Multiple data stream assimilation in a land surface model to improve regional to global simulated carbon budgets: synthesis and prospective with the ORCHIDEE model

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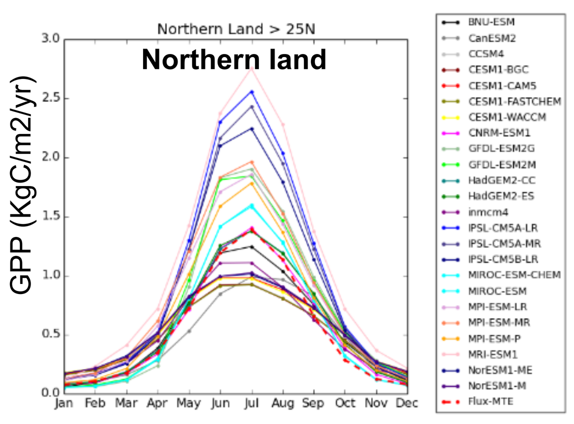
1 Objectives / System description

Introduction

- Disagreement between terrestrial Carbon cycle models is a major source of uncertainty in climate change projections.
- Accurate simulations of Gross Primary Production (GPP) and Respiration are a root of the problem.
- Data assimilation into Land Surface Models (LSMs) allows optimizing key model parameters and initial state, hence reducing the uncertainties in gross/net carbon fluxes.

Ex: GPP from CMIP5 models

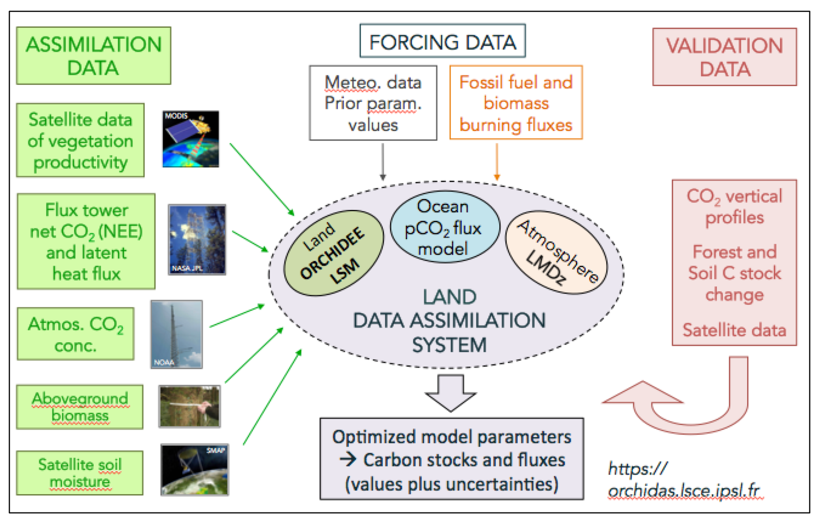


➔Large GPP amplitude & phase differences across CMIP5 models

ORCHIDEE Data Assimilation System

https://orchidas.lsce.ipsl.fr/

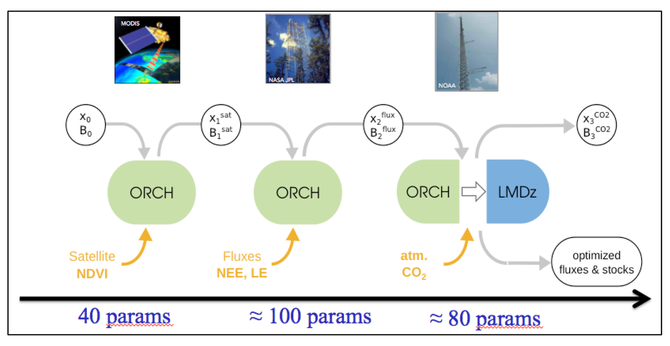
- Carbon Cycle Data Assimilation System (CCDAS) based on the ORCHIDEE Land Surface Model, which is the surface component of the IPSL Earth System Model used for CMIP6 simulations



CCDAS scheme coupling ORCHIDEE & the LMDz atmospheric model :

- Assimilation of multiple data streams related to C/W/E budgets;
- To correct model parameters and initial state

- **Step-wise approach**: A practical solution to assimilate multiple data streams: posterior information (parameter values & errors) is carried from one step to the next *(ex. with NDVI, FluxNet, Atm. Data)*



