisture and thus water availability. Consequently water availability might be an important factor in explaining other than seasonal, e.g. inter-annual, variations of land surface phenology in boreal and arctic regions. Please refer to our response to the first referee (Biogeosciences Discuss., 11, 2014, page C4390) where we explained this issue already in more detail. Our results do not show that light is limiting in all ecosystems but only in arctic, boreal and temperate regions. We found no effects of light on phenology in subtropical and tropical regions (Figure 12 of the main text). The cold temperature and light limited functions were not fully temporally synchronized (Figure 12 of the main text). This indicates that we were able to disentangle the effects of light and cold temperature on phenology.

“Also, one technical point, it would be interesting to see the correlations between these environmental limiting parameters, as their sensitivity and posterior value is conditioned on their prior ranges (which may be unrealistic for certain ecosystems) and the uncertainty on the observations.”

We do not understand what the referee exactly means with this comment.

1) Does the referee want to see correlations between the prior and posterior value of a parameter?

2) Does the referee want to see correlations between all posterior values of all parameters?

Regarding 1, we computed the correlation between the prior parameter value and the respective posterior parameter values from single grid cell optimization experiments of LPJmL-GSI (Figure 3). We found low to moderate correlations between the chosen prior and the optimized posterior parameters (maximum correlation r = 0.54 for TMINBASE). Additionally, prior and posterior parameter ranges were only weakly correlated. This indicates that posterior parameter values had higher correlations with their respective prior parameter values if reliable prior estimates were available (e.g. for ALPHAA from the OP.gc experiment, for ALBEDOLEAF from MODIS, for TMINBASE estimated from Stöckli et al. (2011)). On the other hand, for parameters for which only vague or no prior values were available, posterior values were low correlated (LIGHTEXTCOEFF, TMAXBASE, LIGHTBASE, WATERBASE).

Regarding 2, we computed correlations between posterior parameter values for the four most important phenology parameters of LPJmL-GSI (TMINBASE, LIGHTBASE, WATERBASE and TMAXBASE) (Figure 4). Most correlations are low to moderate (maximum r = 0.69). The correlation between the TMINBASE and WATERBASE parameters is low in PFTs that experience strong permafrost dynamics (BoNS r = 0.2, PoH r = -0.28). This indicates that the water and cold temperature limiting in boreal and arctic regions are only weakly correlated. Indeed, our results show that water availability affects phenology mostly in early spring whereas cold temperature affects phenology during the entire year in boreal and arctic regions (Figure 12 of the main text). These results emphasize the ability to disentangle effects of seasonal air temperature and soil moisture on phenology in boreal and arctic regions.

“The authors have acknowledged some deficiencies with the different datasets in some regions. Could such deficiencies influence one particular parameter value which could then alter the values of other parameters? If so, could this possibly result in an overemphasis of conclusions drawn from analyses using these posterior parameters?”

The generally low correlations between parameters and the differences in the correlation matrices between the different PFTs (Figure 4) suggest that the relationships between parameters are more determined by the climate-FAPAR co-variations than by model structure itself. But indeed we acknowledge that once a constraint dataset is changed subsequent changes in optimized parameter vectors may occur. In our case, it may be especially relevant if the co-variation between the FAPAR datasets and the climate forcing differs widely. For the different PFTs considered, the largest differences in the seasonal cycle between datasets occurs for the temperate broad-leaved evergreen PFT (TeBE, Figure 8 of the main text), but which represents only 0.6 per cent of the land surface. To test the effect of these differences on optimized model parameters we optimized LPJmL-GSI for the TeBE PFT against the GIMMS3g and GL2 datasets, respectively (Figure 2). As expected, we found differences in parameters that control for maximum FAPAR (light extinction coefficient) which compensate for the biases between datasets - the higher light extinction coefficient for GIMMS3g reflects higher mean FAPAR when compared to the GL2 dataset (TeBE, Figure 8 of the main text). We further observe a substantial overlap between the posterior parameter distributions of the parameters controlling the responses to climate conditions. The differences in some of the optimum values found are not completely unexpected, since the seasonality of both products does not really agree, hence, neither should the FAPAR-climate sensitivities that are driven from each of these products. We recognize that the differences between products are still an active topic of discussion (Atzberger et al., 2013; Baret et al., 2013; Fensholt and Proud, 2012; Scheftic et al., 2014). But evaluating which of these datasets embeds a superior representation of vegetation dynamics in these regions falls beyond the scope of this work. Here, the choice of the GIMMS3g dataset for optimization relies mostly on its longer temporal record and the extensive current developments in multi-sensor harmonization (Pinzon and Tucker, 2014) which allow to detect vegetation response to inter-annual climate dynamics (Zeng et al., 2013).

