Land surface model parameter estimation and data assimilation: where are we now and where do we want to go?

Natasha MacBean

Western University

Contributions from: Philippe Peylin, Cédric Bacour, Nina Raoult, Tristan Quaife, Nuno Carvalhais

What is Bayesian DA and why do we need it for land models?

- Bayesian framework: use new information (from observations) to update prior knowledge (theory encoded in model or parameter distributions)

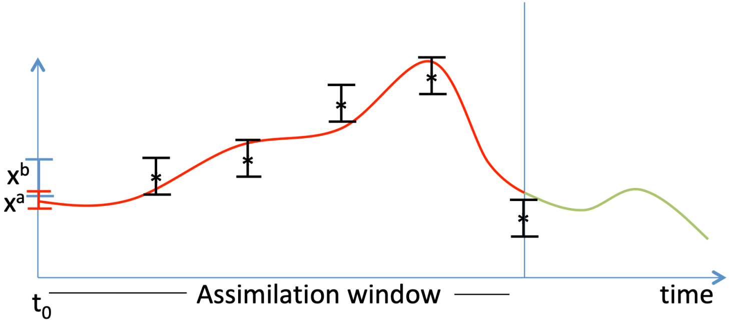
- Quantify and reduce uncertainty model predictions by minimizing a likelihood function (considering uncertainties in both the model, observations and priors)

What is Bayesian DA and why do we need it for land models?

Mainly two approaches:

1. Smoother / Variational

Use all observations over a time widow



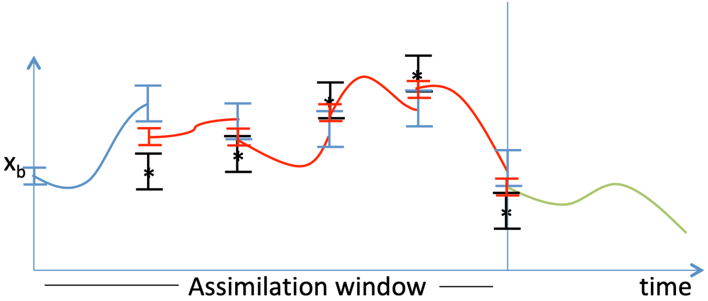
*Observations
background uncertainty, characterised by **B**
observation uncertainty, characterised by **R**

$M(x^a)$
analysis uncertainty.

forecast

2. Filters / Sequential

Use observations sequentially in time as they become available



*Observations
$M(x_b)$
$M(x_a)$
forecast
a-priori uncertainty, characterised by $\mathbf{P}_f$

observation uncertainty, characterised by **R**
analysis uncertainty.

Credit: Alison Fowler:
http://www.met.reading.ac.uk/~darc/training/ecmwf_collaborative_training/EnKF_AFowler.pdf

Global C Cycle Data Assimilation Systems (CCDAS)

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. Widmann[5]

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

Gregor J. Schürmann[1], Thomas Kaminski[2,a], Christoph Köstler[1], Nuno Carvalhais[1], Michael Voßbeck[2,a], Jens Kattge[1], Ralf Giering[3], Christian Rödenbeck[1], Martin Heimann[1], and Sönke Zaehle[1,4]

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

Philippe Peylin[1], Cédric Bacour[2], Natasha MacBean[1], Sébastien Leonard[1], Peter Rayner[1,3], Sylvain Kuppel[1,4], Ernest Koffi[1], Abdou Kane[1], Fabienne Maignan[1], Frédéric Chevallier[1], Philippe Ciais[1], and Pascal Prunet[2]

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 Land Variational Ensemble Data Assimilation Framework: LAVENDAR v1.0.0

Ewan Pinnington[1], Tristan Quaife[1,2], Amos Lawless[1,2], Karina Williams[3], Tim Arkebauer[4], and Dave Scoby[4]

PNAS

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 Willia

An Observation-Driven Approach to Improve Vegetation Phenology in a Global Land Surface Model

Jana Kolassa[1,2], Rolf H. Reichle[2], Randal D. Koster[2], Qing Liu[2,3], Sarith Mahanama[2,3], and Fan-Wei Zeng[2,3]

C cycle parameter DA with LSMs/TBMs

Understanding the effect of disturbance from selective felling on the carbon dynamics of a managed woodland by combining observations with model predictions

Ewan M. Pinnington[1], Eric Casella[2], Sarah L. Dance[1,3], Amos S. Lawless[1,3,4], James I. L. Morison[2], Nancy K. Nichols[1,3,4], Matthew Wilkinson[2], and Tristan L. Quaife[1,4]

Optimal model complexity for terrestrial carbon cycle prediction

Caroline A. Famiglietti[1], T. Luke Smallman[2], Paul A. Levine[3], Sophie Flack-Prain[2], Gregory R. Quetin[1], Victoria Meyer[4], Nicholas C. Parazoo[3], Stephanie G. Stettz[3], Yan Yang[3], Damien Bonal[5], A. Anthony Bloom[3], Mathew Williams[2], and Alexandra G. Konings[1]

Interannual variability in Australia's terrestrial carbon cycle constrained by multiple observation types

Cathy M. Trudinger[1], Vanessa Haverd[2], Peter R. Briggs[2], and Josep G. Canadell[2]

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

V. Haverd[1], M. R. Raupach[1], P. R. Briggs[1], J. G. Canadell[1], P. Isaac[1], C. Pickett-Heaps[1], S. H. Roxburgh[2], E. van Gorsel[1], R. A. Viscarra Rossel[3], and Z. Wang[1,4]

Reconcilable differences: a joint calibration of fine-root turnover times with radiocarbon and minirhizotrons

Bernhard Ahrens[1], Karna Hansson[2], Emily F. Solly[1] and Marion Schrumpf[1]

Cutting out the middleman: calibrating and validating a dynamic vegetation model (ED2-PROSPECT5) using remotely sensed surface reflectance

Alexey N. Shiklomanov[1], Michael C. Dietze[2], Istem Fer[3], Toni Viskari[3], and Shawn P. Serbin[4]

Microbial models with data-driven parameters predict stronger soil carbon responses to climate change

OLEKSANDRA HARARUK[1,2], MATTHEW J. SMITH[2] and YIQI LUO[1,3]

Reviews of DA for C cycle parameter estimation

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. Hooker-Stroud,[8] S. Houweling,[9] T. Kato,[10] J. Kattge,[3] D. Kelley,[8,14] S. Kemp,[8] E. N. Koffi,[7] C. Köstler,[3] P.-P. Mathieu,[11] B. Pinty,[7] C. H. Reick,[6] C. Rödenbeck,[3] R. Schnur,[6] K. Scipal,[11] C. Sebald,[5] T. Stacke,[6] A. Terwisscha van Scheltinga,[8] M. Vossbeck,[1] H. Widmann,[12] and T. Ziehn[13]

Quantifying and Reducing Uncertainty in Global Carbon Cycle Predictions: Lessons and Perspectives From 15 Years of Data Assimilation Studies With the ORCHIDEE Terrestrial Biosphere Model

N. MacBean[1], C. Bacour[2,3], N. Raoult[3], V. Bastrikov[4], E. N. Koffi[5], S. Kuppel[6], F. Maignan[3], C. Ottlé[3], M. Peaucelle[7,8], D. Santaren[3], and P. Peylin[3]

Fundamentals of data assimilation applied to biogeochemistry

Peter J. Rayner[1], Anna M. Michalak[2], and Frédéric Chevallier[3]

Reviews and syntheses: Systematic Earth observations for use in terrestrial carbon cycle data assimilation systems

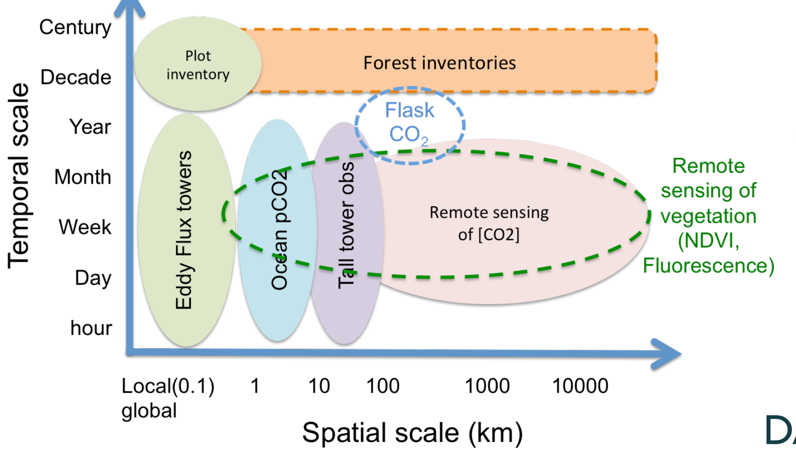
Marko Scholze[1], Michael Buchwitz[2], Wouter Dorigo[3], Luis Guanter[4], and Shaun Quegan[5]

