SATELLITE CARBON CYCLE MODEL-DATA ASSIMILATION

How can we best constrain terrestrial biosphere model carbon cycle predictions using satellite remote sensing data?

1 INTRODUCTION

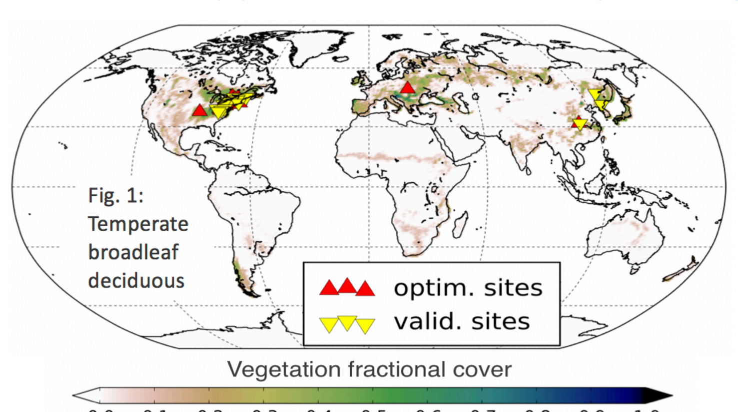
Predicting the fate of the terrestrial carbon, C, sink under future global change strongly relies on our ability to accurately model global scale vegetation dynamics and surface CO_2 fluxes. However, terrestrial biosphere model (TBM) leaf phenology and C cycle processes remain subject to large uncertainties, partly because of unknown or poorly calibrated parameters. Satellite remote sensing (RS) data offer us the possibility to optimize these model parameters for the dominant plant functional types (PFTs) over large spatial scales and in regions that have limited field-based data. Here, we present past studies in which we have used RS data to optimize ORCHIDEE TBM simulations of vegetation phenology and gross C uptake (GPP). We have used our state-of-the art data assimilation (DA) system to investigate the constraint on global GPP brought by assimilating normalized difference vegetation index (NDVI) and solar induced chlorophyll fluorescence (SIF).

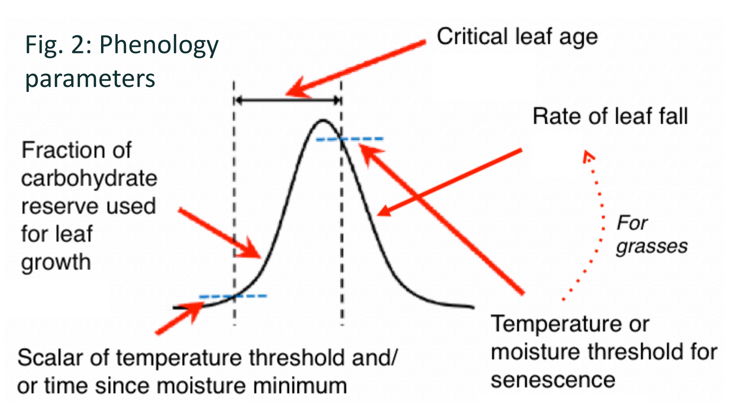
2 ORCHIDEE TBM AND DATA ASSIMILATION METHOD

- ORCHIDEE terrestrial biosphere model the land component of the French IPSL earth system model (version used in IPCC AR5/CMIP5 used here).
- 13 plant functional types (PFTs); big leaf phenology; Farquhar/Collatz C3/C4 photosynth.
- Bayesian data assimilation (DA) algorithm → update prior knowledge of parameter values and distributions based on new information in observations.
- Gradient decent methods (L-BFGS-F and finite difference) to minimize a cost function $J(x)$ that represents the misfit between model and data (red in eq 1), and misfit between new and prior parameter values, taking account uncertainty on parameters (green in eq 1):