Bayesian optimization framework

- Minimization of a cost function with Gaussian error distribution on parameters (x, B) & observations (Y, R)

$$J(x) = \tfrac{1}{2}(H(x)-y)^T R^{-1}(H(x)-y) + \tfrac{1}{2}(x-x_b)^T B^{-1}(x-x_b)$$

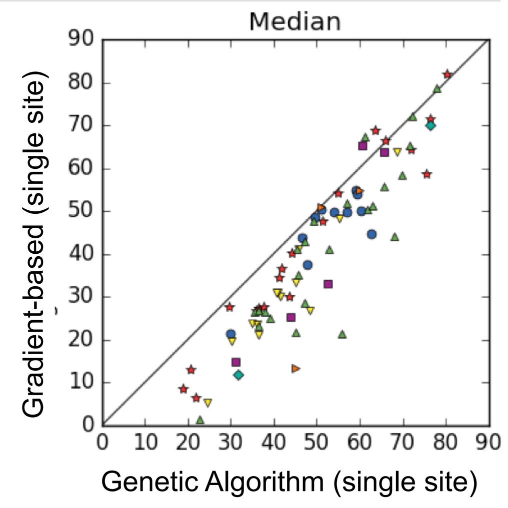
Either

- Gradient-based method (Iterative minimisation)
- Ex: BFGS algorithm Need to compute DJ / Dx

- Monte-Carlo approach (random search)
- Ex: Genetic Algorithm (GA)

Optimisation at 75 FluxNet sites using NEE / LE data

Fig: Model–data RMSD reduction (in %) for Gradient-based versus Genetic (GA) algorithms: Median values across 16 random first-guess tests.



➔ GA is superior to reduce J(x)

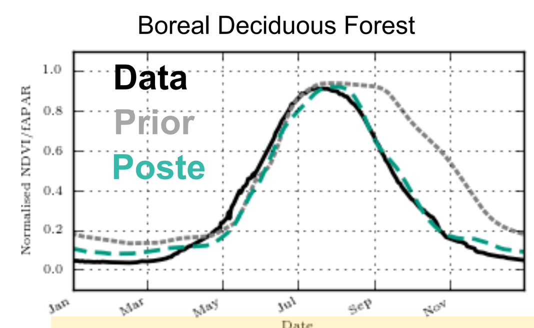
➔ Need several first-guess tests with gradient method

2 Current constraints from main observation data streams

Step1: Assimilation of MODIS-NDVI data

4 phenology parameters / Plant Functional Type (PFT)

MacBean et al., 2015



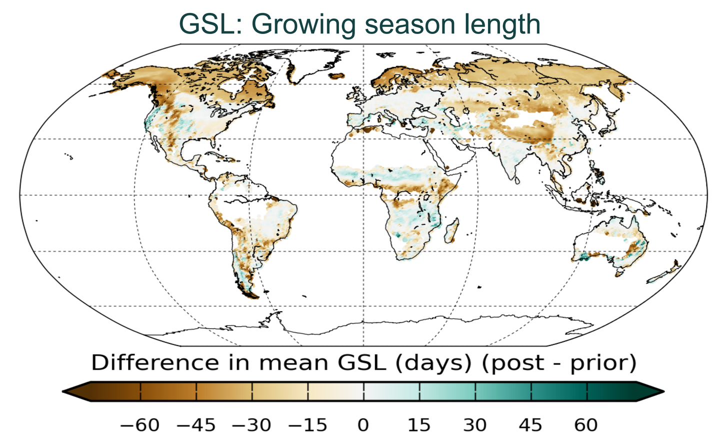
Improvement of the mean model seasonality for most PFTs

➢ Normalised model FAPAR compared to normalised MODIS-NDVI (2000-2008): Optimization of leaf Onset & Senescence

➔Reduction of the simulated growing season length (GSL

➔Mean annual global GPP is decreased by ~10 PgC/yr

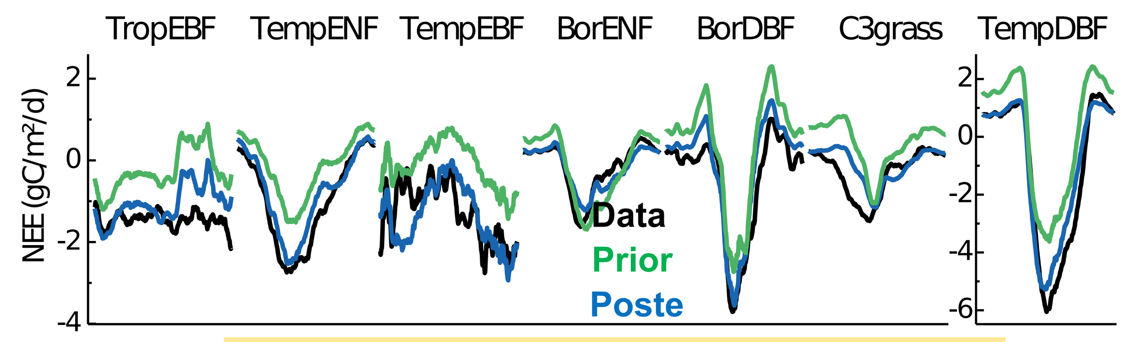
Differences in the simulated GSL between standard and optimised model