Understanding the Land Carbon Cycle with Space Data: Current Status and Prospects

Jean-François Exbrayat[1] · A. Anthony Bloom[2] · Nuno Carvalhais[3,6] · Rico Fischer[4] · Andreas Huth[4,7,8] · Natasha MacBean[5] · Mathew Williams[1]

Reducing uncertainty: the need for data assimilation

Available C-related data streams



Parameter sensitivity analysis

Variational DA

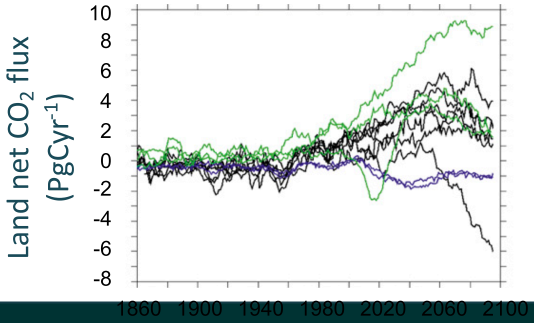
$$J(\mathrm{x}) = \tfrac{1}{2}(\mathbf{H}.\mathrm{x}-\mathrm{y})^{T}\,\mathbf{R}^{-1}(\mathbf{H}.\mathrm{x}-\mathrm{y})$$

Observation term

$$+\ \tfrac{1}{2}(\mathrm{x}-\mathrm{x}_b)^{T}\,\mathbf{B}^{-1}(\mathrm{x}-\mathrm{x}_b)$$

Prior parameter term

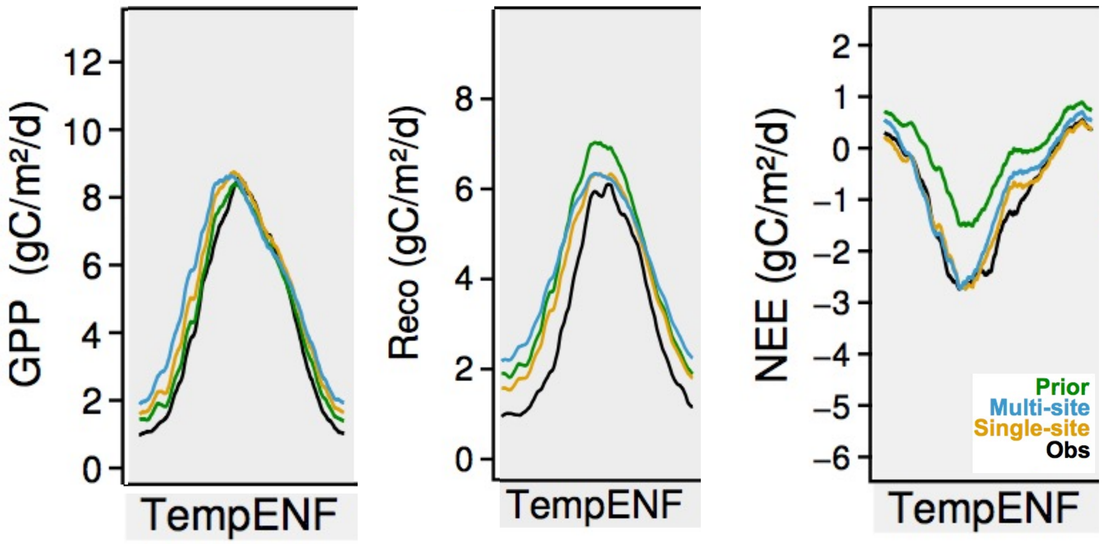
DATA ASSIMILATION → for parameter optimization



Improve:

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

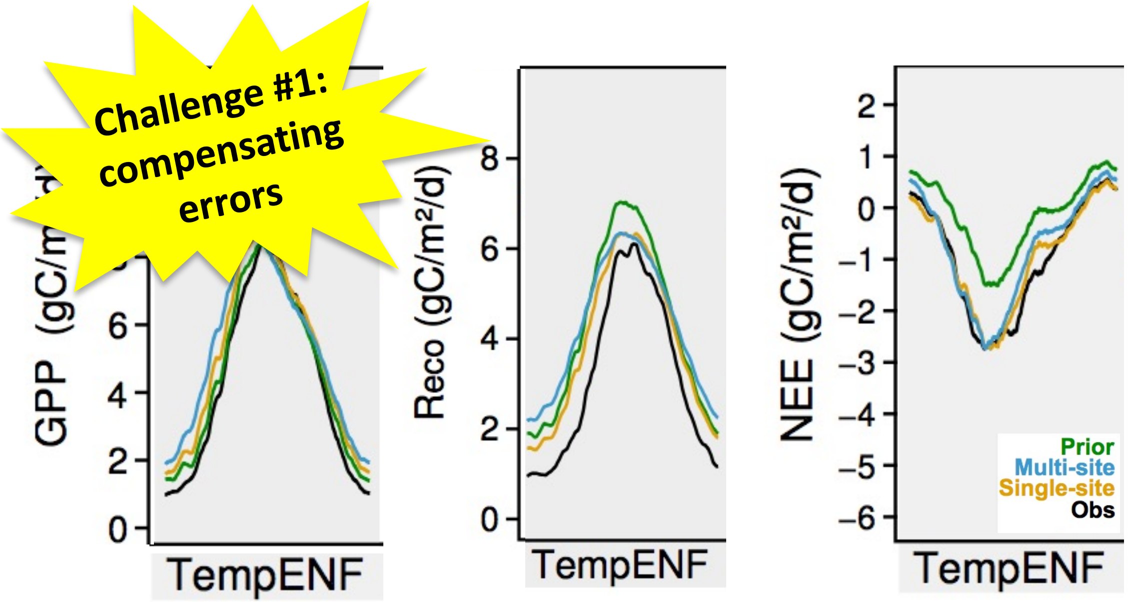
Net CO_2 fluxes constrains C flux seasonal cycle



- Fit NEE mean seasonal cycle well across most PFTs
- Multi-site similar fit to single site optims

Kuppel et al. (2012; 2014) *Biogeosciences*

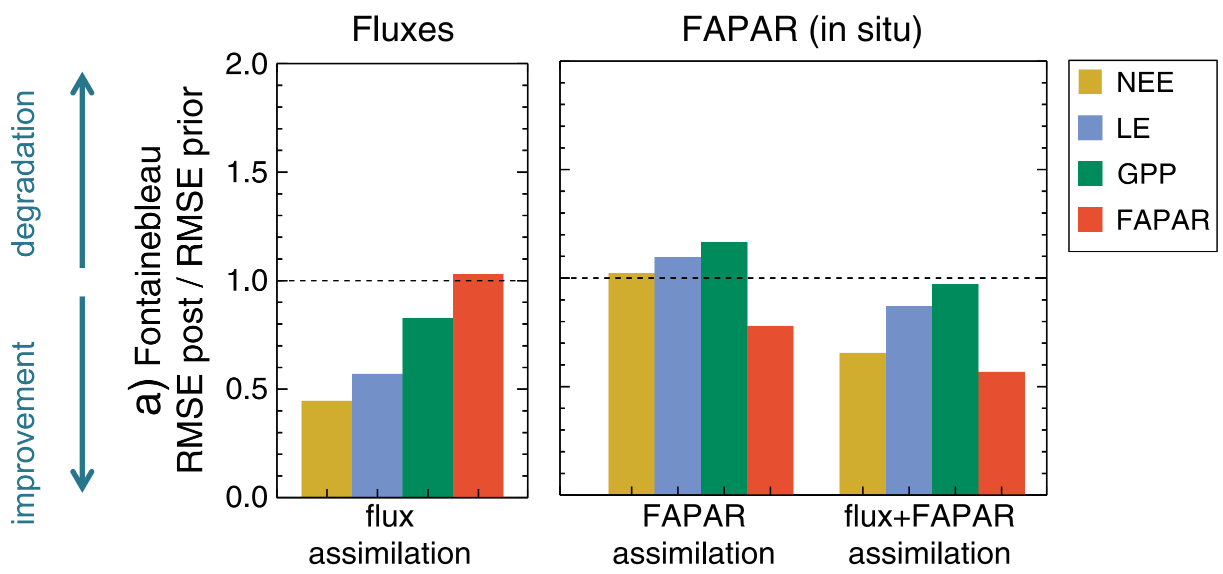
Net CO_2 fluxes constrains C flux seasonal cycle