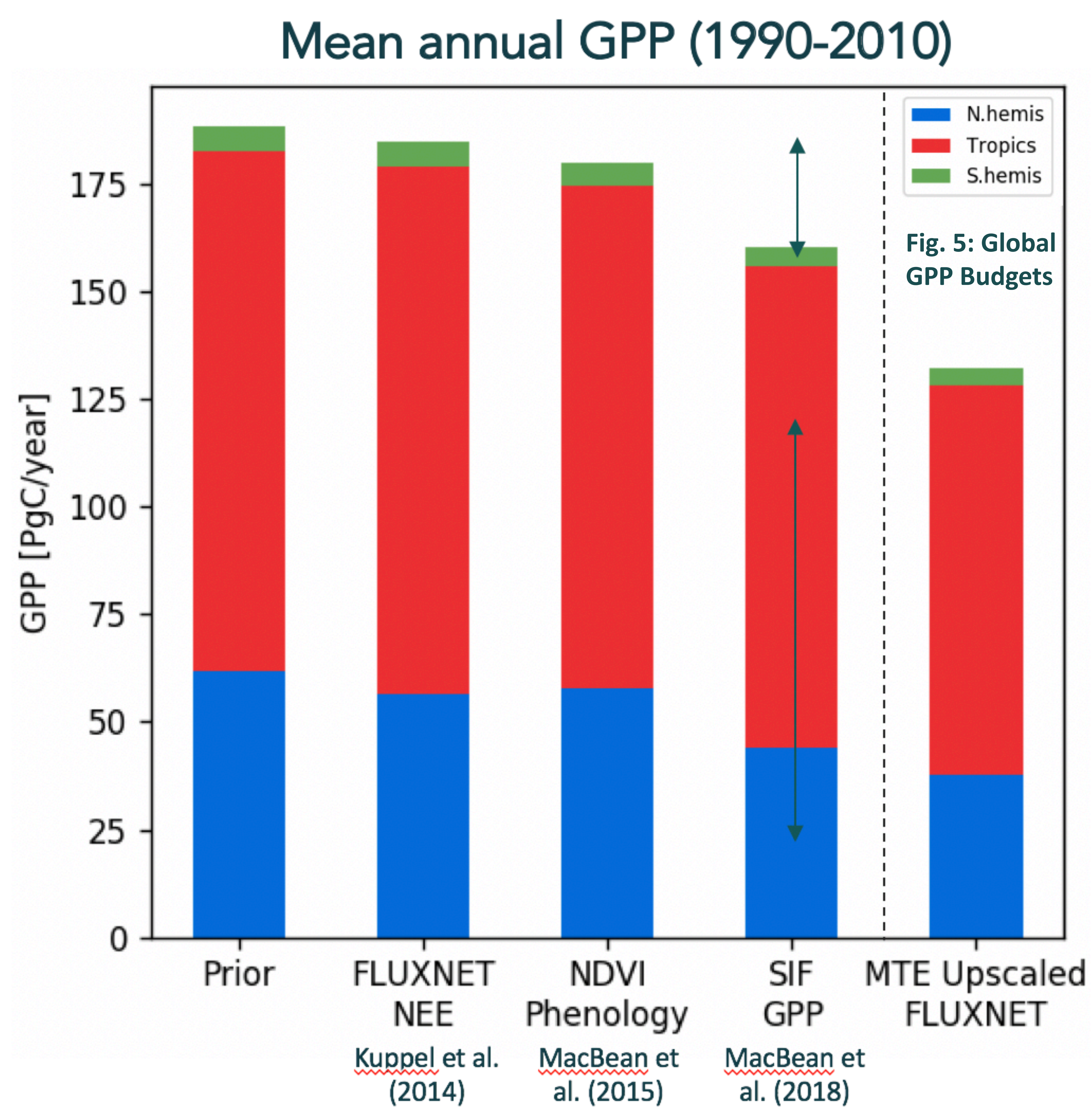
$$J(\mathrm{x}) = \tfrac{1}{2}(\mathbf{M}(\mathrm{x})-\mathrm{y})^{\mathrm{T}}\,\mathbf{R}^{-1}(\mathbf{M}(\mathrm{x})-\mathrm{y}) + \tfrac{1}{2}(\mathrm{x}-\mathrm{x_b})^{\mathrm{T}}\,\mathbf{B}^{-1}(\mathrm{x}-\mathrm{x_b}) \qquad (1)$$

- 15 grid cells per PFT optimized → 1 resultant parameter vector per PFT to run global simulations (see Fig. 1)
- **STUDY 1: Normalized MODIS NDVI data (2000-2008) used to constrain normalized model FAPAR (fraction of absorbed photosynthetic radiation) - (MacBean et al., 2015).**
  - Only parameters related to phenology of deciduous PFTs (see Fig. 2)





- **STUDY 2: GOME-2 Solar Induced Chlorophyll Fluorescence (SIF) data to constrain model gross CO2 fluxes (gross primary productivity – GPP)**
  - Linear relationship between GPP and SIF (MacBean et al., 2018)
  - Mechanistic model between GPP and SIF based on SCOPEv1.61 (Bacour et al., 2019)
  - Parameters related to photosynthesis, phenology and GPP-SIF model.