We further tested how generally the posterior parameter uncertainties (from optimizations with the GIMMS3g dataset) can affect our conclusions about environmental controls for phenology in different ecosystems. For this we sampled ($n = 500$) individuals from the PFT-level optimization experiment that had an AIC difference dAIC <= 2 in comparison to the respective optimum parameter set. These individuals are equally plausible in explaining the observations like the best individual. We run LPJmL-GSI with these 500 single posterior parameter sets and analyzed the distribution of FAPAR and the cold, light, water and heat stress limiting functions for phenology. Given the computational costs of a global quantification of uncertainty based on a 500-element ensemble, we did this analysis only for a few selected grid cells per PFT. We found relatively small uncertainties for all variables (Figure 6). Importantly, the posterior parameter uncertainty did not affect the relative importance of the limiting functions for phenology. In summary, we are convinced that the choice and uncertainty of posterior parameters does not affect our conclusions about the relative importance of environmental controls for vegetation greenness phenology.

5 Minor points

"The sentence structure could be improved in places, for example: p21 lines 21 and 22 p26 line 26 p28 line 6"

We will consider these comments in the revised version.

"Some figure references do not appear to be what they should be, particularly in section 3.2.3"

We will correct this in the revised version.

"p 26 line 12 should be Congo Basin."

We cannot find this reference in our manuscript. A more specific suggestion would be very useful.

"In figure E2 the y and x axis scale and labels could be removed except on left and bottom in order to make figures bigger and more easy to see."

We will consider this in the revised version.

6 References

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7 Extended figure captions

Figure 1: Latitudinal gradients of evapotranspiration with its components.

Figure 2: Mean seasonal cycle (1982-2011) of ET, evaporation, interception and transpiration spatially averaged for PFTs.

Figure 3: Scatterplots and correlations between prior and posterior values of LPJmL-GSI model parameters from single grid cell optimization experiments (GSI.gc). Each dot represents the optimized parameter value from a single grid cell optimization experiment. In each experiment the same prior value was used (PFT-dependent). For TMAXBASE and WATERBASE the same prior parameter value was used for all PFTs. Vertical dashed lines indicate the lower and upper limit of the prior parameter range. The blue line is a linear regression between prior and posterior parameter value. Blue Numbers on top of each plot are Spearman correlation coefficients between (1) prior and posterior parameter value and between (2) prior parameter range and posterior parameter range.

Figure 4: Correlations between posterior parameters for the four limiting functions for phenology in LPJmL-GSI grouped per PFT. Correlation matrices were computed based on all “best” individuals (i.e. parameters sets) from PFT-level optimization experiments (GSI.pft). “Best” individuals have an AIC difference of dAIC <= 2 in comparison to the individual with the lowest AIC, i.e. they are equally plausible. Numbers are Pearson correlation coefficients. Lines in the scatter plots are LOWESS smoothing lines (locally-weighted polynomial regression).

Figure 5: Posterior parameter uncertainty and sensitivity from the optimization of the TeBE PFT against the GIMMS3g and GL2 FAPAR datasets, respectively. The range of the x-axes agrees with the prior parameter ranges. Only parameter values from individuals with dAIC <= 2 are shown.

Figure 6: Posterior uncertainty in the mean seasonal cycles of FAPAR and the cold, light, water and heat stress limiting functions for phenology for four example grid cells.

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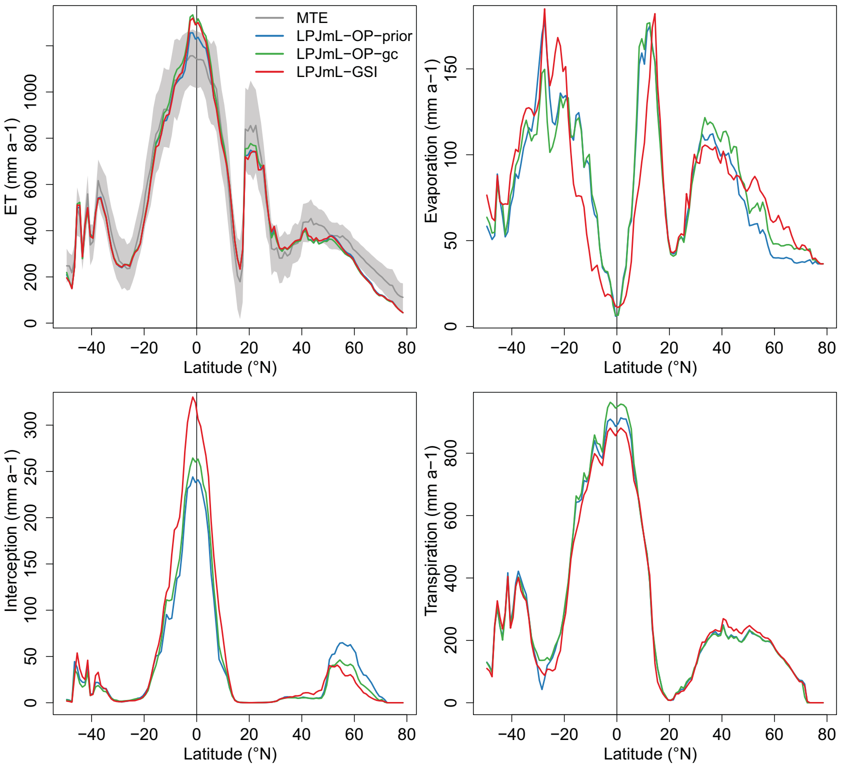

Fig. 1. Latitudinal gradients of evapotranspiration with its components.