- Fit NEE mean seasonal cycle well across most PFTs
- Multi-site similar fit to single site optim

Kuppel et al. (2014) *Biogeosciences*

Challenges of multiple data stream assimilation → fluxes + satellite FAPAR



- Fontainebleau (Oak forest) : RMSE post / RMSE prior

Bacour et al. (2015) *JGR-B*

Challenges of model-data inconsistencies/data biases

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]

Challenge #2: model-data inconsistencies/biases – specifying errors properly

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

C. Bacour[1,2], P. Peylin[2], N. MacBean[2], P. J. Rayner[2,3], F. Delage[2,4], F. Chevallier[2], M. Weiss[5], J. Demarty[5,6], D. Santaren[7,8], F. Baret[5], D. Berveiller[9], E. Dufrêne[9], and P. Prunet[1]

Balancing multiple constraints in model-data integration: Weights and the parameter block approach

T. Wutzler[1] and N. Carvalhais[1,2]

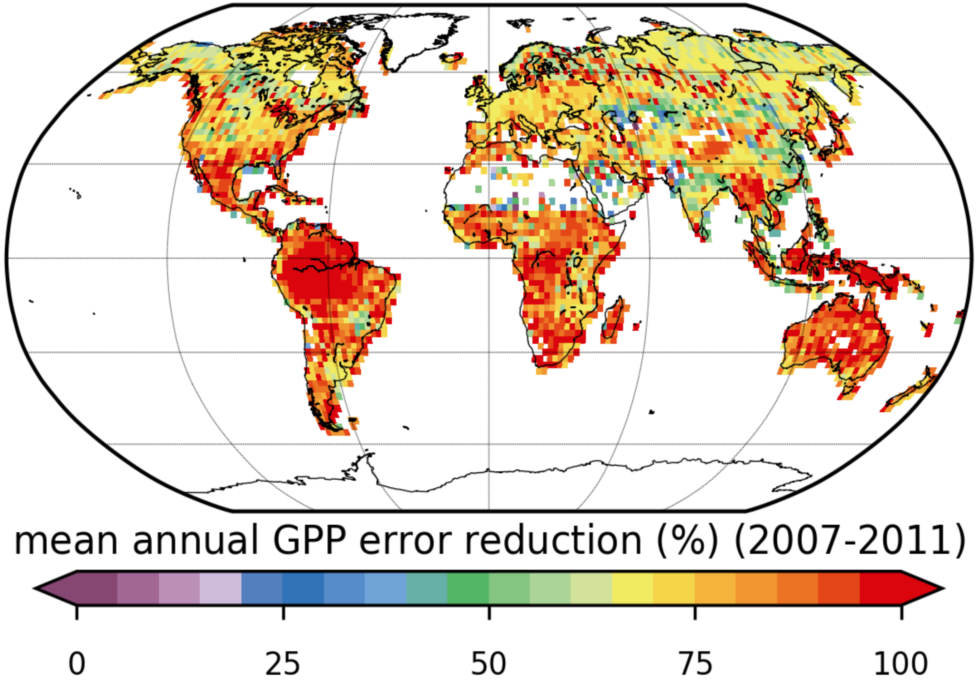
Differences Between OCO-2 and GOME-2 SIF Products From a Model-Data Fusion Perspective

C. Bacour[1], F. Maignan[2], P. Peylin[2], N. MacBean[3], V. Bastrikov[2], J. Joiner[4], P. Köhler[5], L. Guanter[6], and C. Frankenberg[5,7]

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

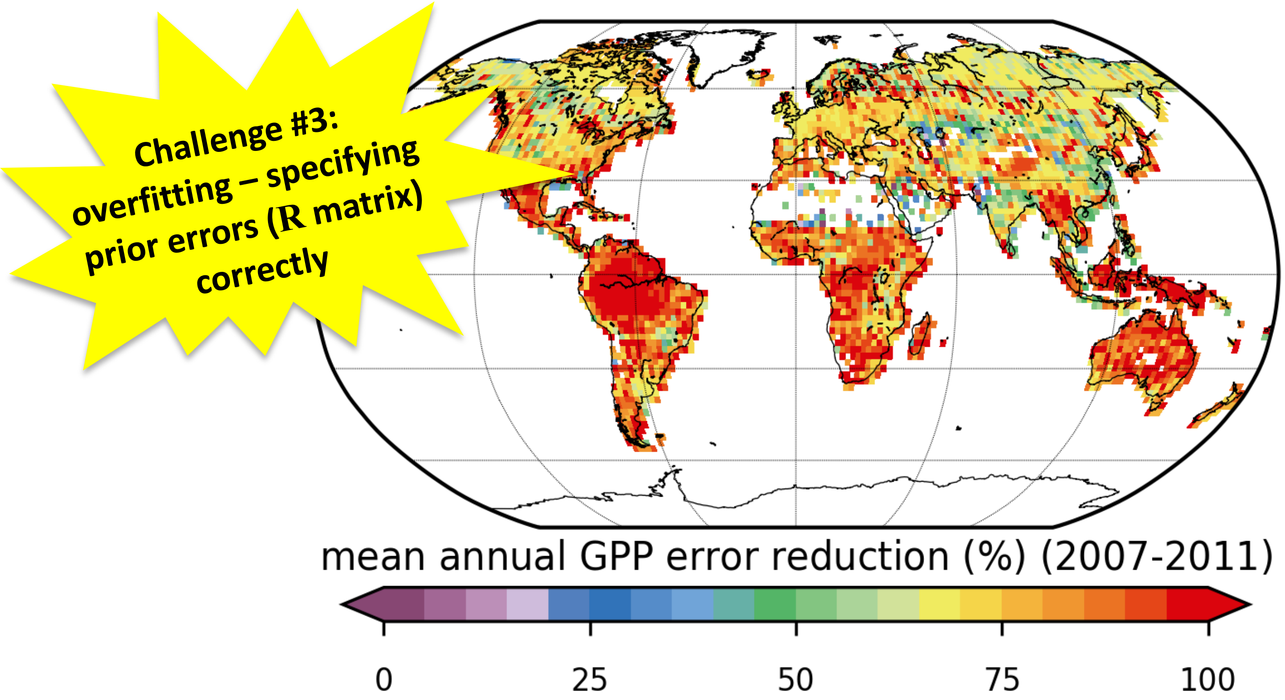
Natasha MacBean[1], Philippe Peylin[1], Frédéric Chevallier[1], Marko Scholze[2], and Gregor Schürmann[3]

