

Multi-purpose, modularized, testable, and
fully constrained against multiple datasets:
A Vision for the Future of Land Surface Model Development

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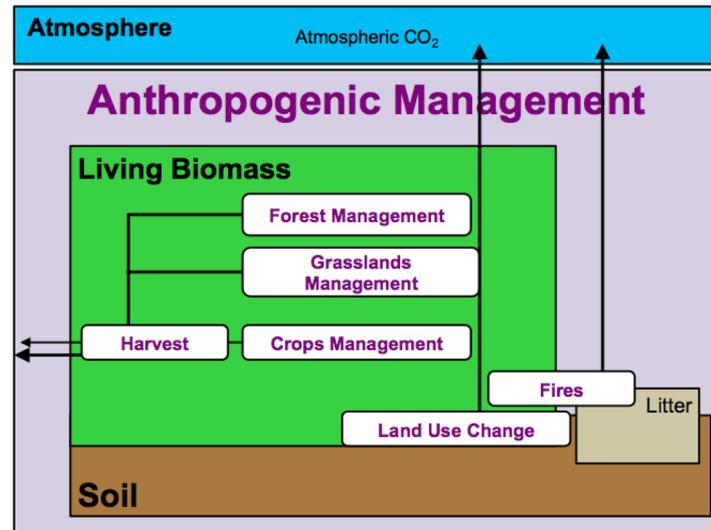
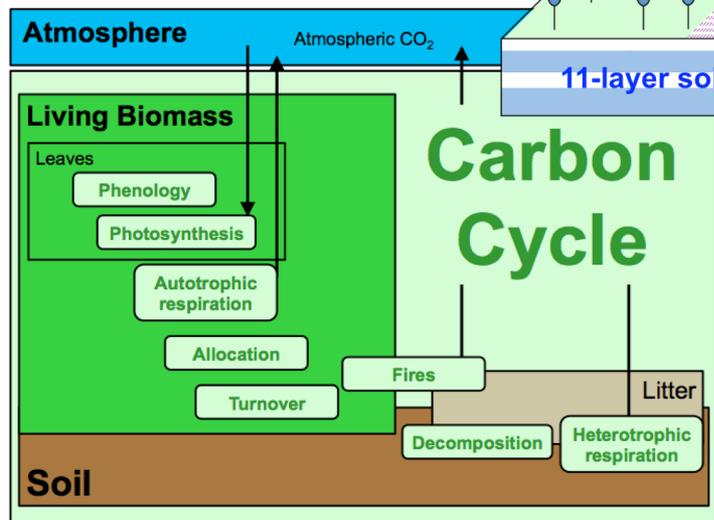
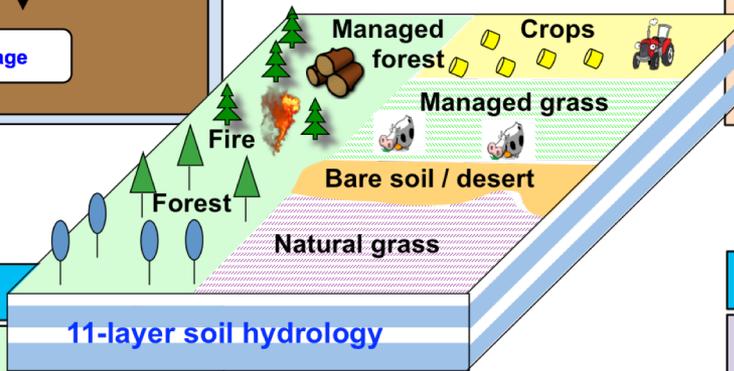
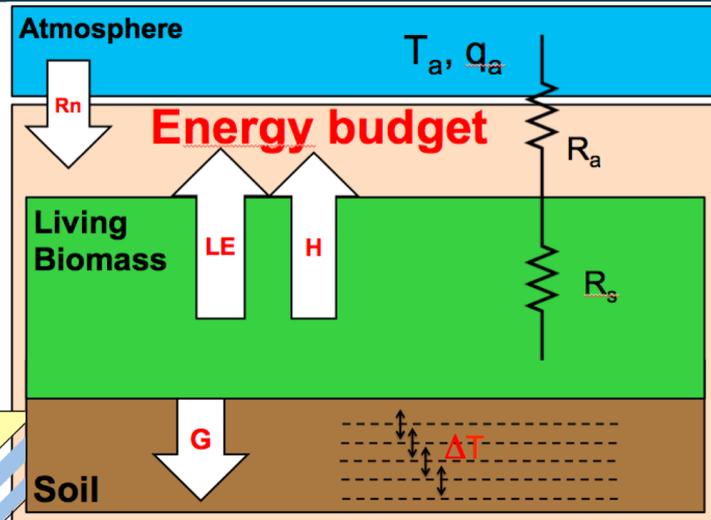
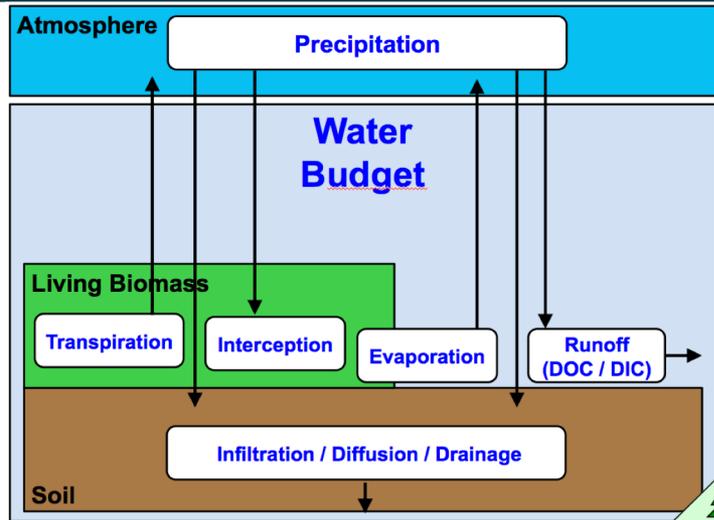
Andy Fox, Dave Moore

Outline

Data assimilation as a tool for reducing uncertainty in land surface models

- Highlights with the ORCHIDEE LSM
- Challenges we face
- Future perspectives

Global terrestrial biosphere models (TBMs)

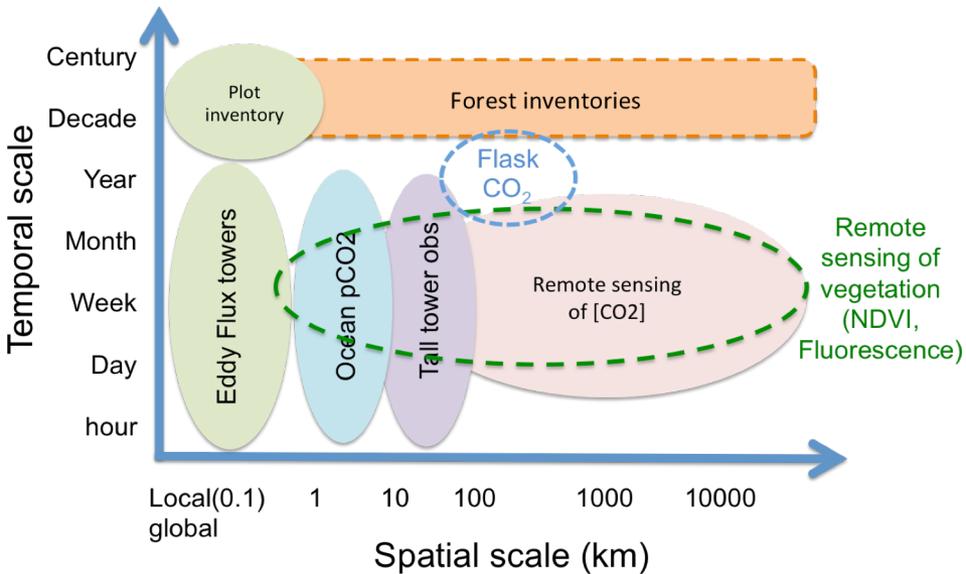


ORCHIDEE
TBM

13 Plant
Functional
Types (PFTs)

Reducing uncertainty: the need for model – data integration

Available C-related data streams

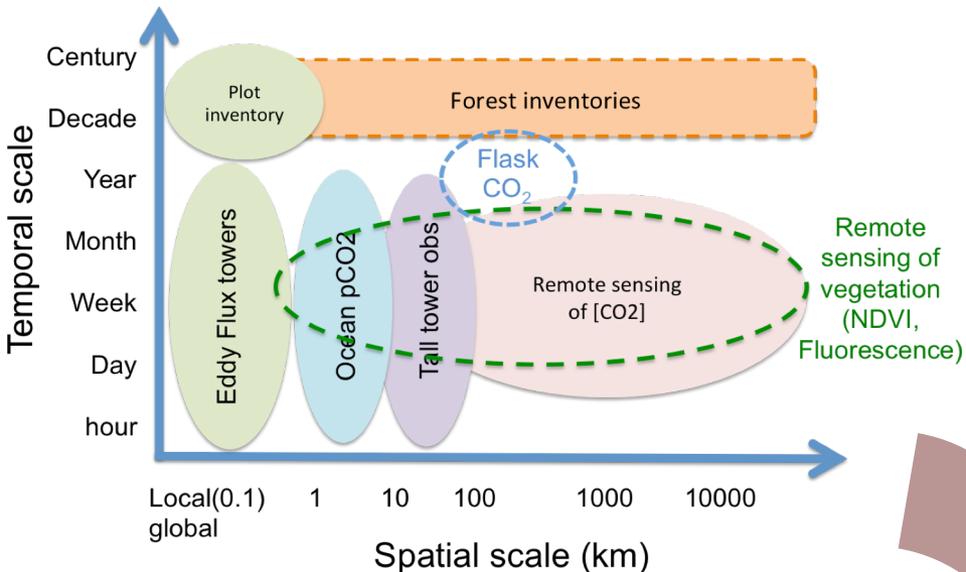


$$\begin{aligned}
 J(\mathbf{x}) = & \underbrace{\frac{1}{2}(\mathbf{M}(\mathbf{x}) - \mathbf{y})^T \mathbf{R}^{-1}(\mathbf{M}(\mathbf{x}) - \mathbf{y})}_{\text{Observation term}} \\
 & + \underbrace{\frac{1}{2}(\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b)}_{\text{Prior parameter term}}
 \end{aligned}$$

Model → Parameters → Obs → Model-data mismatch
 Prior parameters →

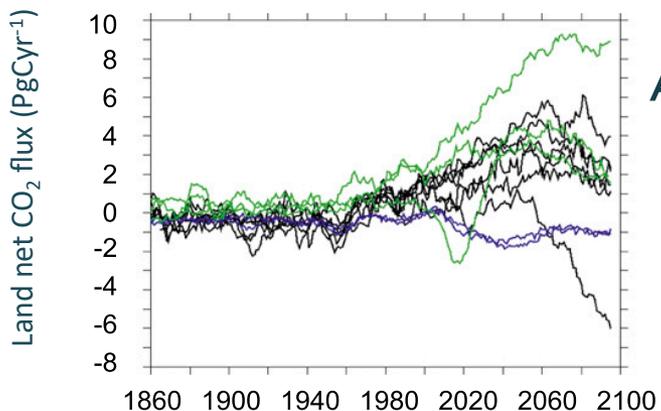
Reducing uncertainty: the need for model – data integration

Available C-related data streams



$$J(\mathbf{x}) = \underbrace{\frac{1}{2}(\mathbf{M}(\mathbf{x}) - \mathbf{y})^T \mathbf{R}^{-1}(\mathbf{M}(\mathbf{x}) - \mathbf{y})}_{\text{Observation term}} + \underbrace{\frac{1}{2}(\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b)}_{\text{Prior parameter term}}$$

Labels in the diagram: Model, Parameters, Obs, Model-data mismatch, Prior parameters.