Step2: Assimilation of NEE / LE daily fluxes (75 FluxNet sites)

≈ 20 parameters / PFT

Kuppel et al., 2014



Mean seasonal cycle (average across all sites of each PFT)

➔Optimization of photosynthesis, respiration and allocation parameters

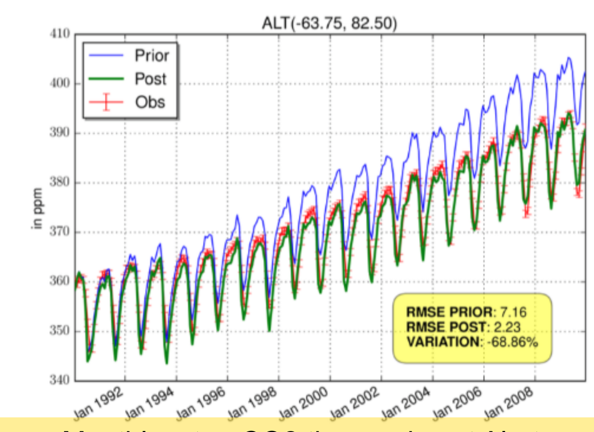
➔Correction of the NEE amplitude & phase through corrections of the GPP and TER fluxes in agreement with those estimated from the NEE data.

➔Global simulations with optim parameters improve the simulated atmospheric CO_2 concentrations.

Step3: Assimilation of Atmospheric $[CO_2]$ data (53 sites)

≈ 120 parameters in total

Peylin et al., 2015



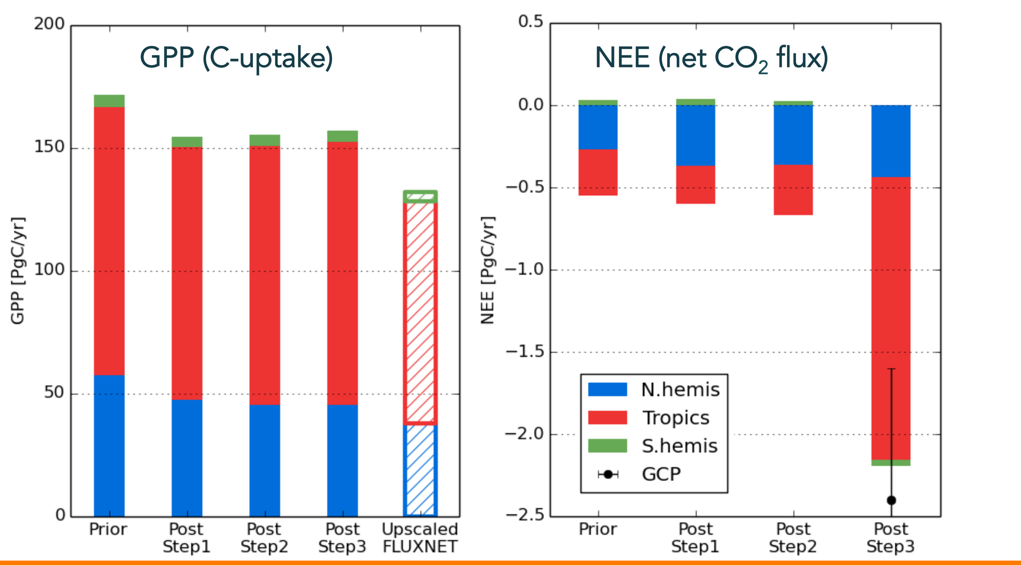
Monthly atm, CO2 time series at Alert (observed and simulated)

- Coupling ORCHIDEE with LMDz transport model
- Assimilate $[CO_2]$ data over 1990 - 2010
- Optimize all parameters + regional soil C pools

➔ Significant correction of the net carbon fluxes to match the observed atmospheric CO_2 trend; only small improvement of the inter-annual CO_2 concentration variations

Prior and posterior GPP/NEE fluxes (by latitude bands) from each step: comparison with the GPP from a data-driven model (Jung et al. 2011) & the NEE from the GCP budget (LeQuere et al. 2015).

