



MAX-PLANCK-GESELLSCHAFT

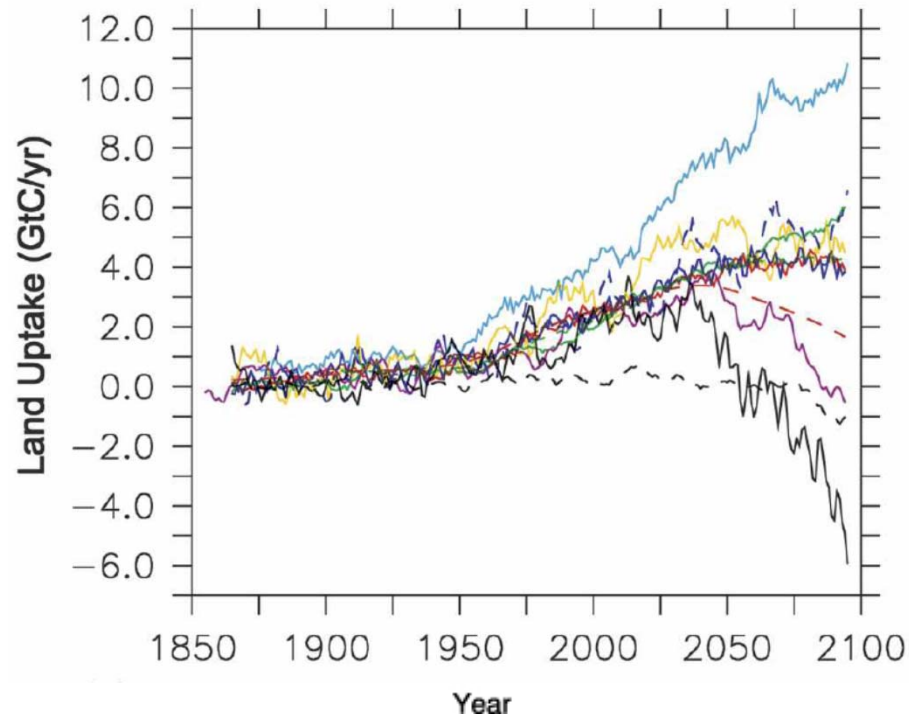


From observations to prediction through model-data integration: the importance of multiple constraints

Markus Reichstein, Nuno Carvalhais, Gregor Schürmann,
Thomas Wutzler, Matthias Forkel, Soenke Zaehle

Max-Planck Institute for Biogeochemistry, Jena
Department of Biogeochemical Integration

Motivation: carbon cycle uncertainty



Friedlingstein et al. (2006)

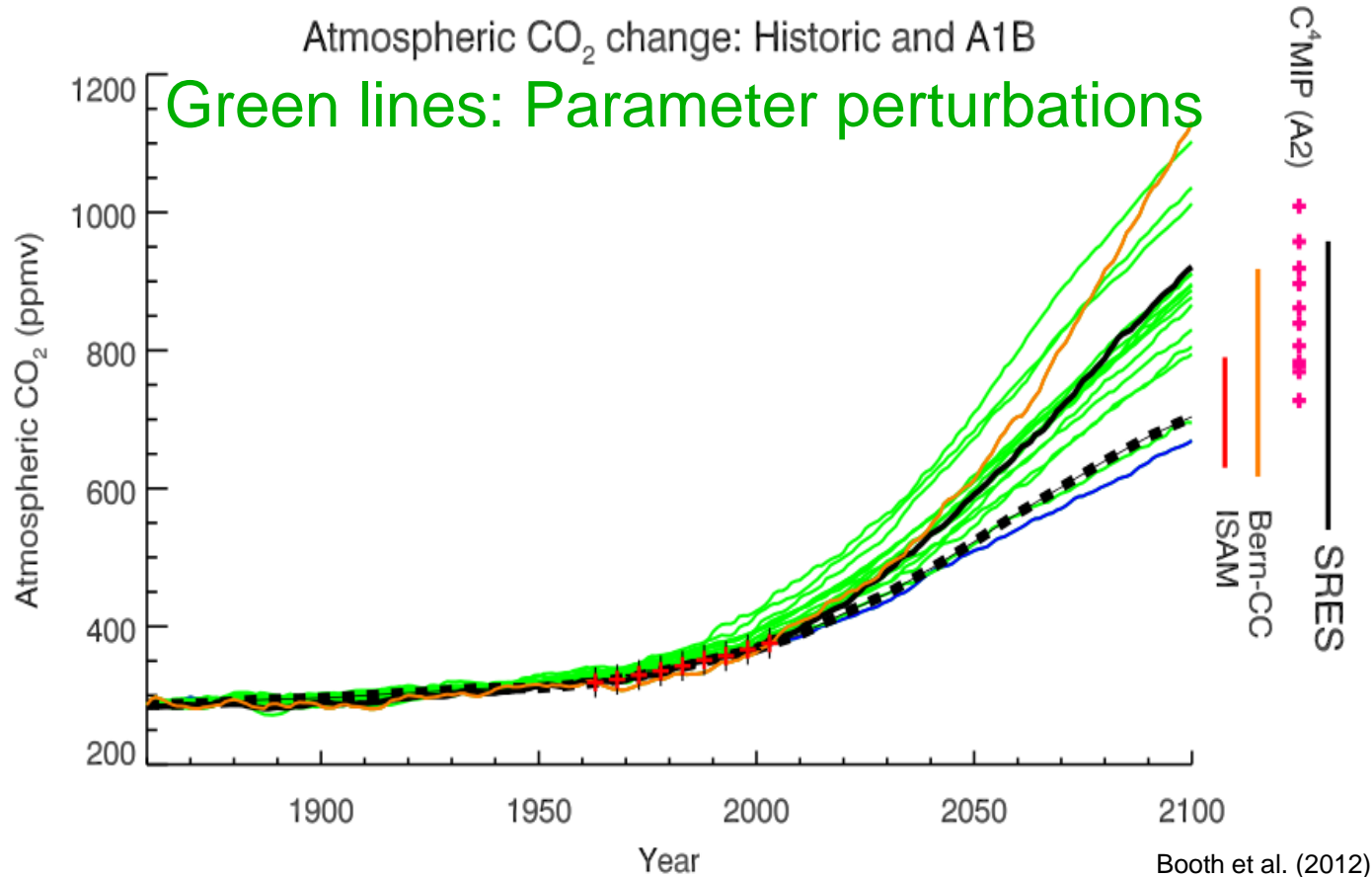


~1 Pbyte/year
(~200 Billion bibles [2e8] or 50 Lib of Congress)

Potential sources of uncertainty

- model structure
 - missing processes
 - misrepresentation of states dynamics
- parameterizations
 - wrong sensitivities
- initial conditions
 - inappropriate characterization of ecosystem states

Previous tests on parameter uncertainties



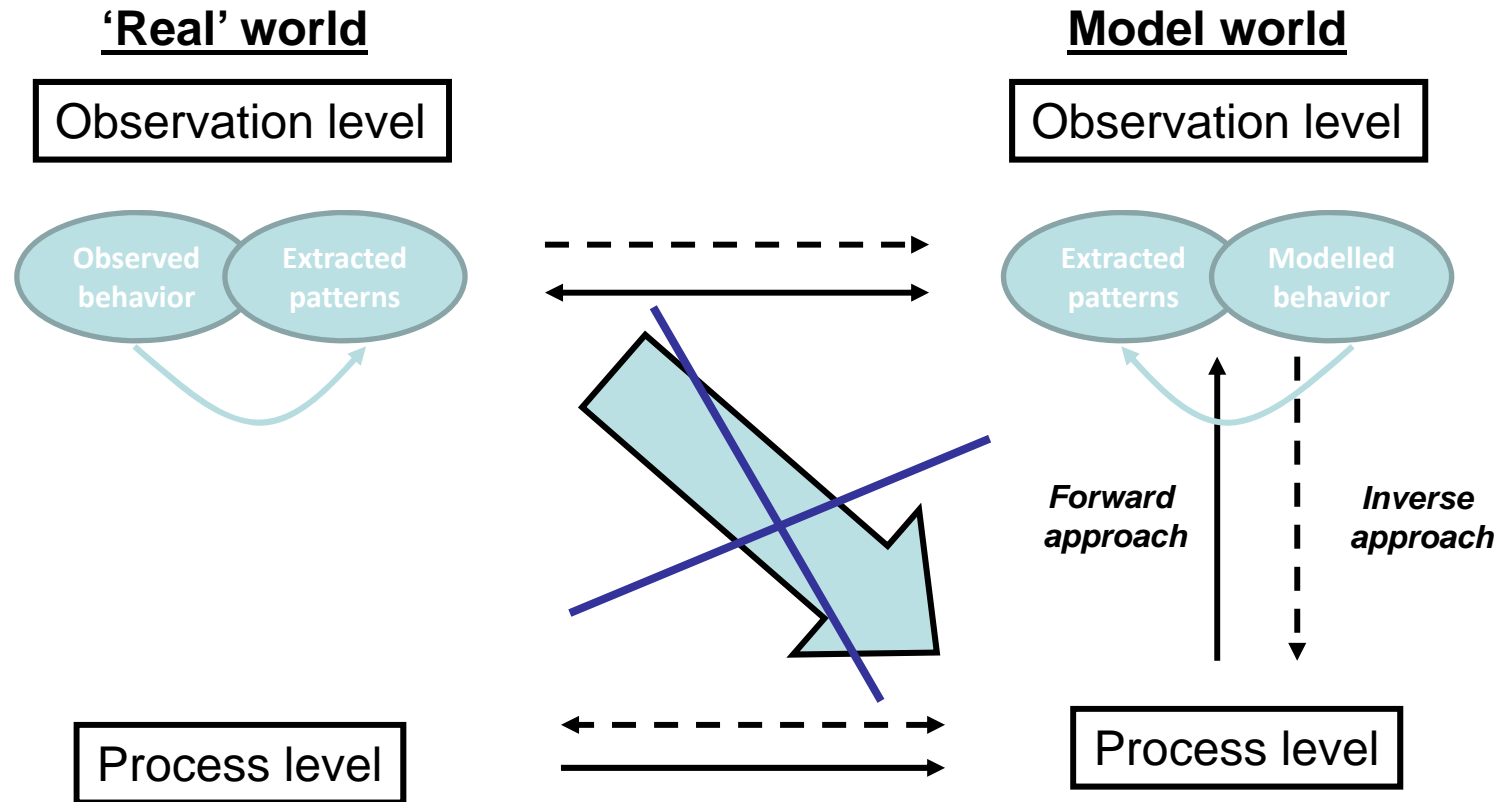
Model spread caused by parameters of the terrestrial component
Highly parameterized formulations

Potential sources of uncertainty

- model structure
 - missing processes
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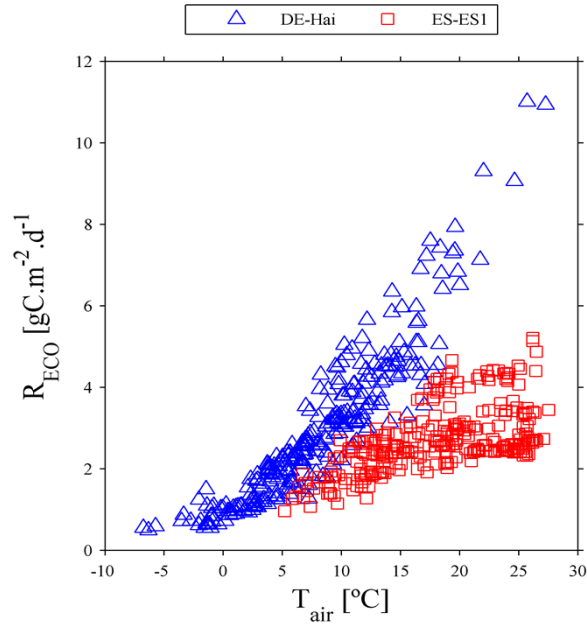
Explore the information content of observations from ecosystem to regional/global scales

Linking models and observations



Linking models and observations

Reichstein et al. 2005

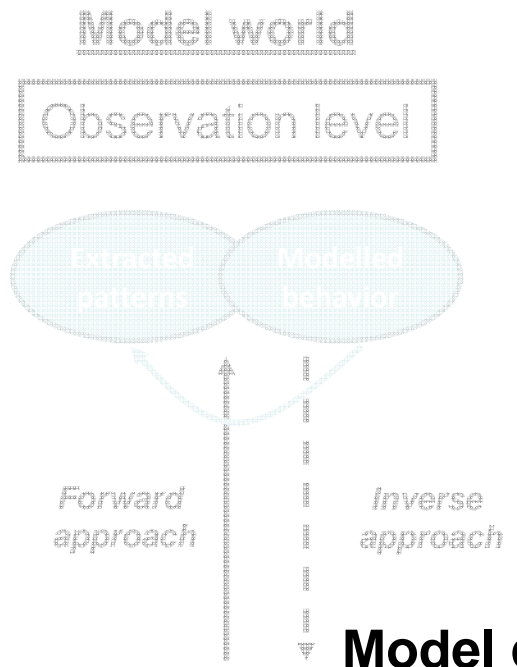
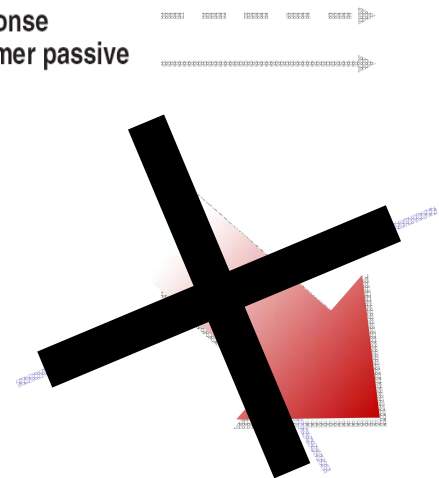


Process level

Confounded response
summer active

Direct 'true' response to temperature

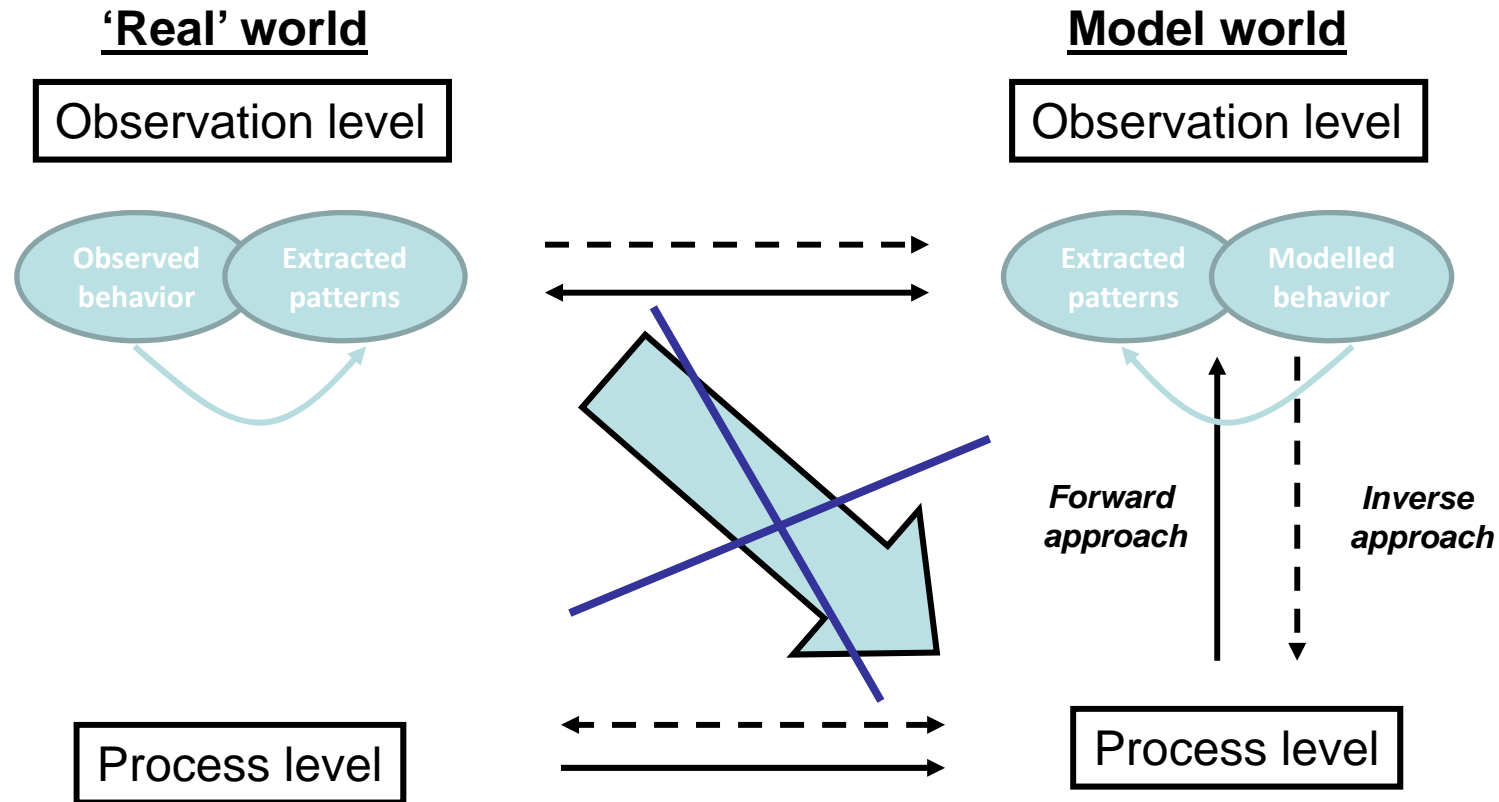
Confounded response
summer passive



```

if (tsoil < -10.0)
{
    /* no decomp processes for tsoil < -10.0 C */
    t_scalar = 0.0;
}
else
{
    tk = tsoil + 273.15;
    t_scalar = exp(308.56*((1.0/71.02)-(1.0/(tk-227.13))));
}
    
```