Model overfitting



MacBean et al. (2018) *Sci. Rep.*

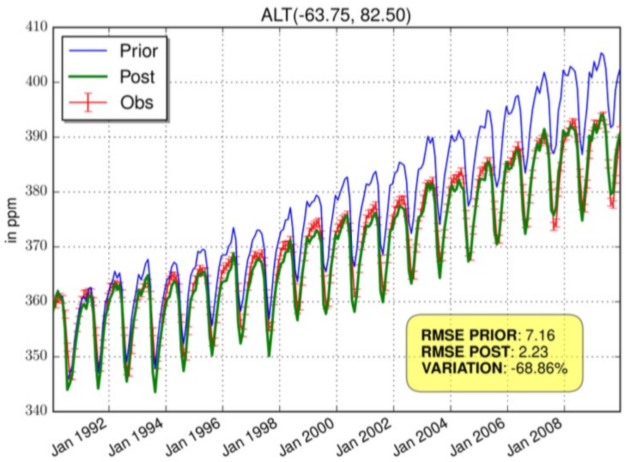
Model overfitting

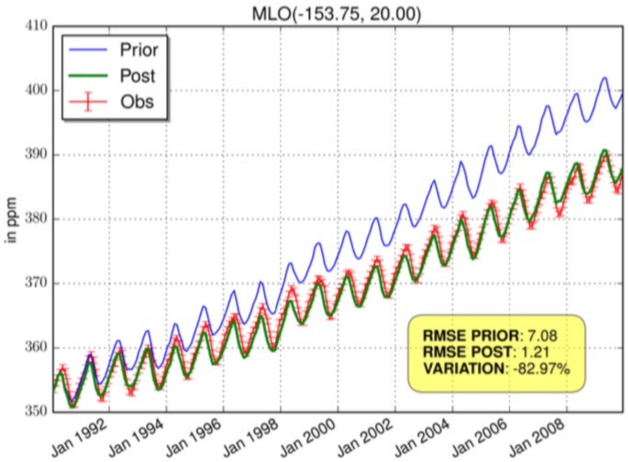


MacBean et al. (2018) *Sci. Rep.*

Atmospheric CO_2 constrains trend in the net C sink

- Reduced total soil carbon content (soil C scalar)
- Changed soil respiration parameters
- Better fit to long-term (20 year) trend in atm. [CO_2] data



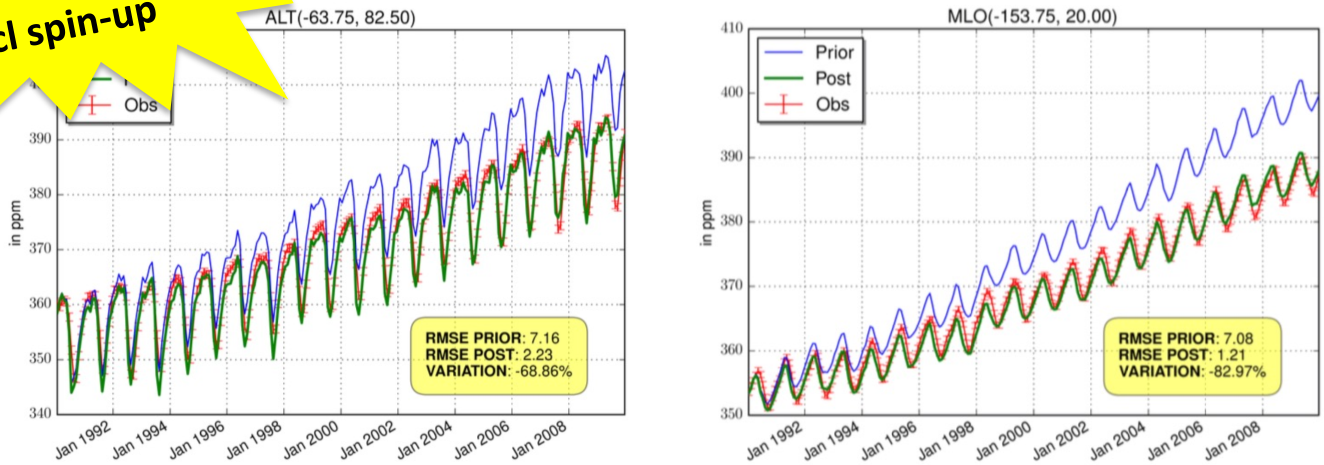


Peylin et al. (2016) *GMD*

Atmospheric CO_2 constrains trend in the net C sink

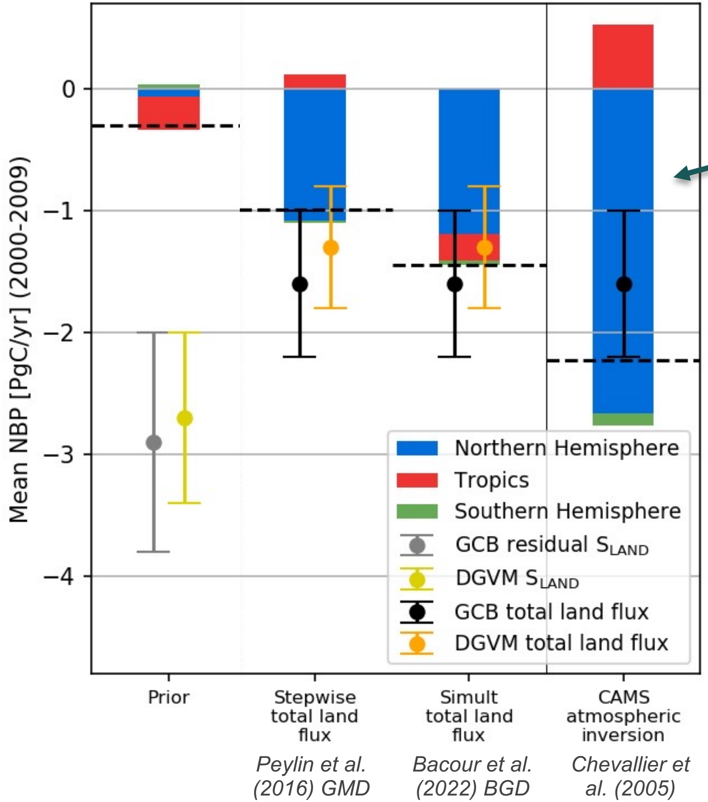
- Red[...]ced total soil carbon content (soil C scalar)
- [...]anged soil respiration parameters
- [...] long-term (20 year) trend in atm. [CO_2] data

Challenge #4: need accurate initial soil C OR incl spin-up



Peylin et al. (2016) *GMD*

Global net CO_2 flux: different DA configurations cf. atmospheric inversions

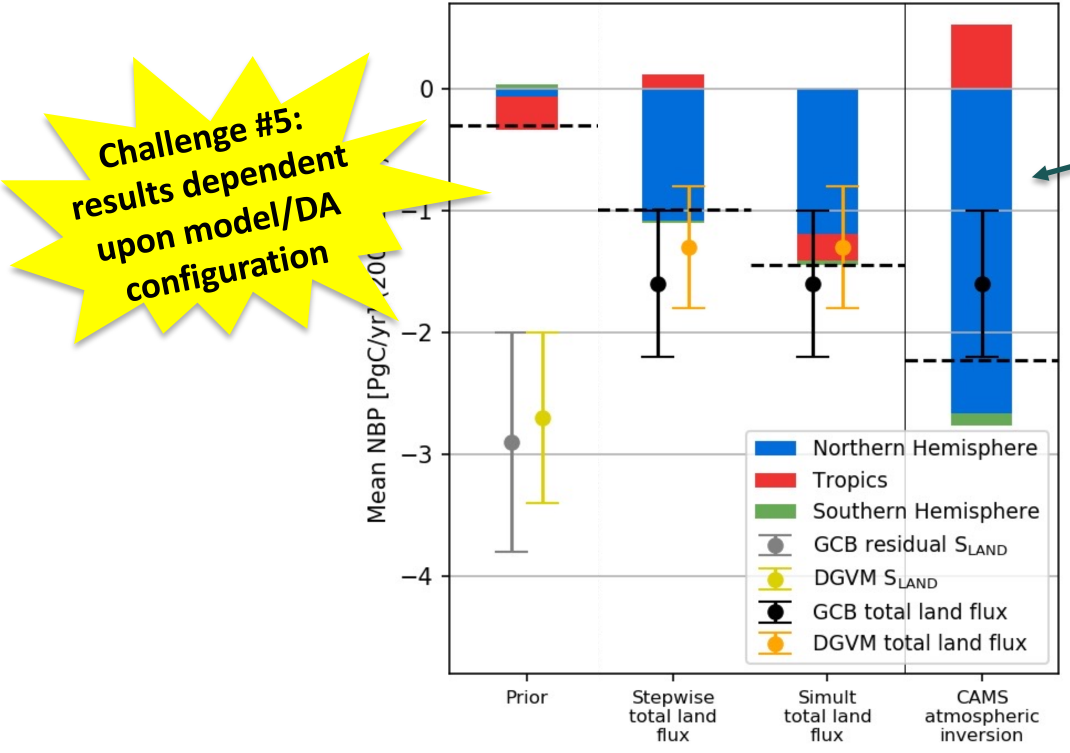


Independent "top-down" estimate (atmospheric inversion)

Which region has the strongest C sink?