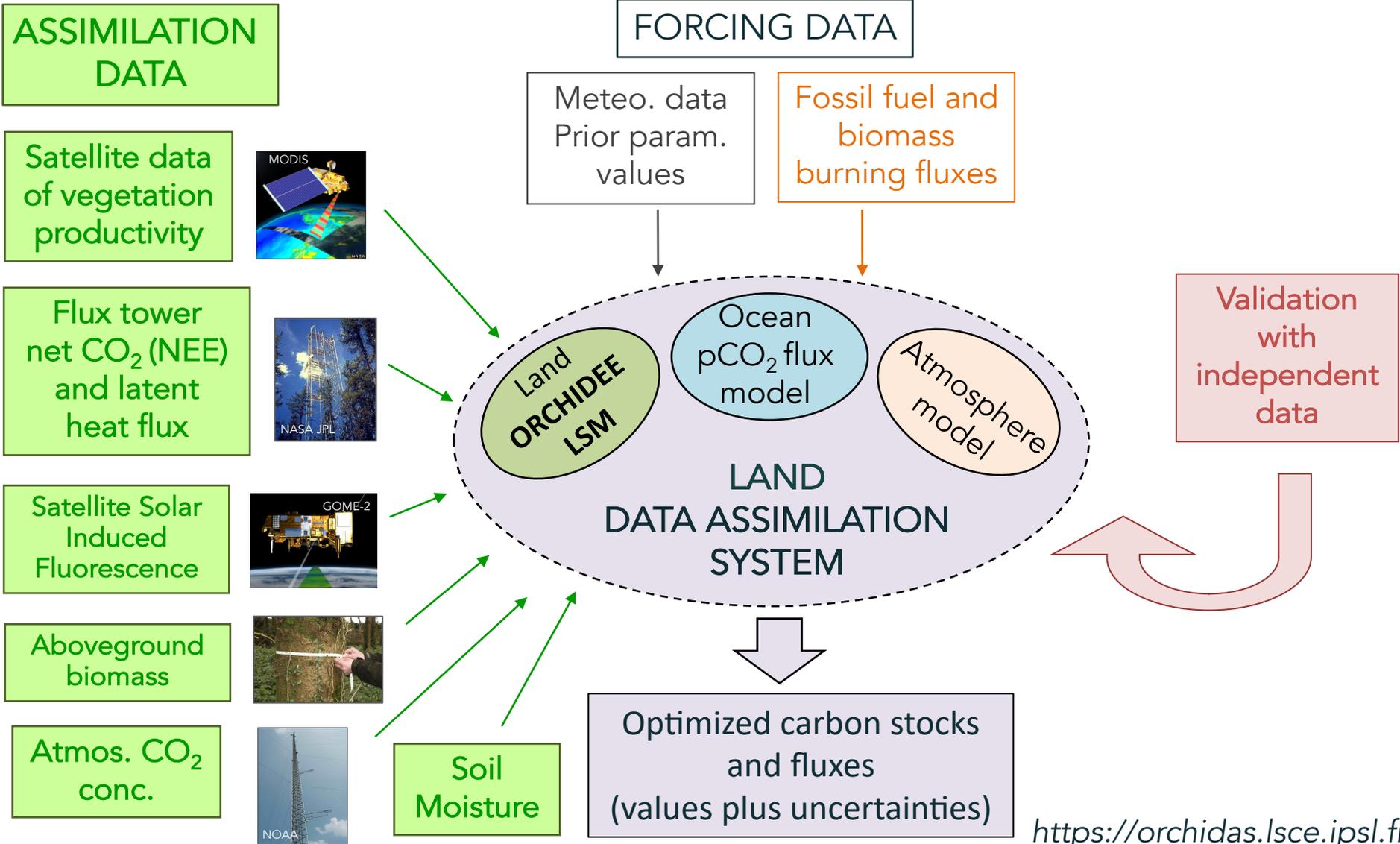


**DATA
ASSIMILATION**

Improve:

- C land budget estimates
- Quantify & reduce uncertainty
- Future climate predictions
- Process understanding

Global Data Assimilation System – ORCHIDEE LSM



Highlights of ORCHIDEE model parameter optimization so far...



ORCHIDEE
LAND SURFACE MODEL

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

ORCHIDEE Data Assimilation Systems

Institut Pierre Simon Laplace / Laboratoire des Sciences du Climat et de l'Environnement



ORCHIDAS
DATA ASSIMILATION SYSTEMS



Overview

Results

Publications

Tutorials

People

Contact

GLOBAL BIOGEOCHEMICAL CYCLES, VOL. 21, GB2013, doi:10.1029/2006GB002834, 2007

Optimizing a process-based ecosystem model with eddy-covariance flux measurements: A pine forest in southern France

Diego Santaren¹, Philippe Peylin^{1,2}, Nicolas Viovy¹, and Philippe Ciais¹

Geosci. Model Dev., 7, 2581–2597, 2014

Model–data fusion across ecosystems: from multisite optimizations to global simulations

S. Kuppel^{1,2}, P. Peylin¹, F. Maignan¹, F. Chevallier¹, G. Kiely³, L. Montagnani⁴, and A. Cescatti⁵

Biogeosciences, 12, 7185–7208, 2015

Using satellite data to improve the leaf phenology of a global terrestrial biosphere model

N. MacBean¹, F. Maignan¹, P. Peylin¹, C. Bacour², F.-M. Bréon¹, and P. Ciais¹

Geosci. Model Dev., 9, 3321–3346, 2016

A new stepwise carbon cycle data assimilation system using multiple data streams to constrain the simulated land surface carbon cycle

Philippe Peylin¹, Cédric Bacour², Natasha MacBean¹, Sébastien Leonard¹, Peter Rayner^{1,3}, Sylvain Kuppel^{1,4}, Ernest Koffi¹, Abdou Kane¹, Fabienne Maignan¹, Frédéric Chevallier¹, Philippe Ciais¹, and Pascal Prunet²

Biogeosciences, 9, 3757–3776, 2012

Constraining a global ecosystem model with multi-site eddy-covariance data

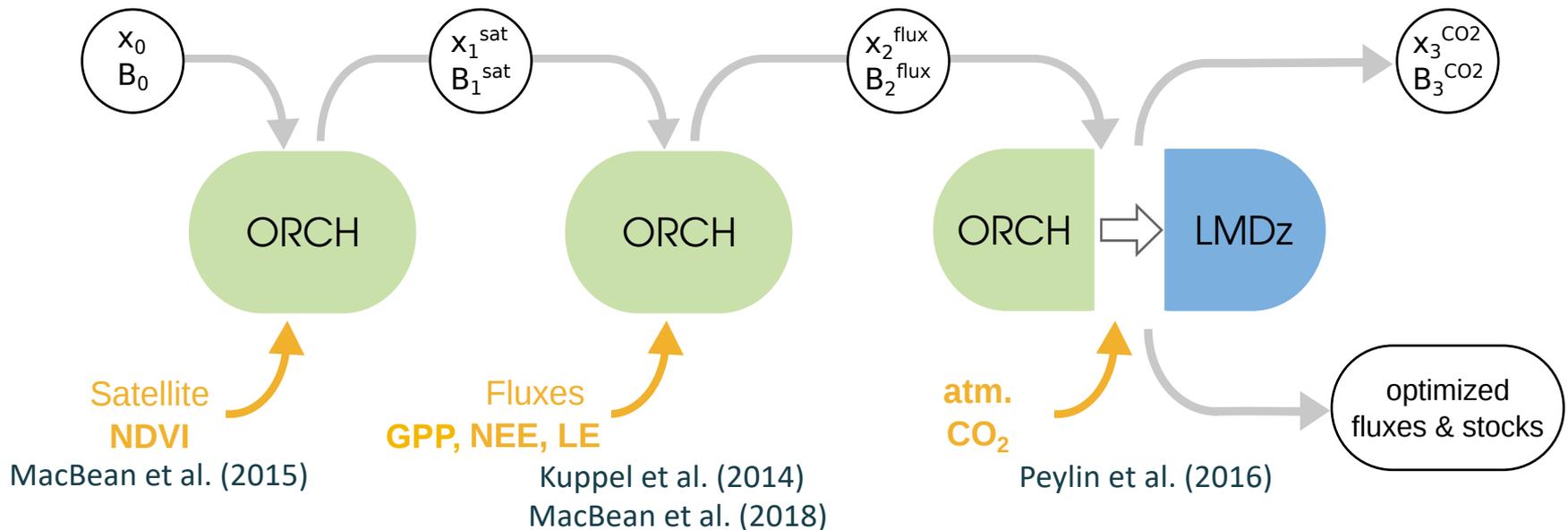
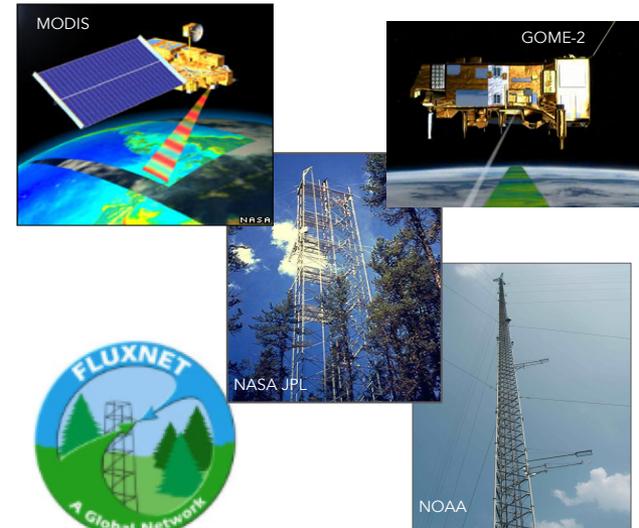
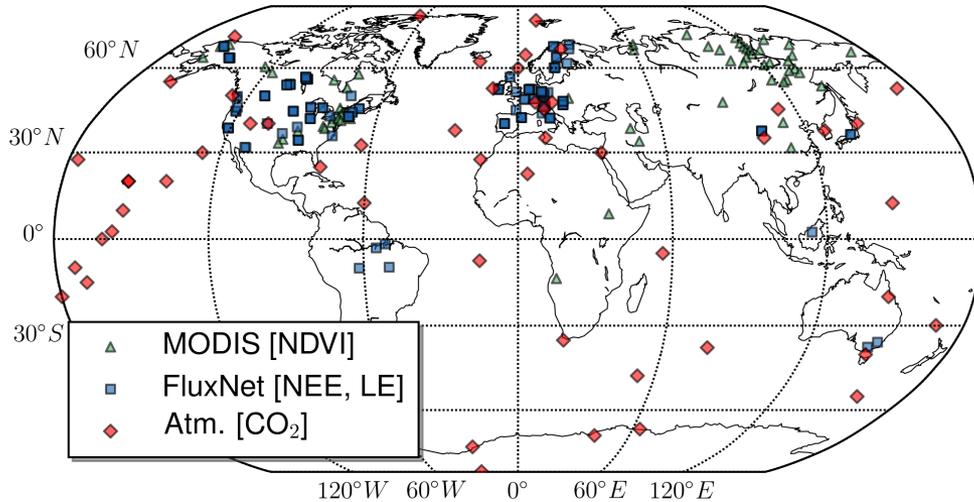
S. Kuppel¹, P. Peylin^{1,2}, F. Chevallier¹, C. Bacour³, F. Maignan¹, and A. D. Richardson⁴