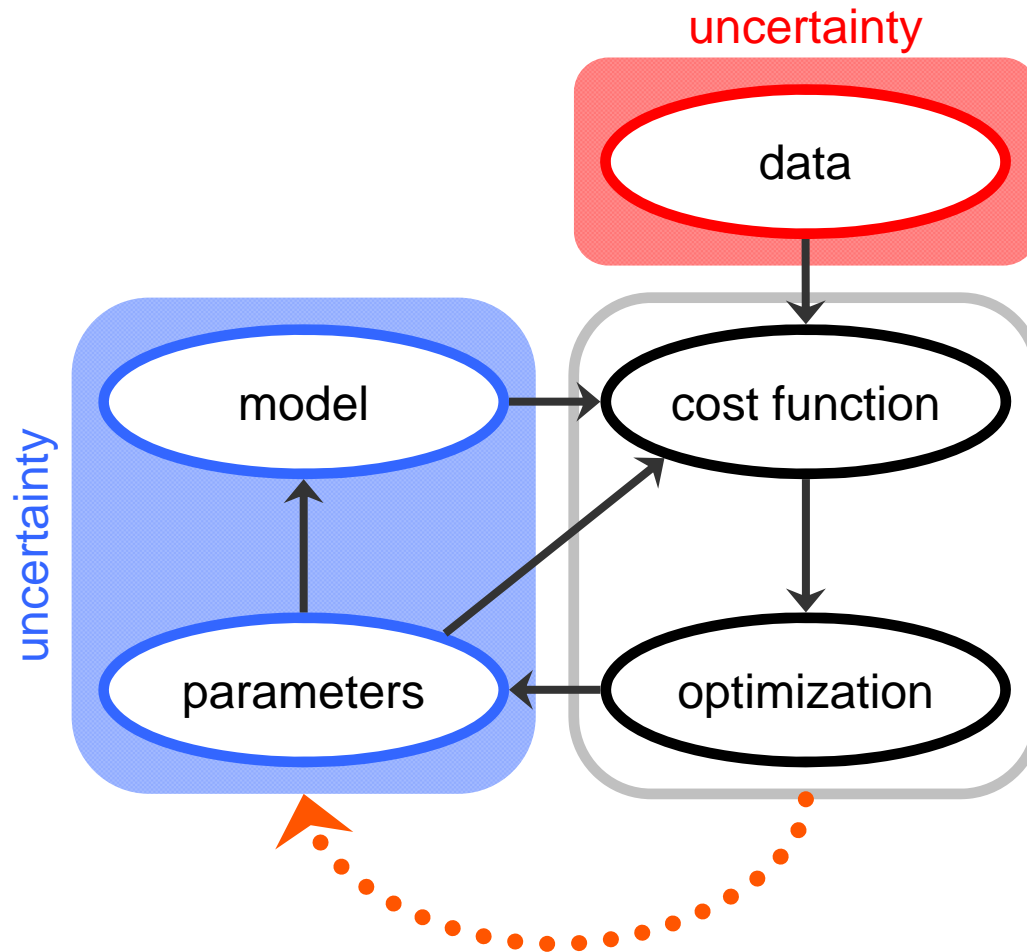
Linking models and observations



Challenge:

Extract generalized information from data sets, confront these with model behavior and interpret differences in a system-oriented way

Inversion methods



Model-data integration

- Cost functions
 - Single versus multiple constraints approaches

$$\Omega = \frac{1}{2} \sum_{i=1}^M \frac{1}{N_i} \left\{ \sum_{n=1}^{N_i} \frac{[\hat{y}_{i,n}(x, \mathbf{p}) - y_{i,n}]^2}{\sigma_{i,n}^2} \right\} + \frac{1}{2} \sum_{k=1}^Q \frac{(\hat{p}_k - p_k)^2}{\sigma_{p,k}^2}$$

Model-data integration

- Cost functions
 - Single versus multiple constraints approaches

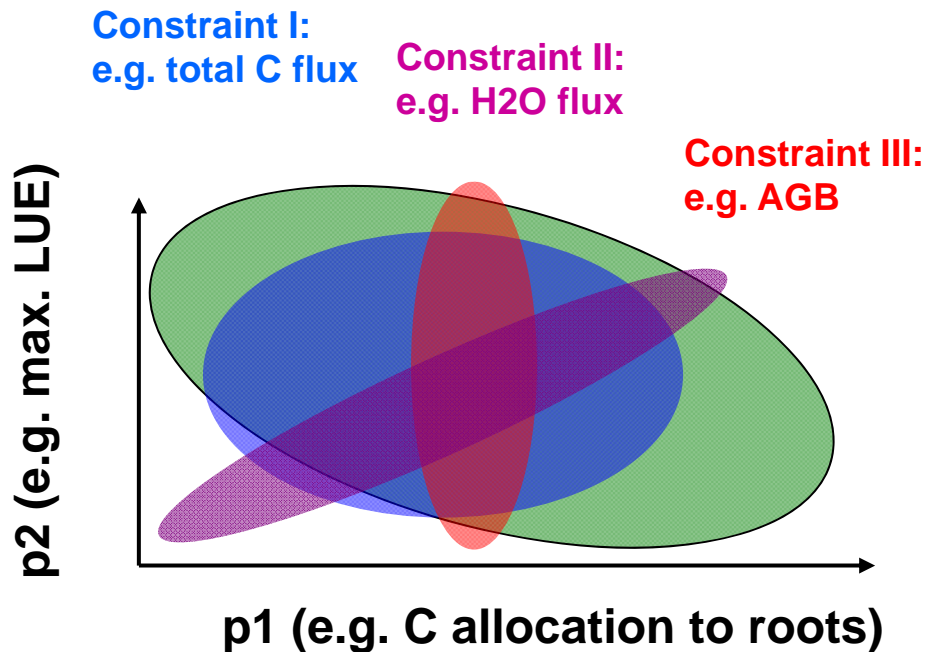
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Annotations:

- data streams → M
- model estimates → $\hat{y}_{i,n}$
- observations → $y_{i,n}$
- a priori parameter → p_k
- parameter vector → \mathbf{p}
- obs. uncertainty → $\sigma_{i,n}^2$
- par. uncertainty → $\sigma_{p,k}^2$

Multiple-constraint model identification & parameter estimation...

Challenges: Equifinality, Over-parameterisation
(e.g. Knorr et al. 2005, Reichstein et al. 2005)



- Bayesian model calibration against different constraints
- Extension of the approach to test different model structures and process representations (Model identification)

Addressing present and future variability in ecosystem carbon fluxes
through modeling ensembles and model-data fusion approaches

INFUSION

Nuno Carvalhais, Marcel van Oijen, Trevor Keenan, Natasha MacBean, Philippe Peylin, Anja Rammig, Susanne Rolinski, Tea Thum, André Granier, Dennis Loustau, Gregor Schuermann, Soenke Zaehle, Christian Beer, Miguel Mahecha, Jakob Zscheischler, Andrew Richardson and Markus Reichstein

models

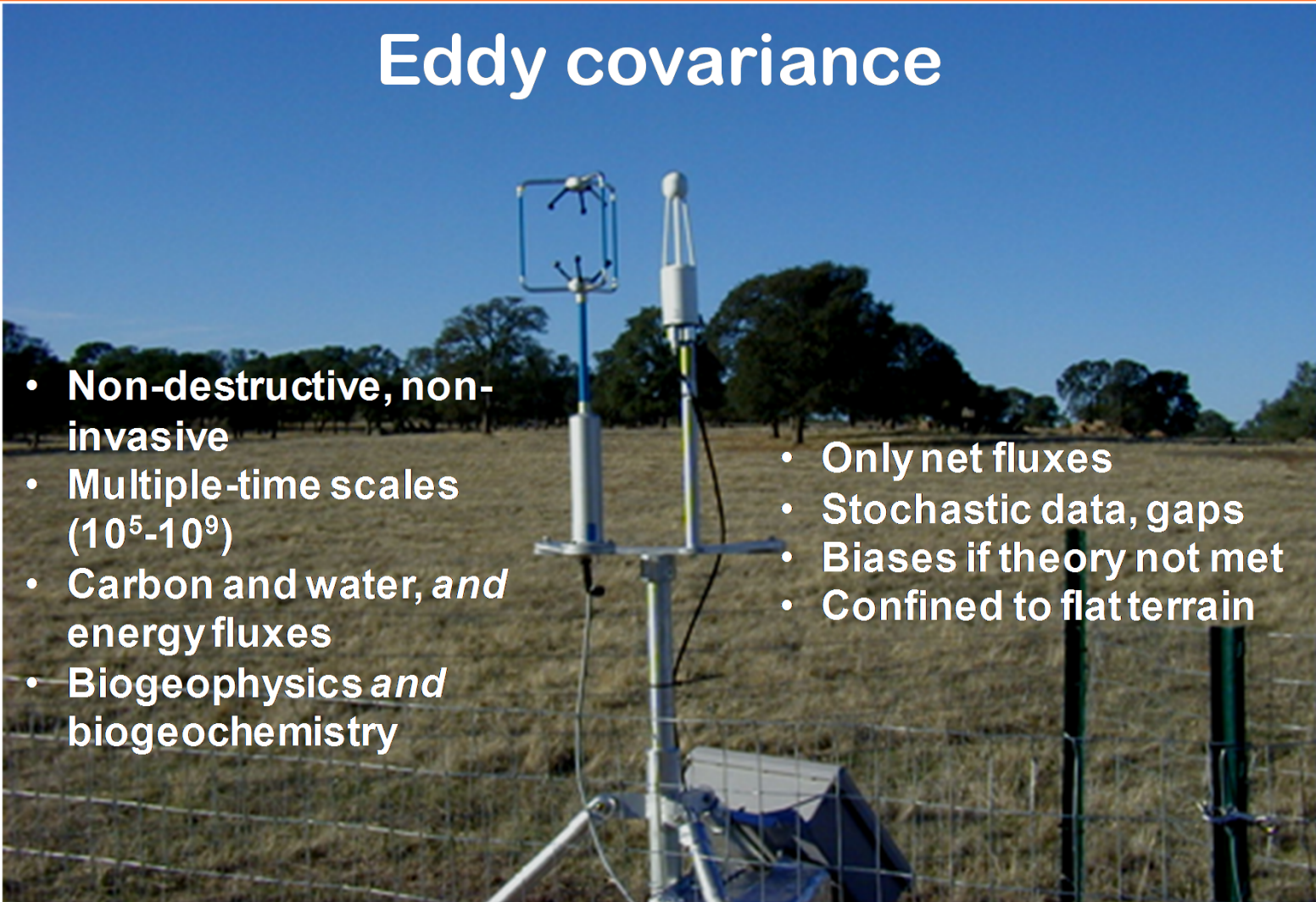
- BASFOR [CEH]
- FoBAAR [Harvard]
- JSBACH [MPI BGC]
- LPJ [PIK]
- ORCHIDEE [LSCE]

Hesse: deciduous broadleaf forest, beech; Cfb - Warm temperate fully humid with warm summer



Quantifying ecosystem-atmosphere interactions

Eddy covariance

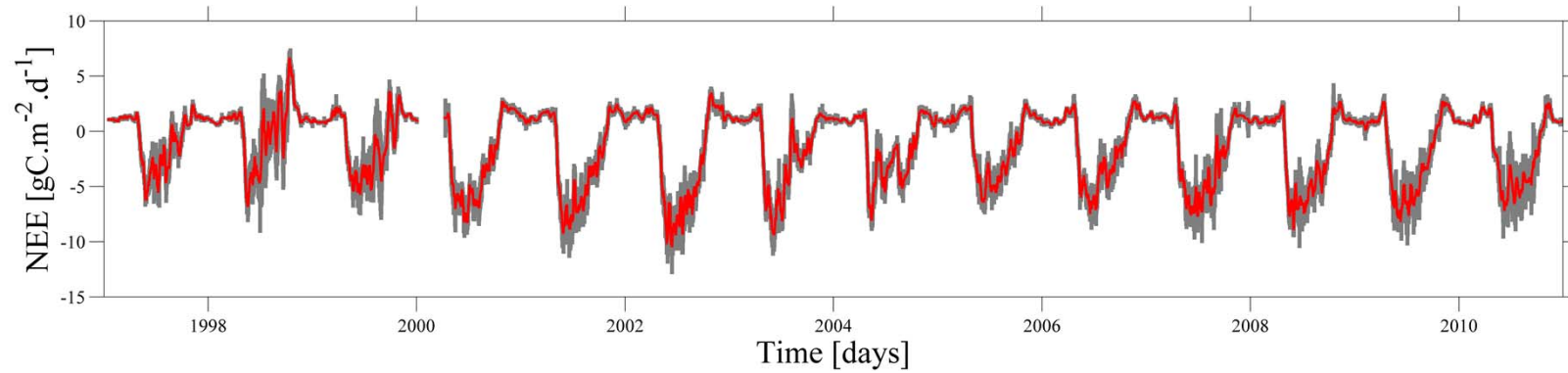
- 
- A photograph of an eddy covariance measurement tower in a field. The tower is a tall, silver metal pole with a white cylindrical sensor at the top. A blue frame with four sensors is mounted on the pole. The background shows a grassy field with trees under a clear blue sky. A wire fence is in the foreground.
- **Non-destructive, non-invasive**
 - **Multiple-time scales (10^5 - 10^9)**
 - **Carbon and water, *and* energy fluxes**
 - **Biogeophysics *and* biogeochemistry**
 - **Only net fluxes**
 - **Stochastic data, gaps**
 - **Biases if theory not met**
 - **Confined to flat terrain**

Data & uncertainties

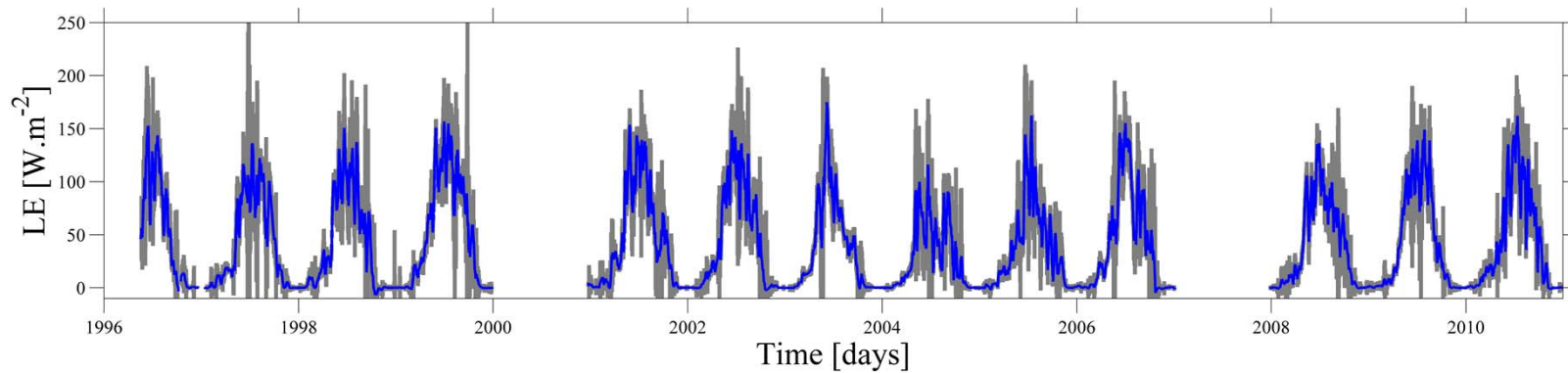
- Eddy covariance fluxes
 - Net Ecosystem Exchange (NEE)
 - random and u^* thresholds
 - Latent heat fluxes (LE)
 - random and EBC method

Data : flux measurements

NEE and NEE uncertainties



LE and LE uncertainties



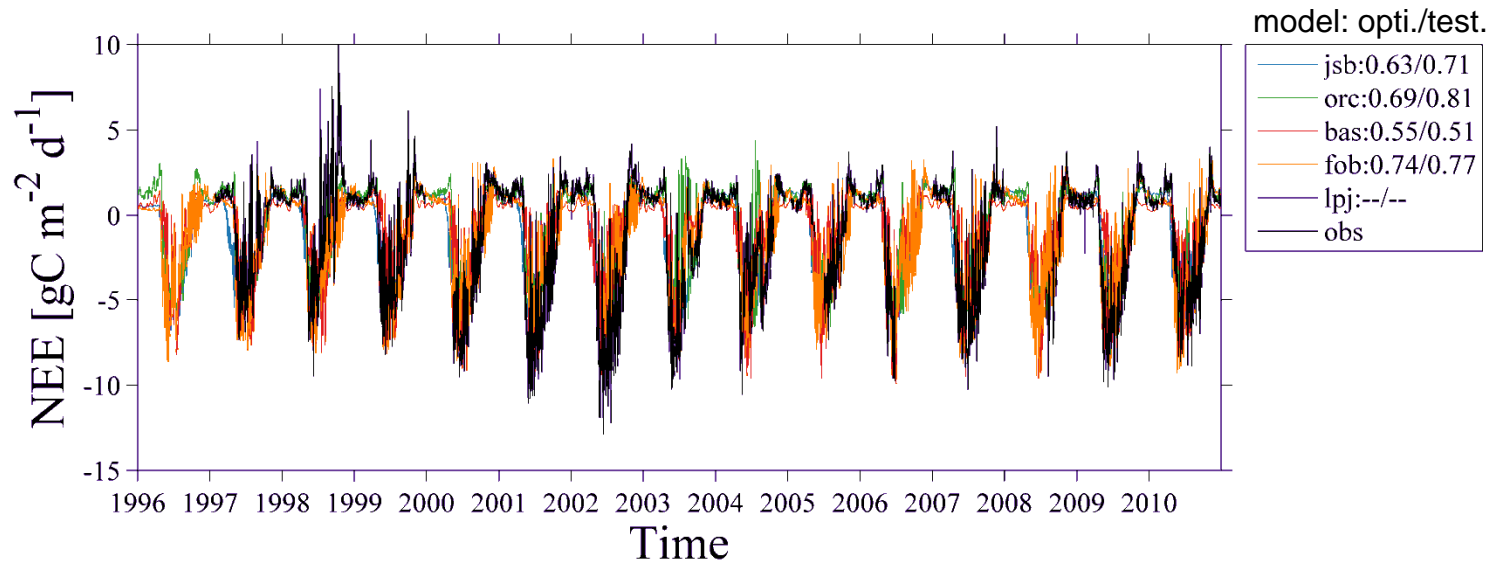
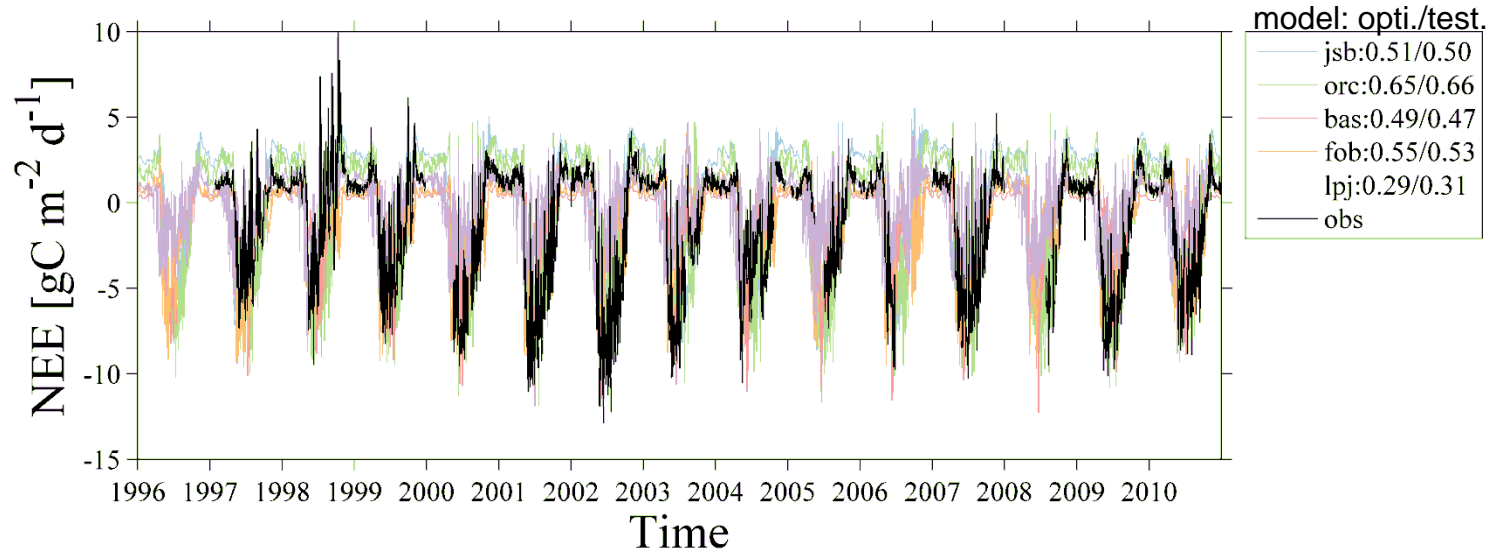
Data & uncertainties