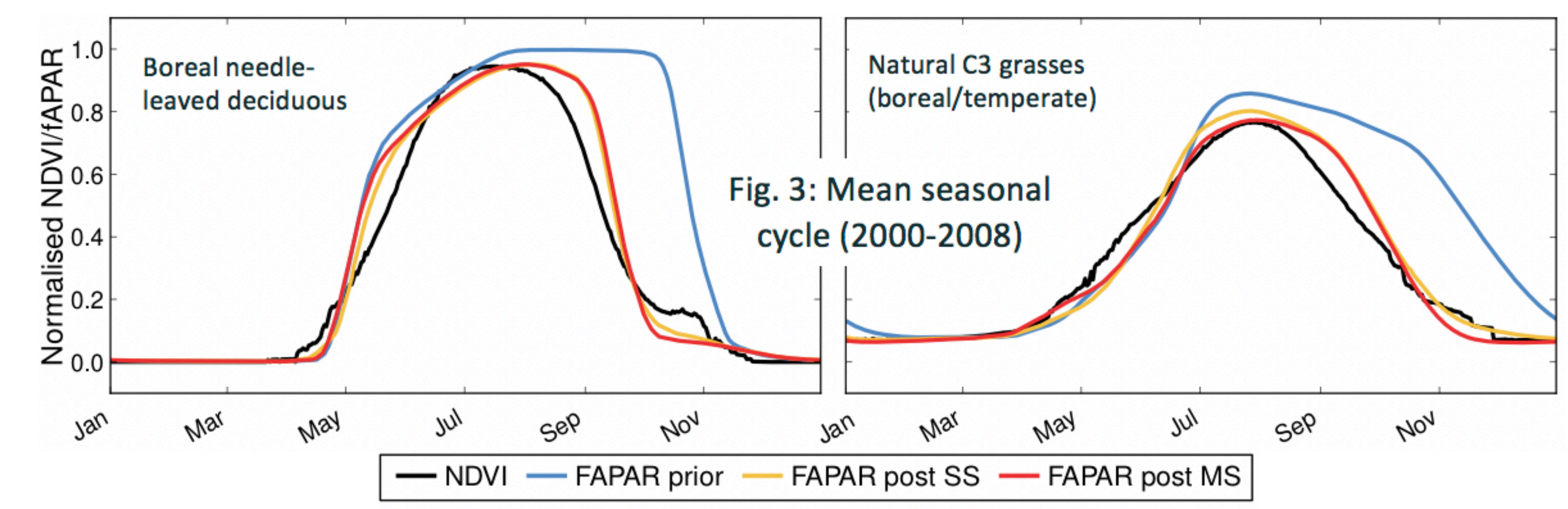


5 Impact on global GPP budgets

- Optimizing net CO_2 fluxes using FLUXNET data from 53 sites globally/7 PFTs (Kuppel et al., 2014; not shown here) actually had least impact on global GPP budgets (Fig. 5)
- NDVI reduced growing season length → small impact on GPP in both NH and Tropics
- SIF has greatest constraint on global GPP budgets due to strong decreases in positive model bias in both NH and Tropics → redistribution of global GPP & better compares to independent data-derived estimate from upscaled Fluxnet data (Jung et al., 2011).