SCIENTIFIC REPORTS | (2018) 8:1973 | DOI:10.1038/s41598-018-20024-w

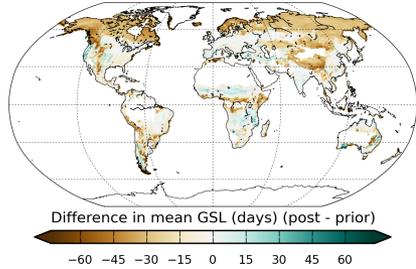
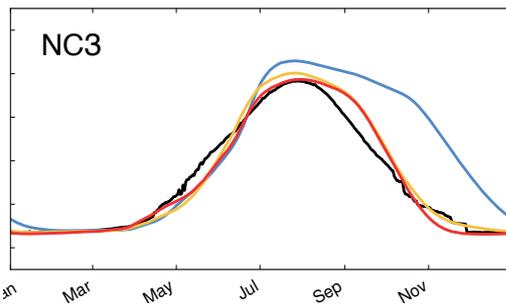
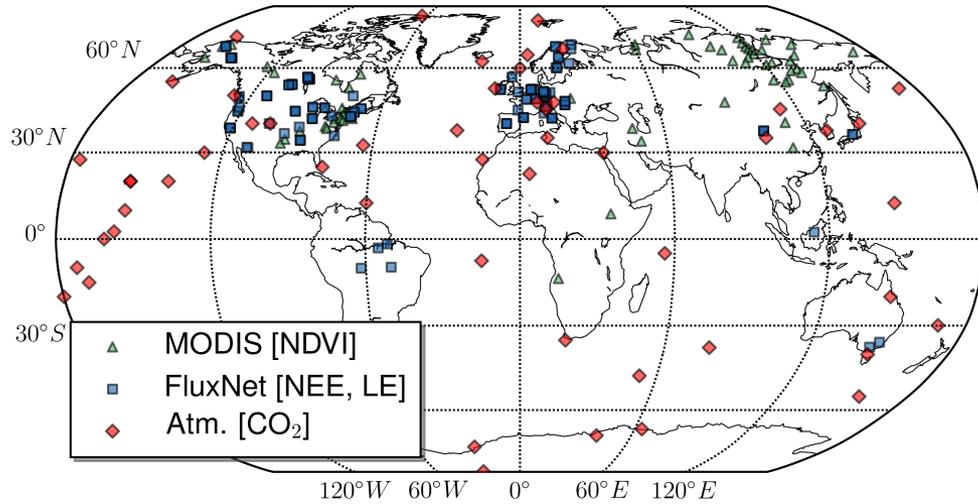
Strong constraint on modelled global carbon uptake using solar-induced chlorophyll fluorescence data

Natasha MacBean^{1,2}, Fabienne Maignan¹, Cédric Bacour³, Philip Lewis^{4,5}, Philippe Peylin¹, Luis Guanter⁶, Philipp Köhler⁷, Jose Gómez-Dans^{4,5} & Mathias Disney^{4,5}

Multiple constraint on global carbon stocks and fluxes

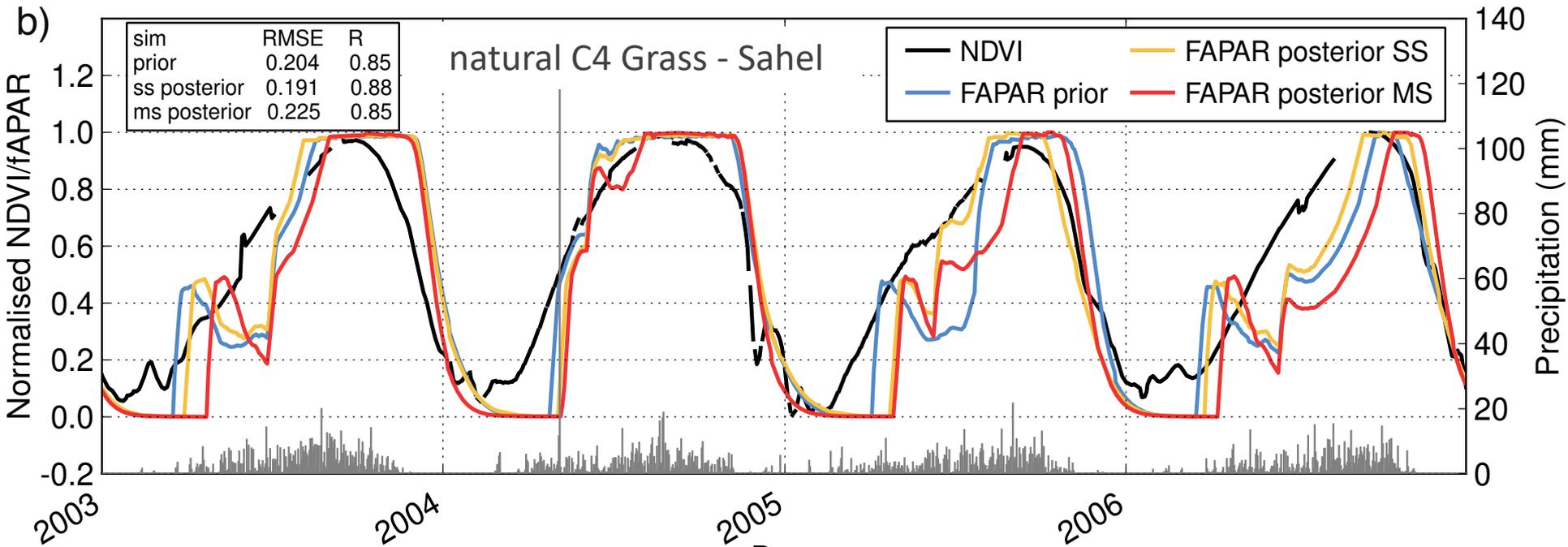


Multiple constraint on global carbon stocks and fluxes



MacBean et al. (2015)

→ Insight into vegetation dynamics in semi-arid/dryland ecosystems...

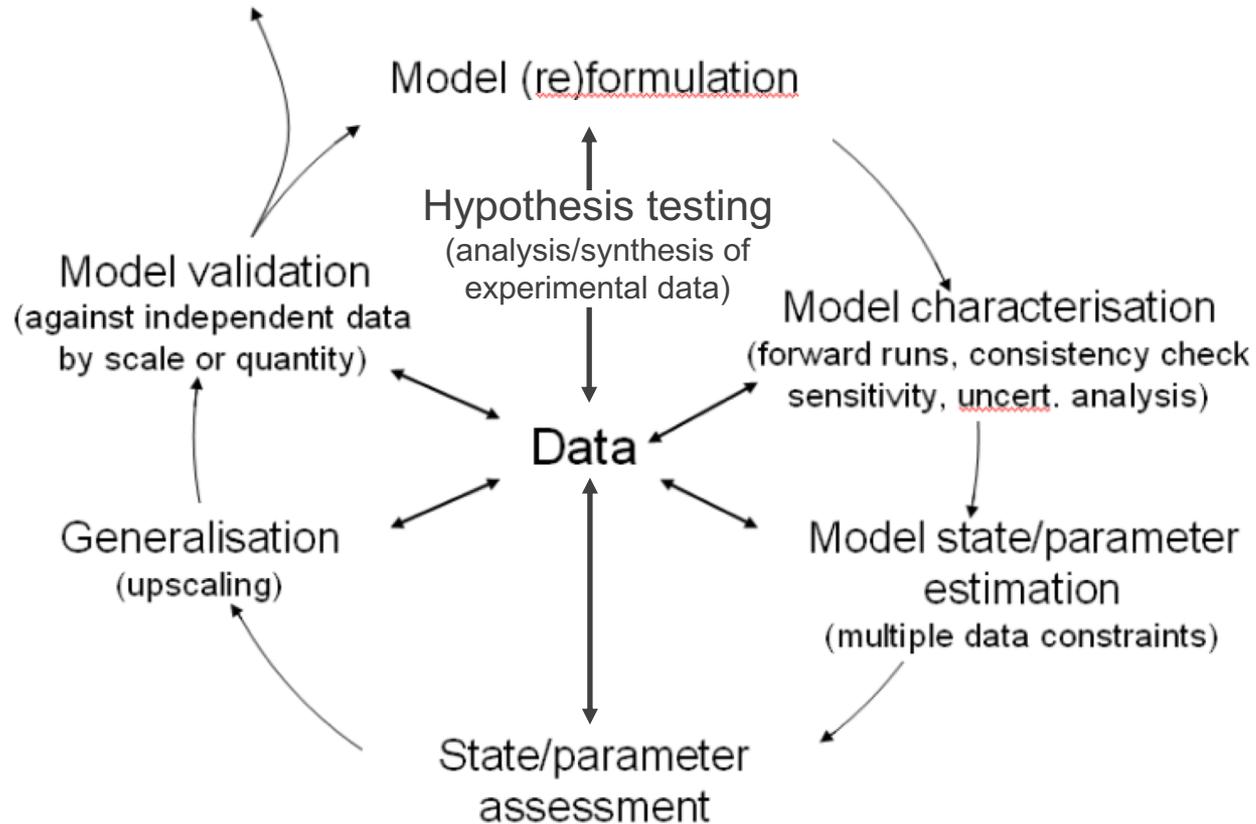


➤ Leaf onset/senescence controlled by moisture availability in these ecosystems (time since moisture minimum)

➤ *How does moisture availability control leaf dynamics?*

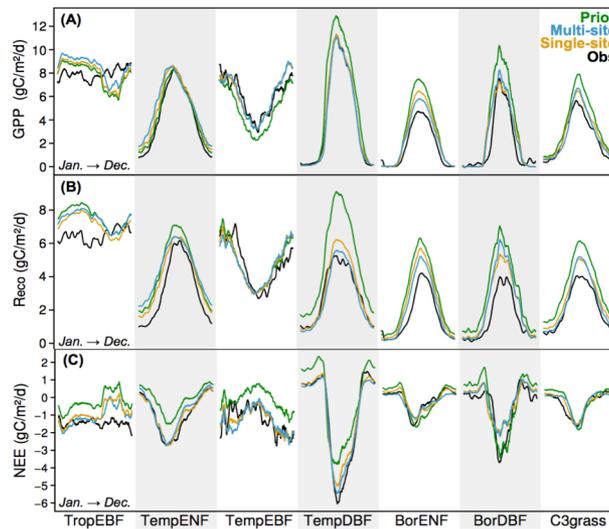
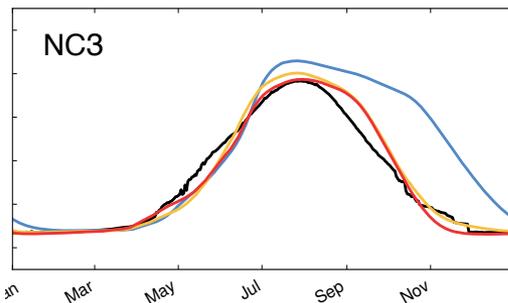
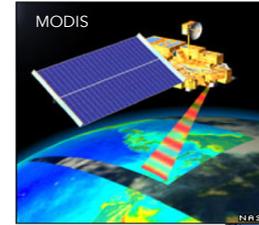
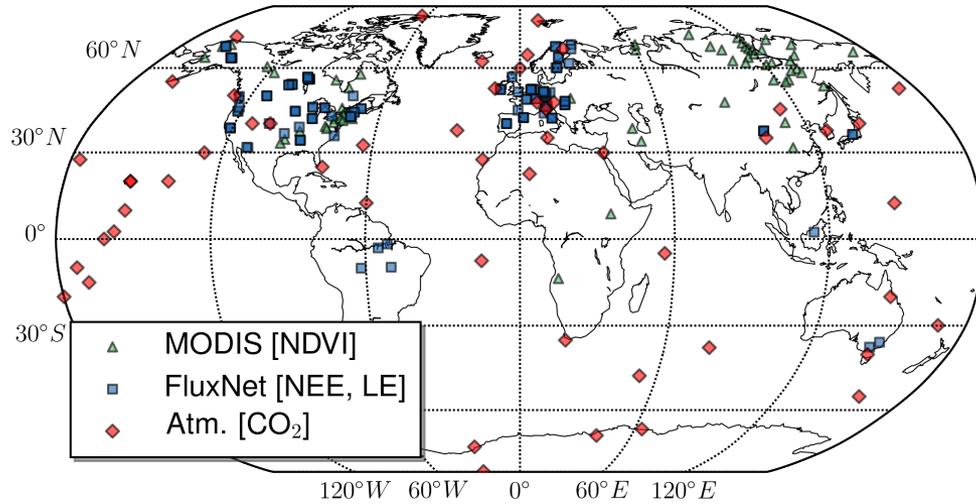
Improving models | Reducing uncertainty → the model development cycle