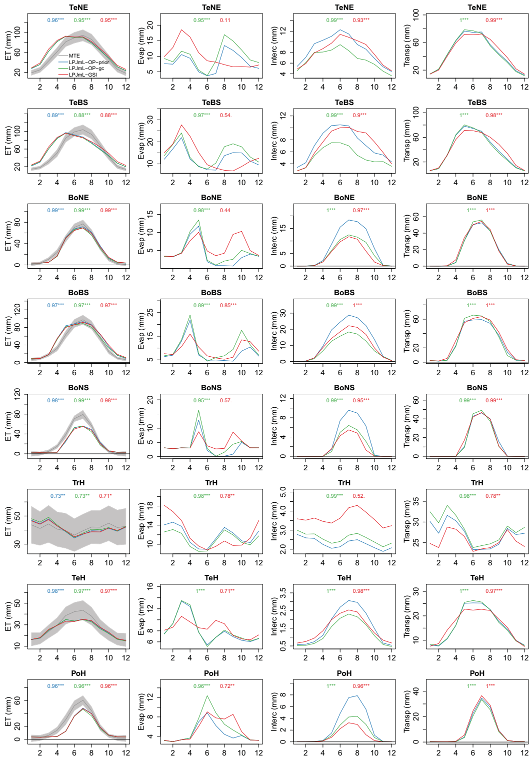

Fig. 2. Mean seasonal cycle (1982-2011) of ET, evaporation, interception and transpiration spatially averaged for PFTs.

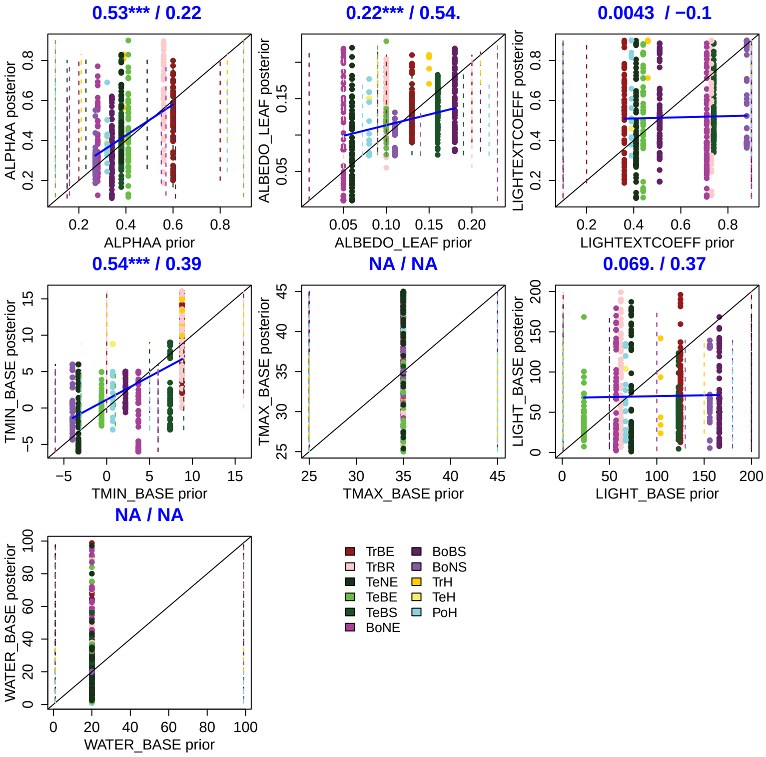

Fig. 3. Scatterplots and correlations between prior and posterior values of LPJmL-GSI model parameters from single grid cell optimization experiments (GSI.gc). (see extended figure caption)