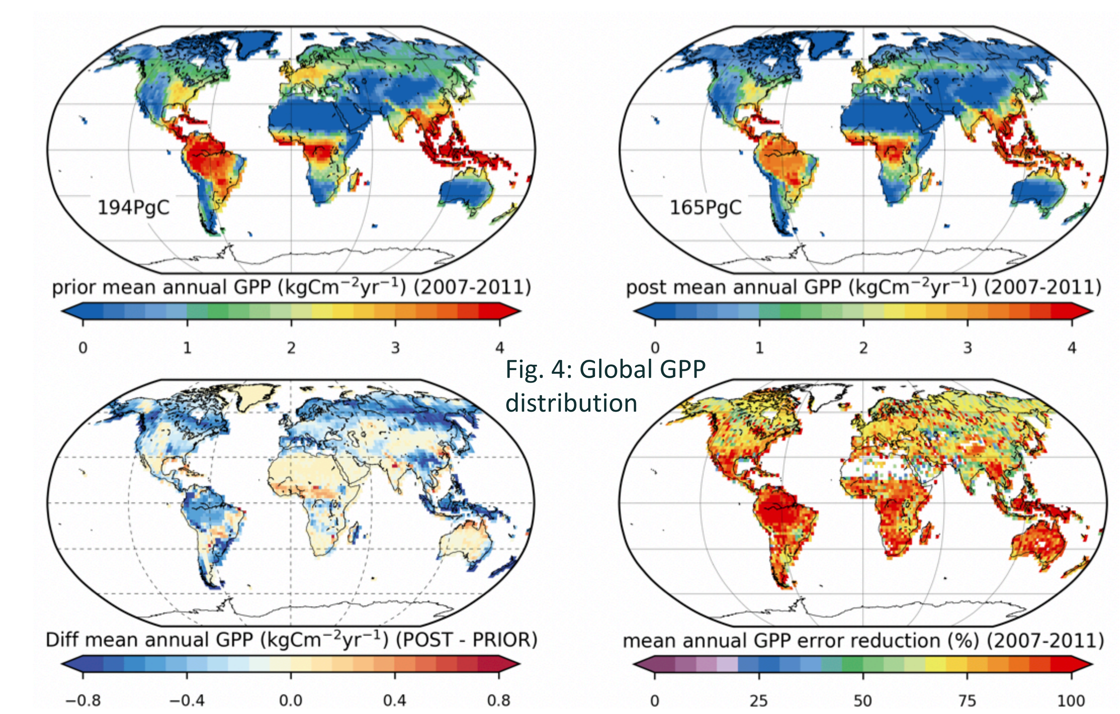
3 USING NDVI TO CONSTRAIN SEASONAL LEAF PHENOLOGY

- Optimization of phenology parameters shortened the growing season due to a earlier start to senescence (higher temp/moisture senescence thresholds) (MacBean et al., 2015)
- All temperate and boreal deciduous PFTs → however, no constraint for semi-arid PFT phenology



4 SATELLITE SIF FOR CONSTRAINING GLOBAL GPP

- Decrease in global GPP magnitude for all PFTs
- …except for moisture-driven PFTs
- Highest decrease in NH extra tropics → shift in global GPP distribution
- Strong reduction in uncertainty (~83%)



6 ONGOING AND FUTURE STUDIES

- Is there a difference in SIF constraint on GPP between linear vs mechanistic SIF-GPP model? (Kashif Mahmud working w/ NM.
- Do we gain information in the assimilation when using *both* NDVI and SIF to constrain photosynthesis, phenology and parameters of SIF-GPP model? (KM with NM).
- Do we need to include leaf biomass parameters when optimizing phenology and GPP? (NM and CB).
- Can issues with joint assimilation of satellite FAPAR and FLUXNET data (model degradation to other variable) be improved if we remove the big leaf model and instead have of multi-layer canopy? (NR, JGD, NM and PP as part EU H2020 MULTIPLY Project: http://www.multiply-h2020.eu).

Natasha MacBean[1] (nmacbean@indiana.edu), Cédric Bacour[2], Fabienne Maignan[3], Philippe Peylin[3], Vladislav Bastrikov[3], Nina Raoult[3], Jose Gomez-Dans[4].

[1]Indiana University - Bloomington, [2]NOVELTIS, France, [3]Laboratoire des Sciences du Climat et de l'Environnement, [4]University College London.

References: MacBean et al., 2015, BG; MacBean et al. (2018), Scientific Reports; Bacour et al. (2019), JGR-B; Kuppel et al. (2014), GMD; Bacour et al. (2015), JGR-B.