MacBean et al. (2022) *GBC*

Global net CO_2 flux: different DA configurations cf. atmospheric inversions



Peylin et al. (2016) GMD

Bacour et al. (2022) BGD

Chevallier et al. (2005)

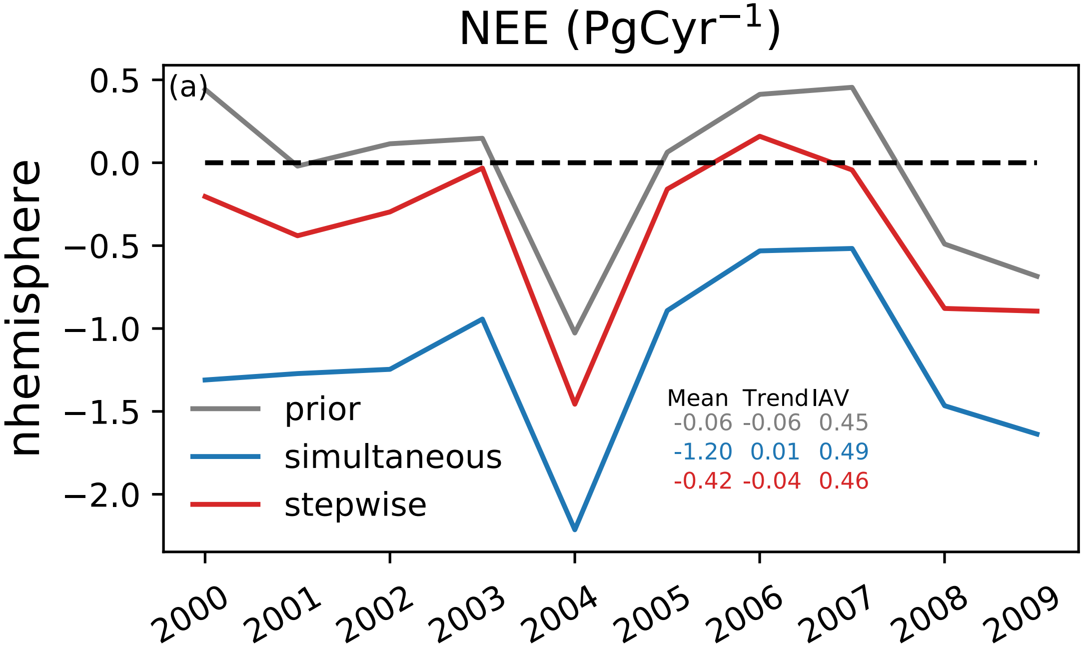
Independent "top-down" estimate (atmospheric inversion)

Which region has the strongest C sink?

MacBean et al. (2022) *GBC*

Remaining challenges of C cycle DA related to timescale…

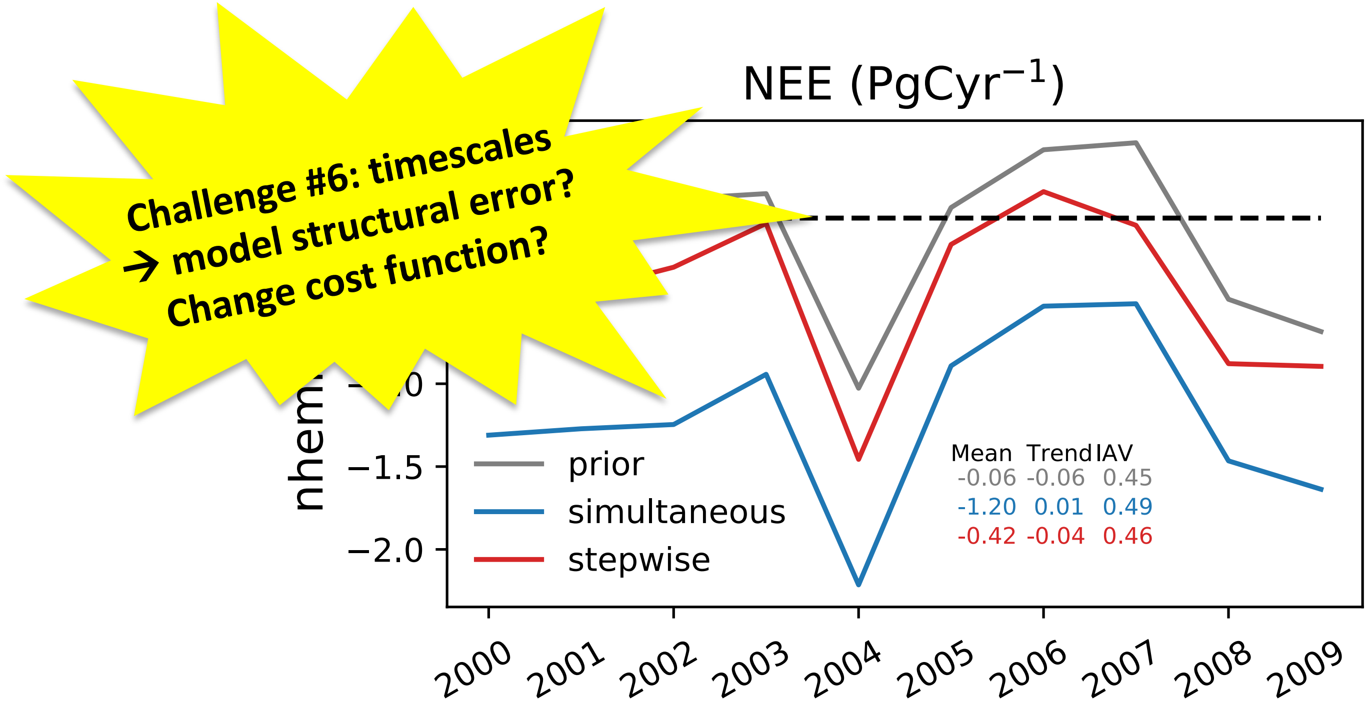
- So far: not much change in trend or IAV at regional scales…



MacBean et al. (2022) GBC

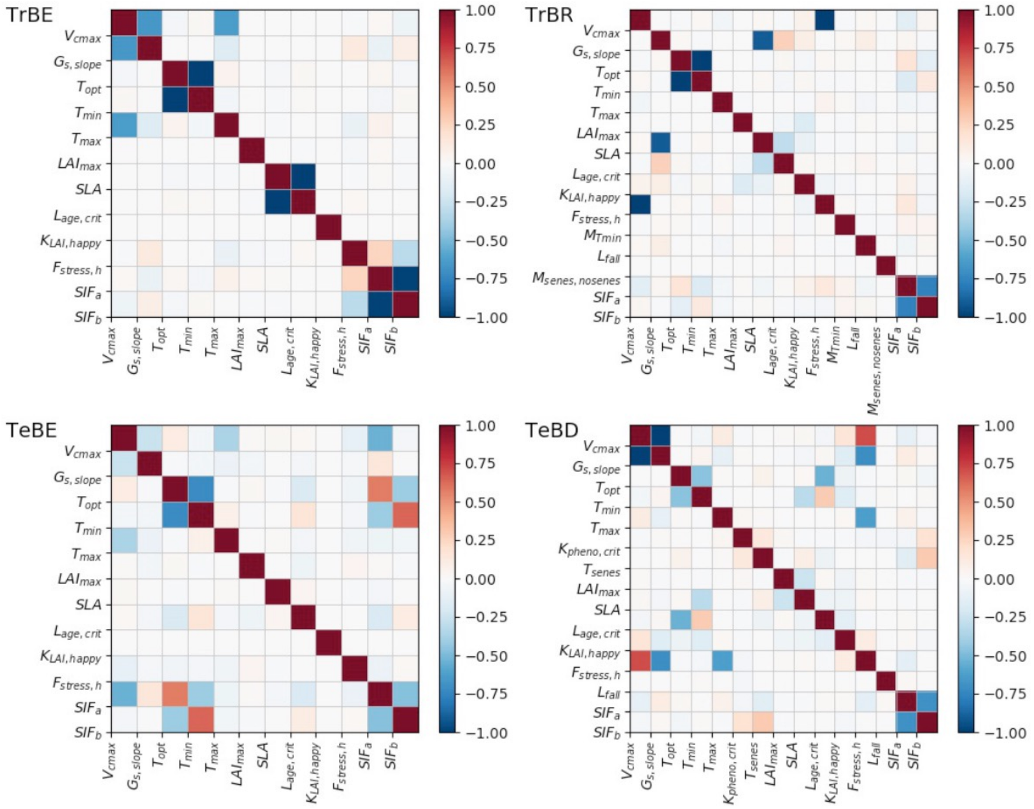
Remaining challenges of C cycle DA related to timescale…