- Eddy covariance fluxes
 - Net Ecosystem Exchange (NEE)
 - random and u^* thresholds
 - Latent heat fluxes (LE)
 - random and EBC method
- Ancillary biometric data
 - AGB and AGB increments
 - natural variability, observational and parametric uncertainties in DBH curves
 - Total soil carbon stocks
 - Spatial variability and total profile representation

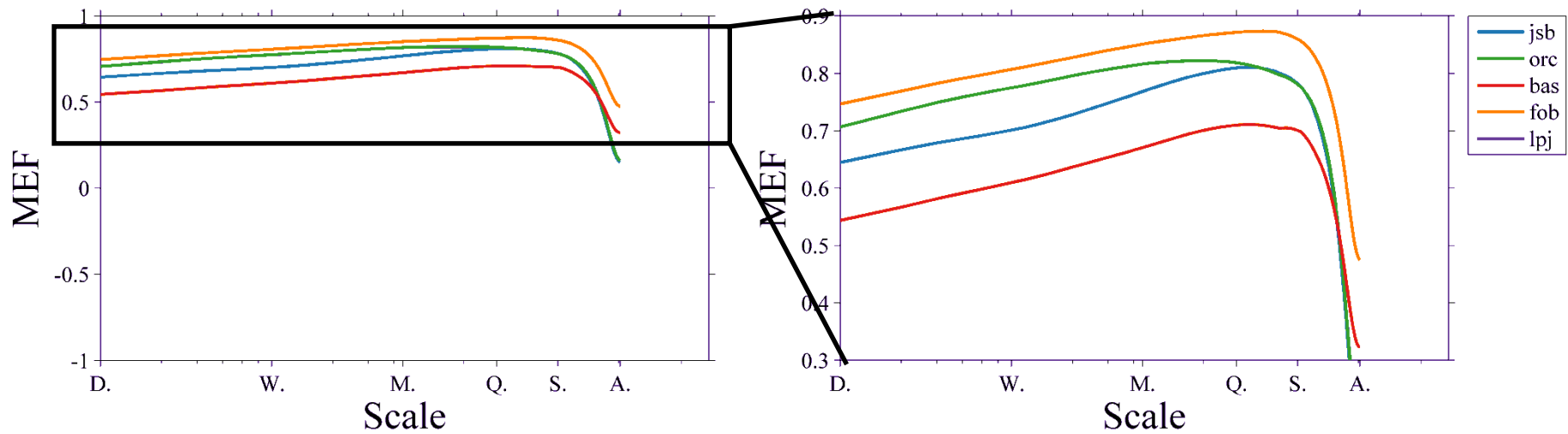
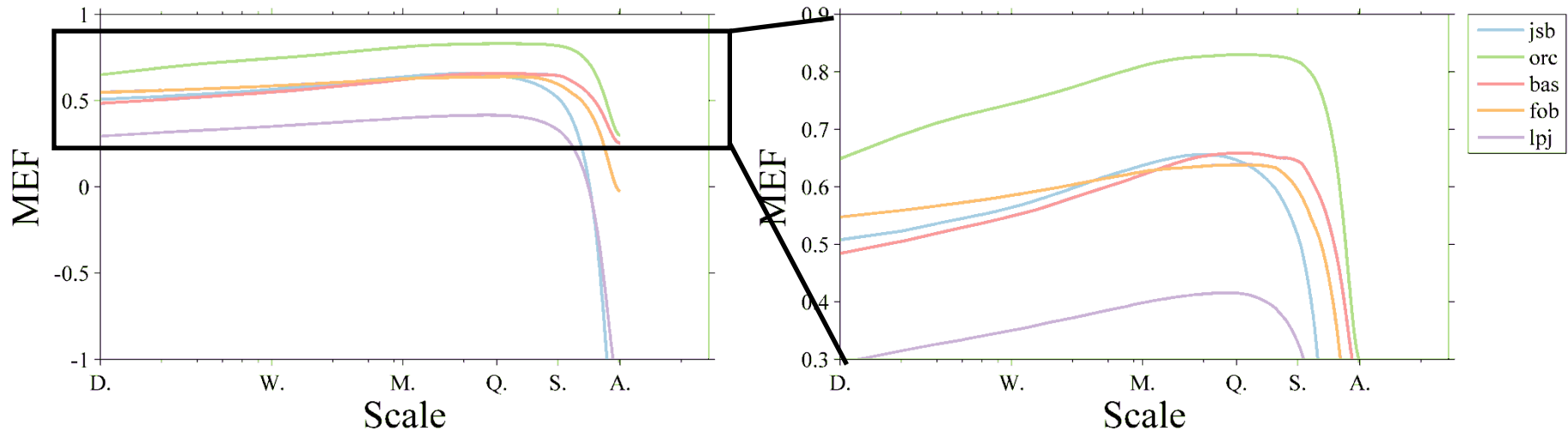
formal consideration of uncertainties in model-data integration

Multi-model MDF : Hesse : NEE

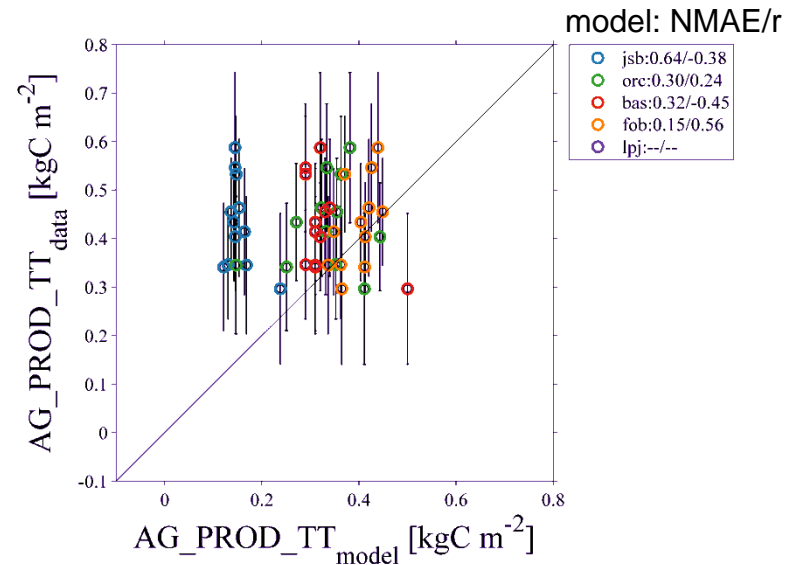
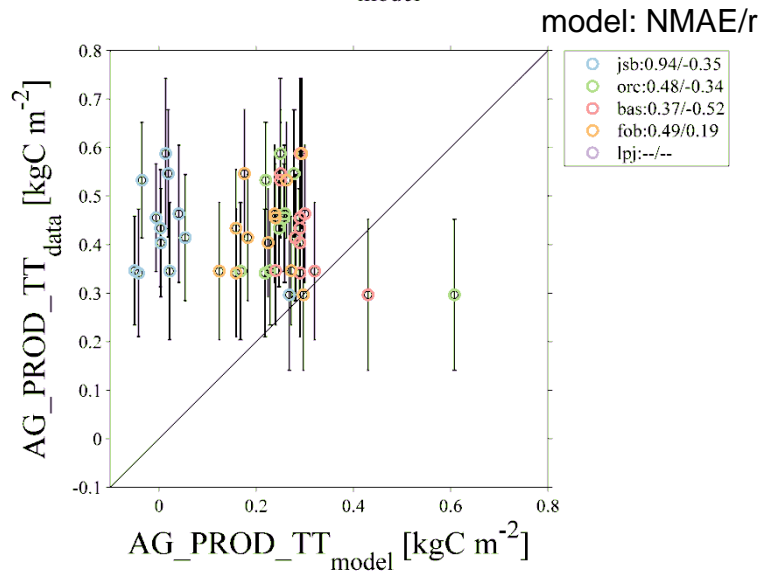
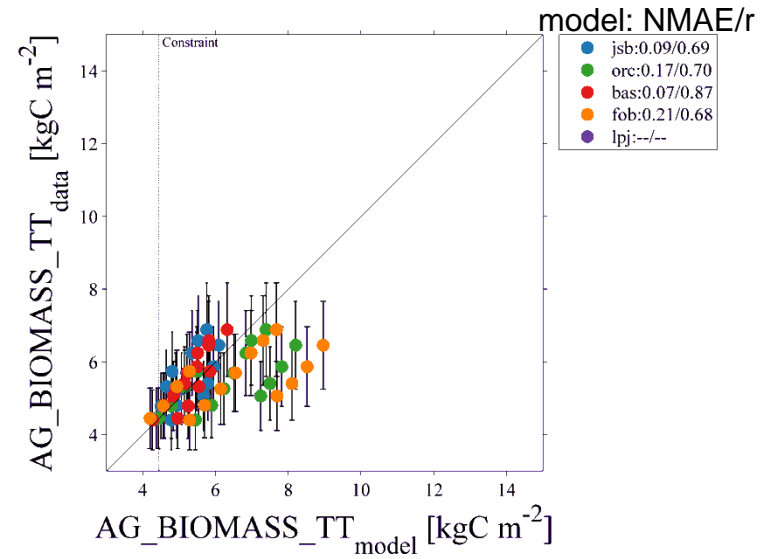
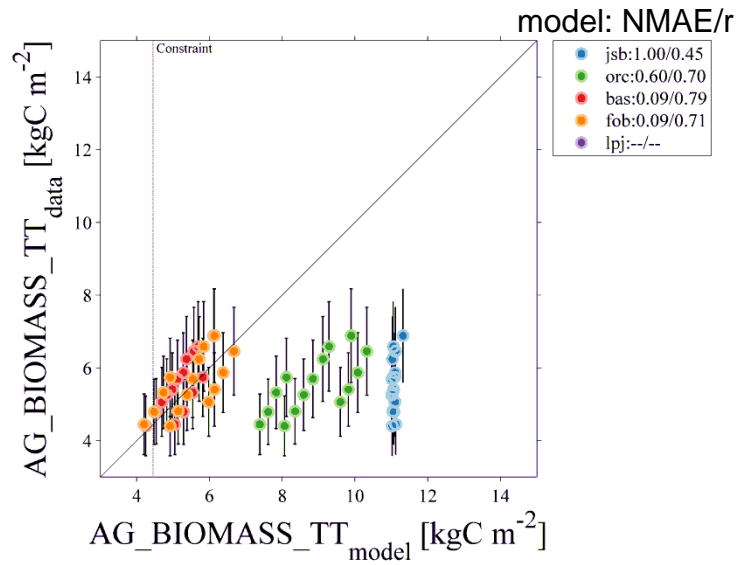
optimized
↓