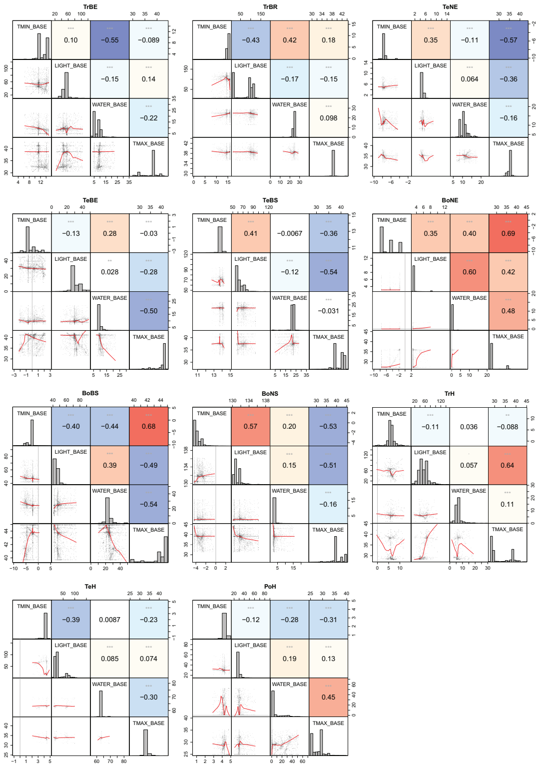

Fig. 4. Correlations between posterior parameters for the four limiting functions for phenology in LPJmL-GSI grouped per PFT. (see extended figure caption)

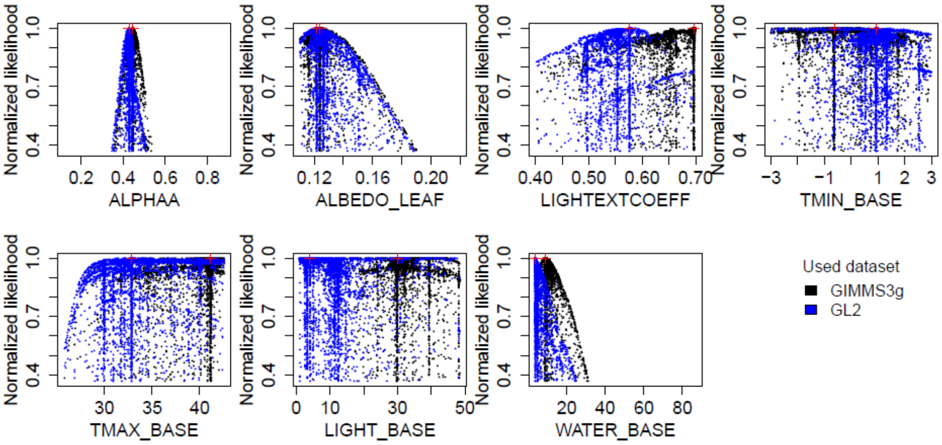

Fig. 5. Posterior parameter uncertainty and sensitivity from the optimization of the TeBE PFT against the GIMMS3g and GL2 FAPAR datasets, respectively. (see extended figure caption)

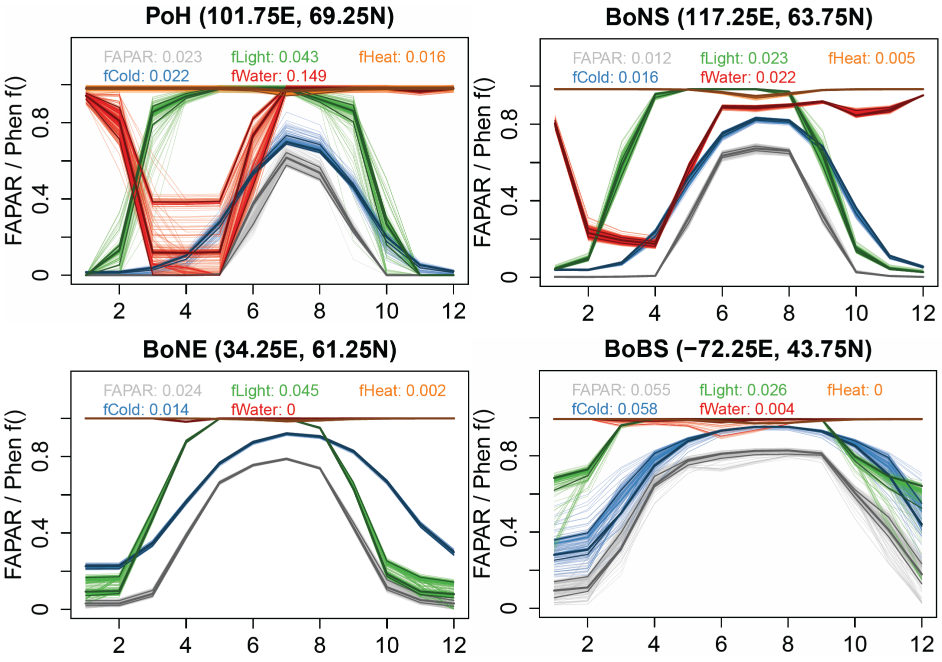

Fig. 6. Posterior uncertainty in the mean seasonal cycles of FAPAR and the cold, light, water and heat stress limiting functions for phenology for four example grid cells.