➢ So far: not much change in trend or IAV at regional scales…



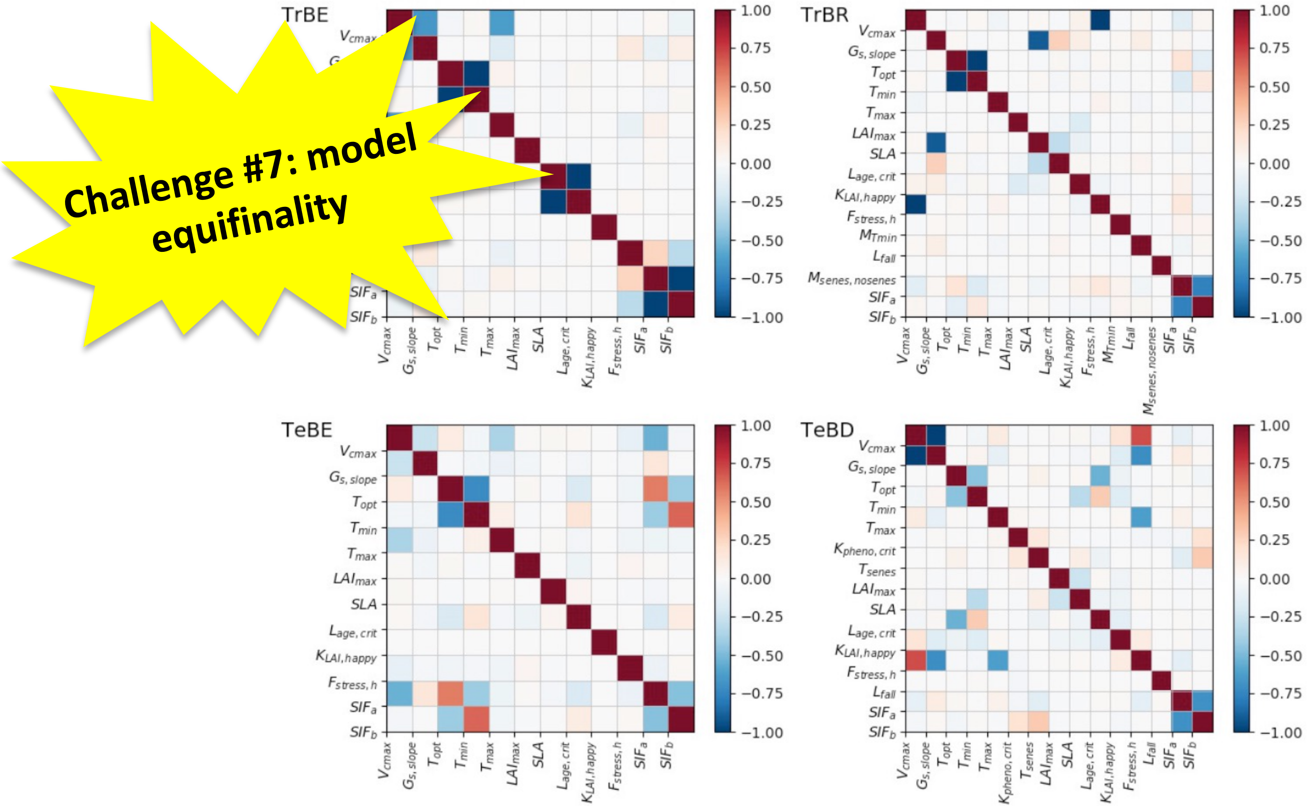
MacBean et al. (2022) GBC

Parameter error correlations



MacBean et al. (2018) Sci.Rep.

Parameter error correlations



MacBean et al. (2018) Sci.Rep.

Soil moisture parameter estimation

Improving soil moisture prediction of a high-resolution land surface model by parameterising pedotransfer functions through assimilation of SMAP satellite data

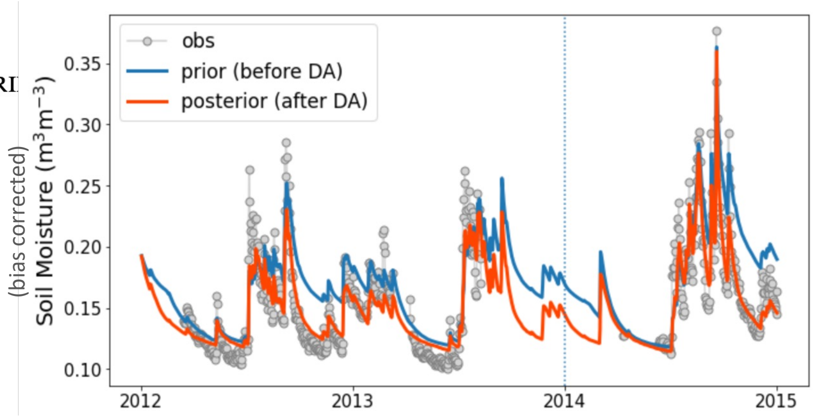
Ewan Pinnington[1], Javier Amezcua[1], Elizabeth Cooper[2], Simon Dadson[2,3], Rich Ellis[2], Jian Peng[5,6], Emma Robinson[2], Ross Morrison[2], Simon Osborne[4], and Tristan Quaife[1]

Simultaneous assimilation of SMOS soil moisture and atmospheric CO_2 in-situ observations to constrain the global terrestrial carbon cycle

M. Scholze[a,*], T. Kaminski[b,1], W. Knorr[a], S. Blessing[c], M. Vossbeck[b,1], J.P. Grant[a], K. Scipal[d]

Evaluating and Optimizing Surface Soil Moisture Drydowns in the ORCHIDEE Land Surface Model at In Situ Locations

NINA RAOULT,[a] CATHERINE OTTLÉ,[a] PHILIPPE PEYLIN,[a] VLADISLAV BASTRI



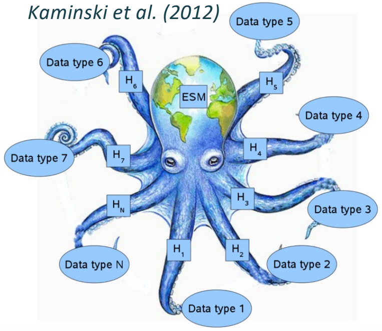
Solutions?

More "DA Science" studies needed!

- **Testing DA configurations** → timescale, record length observation frequency and uncertainty, data type and weight in cost function, #sites, #PFTs, #parameters, processes to which they're sensitive, prior bounds, different cost functions, etc)
- **Synthetic expts w/ known "true" parameters** (OSSEs)
- **Accurate characterization of observation error covariance matrix** ($\mathbf{R}$)
  - Lessons from atmospheric DA community
  - Hunt for model-data inconsistencies
  - Data biases and autocorrelations

More "DA Science" studies needed!