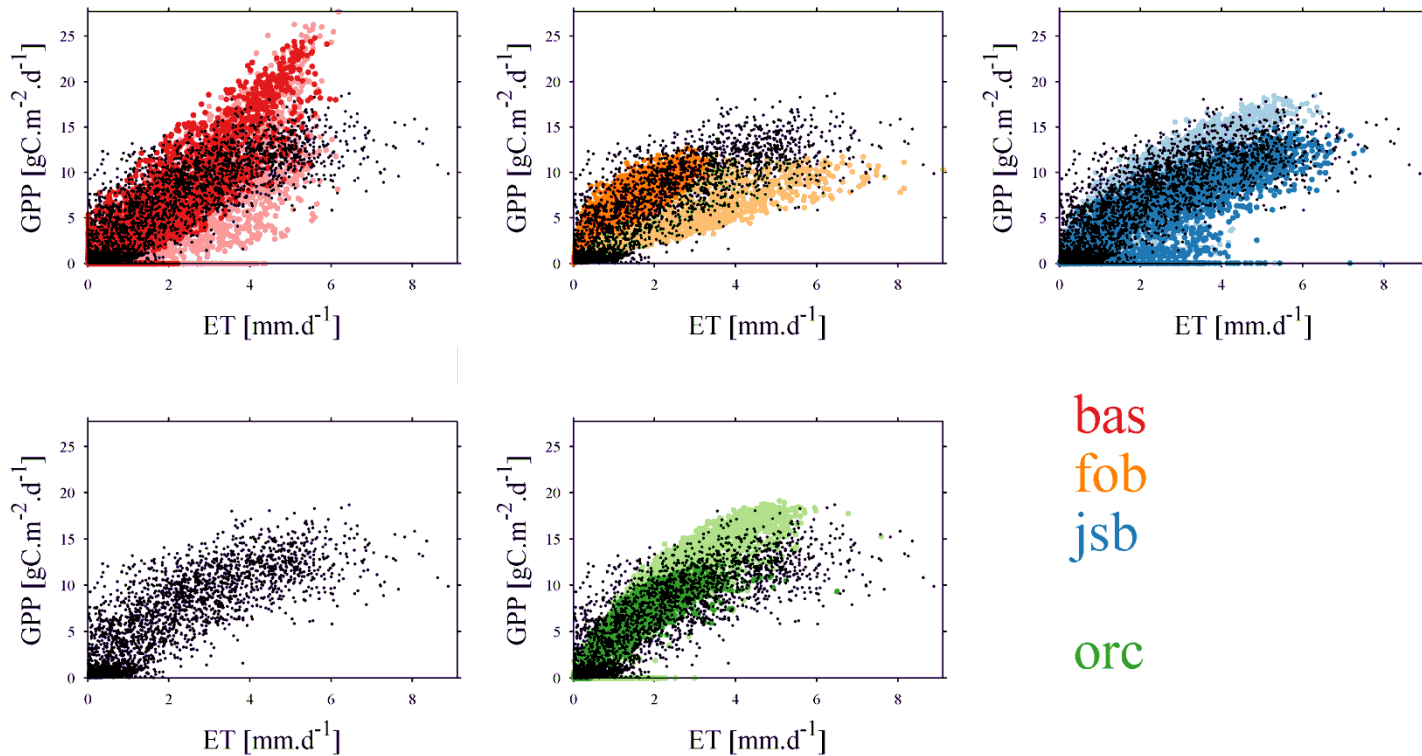
Hesse : misfits vs time scales



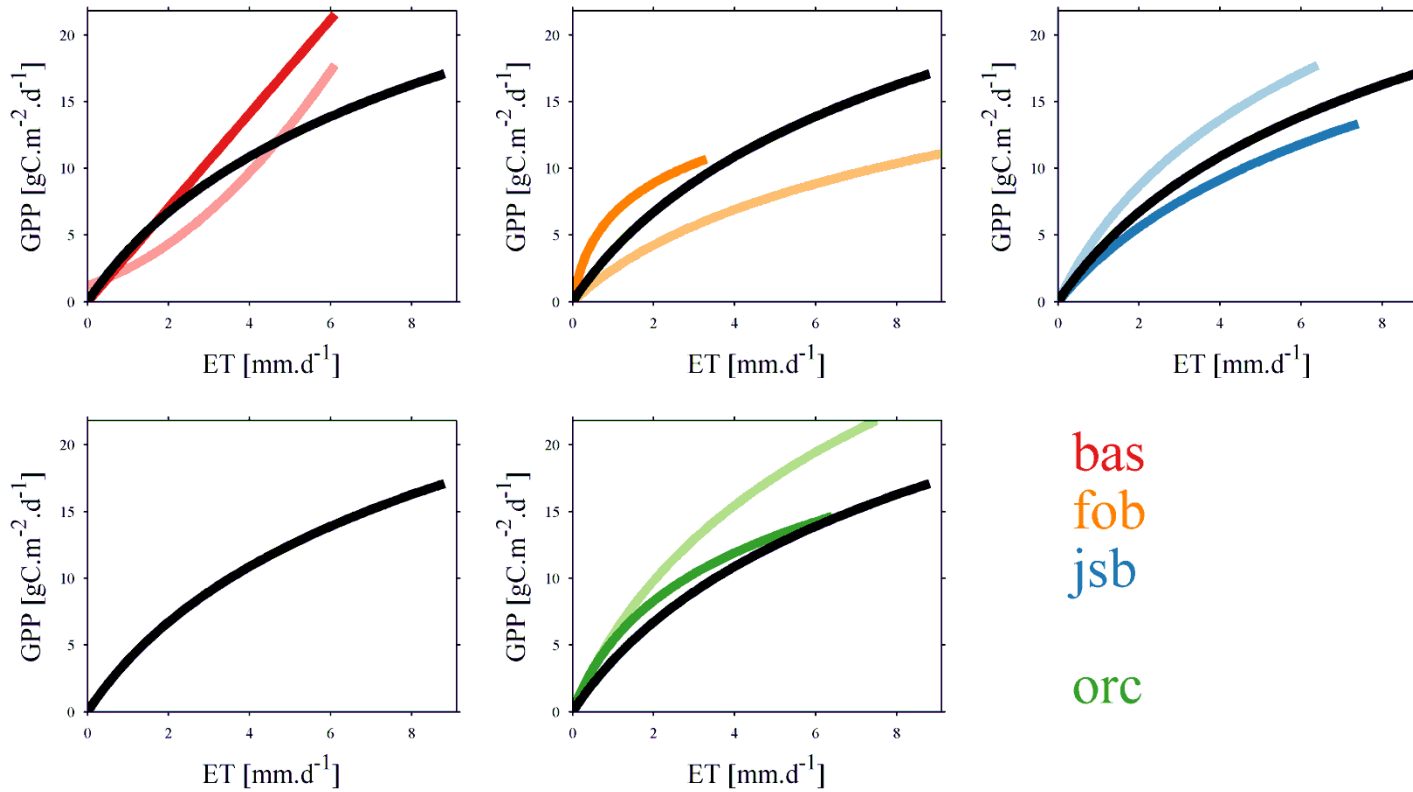
mdf : Hesse : vegetation stocks



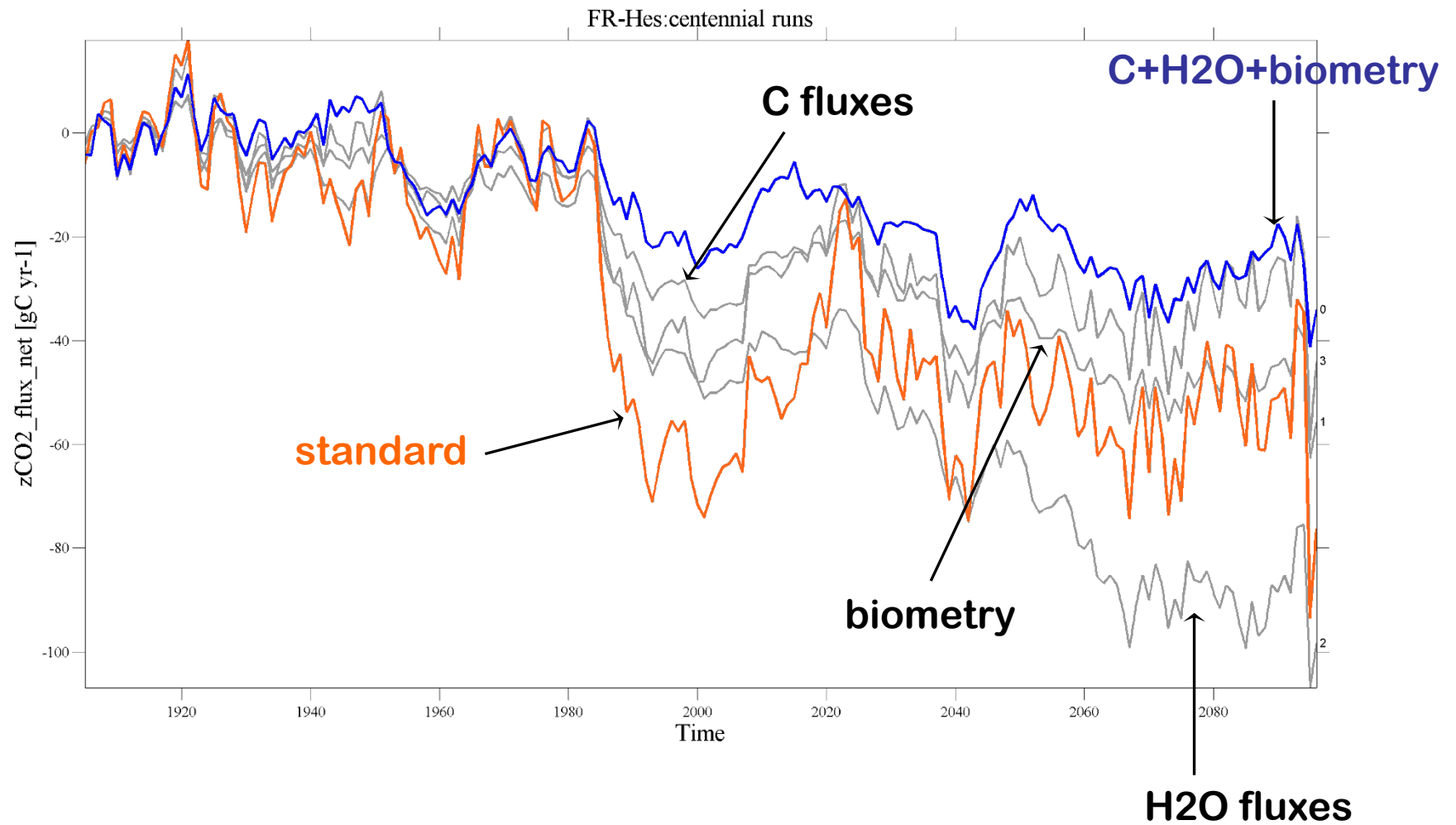
Description of water use efficiency



Description of water use efficiency



JSBACH : implications of multiple constraints

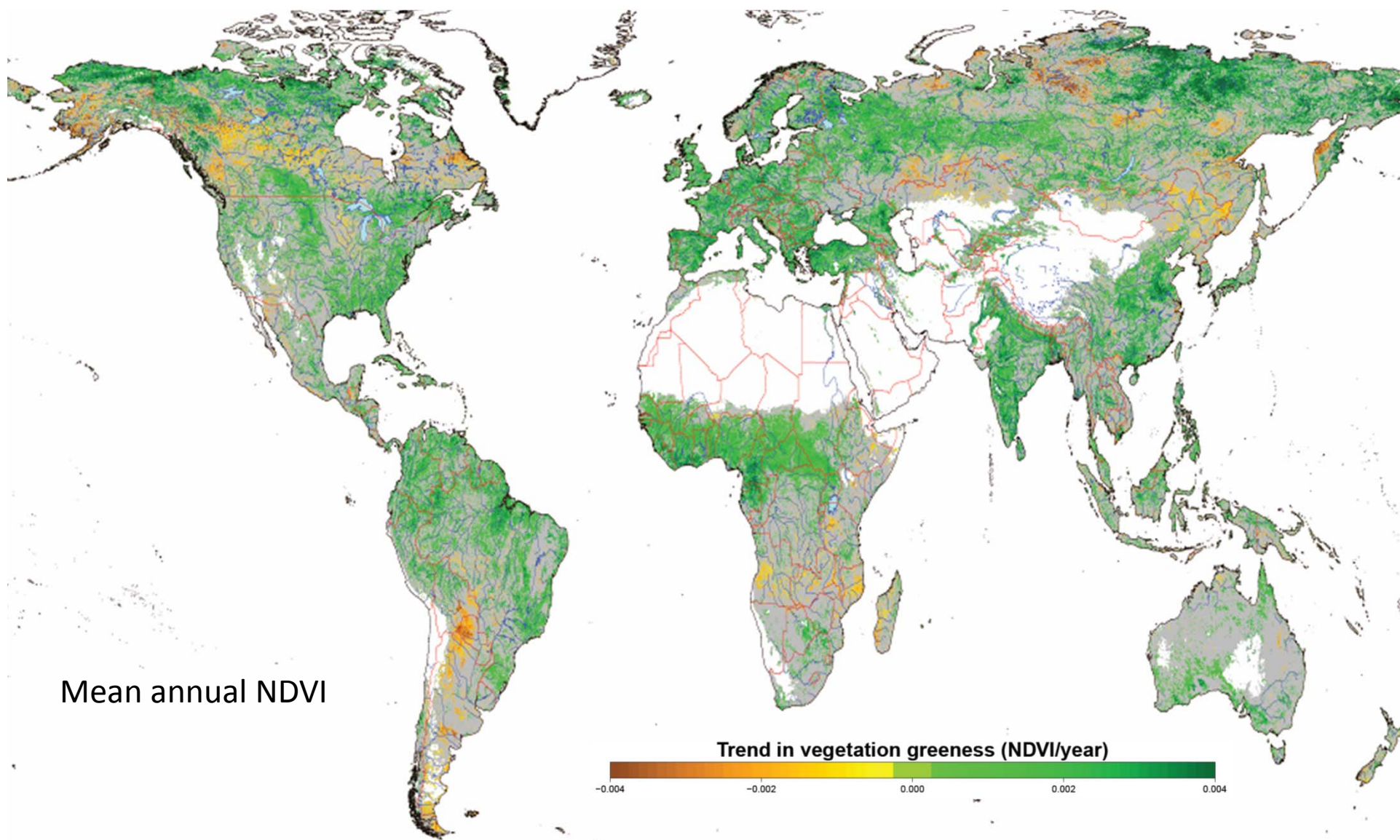


Exploring seasonal and decadal dynamics of phenology

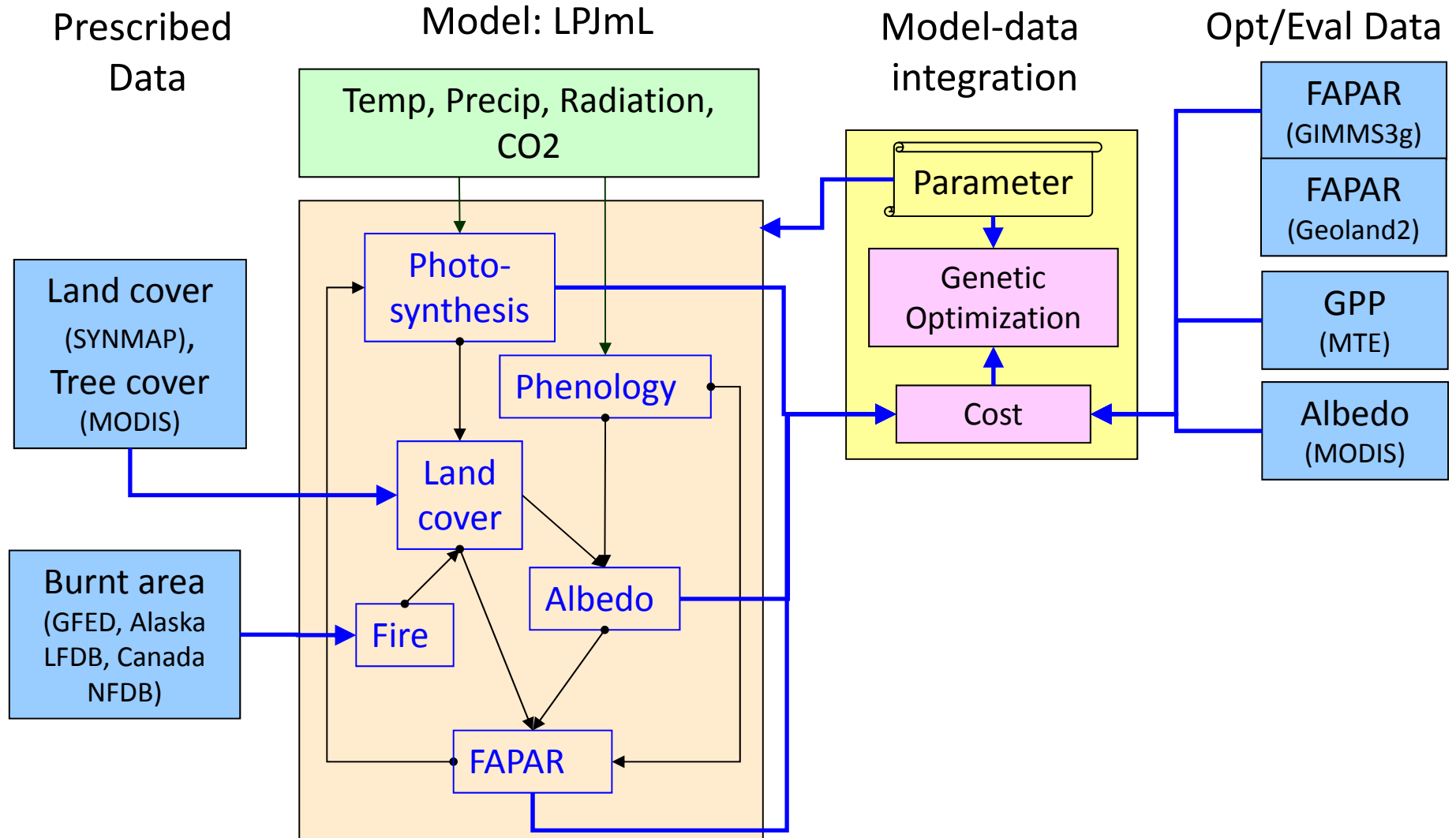
LPJML-MDI

Forkel et al., BGD, 2014; Forkel et al, in prep.

Trends in vegetation greenness 1982-2011

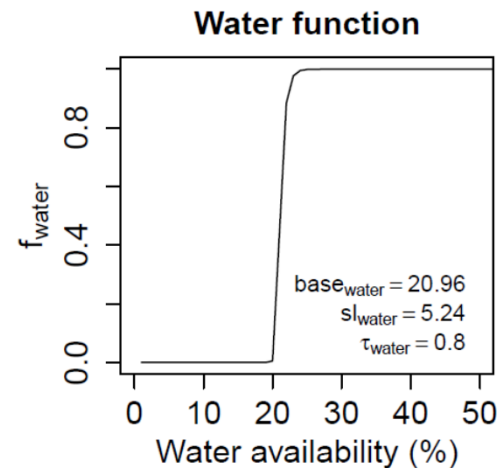
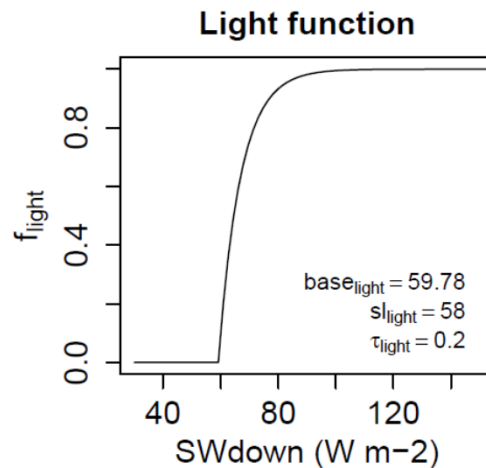
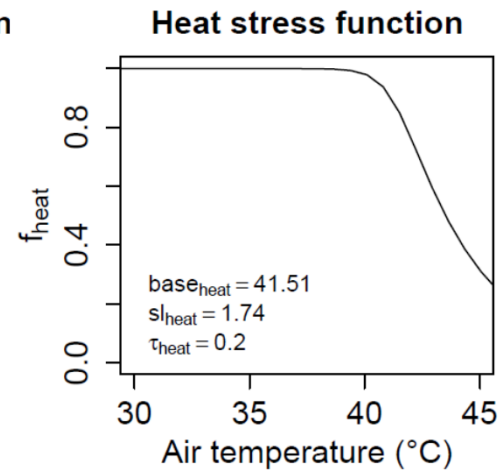
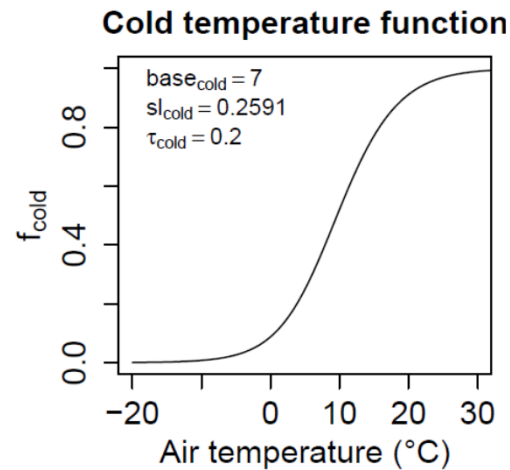


LPJmL-MDI setup



New phenology scheme based on GSI

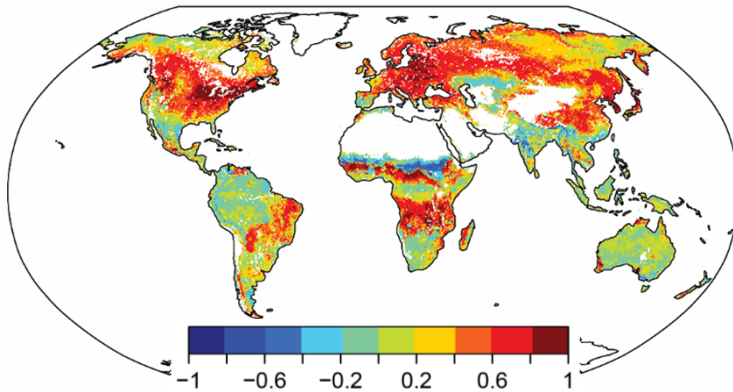
[Jolly et al., 2005]