Model application

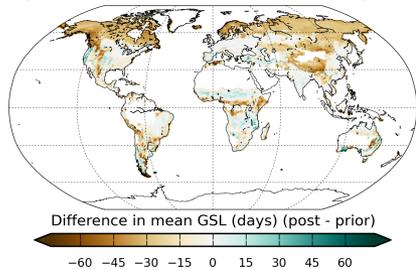


Adapted from Williams et al. (2009)

Multiple constraint on global carbon stocks and fluxes

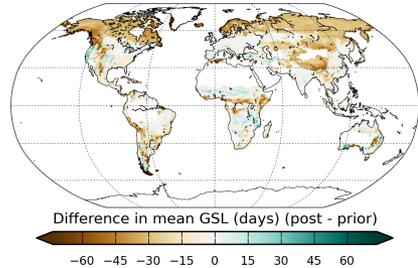
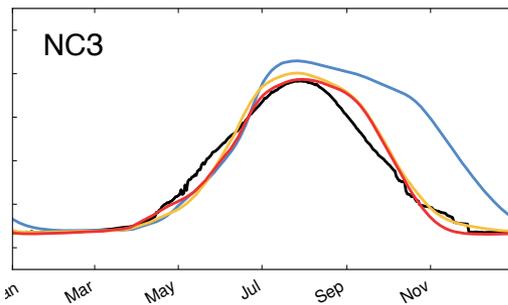
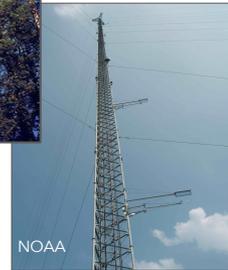
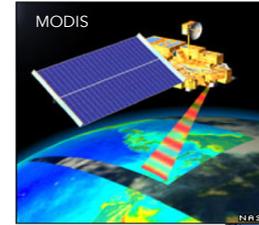
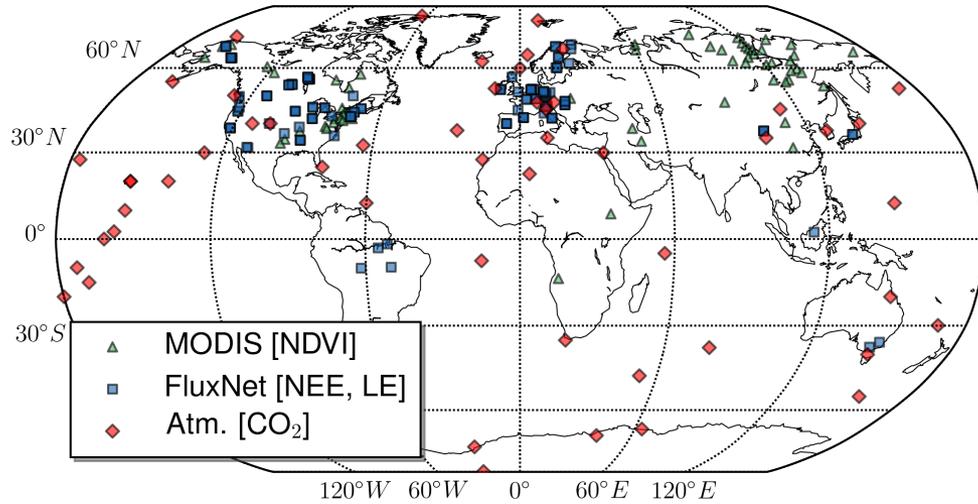


Kuppel et al. (2014)

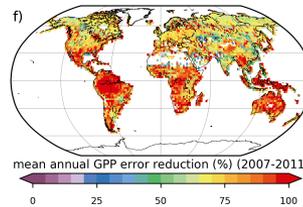
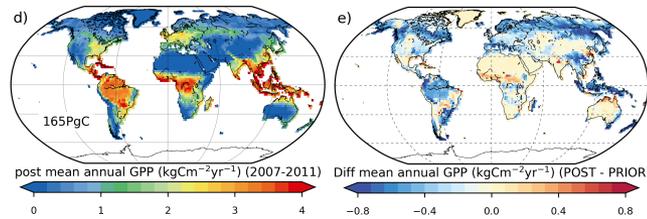


MacBean et al. (2015)

Multiple constraint on global carbon stocks and fluxes

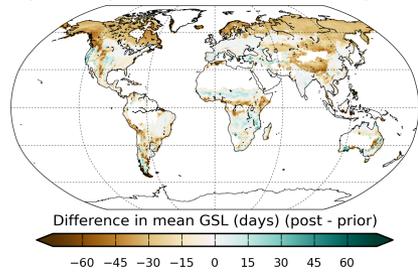
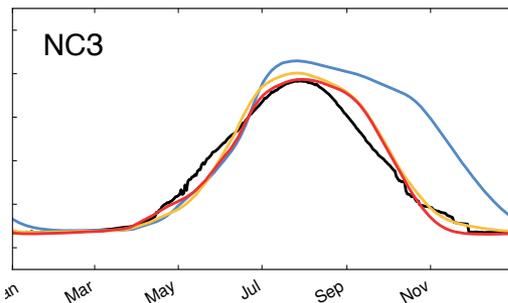
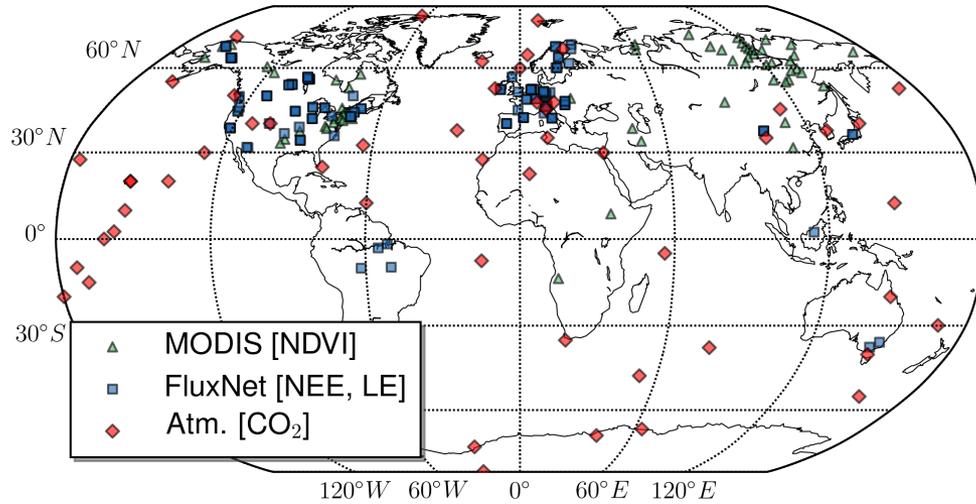


MacBean et al. (2015)

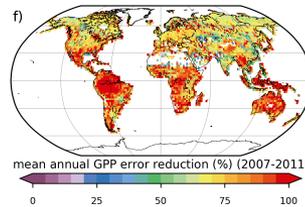
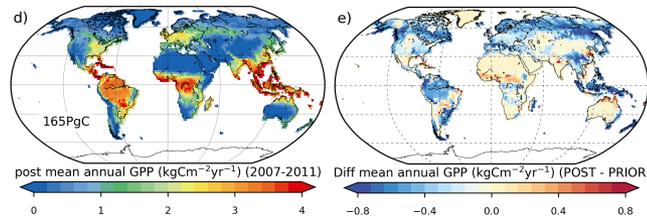


MacBean et al. (2018)

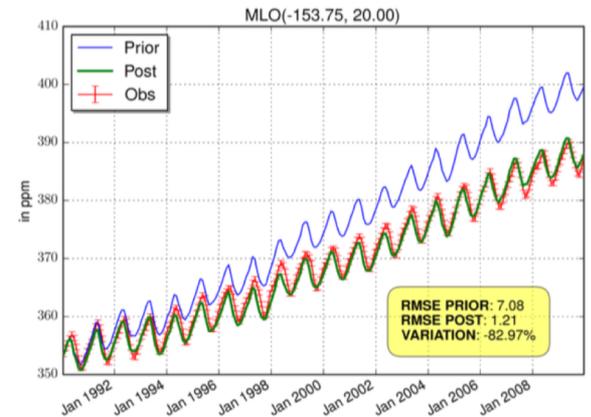
Multiple constraint on global carbon stocks and fluxes



MacBean et al. (2015)

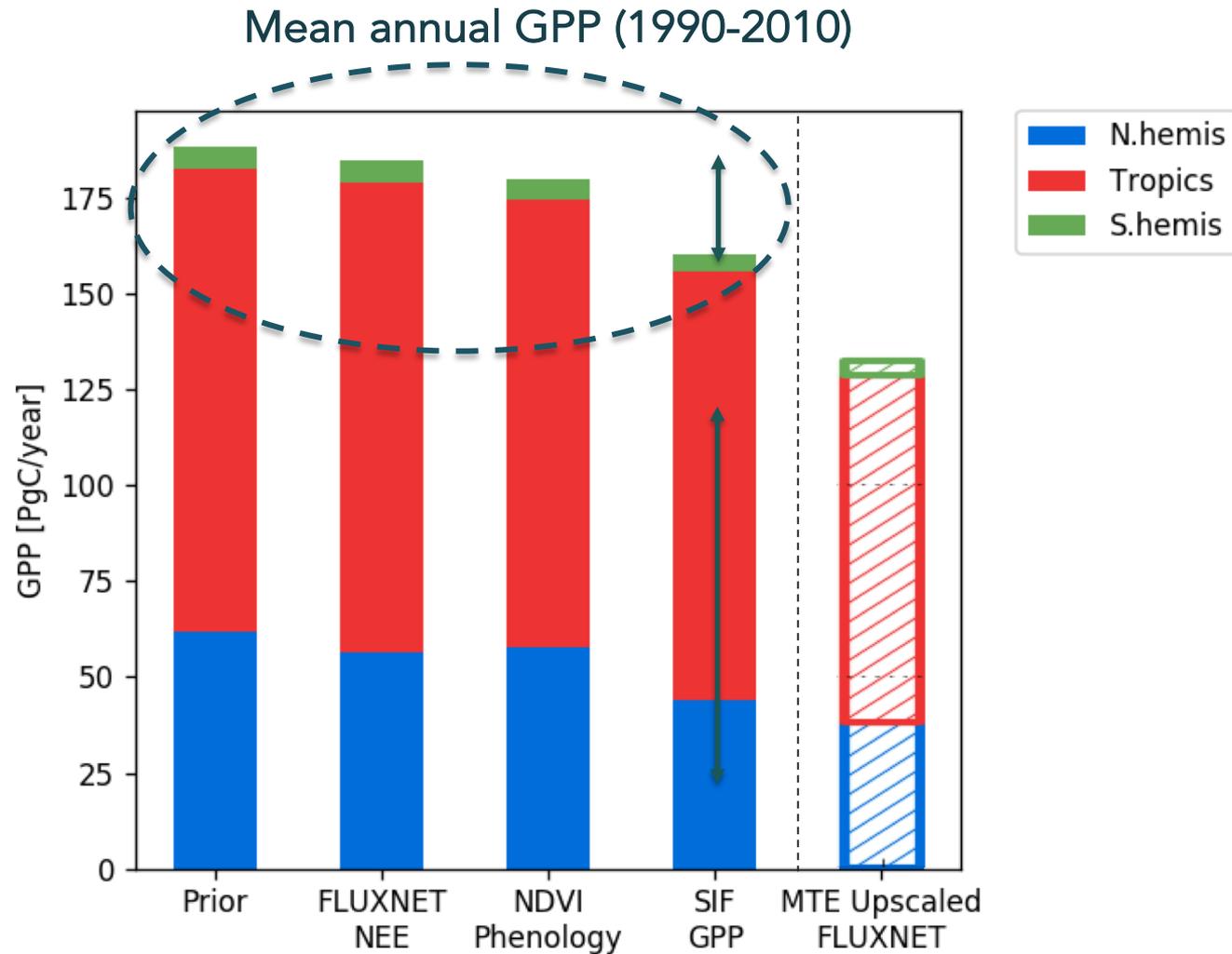


MacBean et al. (2018)