Kaminski et al. (2012)



Climatic and phenological controls on coherent regional interannual variability of carbon dioxide flux in a heterogeneous landscape

Ankur R. Desai[1]

Parameter and prediction uncertainty in an optimized terrestrial carbon cycle model: Effects of constraining variables and data record length

Daniel M. Ricciuto,[1] Anthony W. King,[1] D. Dragoni,[2] and Wilfred M. Post[1]

Estimating transpiration and the sensitivity of carbon uptake to water availability in a subalpine forest using a simple ecosystem process model informed by measured net CO_2 and H_2O fluxes

David J.P. Moore[a,d,], Jia Hu[b], William J. Sacks[c], David S. Schimel[d,e], Russell K. Monson[a,b]*

Implications of the carbon cycle steady state assumption for biogeochemical modeling performance and inverse parameter retrieval

Nuno Carvalhais,[1,2] Markus Reichstein,[2] Júlia Seixas,[1] G. James Collatz,[3] João Santos Pereira,[4] Paul Berbigier,[5] Arnaud Carrara,[6] André Granier,[7]

Quantifying the model structural error in carbon cycle data assimilation systems

S. Kuppel, F. Chevallier, and P. Peylin

Balancing multiple constraints in model-data integration: Weights and the parameter block approach

T. Wutzler[1] and N. Carvalhais[1,2]

Rate my data: quantifying the value of ecological data for the development of models of the terrestrial carbon cycle

Trevor F. Keenan,[1,4] Eric A. Davidson,[2] J. William Munger,[3] and Andrew D. Richardson[1]

More "DA Science" studies needed → new methods

- **Testing different DA methods:** sequential vs variational, gradient based vs global search vs ensemble methods
- **DA vs ML vs hybrid →** increase computational efficiency
- **Testing new observations:** e.g., radiocarbon for soil C turnover

Linking big models to big data: efficient ecosystem model calibration through Bayesian model emulation

Istem Fer[1], Ryan Kelly[2], Paul R. Moorcroft[3], Andrew D. Richardson[4,5], Elizabeth M. Cowder
Michael C. Dietze[1]

Bayesian calibration of terrestrial ecosystem models: a study of advanced Markov chain Monte Carlo methods

Dan Lu[1], Daniel Ricciuto[2], Anthony Walker[2], Cosmin Safta[3], and William Munger[4]

Capturing site-to-site variability through Hierarchical Bayesian calibration of a process-based dynamic vegetation model

Istem Fer, Alexey Shiklomanov, Kimberly A. Novick, Christopher M. Gough, M. Altaf Arain, Jiquan Chen, Bailey Murphy, Ankur R. Desai, Michael C. Dietze

Land surface model parameter optimisation using in situ flux data: comparison of gradient-based versus random search algorithms (a case study using ORCHIDEE v1.9.5.2)

Vladislav Bastrikov[1,2], Natasha MacBean[1,a], Cédric Bacour[3], Diego Santaren[1], Sylvain Kuppel[4], and Philippe Peylin[1]

OptIC project: An intercomparison of optimization techniques for parameter estimation in terrestrial biogeochemical models

Cathy M. Trudinger,[1] Michael R. Raupach,[2] Peter J. Rayner,[3] Jens Kattge,[4] Qing Liu,[5] Bernard Pak,[1] Markus Reichstein,[4] Luigi Renzullo,[6] Andrew D. Richardson,[7]

New methods

The Land Variational Ensemble Data Assimilation Framework: LAVENDAR v1.0.0

Ewan Pinnington[1], Tristan Quaife[1,2], Amos Lawless[1,2], Karina Williams[3], Tim Arkebauer[4], and Dave Scoby[4]

- Essentially 4DVar without needing an adjoint or TLM
- Ensemble generation and analysis are completely separate
- We typical use 20-50 ensemble members → can be slow, depending on problem
- **But** analysis step is *extremely fast*
  → Don’t need to run the model!
  → 9M observations in a few minutes for Africa example
- Consequently, once an ensemble is built it is possible to run multiple experiments with it → E.g. to examine the impact of different observations
- https://github.com/tquaife/4DEnVar_engine

Model equifinality and parameter selection

- **Broad sensitivity analysis** → ML can help
- **Identify parameter relationships** → mine trait databases + recommendations for data collection
- **Use ecological knowledge in minimisation**

Model equifinality and parameter selection

Covariations between plant functional traits emerge from constraining parameterization of a terrestrial biosphere model

Marc Peaucelle[1,2] | Cédric Bacour[3] | Philippe Ciais[1] | Nicolas Vuichard[1] |
Sylvain Kuppel[4] | Josep Peñuelas[2,5] | Luca Belelli Marchesini[6,7] |
Peter D. Blanken[8] | Nina Buchmann[9] | Jiquan Chen[10] | Nicolas
Ankur R. Desai[12] | Eric Dufrene[11] | Damiano Gianelle[6] | Cristina Gin
Carsten Gruening[14] | Carole Helfter[15] | Lukas Hörtnagl[9] | And
Richard Joffre[17] | Tomomichi Kato[18,19] | Thomas E. Kolb[20] | Bever
Anders Lindroth[22] | Ivan Mammarella[23] | Lutz Merbold[24] | Stefano Minerbi |
Leonardo Montagnani[25,26] | Ladislav Šigut[27] | Mark Sutton[15] | Andrej Varlagin[28] |
Timo Vesala[29,30] | Georg Wohlfahrt[31] | Sebastian Wolf[32] | Dan Yakir[33] |
Nicolas Viovy[1]

Improving the predictability of global CO_2 assimilation rates under climate change

T. Ziehn,[1] J. Kattge,[2] W. Knorr,[1,3] and M. Scholze[1]

Constraining ecosystem carbon dynamics in a data-limited world: integrating ecological "common sense" in a model–data fusion framework

A. A. Bloom[1,*] and M. Williams[1]

Investigating the role of prior and observation error correlations in improving a model forecast of forest carbon balance using Four-dimensional Variational data assimilation

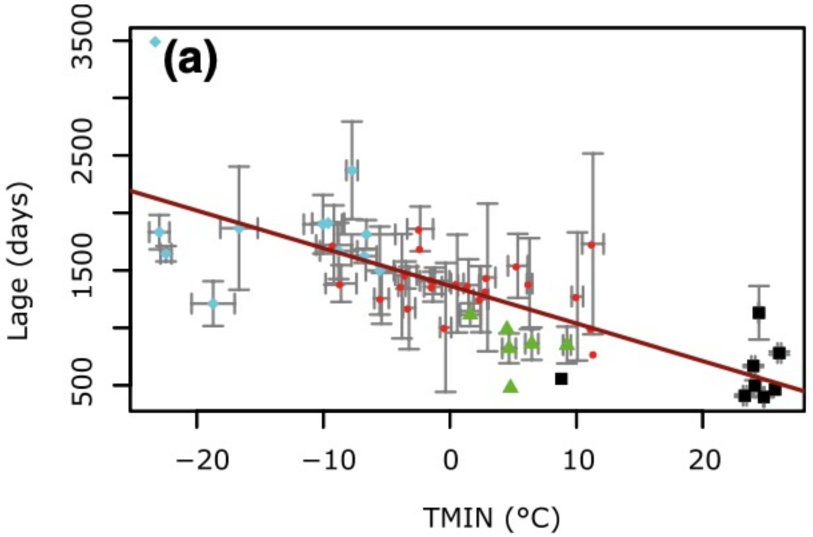
Ewan M. Pinnington[a,*], Eric Casella[c], Sarah L. Dance[a,b], Amos S. Lawless[a,b,d], James I.L. Morison[c], Nancy K. Nichols[a,b,d], Matthew Wilkinson[c], Tristan L. Quaife[a,d]

Model equifinality and parameter selection

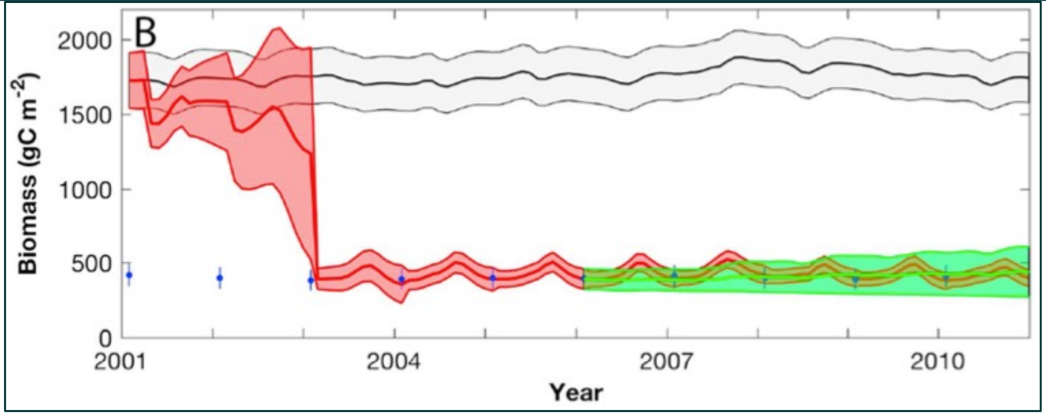
Covariations between plant functional traits emerge from constraining parameterization of a terrestrial biosphere model

Marc Peaucelle[1,2] | Cédric Bacour[3] | Philippe Ciais[1] | Nicolas Vuichard[1] |