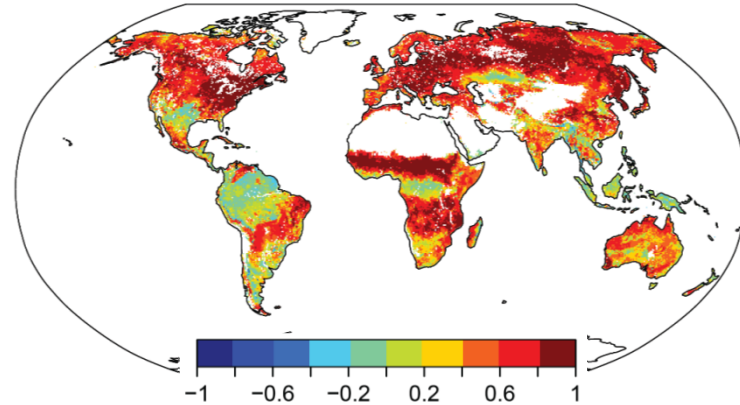
New phenology scheme based on GSI

[Jolly et al., 2005]

a) Cor LPJmL-OP-prior ~ GIMMS3g

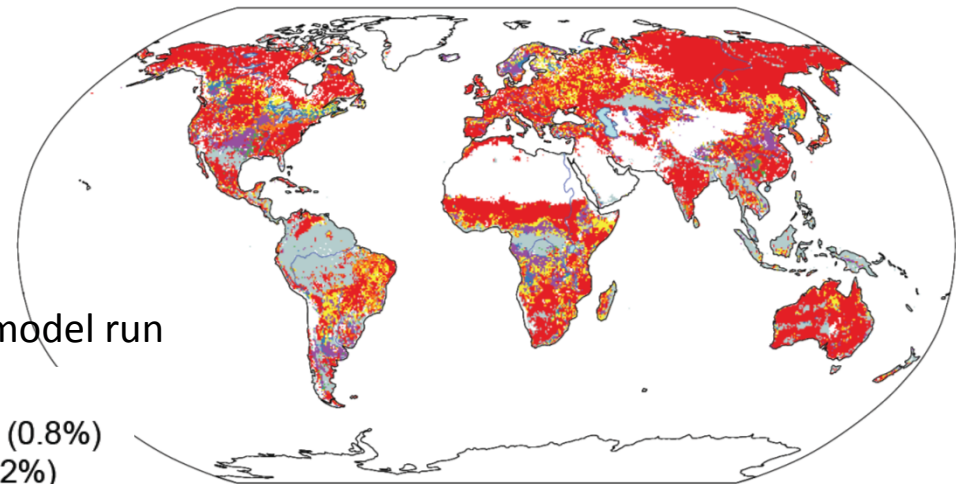


b) Cor LPJmL-GSI ~ GIMMS3g

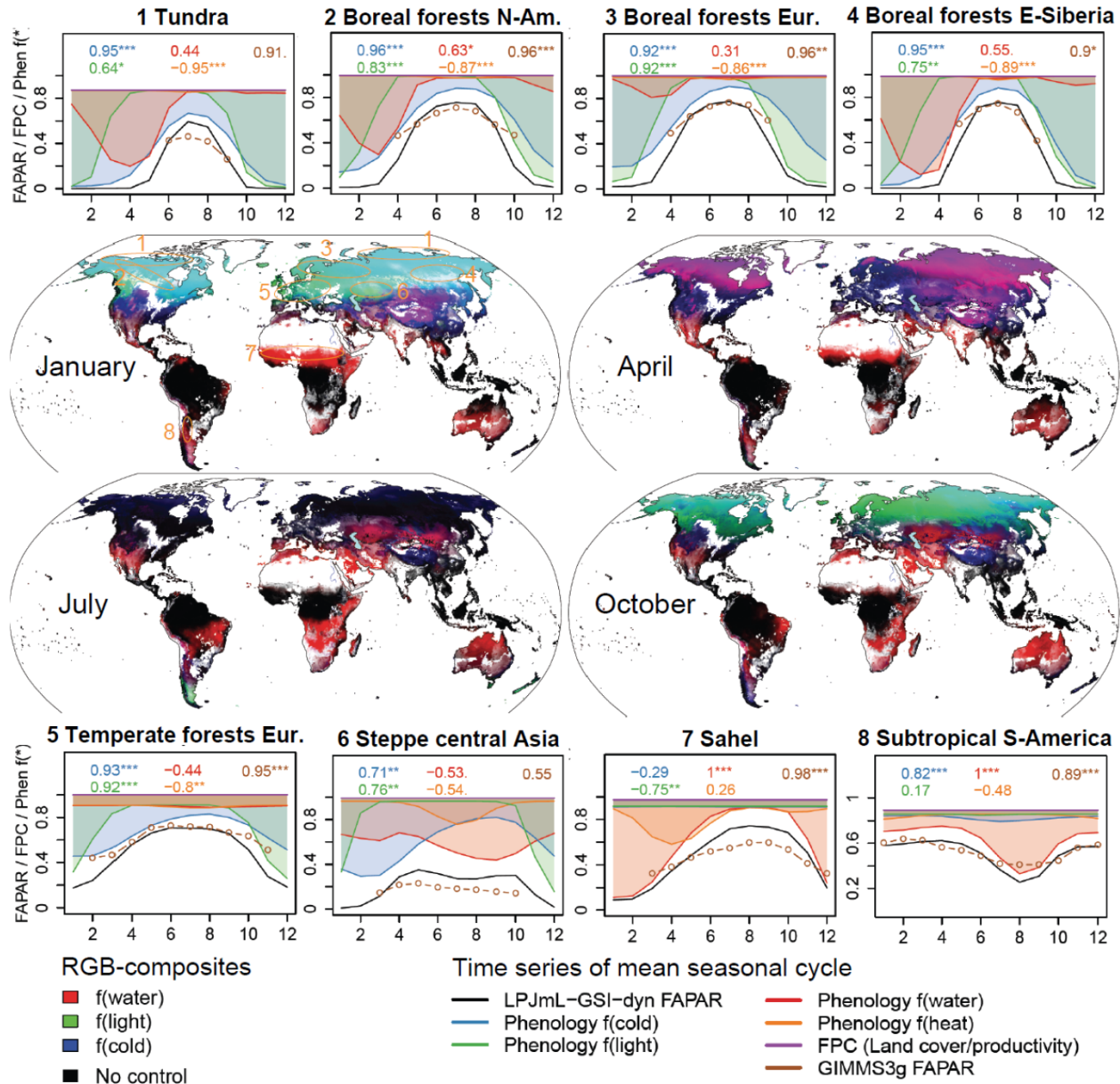


c) Best LPJmL model run

- Cor < 0.2 (10%)
- LPJmL-OP-dyn (0.8%)
- LPJmL-OP-gc (2%)
- LPJmL-GSI (60%)
- LPJmL-OP-dyn + LPJmL-OP-gc (8%)
- LPJmL-OP-dyn + LPJmL-GSI (5%)
- LPJmL-OP-gc + LPJmL-GSI (10%)

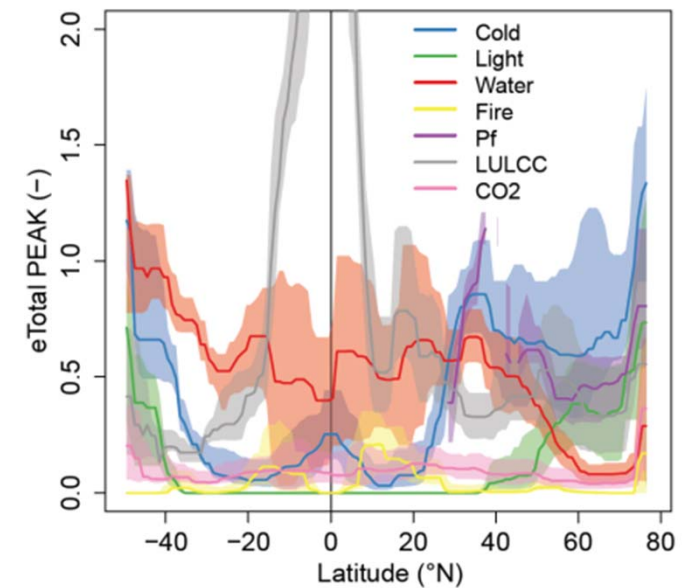
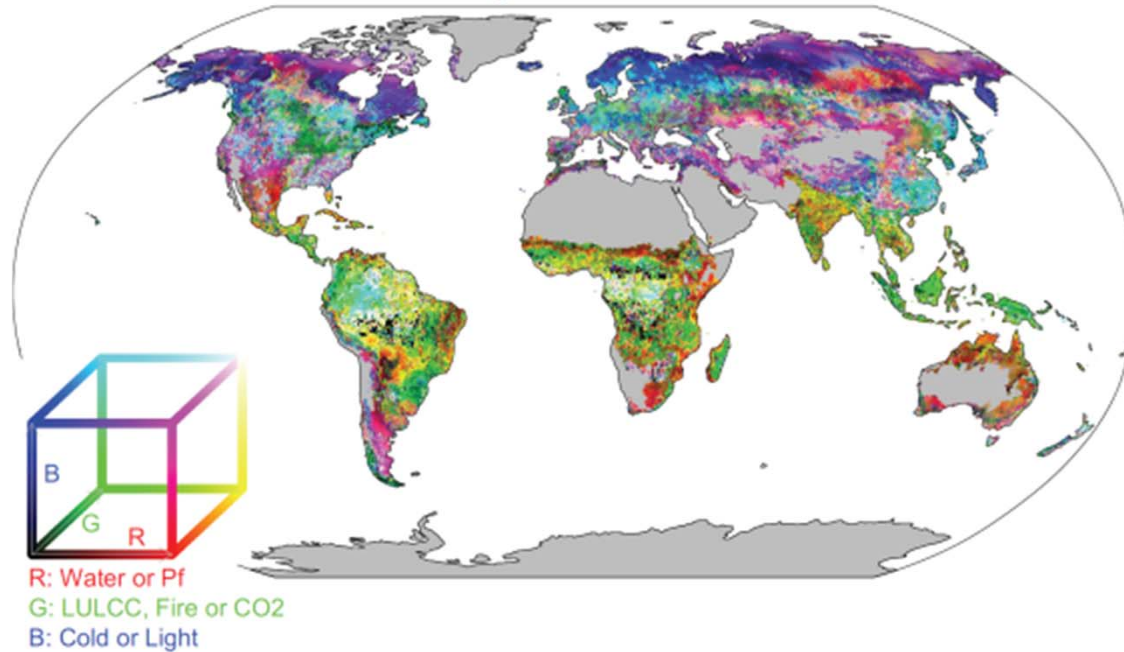


Seasonal controls on phenological development



Drivers of annual and decadal variability

a) eTotal PEAK



Improving the Modelled Global Terrestrial Carbon Cycle by
Assimilating CO₂ Mole Fractions and FAPAR with the
MPI – Carbon Cycle Data Assimilation System

MPI-CCDAS

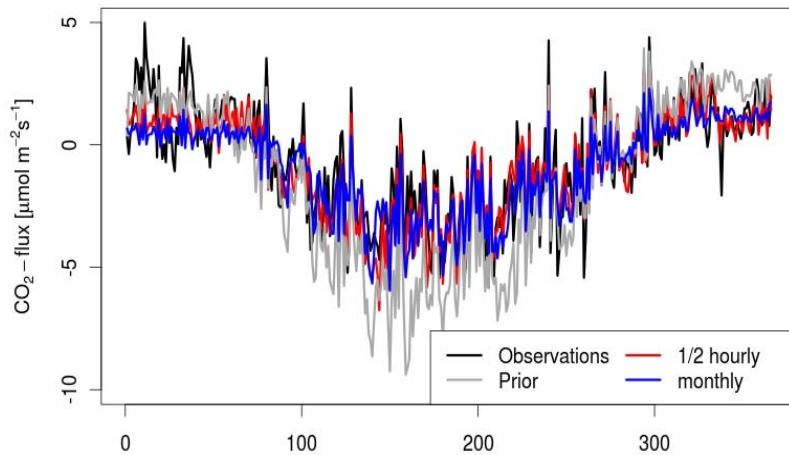
Schuermann et al., in prep.

Site & global scale optimizations

Site scale

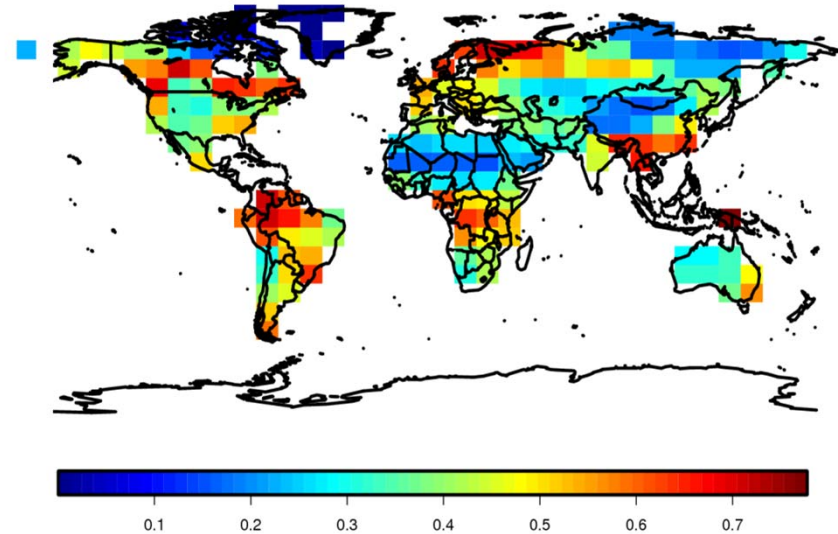
Global scale

Net Ecosystem Exchange



Fluxnet NEE

FAPAR



CO2 mole fractions

Satellite observations for both

Details of the exercise

Spatial resolution of $8^{\circ} \times 10^{\circ}$

Assimilating 2 years (2008 & 2009)

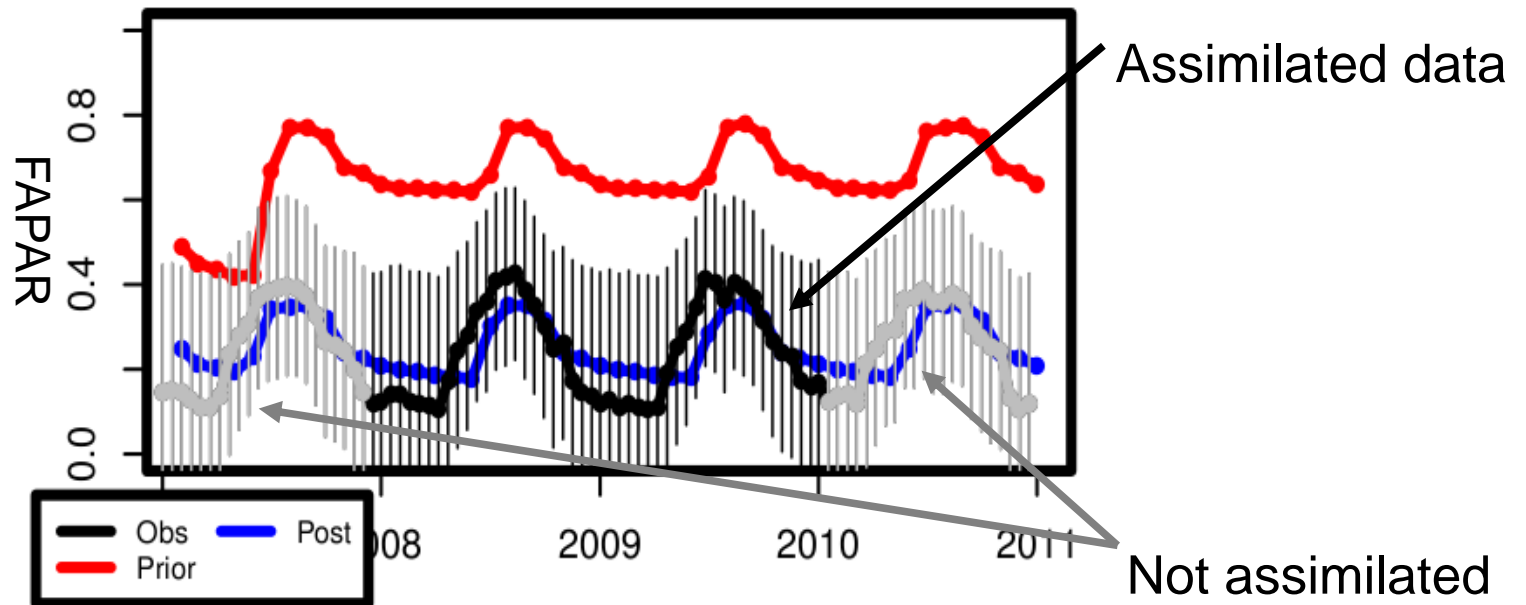
1 year (2007) as spin-up

1 year (2010) as “evaluation”

Prior: JSBACH without having seen observations

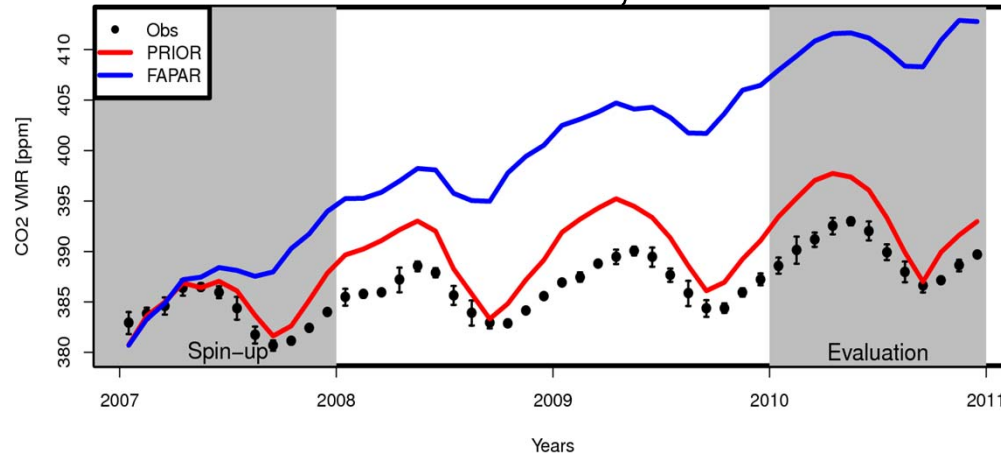
Post(erior): JSBACH with improved parameters/initial conditions after having seen observations

North American Evergreen pixel

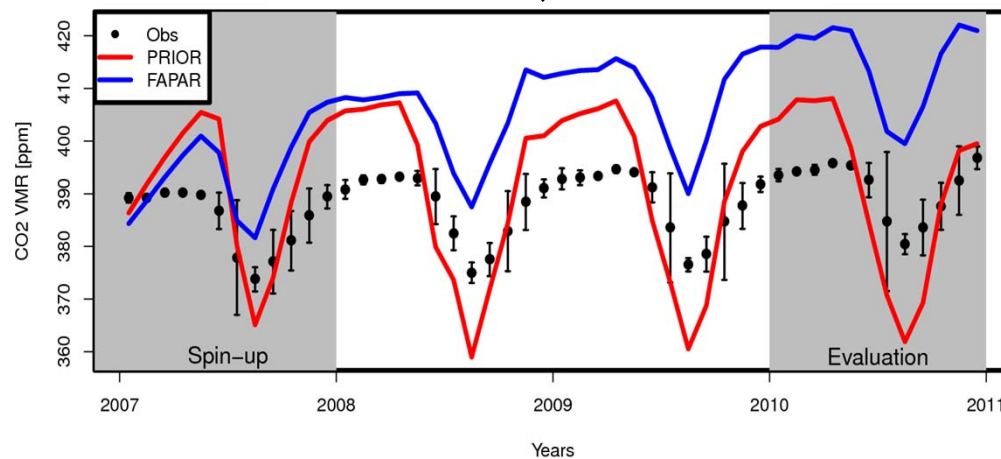


CO₂ (FAPAR assimilation)