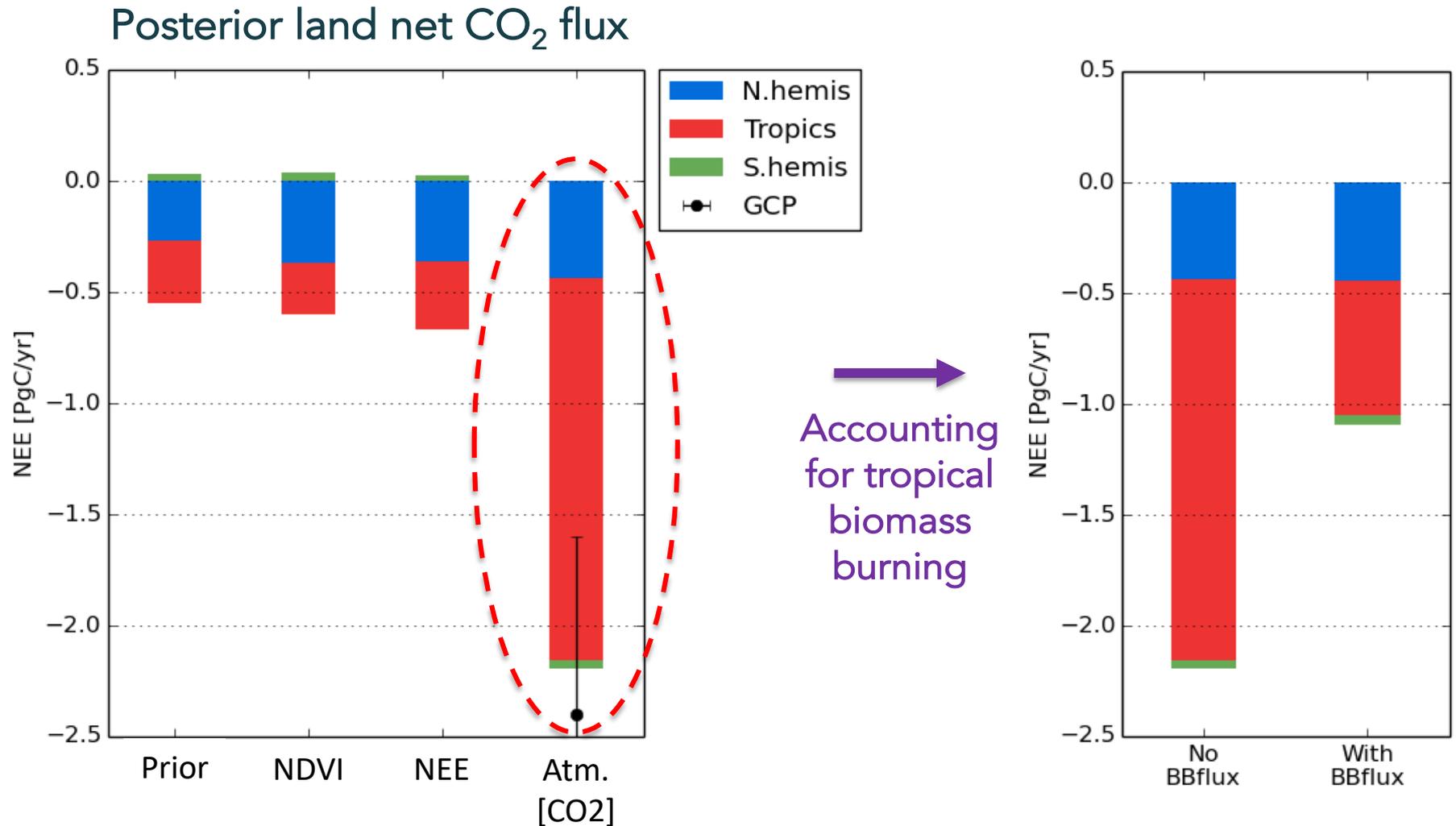


Peylin et al. (2016)

Satellites help us constrain GPP magnitude and global spatial distribution

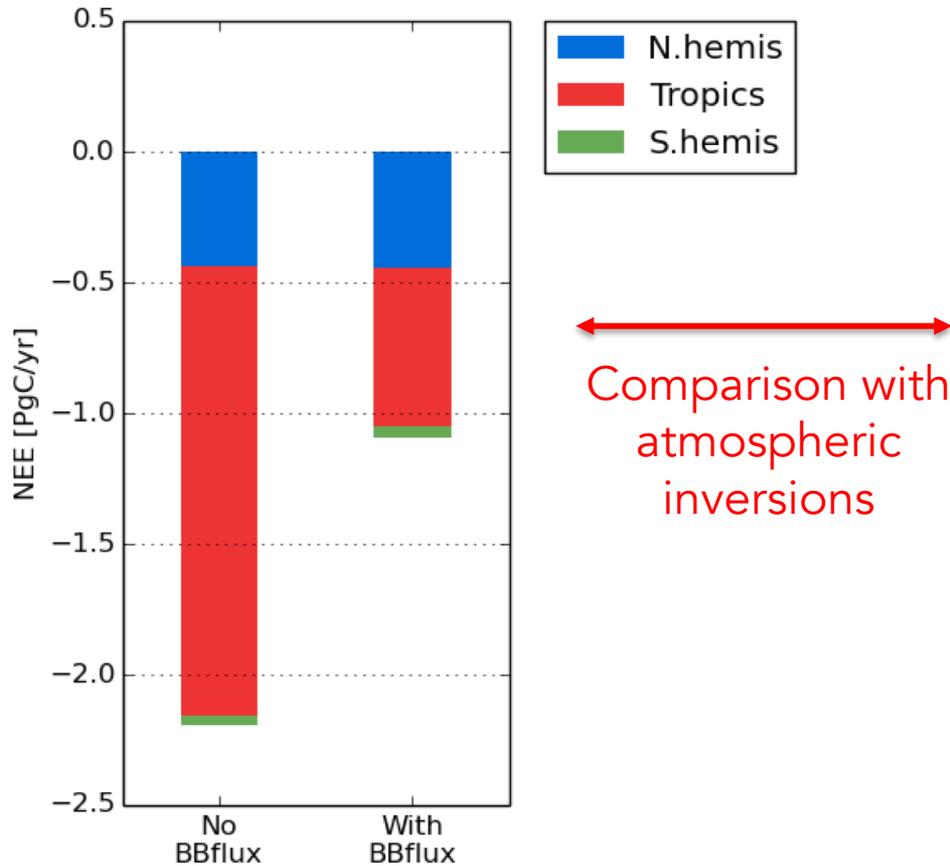


Atmospheric [CO₂] data help us constrain spatial distribution of net CO₂ fluxes

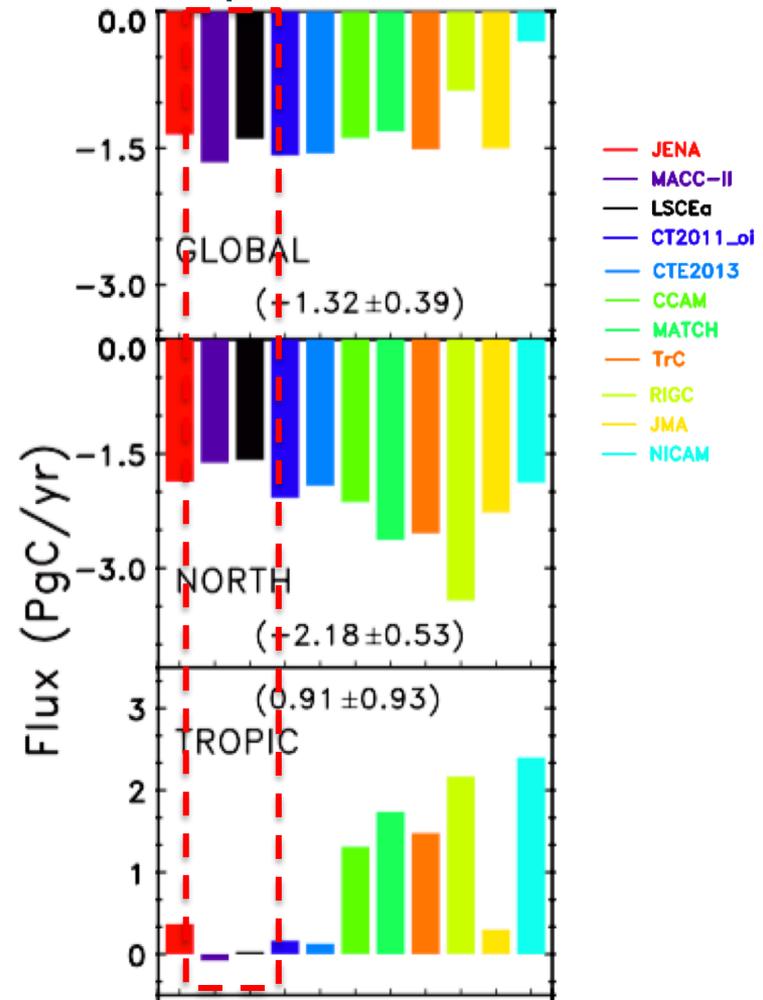


Toward a comparison with atmospheric inversions

Posterior land net CO₂ flux



Land net CO₂ flux from suite of atmospheric inversions



Outline

Data assimilation as a tool for reducing uncertainty in land surface models

- Highlights with the ORCHIDEE LSM
- *But we face challenges...*
- Future perspectives