➔ Net C flux mainly constrained by the $[CO_2]$ data

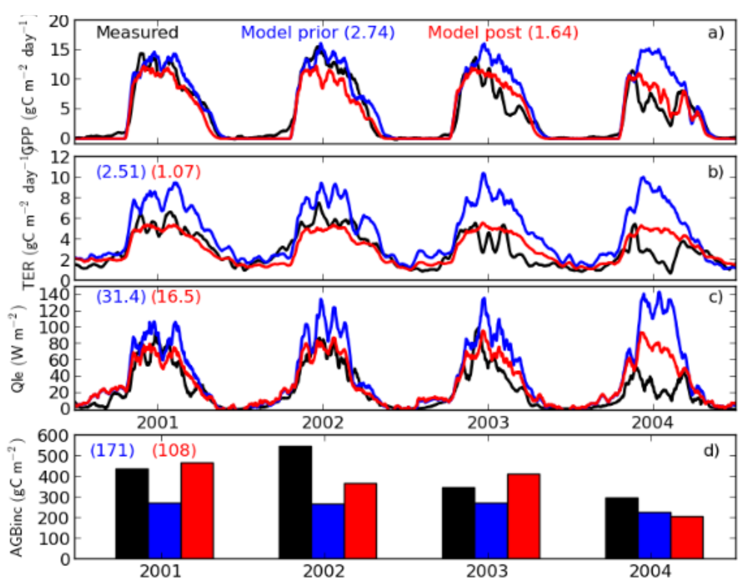


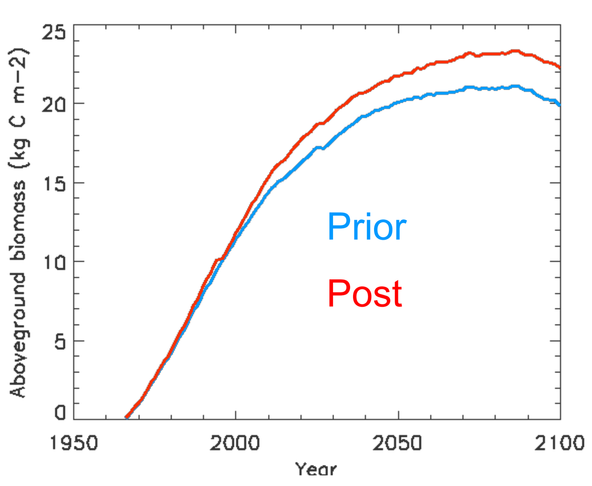
3 Potential global constraint from new data streams

Forest Biomass data (future ESA-BIOMASS mission)

- Joint assimilation of daily **NEE** & **LE fluxes** and annual Above Ground Biomass increment (**ABG**) at a deciduous forest site (22 parameters optimized)

Hesse site: daily fluxes and annual ABG increments, before and after optimization, compared to observations





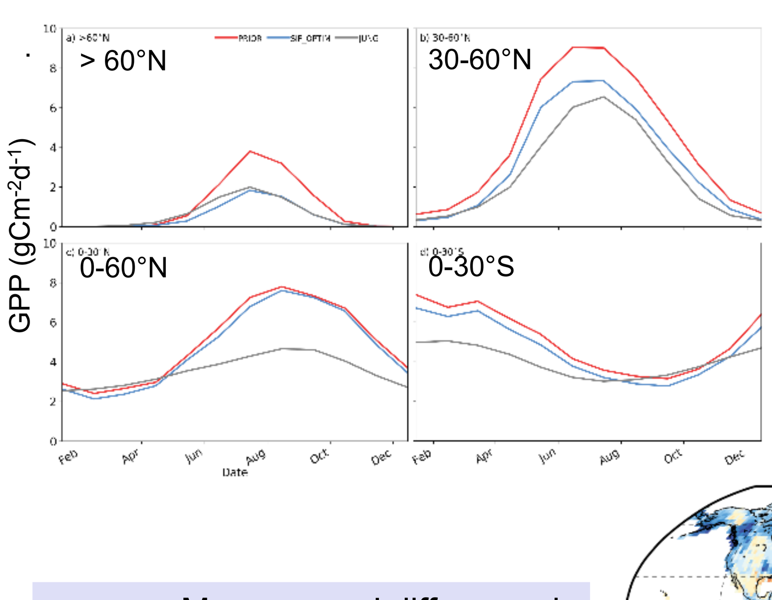
Impact of the optimisation on the future simulated annual ABG (using a climate scenario from CMIP5)