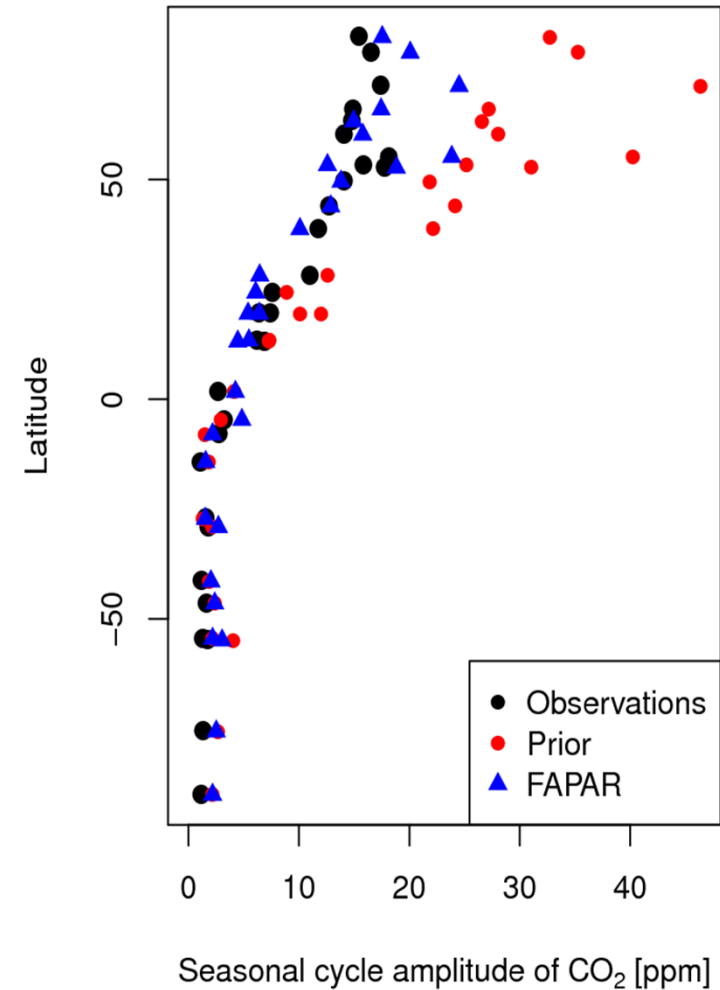
Mauna Loa, Hawaii



Barrow, Alaska

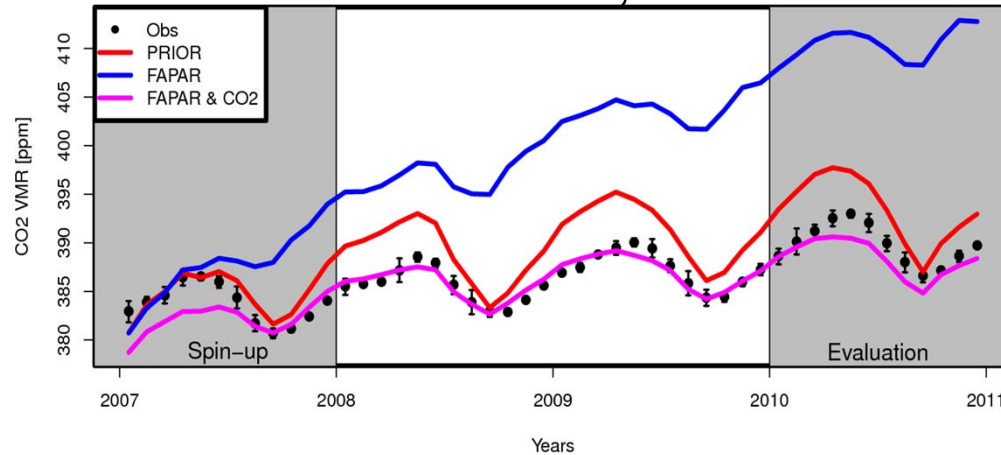


Latitudinal gradient of mean seasonal cycle amplitude

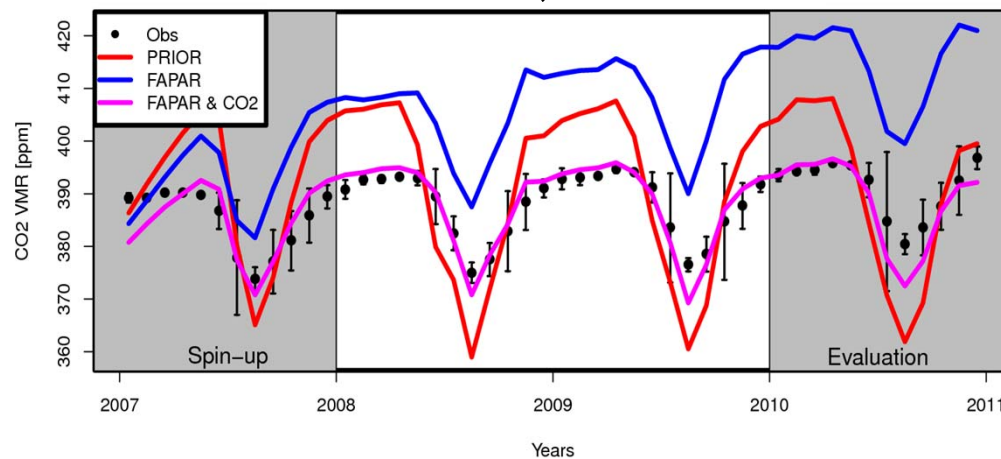


CO₂ (FAPAR & CO₂ assimilation)

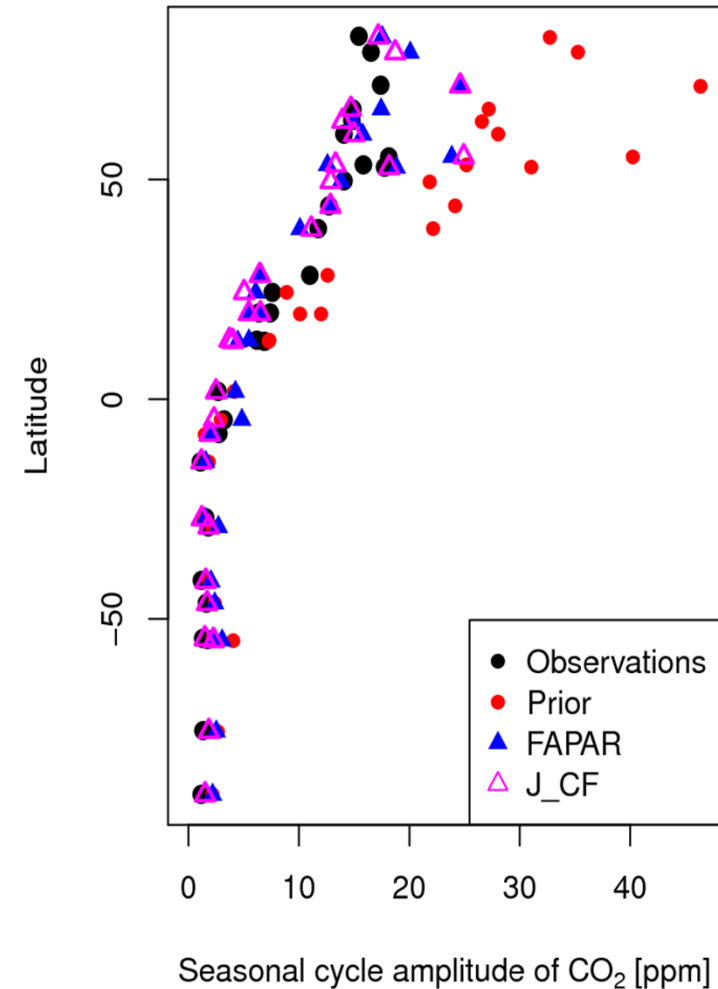
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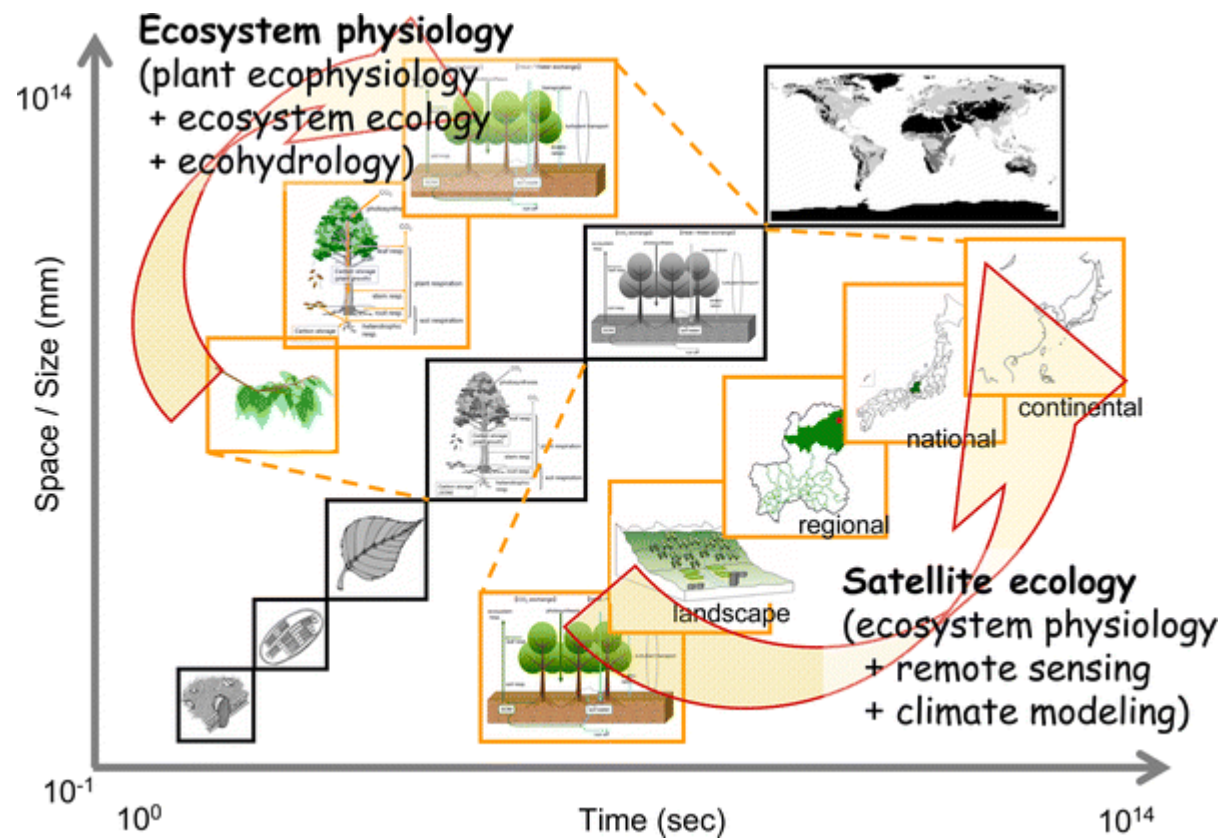
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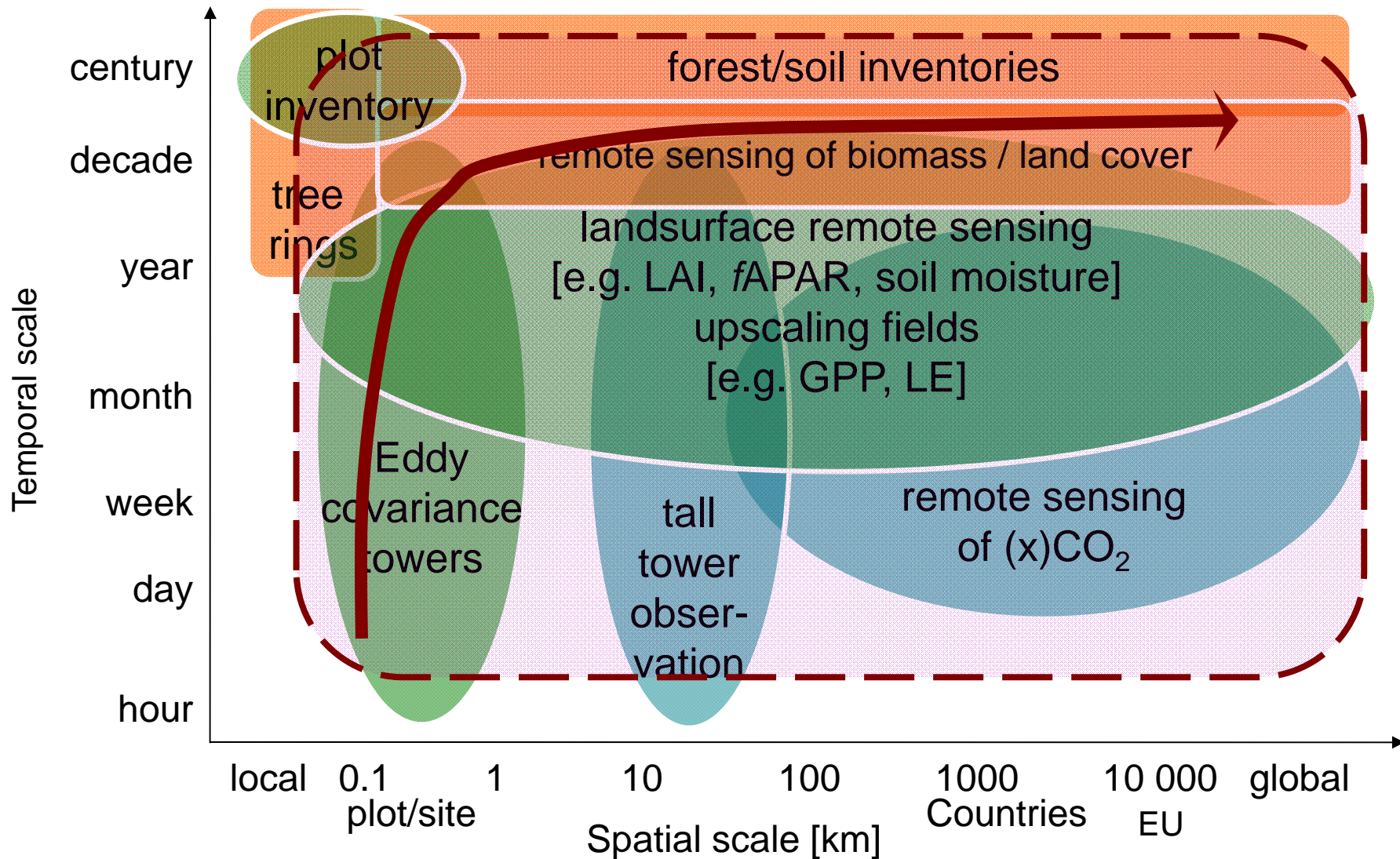
Conclusions

- importance of multiple data streams in model-data integration exercises
 - further constrained parameterizations
 - consistency with observed states
 - addressing equifinality
 - predictive uncertainty
- significant implications for diagnostic and prognostic model runs
- remote sensing provide unique constraints to integrate site-level and regional to global scales dynamics of responses of terrestrial ecosystem to climate variability
- allocation / lag effects and the carbon-hydrological cycle

processes and observations spanning from wide scales

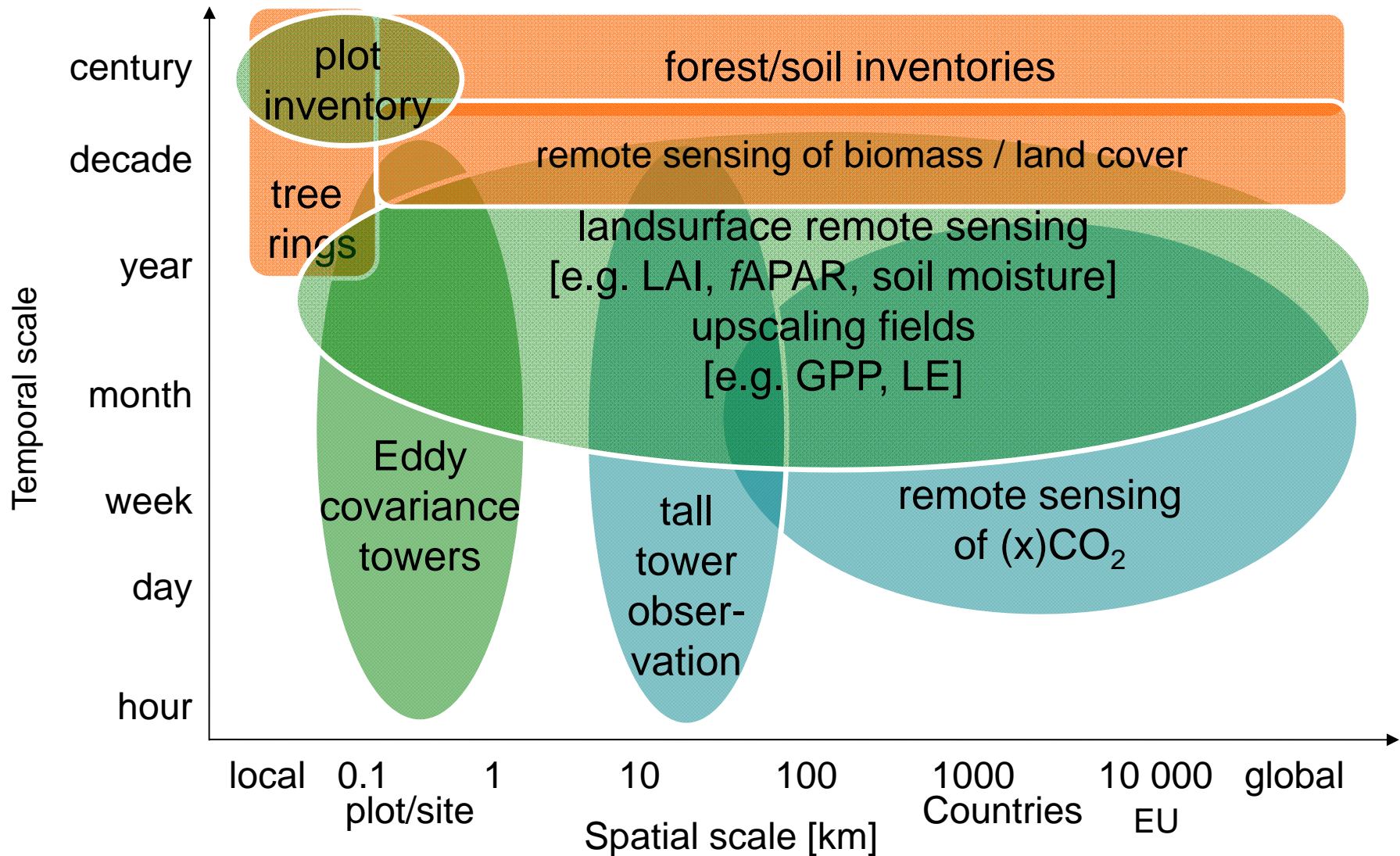


Observational scales



THANK YOU!

observational scales



From ecosystem level to regional/global scales

- Parameterizations
 - Based on biotic and abiotic covariates (e.g. Carvalhais et al., 2010; Horn and Shulz, 2011)
 - Based on spatial/temporal distributions of plant functional types

Acknowledge:

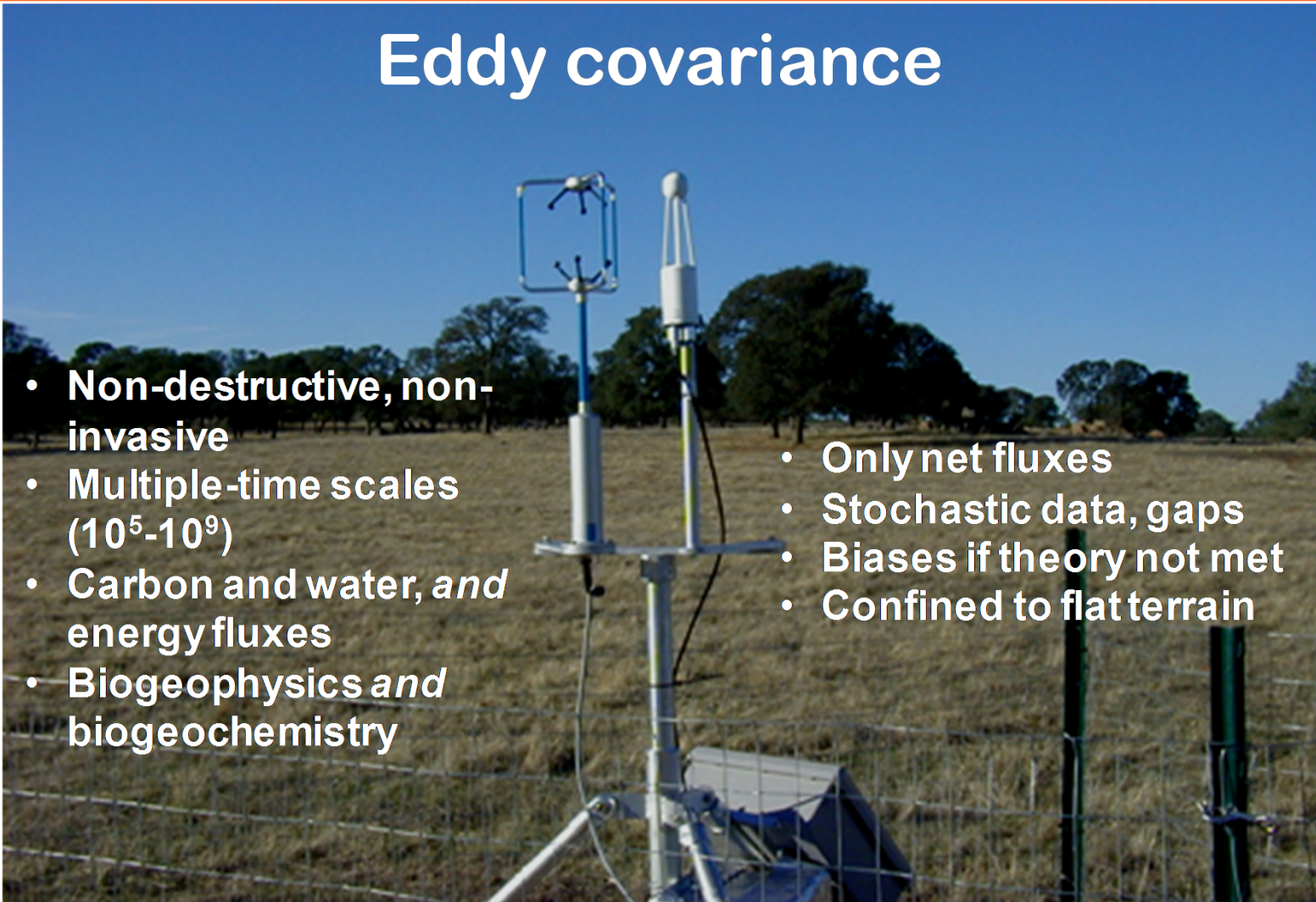
- Site particularities (e.g. ground water access, disturbance history/initial conditions, ...)
- Determination of site representativeness



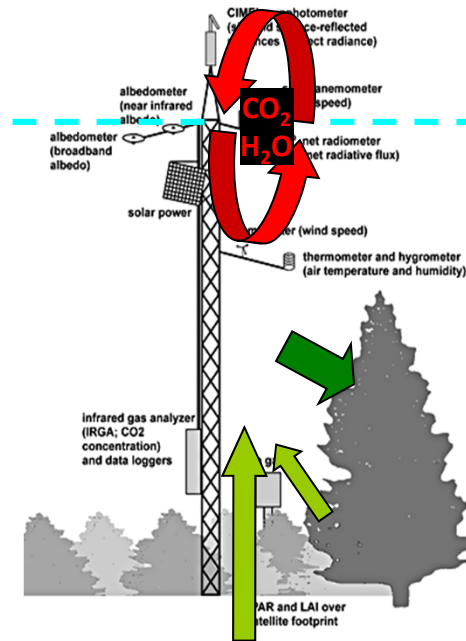


Quantifying ecosystem-atmosphere interactions

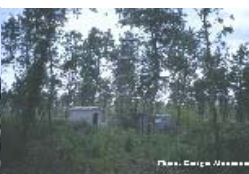
Eddy covariance

- 
- A photograph of an eddy covariance measurement tower in a field. The tower is a tall, silver metal pole with a white cylindrical sensor at the top. A blue frame with four sensors is mounted on the tower. The background shows a grassy field with trees under a clear blue sky. A wire fence is in the foreground.
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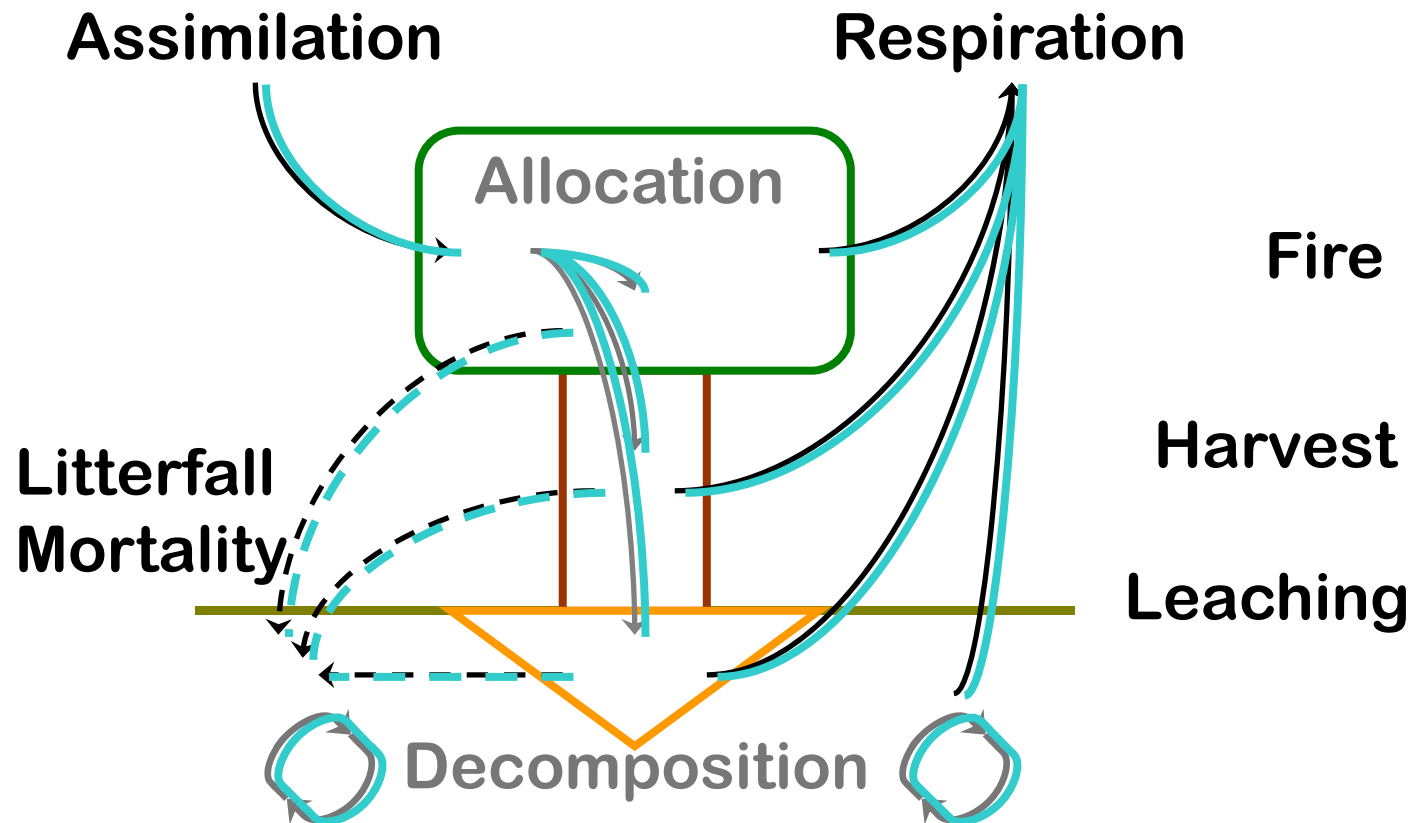
ecosystem fluxes



$$NEP = (GPP - R_A) - R_H$$

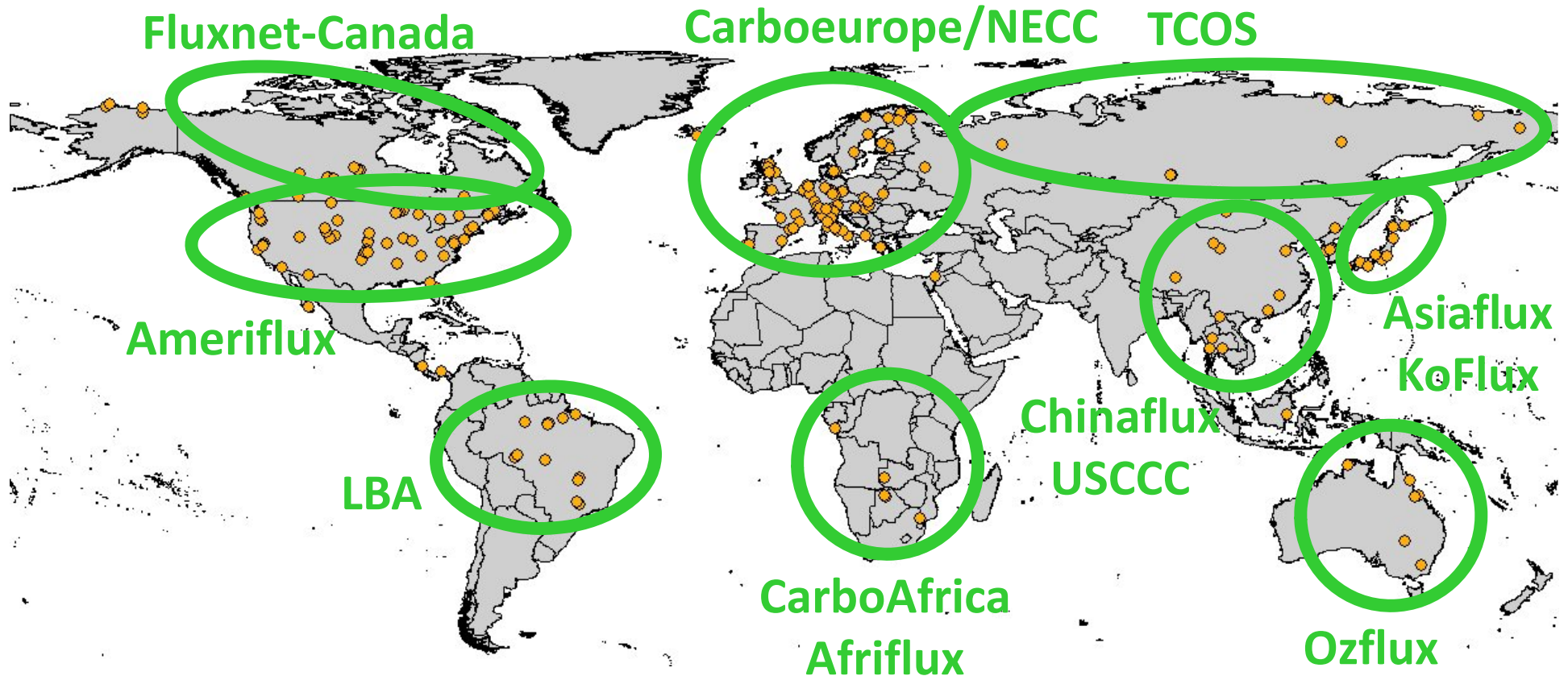


Ecosystem C cycling and fluxes



[Adapted from Lasslop 2010]

FLUXNET: a network of network of eddy covariance sites



La Thuille data set:

- >950 site-years from >250 sites
- Standardized u^* -filtering, gap-filling, flux-partitioning and uncertainties (Aubinet et al. 2001, Foken et al. 2003, Reichstein et al. 2005, Richardson et al. 2006, Papale et al. 2006, Moffat et al. 2007, Desai et al. 2008, Lasslop et al. 2008)



(Direct)
observations

Empirical
'models'

Remote sensing
models (CASA,
MOD17)

Offline
DGVM

(Free-running)
C⁴-models



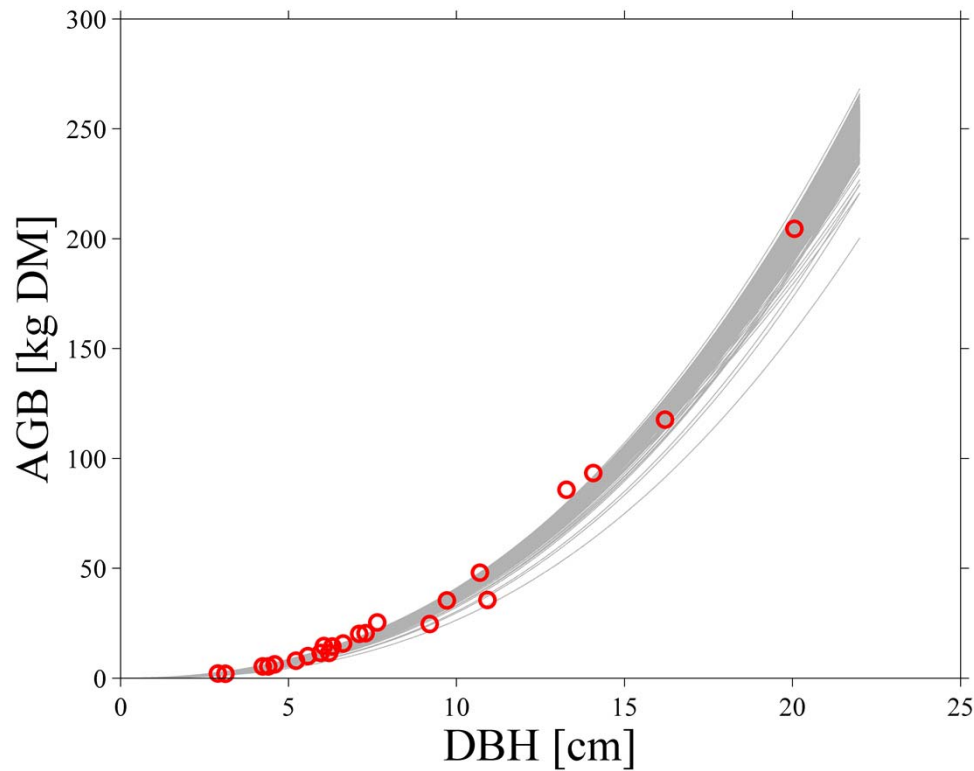
Assumptions about system



Observational input

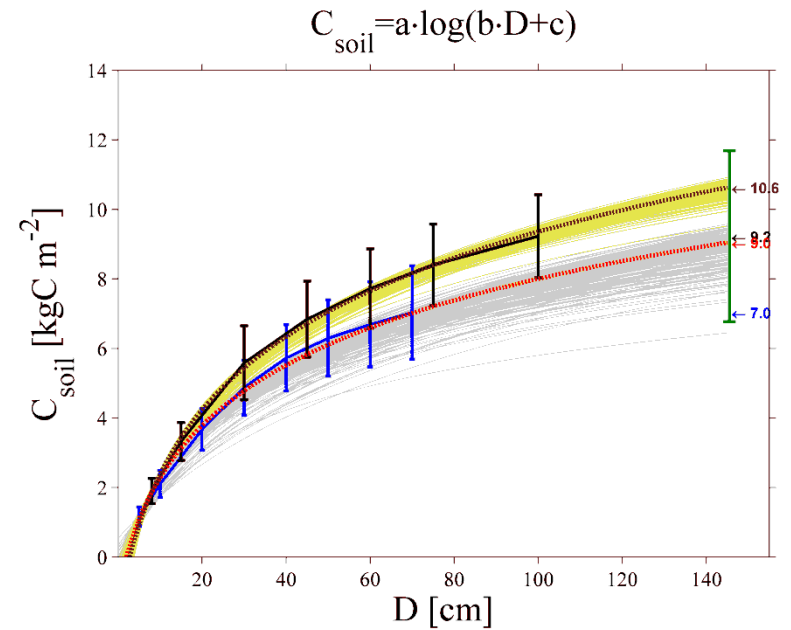
Data : vegetation and soil C stocks

AGB and AGB increments



[Wutzler et al., 2008]