Progress in using multiple datasets to constrain models



Agricultural and Forest Meteorology

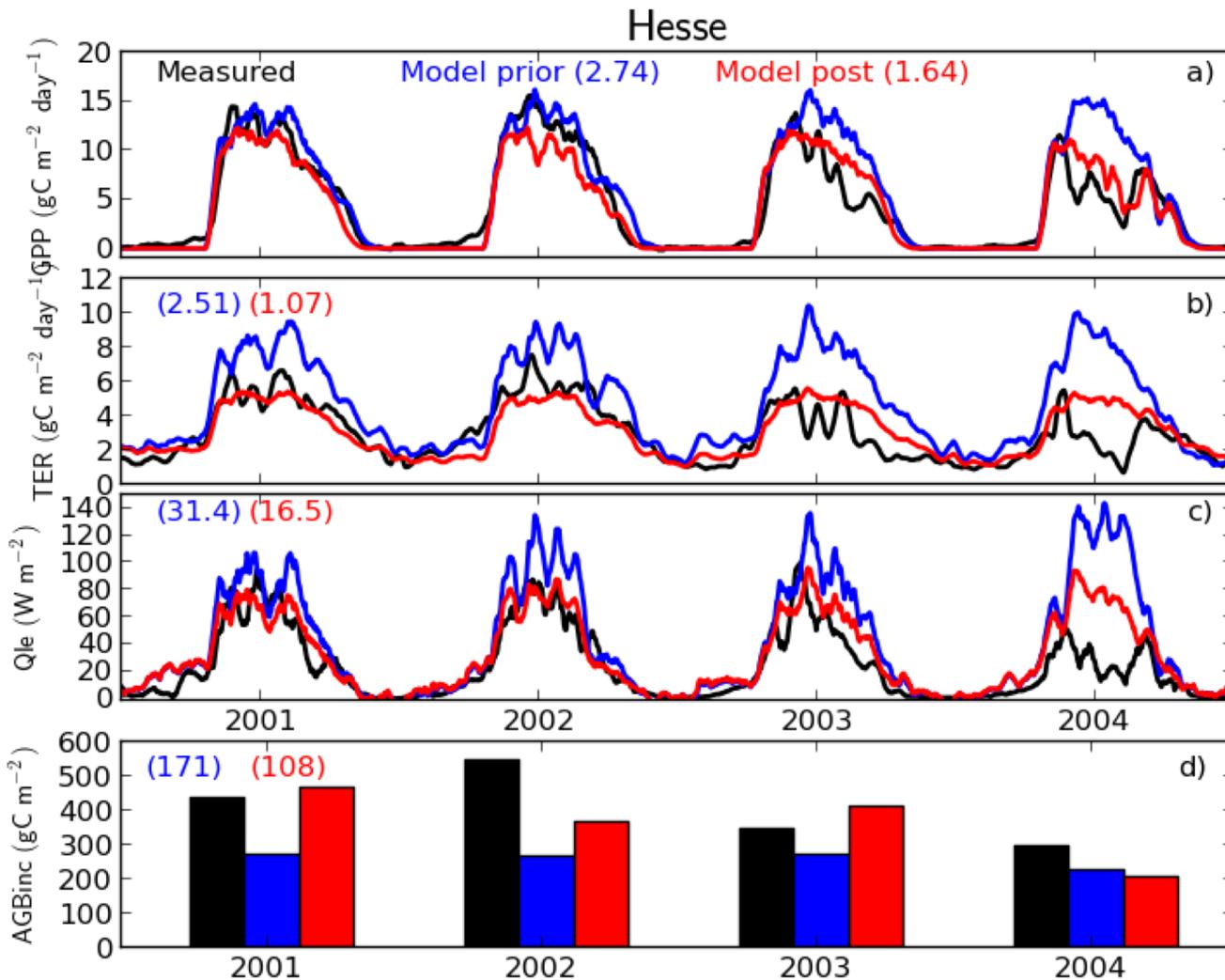
The potential benefit of using forest biomass data in addition to carbon and water flux measurements to constrain ecosystem model parameters: Case studies at two temperate forest sites

T. Thum^{a,*}, N. MacBean^b, P. Peylin^b, C. Bacour^c, D. Santaren^b, B. Longdoz^d, D. Loustau^e, P. Ciais^b



Challenges of multiple data stream assimilation

→ fluxes + aboveground biomass increment



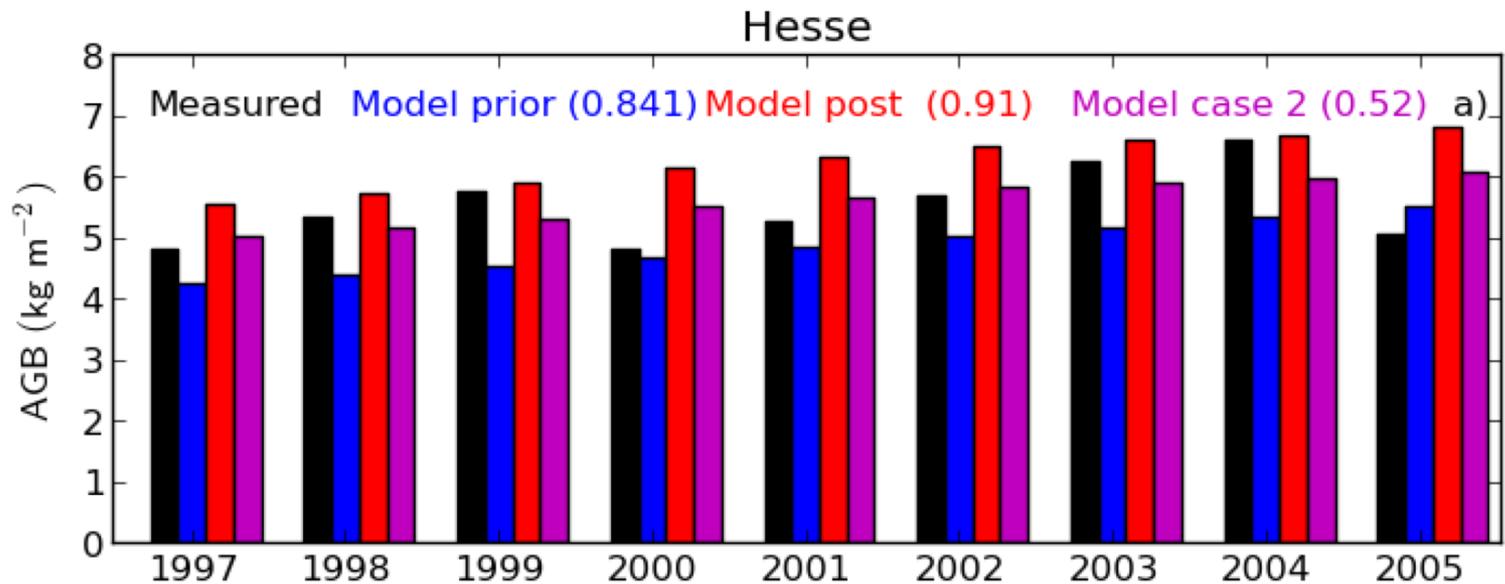
- Assimilate obs:
- GPP
 - Reco (TER)
 - Latent Heat (Qle)
 - **AGB increment**

- Optimise params:
- photosynthesis
 - respiration
 - energy balance
 - soil water avail.
 - phenology
 - **allocation**

Thum, T., et al. (2017), The potential of forest biomass data in addition to carbon and water flux measurements to constrain ecosystem model parameters: Case studies at two temperate forest sites, *Agric. For. Meteorol.*, 234, 48-65

Challenges of multiple data stream assimilation

→ fluxes + aboveground biomass increment



- Assimilate AGB increment degrades fit to *total* AGB obs
- Assimilate total AGB
- Optimise turnover rate
- *BUT missing model processes?*

Thum, T., et al. (2017), The potential of forest biomass data in addition to carbon and water flux measurements to constrain ecosystem model parameters: Case studies at two temperate forest sites, *Agric. For. Meteorol.*, 234, 48-65.

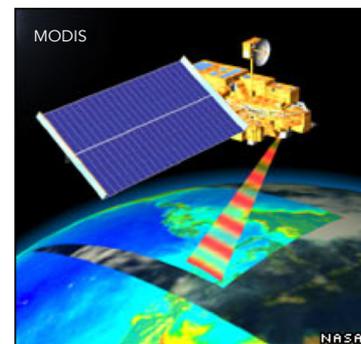
Progress in using multiple datasets to constrain models



Agricultural and Forest Meteorology

The potential benefit of using forest biomass data in addition to carbon and water flux measurements to constrain ecosystem model parameters: Case studies at two temperate forest sites

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Journal of Geophysical Research: Biogeosciences

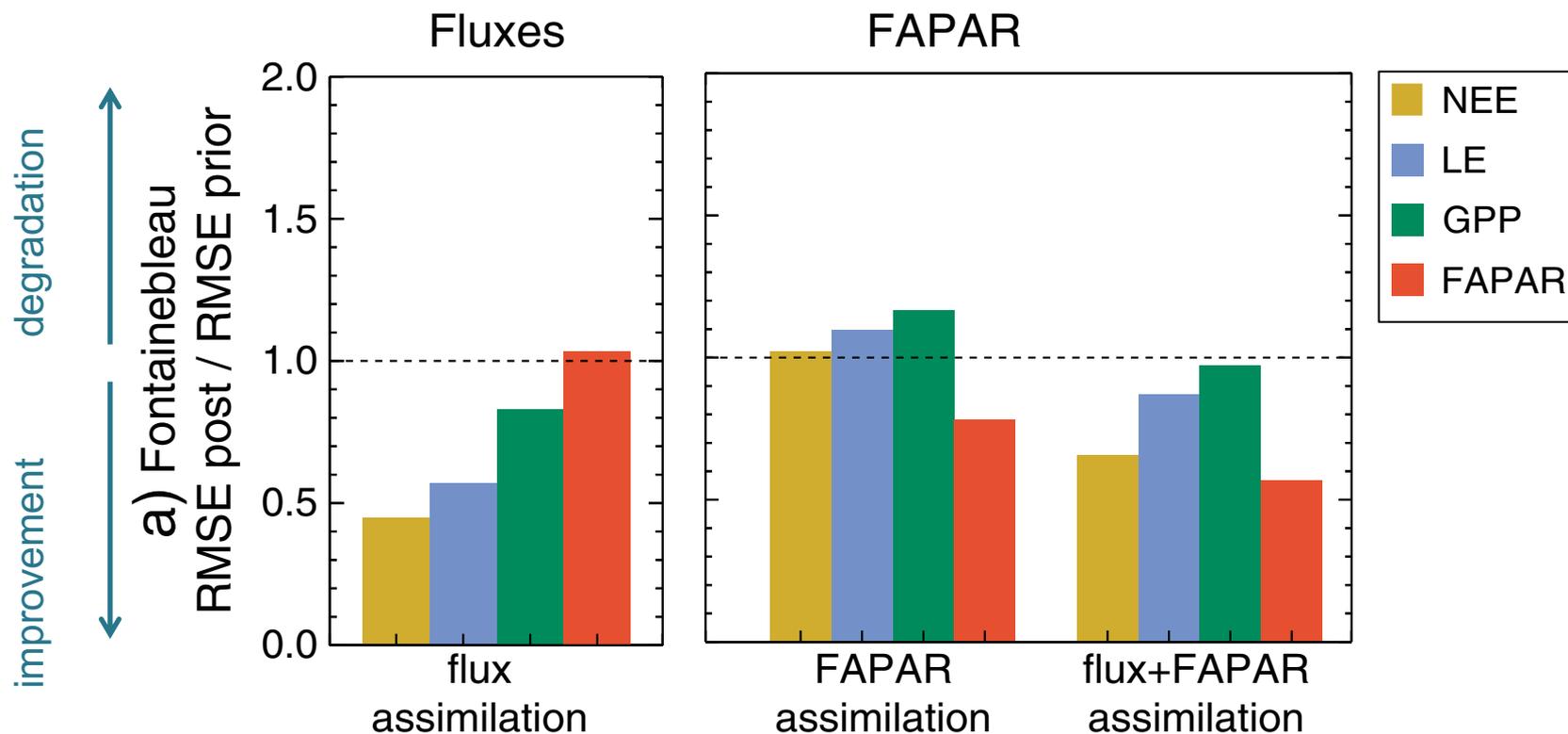


Joint assimilation of eddy covariance flux measurements and FAPAR products over temperate forests within a process-oriented biosphere model

C. Bacour^{1,2}, P. Peylin², N. MacBean², P. J. Rayner^{2,3}, F. Delage^{2,4}, F. Chevallier², M. Weiss⁵, J. Demarty^{5,6}, D. Santaren^{7,8}, F. Baret⁵, D. Berveiller⁹, E. Dufrêne⁹, and P. Prunet¹

Challenges of multiple data stream assimilation

→ fluxes + satellite FAPAR



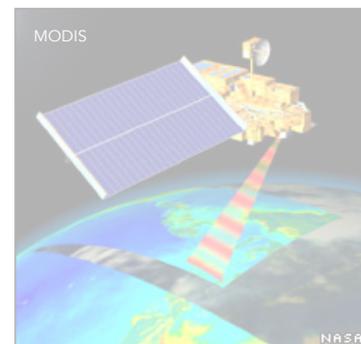
Challenges and progress in using multiple datasets to constrain models