➔Use of **ABG increment** strongly constraint the allocation parameters of ORCHIDEE

➔Need to improve mortality processes (natural and anthropogenic thinning) to properly use future BIOMASS data

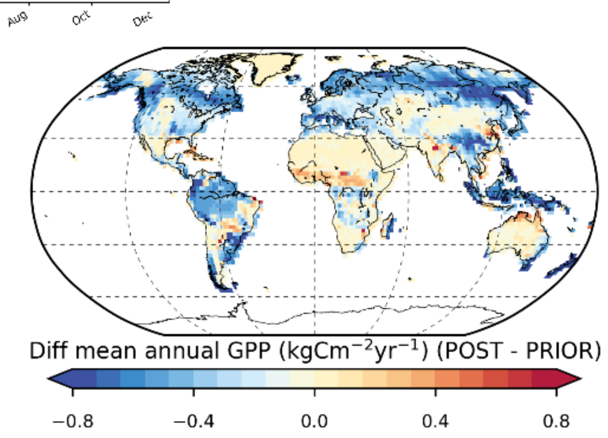
Sun-Induced Fluorescence (SIF) (existing satellite products, FLEX)

- Multi-pixel assimilation of GOME-2 SIF products (2007-2011)
- Simple linear relationship per PFT: ***GPP = a.SIF +b***
- Optimization of photosynthesis parameters plus a & b



Evaluation of the GPP seasonality by latitudinal bands versus Jung et al. (2011) GPP FluxNet-derived product

Mean annual difference in simulated GPP before and after assimilation of GOME-2 SIF data (MacBean et al., submitted)



➔Improvement of GPP seasonality and magnitude (vs Jung et al.); 28 PgC/year reduction in global annual mean

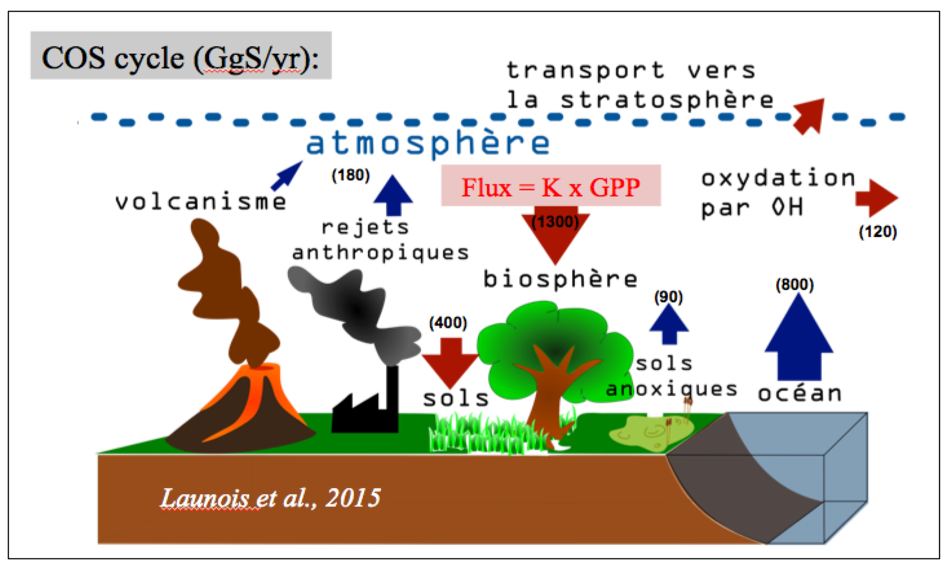
➔Strong constraint on photosynthesis parameters

➔Inclusion of a mechanistic SIF model in ORCHIDEE (on-going) should allow to better exploit satellite SIF data.

➔Nevertheless, uncertainties on SIF products (e.g. magnitude) currently limits their potentials;

Atmospheric [COS] data (existing in-situ / satellite data)

➔ A new tracer of photosynthesis



- Uptake of COS by vegetation is proportional to CO_2 uptake (GPP) with a relative uptake ratio (Seibt et al. 2010)

➔ **Use atmospheric CO_2/COS to constrain GPP seas-cycle**

➔ Example below shows: i) Too large GPP amplitude at high lat for ORCHIDEE and ii) GPP phase shift for CLM4CN models.