Parameters		*r*	PFT
Lage	**SLA**	−0.67	ever
		−0.53	bro
		−0.63	All
Lage	Vcmax	−0.90	Bro
		−0.65	Dec
		−0.59	All
gslope	**Lage**	−0.70	Bro
		−0.57	Grass



State Data Assimilation for updating C stocks and fluxes with CLM



Evaluation of a Data Assimilation System for Land Surface Models Using CLM4.5

Andrew M. Fox[1], Timothy J. Hoar[2], Jeffrey L. Anderson[2], Avelino F. Arellano[3], William K. Smith[1], Marcy E. Litvak[4], Natasha MacBean[1], David S. Schimel[5], and David J. P. Moore[1]

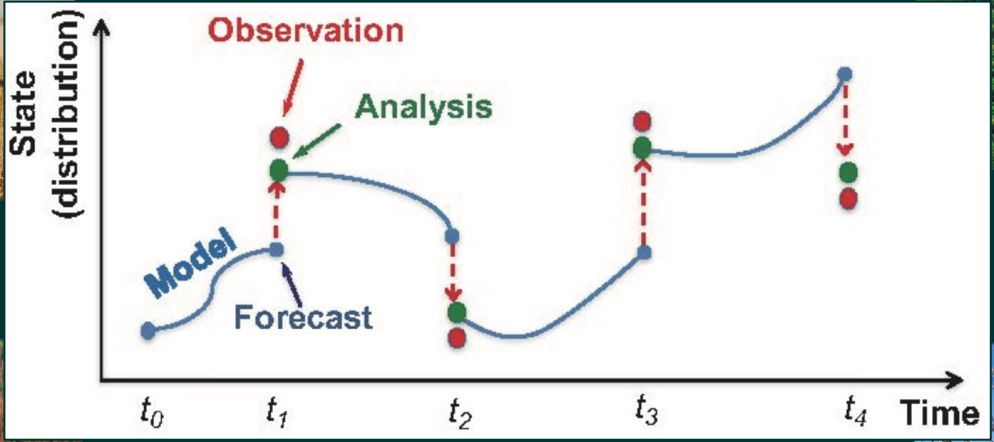
Assimilation of Global Satellite Leaf Area Estimates Reduces Modeled Global Carbon Uptake and Energy Loss by Terrestrial Ecosystems

Andrew M. Fox[1], Xueli Huo[2], Timothy J. Hoar[3], Hamid Dashti[2], William K. Smith[2], Natasha MacBean[4], Jeffrey L. Anderson[3], Matthew Roby[2], and David J. P. Moore[2]

Improving CLM5.0 Biomass and Carbon Exchange Across the Western United States Using a Data Assimilation System

Brett Raczka[1,2], Timothy J. Hoar[3], Henrique F. Duarte[4,5], Andrew M. Fox[6], Jeffrey L. Anderson[3], David R. Bowling[1,4], and John C. Lin[4]

Future Research: State DA for Optimizing initial C stocks and updating after Land Use/Cover Change + Parameter DA/optimization?



→ Better estimate impacts of past/ongoing change on carbon stocks, water, and climate

Join the Land DA Community!!

Land Data Assimilation Community About Join! Events News and Opportunities Publications Training

Land DA Community

Welcome to the Land DA Community Website!

Email

Github

Welcome to the Land DA Community Website!

This website will serve as a hub for all Land DA Community activities, resources, and announcements.

Please check out the pages above to see past and planned events, DA tutorials, land DA-related publications, job adverts, and more! You can also join the land DA community email listserv by clicking on the "Join!" tab above. Let us know via email if you have any suggestions for how to improve this website.

– *This website is maintained by the AIMES Land DA Working Group. Find out more here.*

https://land-da-community.github.io

https://aimesproject.org/ldawg/

June 14-16, 2021 | 9:00-12:00 EDT | Virtual Workshop

Tackling Technical Challenges in Land Data Assimilation

Organizers†: Natasha MacBean[1], Andy Fox[2], Jana Kolassa[3], Tristan Quaife[4]

[1]Indiana University, [2]Joint Center for Satellite Data Assimilation, [3]NASA GMAO, [4]University of Reading

About: This workshop will bring together land DA scientists to highlight the range of DA methods used within the community, discuss challenges facing different modeling communities, and identify strategies for addressing those challenges.

Themes:

1. Applicability of data assimilation approaches across different land modeling communities
2. Emerging techniques
3. Challenges in dealing with observations

Speakers: Anthony Bloom, NASA/JPL; Bertrand Bonan, Météo France; Patricia De Rosnay, ECMWF; Jianzhi Dong, USDA; Clara Draper, NOAA/ESRL; Moha El Gharamti, NCAR/UCAR; Istem Fer, Finnish Meteorological Institute; Manuela Girotto, UC Berkeley; Breo Gomez, UK Met Office; Jina Jeong, Vrije Universiteit Amsterdam; Sujay Kumar, NASA/GSFC; Eunjee Lee, NASA/GSFC; Ewan Pinnington, University of Reading; Ann Raiho, Colorado State University; Nina Raoult, LSCE; Marko Scholze, Lund University; Susan Steele-Dunn, TU Delft; Joanne Waller, UK Met Office

Register: aimesproject.org/LDA_workshop
Questions: aimes@futureearth.org

AIMES analysis, integration, and modeling of the earth system

†Organized by the AIMES Land Data Assimilation Working Group

futurearth

June 14-16, 2021 | 9:00-12:00 EDT | Virtual Workshop

Tackling Technical

https://doi.org/10.1175/BAMS-D-21-0228.1

BAMS

Meeting Summary

Building a Land Data Assimilation Community to Tackle Technical Challenges in Quantifying and Reducing Uncertainty in Land Model Predictions

Natasha MacBean, Hannah Liddy, Tristan Quaife, Jana Kolassa, and Andrew Fox

Met Office; Jina Jeong, Vrije Universiteit Amsterdam; Sujay Kumar, NASA/GSFC; Eunjee Lee, NASA/GSFC; Ewan Pinnington, University of Reading; Ann Raiho, Colorado State University; Nina Raoult, LSCE; Marko Scholze, Lund University; Susan Steele-Dunn, TU Delft; Joanne Waller, UK Met Office

†Organized by the AIMES Land Data Assimilation Working Group

Register: aimesproject.org/LDA_workshop
Questions: aimes@futureearth.org

futurearth

June 13-15, 2022 | 10:00-1:00 EDT | Virtual Workshop

futurearth AIMES analysis, integration, and modeling of the earth system

2nd Annual Land Data Assimilation Community Virtual Workshop

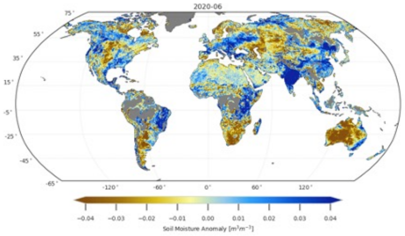
New Directions in Land Data Assimilation

OPEN REGISTRATION

About: This workshop will bring together land DA scientists to address the technical challenges we face in implementing DA systems by exchanging knowledge across all groups working in land DA and building a community of practice and collaboration in land DA.

Themes: (1) Machine Learning in Land DA (2) Novel Observations and Approaches (3) Ensemble DA Methods

Speakers: Cédric Bacour, LSCE/IPSL; Timothée Corchia, CNRM; Kenneth J. Davis, Pennsylvania State University; Michael Dietze, Boston University; Clara Draper, NOAA; Shunji Kotsuki, Chiba University; Sujay Kumar, NASA GSFC; Paul A. Levine, Jet Propulsion Lab at Caltech; Yiqi Luo, Northern Arizona University; Shuang Ma, Jet Propulsion Lab at Caltech; Philippe Peylin, CNRS-LSCE; Xu Shan, TU Delft; Daiva Shiojiri, Chiba University; Feng Tao, Tsinghua University; Yijian Zeng, University of Twente



MORE INFO / REGISTER
aimesproject.org/lda_workshop_2022/

QUESTIONS
aimes@futureearth.org

- ➢ **PROPOSE A BREAKOUT GROUP**
- ➢ **SUBMIT A POSTER (15th April)**
- ➢ **ADVERTISE JOB OPENINGS**
- ➢ **REGISTER (1st June)**

†Organized by the AIMES Land DA Working Group