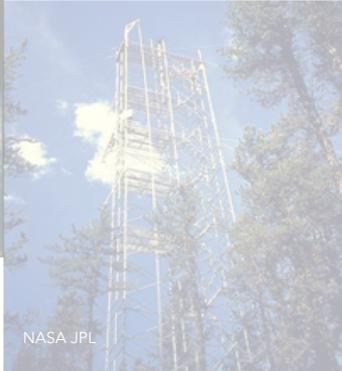
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Journal of Geophysical Research: Biogeosciences



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Geosci. Model Dev., 9, 3569–3588, 2016

Consistent assimilation of multiple data streams in a carbon cycle data assimilation system

Natasha MacBean¹, Philippe Peylin¹, Frédéric Chevallier¹, Marko Scholze², and Gregor Schürmann³

Challenges of multiple data stream assimilation → perspectives for land surface modelers

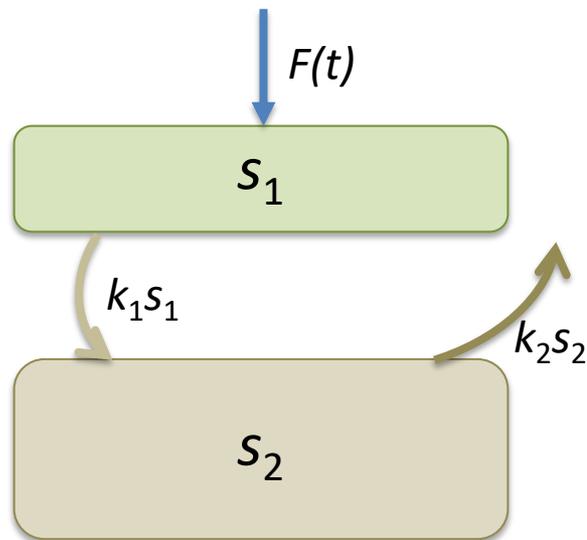
- Biases in observations or inconsistencies between observations and the model
- Proper characterization of the parameter and observation error covariance matrices, particularly issues of #obs and covariance between obs
- Step-wise vs simultaneous approaches in the case of computational constraints
- Assumptions of the inversion algorithm (derivative vs global random search)

Challenges of multiple data stream assimilation

→ Toy model examples

E.g. Simple C cycle model (2 pools)

$$\frac{ds_1}{dt} = F(t) \left(\frac{s_1}{p_1 + s_1} \right) \left(\frac{s_2}{p_2 + s_2} \right) - k_1 s_1 + s_0$$
$$\frac{ds_2}{dt} = k_1 s_1 - k_2 s_2.$$



- Observations of s_1 and s_2 pools
- 'k' and 'p' parameters for each pool
- Synthetic "pseudo obs" tests
- Bias in s_2 pool → not taken into account in cost function

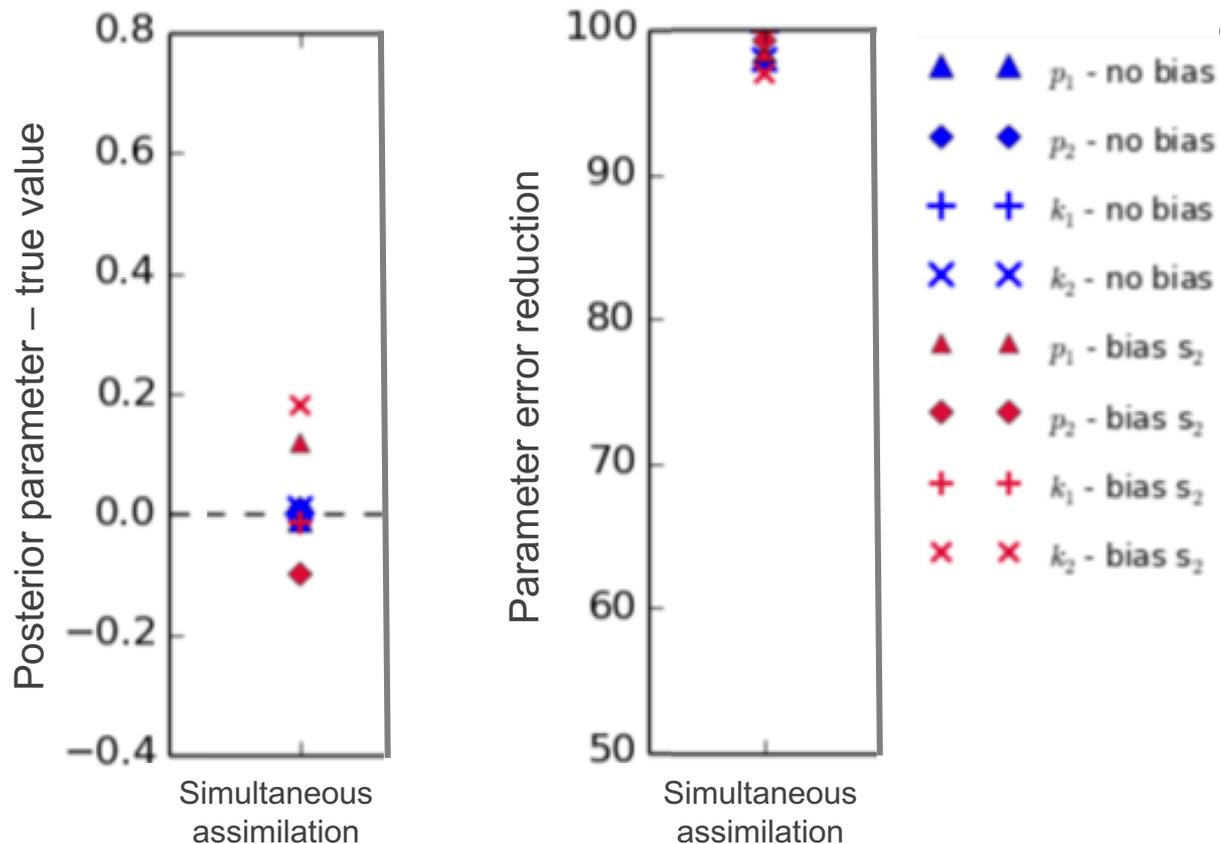
Challenges of multiple data stream assimilation

→ e.g. bias in obs not accounted for cost function

→ Comparison with and without bias in s_2 observation

$$\frac{ds_1}{dt} = F(t) \left(\frac{s_1}{p_1 + s_1} \right) \left(\frac{s_2}{p_2 + s_2} \right) - k_1 s_1 + s_0$$

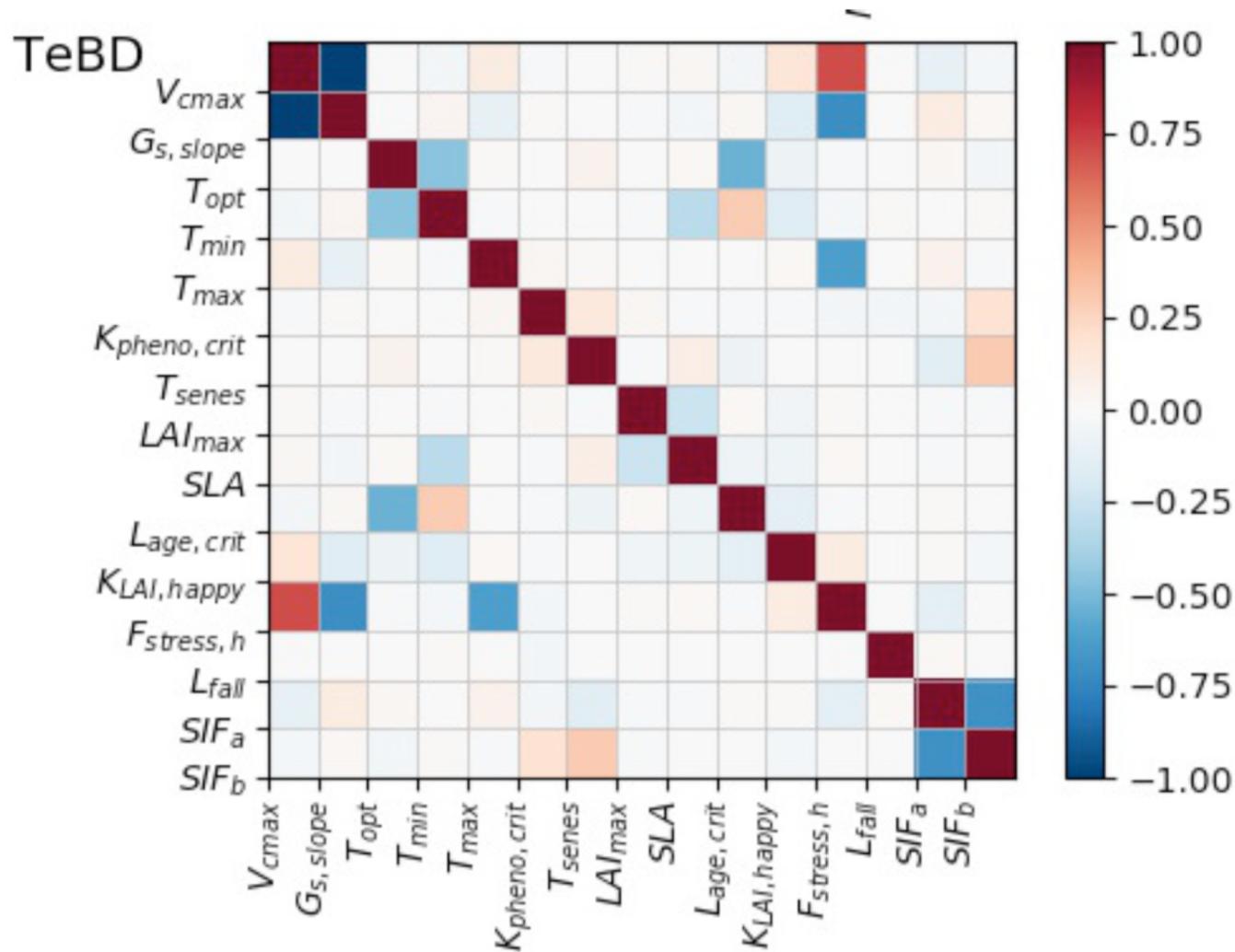
$$\frac{ds_2}{dt} = k_1 s_1 - k_2 s_2.$$



MacBean, N., P. Peylin, F. Chevallier, M. Scholze and G. Schürmann (2016), Consistent assimilation of multiple data streams in a carbon cycle data assimilation system, *Geosci. Model Dev.*, 9, 3569-3588.

A note on parameter correlation and model equifinality

→ problem in complex *and* simple models...



Outline

Data assimilation as a tool for reducing uncertainty in land surface models

- Highlights with the ORCHIDEE LSM
- Challenges we face
- *Where to next?*

Global Data Assimilation System – global CCDAS

GLOBAL BIOGEOCHEMICAL CYCLES, VOL. 19, GB2026, doi:10.1029/2004GB002254, 2005

Two decades of terrestrial carbon fluxes from a carbon cycle data assimilation system (CCDAS)

P. J. Rayner,^{1,2} M. Scholze,^{3,4} W. Knorr,^{4,5} T. Kaminski,⁶ R. Giering,⁶ and H. Widmann⁵

Geosci. Model Dev., 9, 2999–3026, 2016

Constraining a land-surface model with multiple observations by application of the MPI-Carbon Cycle Data Assimilation System V1.0

Gregor J. Schürmann¹, Thomas Kaminski^{2,a}, Christoph Köstler¹, Nuno Carvalhais¹, Michael Voßbeck^{2,a}, Jens Kattge¹, Ralf Giering³, Christian Rödenbeck¹, Martin Heimann¹, and Sönke Zaehle^{1,4}

Geosci. Model Dev., 9, 2833–2852, 2016

Land-surface parameter optimisation using data assimilation techniques: the adJULES system V1.0

Nina M. Raoult, Tim E. Jupp, Peter M. Cox, and Catherine M. Luke

The decadal state of the terrestrial carbon cycle: Global retrievals of terrestrial carbon allocation, pools, and residence times

A. Anthony Bloom^{a,b,c,1}, Jean-François Exbrayat^{b,c}, Ivar R. van der Velde^d, Liang Feng^{b,c}, and Mathew Williams^{b,c}

Biogeosciences, 10, 583–606, 2013

The climate dependence of the terrestrial carbon cycle, including parameter and structural uncertainties

M. J. Smith, D. W. Purves, M. C. Vanderwel, V. Lyutsarev, and S. Emmott

JOURNAL OF GEOPHYSICAL RESEARCH: BIOGEOSCIENCES, VOL. 118, 1–13, doi:10.1002/jgrg.20118, 2013

The BETHY/JSBACH Carbon Cycle Data Assimilation System: experiences and challenges

T. Kaminski,¹ W. Knorr,² G. Schürmann,³ M. Scholze,² P. J. Rayner,⁴ S. Zaehle,³ S. Blessing,¹ W. Dorigo,⁵ V. Gayler,⁶ R. Giering,¹ N. Gobron,⁷ J. P. Grant,² M. Heimann,³ A. Heuguen-Steudl,⁸ S. Houmela,⁹ T. Kato,¹⁰ J. Kattner,³ D. Keller,^{8,14}

Biogeosciences, 11, 7025–7050, 2014

Identifying environmental controls on vegetation greenness phenology through model–data integration

M. Forkel¹, N. Carvalhais^{1,2}, S. Schaphoff³, W. v. Bloh³, M. Migliavacca¹, M. Thurner^{1,4}, and K. Thonicke³

Biogeosciences, 10, 2011–2040, 2013

Multiple observation types reduce uncertainty in Australia's terrestrial carbon and water cycles

V. Haverd¹, M. R. Raupach¹, P. R. Briggs¹, J. G. Canadell¹, P. Isaac¹, C. Pickett-Heaps¹, S. H. Roxburgh², E. van Gorsel¹, R. A. Viscarra Rossel³, and Z. Wang^{1,4}

Geosci. Model Dev., 9, 3321–3346, 2016

A new stepwise carbon cycle data assimilation system using multiple data streams to constrain the simulated land surface carbon cycle

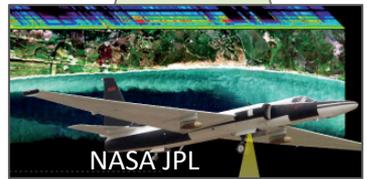
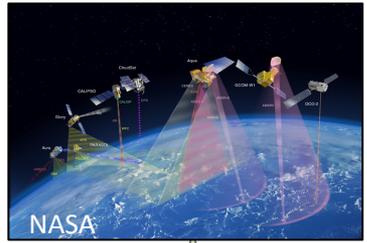
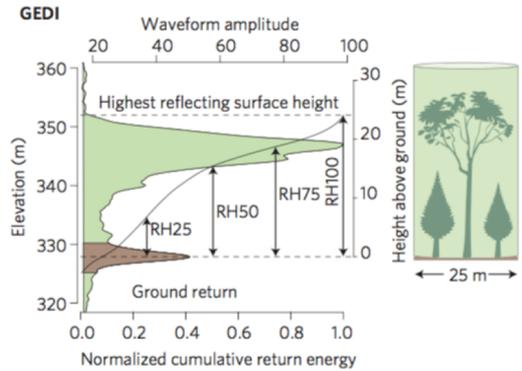
Philippe Peylin¹, Cédric Bacour², Natasha MacBean¹, Sébastien Leonard¹, Peter Rayner^{1,3}, Sylvain Kuppel^{1,4}, Ernest Koffi¹, Abdou Kane¹, Fabienne Maignan¹, Frédéric Chevallier¹, Philippe Ciais¹, and Pascal Prunet²

Model data assimilation in the "Big Data" era

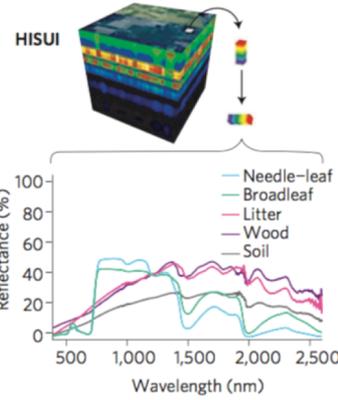
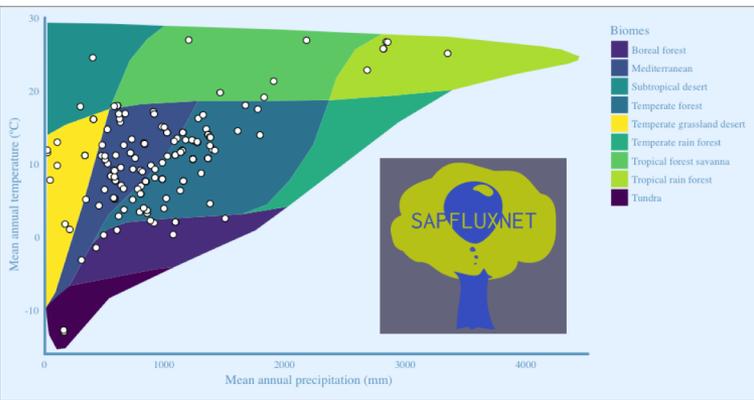
→ short-term processes

➤ New ISS and satellite products, FLUXNET, SAPFLUXNET, ISMN

International soil moisture network (ISMN)

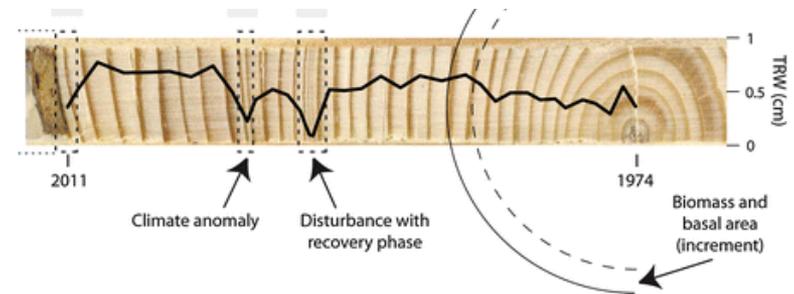
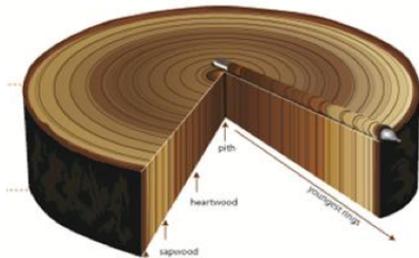


↑ Relationships across scales ↓



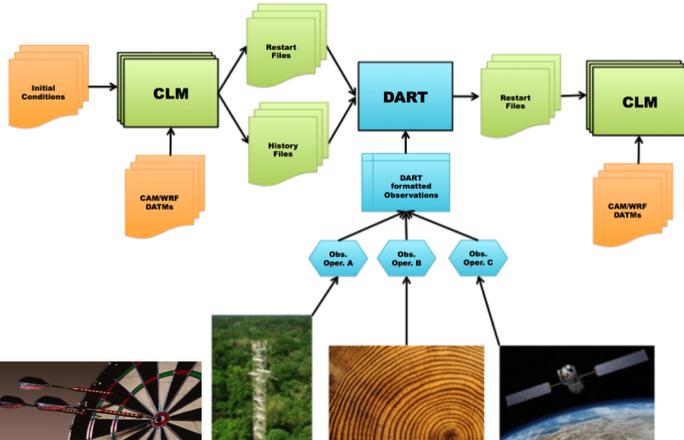
Model data assimilation in the "Big Data" era → long-term processes and CO₂/climate sensitivities

➤ FACE sites, manipulation expts (DroughtNet), Tree rings (ITRDB)

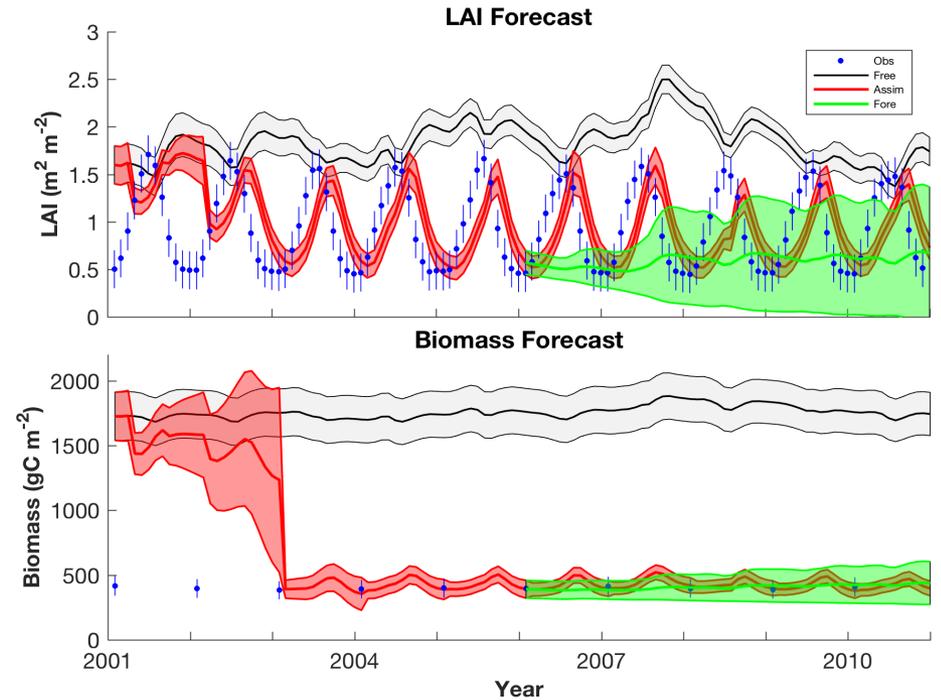


Improving carbon cycle prediction using *state* data assimilation with CLM-DART (led by Andy Fox + Tim Hoar & Jeff Anderson)

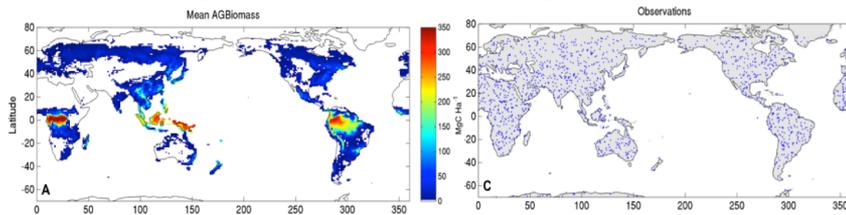
1. Added carbon cycle relevant observations to CLM-DART workflow



2. Assimilating leaf area and biomass obs. improves seasonality and prediction



3. Currently testing approach globally with observing system simulation experiments



Data assimilation wish list

- Better quantification of observation errors and their correlations
- Methods for quantification of model structural error
- Sensitivity analyses
- Resolve inconsistencies between model representation and observations → keep data in mind when developing models
- Modularized code → can optimize more easily & test different processes/structure/complexity
- Think about the terms in the cost function (relationships between variables, sensitivities, emerging constraints)
- Updated inversion algorithms
- Operational DA with newer versions of models

Wish list for land surface model development

- There is a clear need to better quantify and reduce uncertainty of C budget estimates/projections
- Need more time, people, funding, and recognition for technical testing, experiments, and developments
- *Move to a more diverse set of uses for these models?*
 - *Hypothesis testing*
 - *Stakeholder adaptation/mitigation planning and policy decision making? E.g. short-term agricultural productivity and drought monitoring?*

Thank you for listening! Any questions?

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