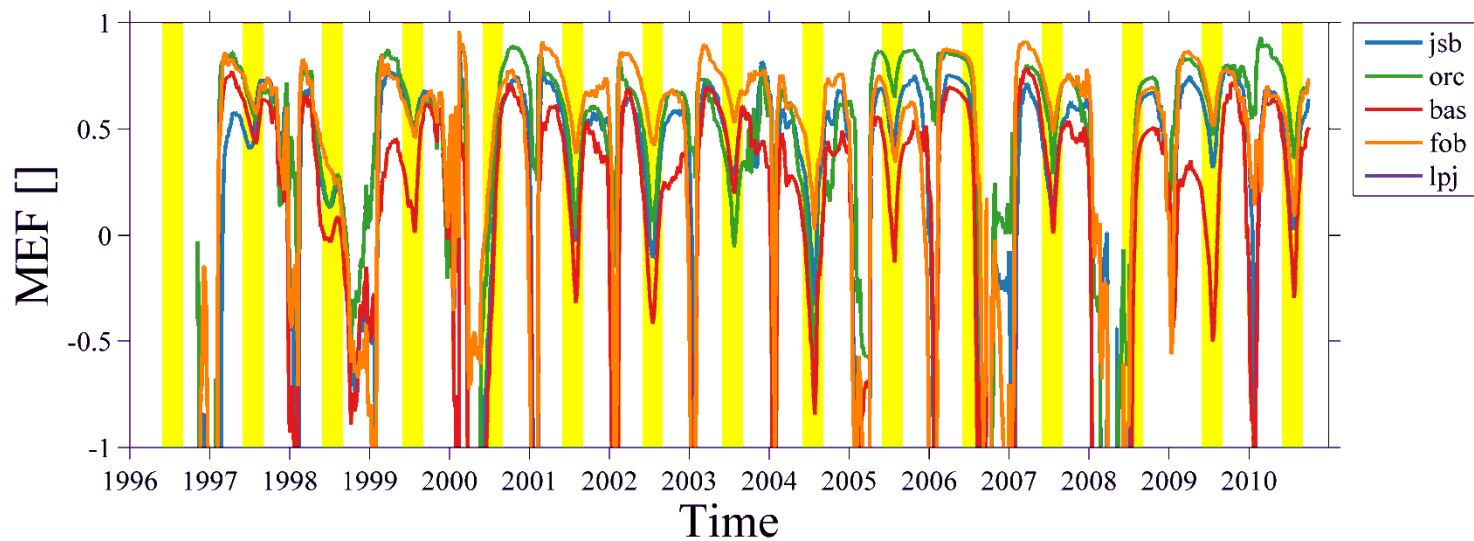
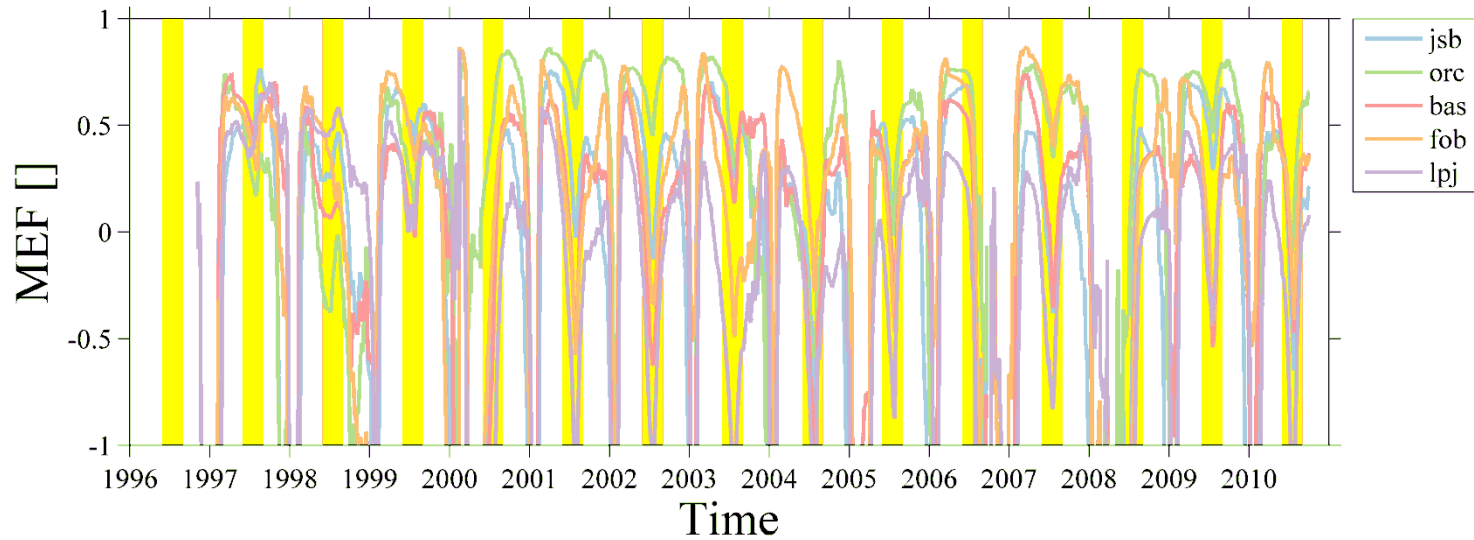
Soil C stocks



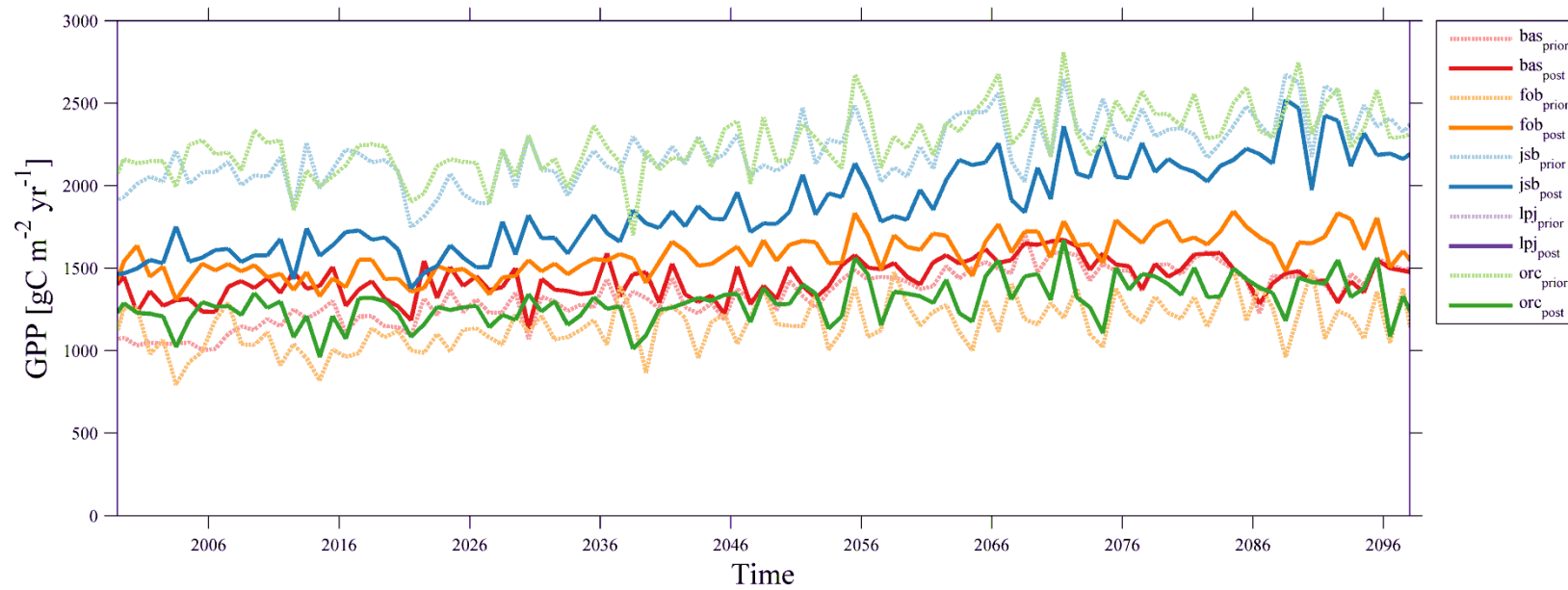
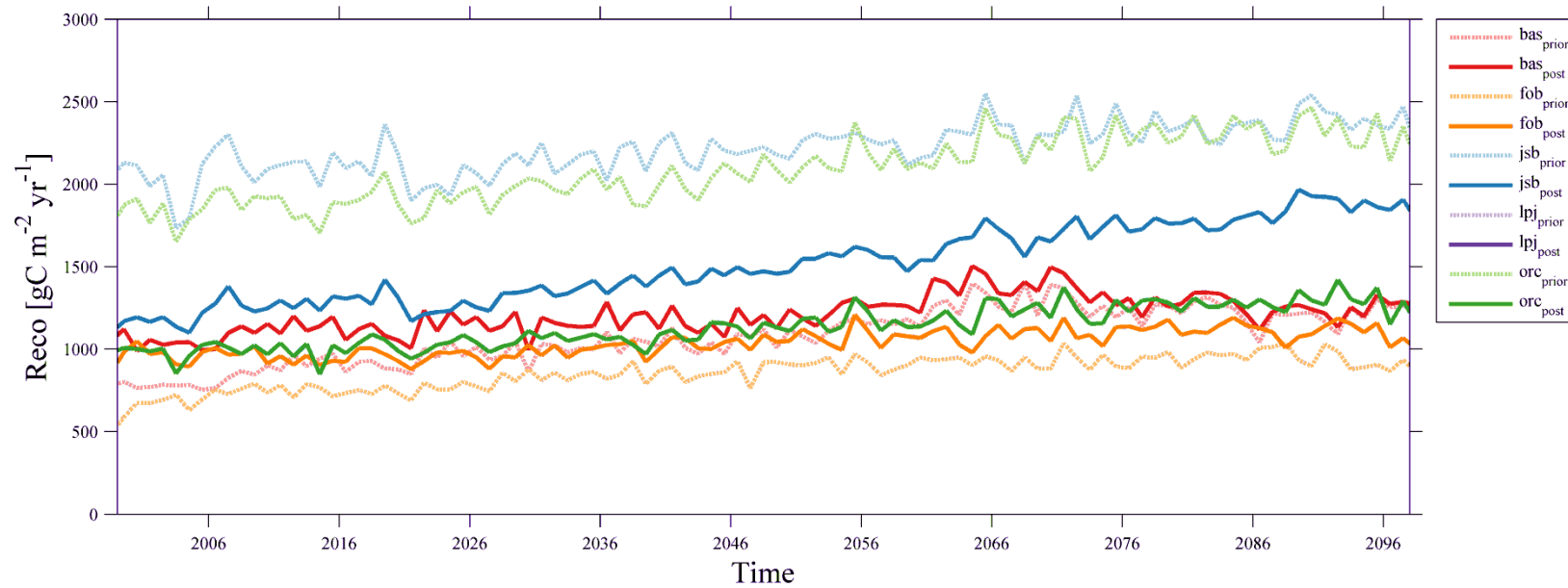
[Carvalhais et al., in prep.]

Hesse : seasonal misfits : window180days

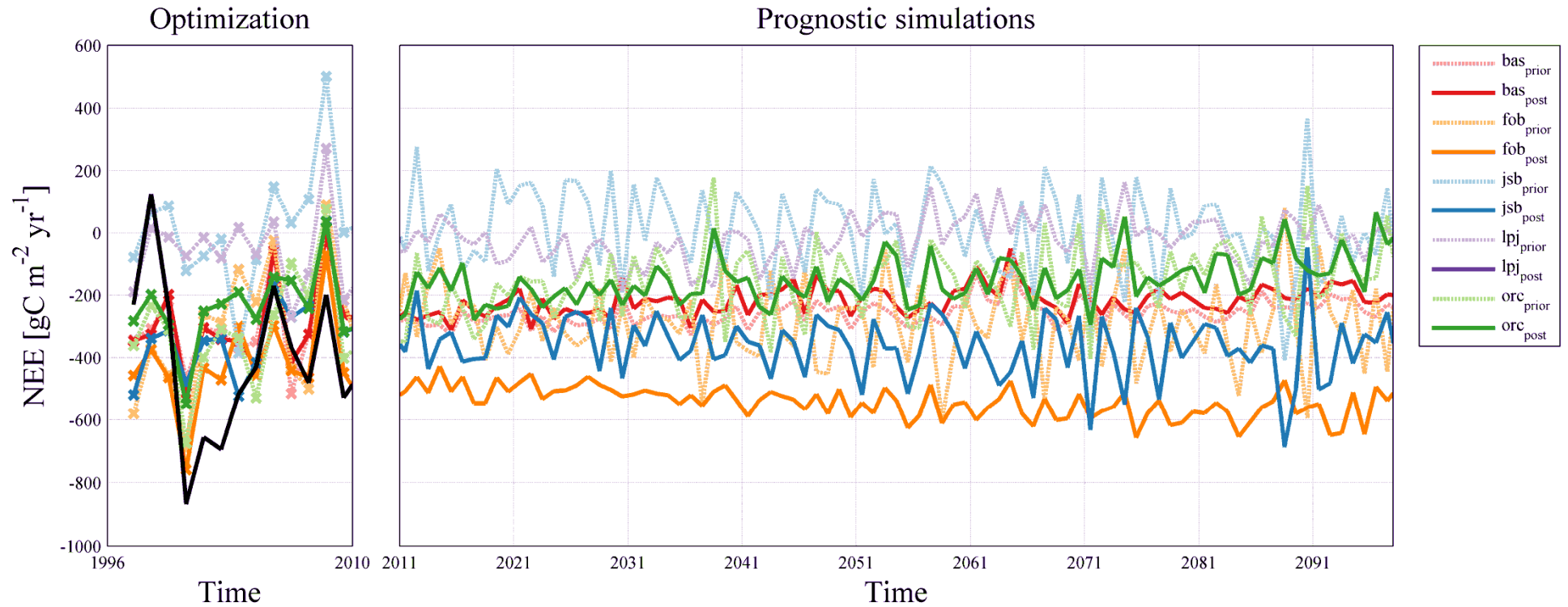
optimized
↓



Changes in prognostic gross fluxes



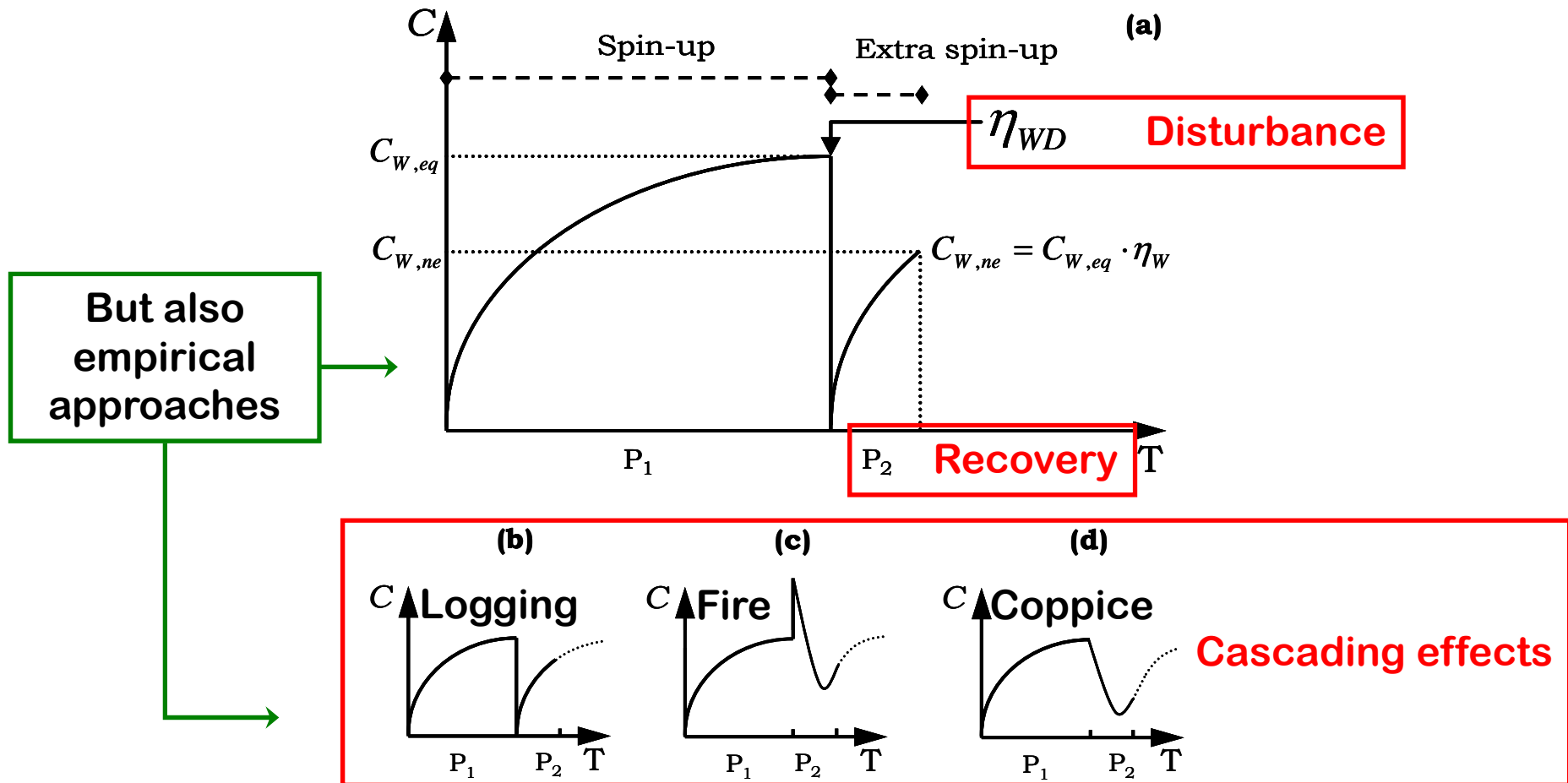
Changes in net ecosystem fluxes



Not a clear sign of spread reduction

**ADDRESSING DIFFERENT RECOVERY DYNAMICS
WITH FLUX AND BIOMETRIC CONSTRAINTS**

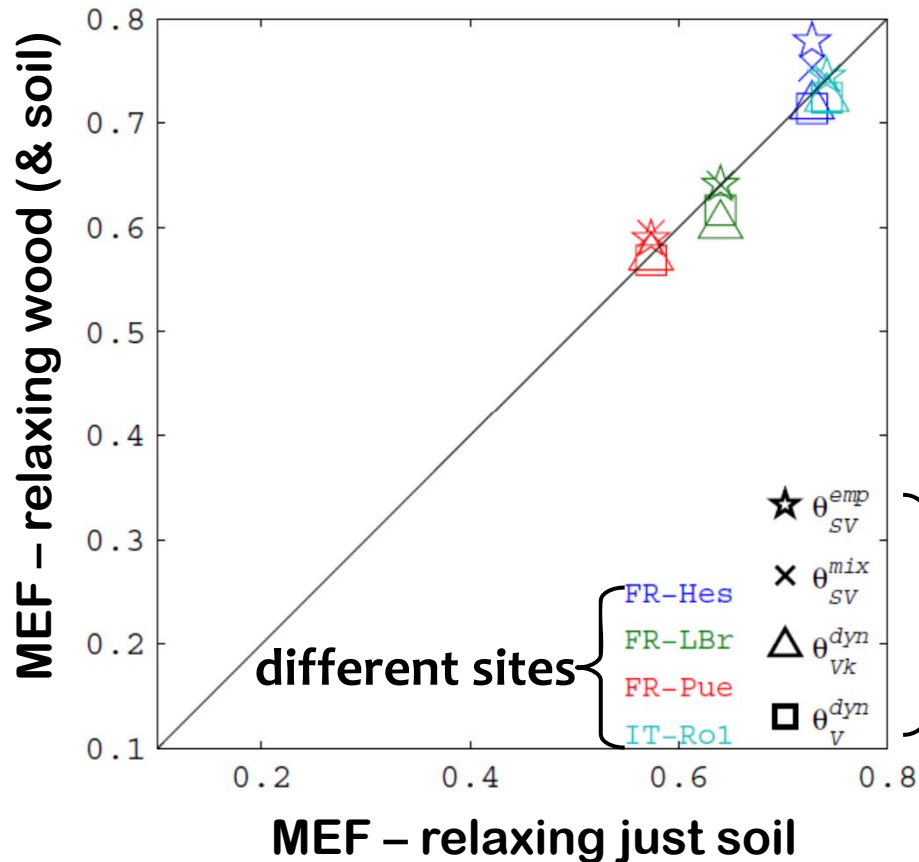
Challenging dynamics



[Carvalho et al., 2010]

Scenario differentiation

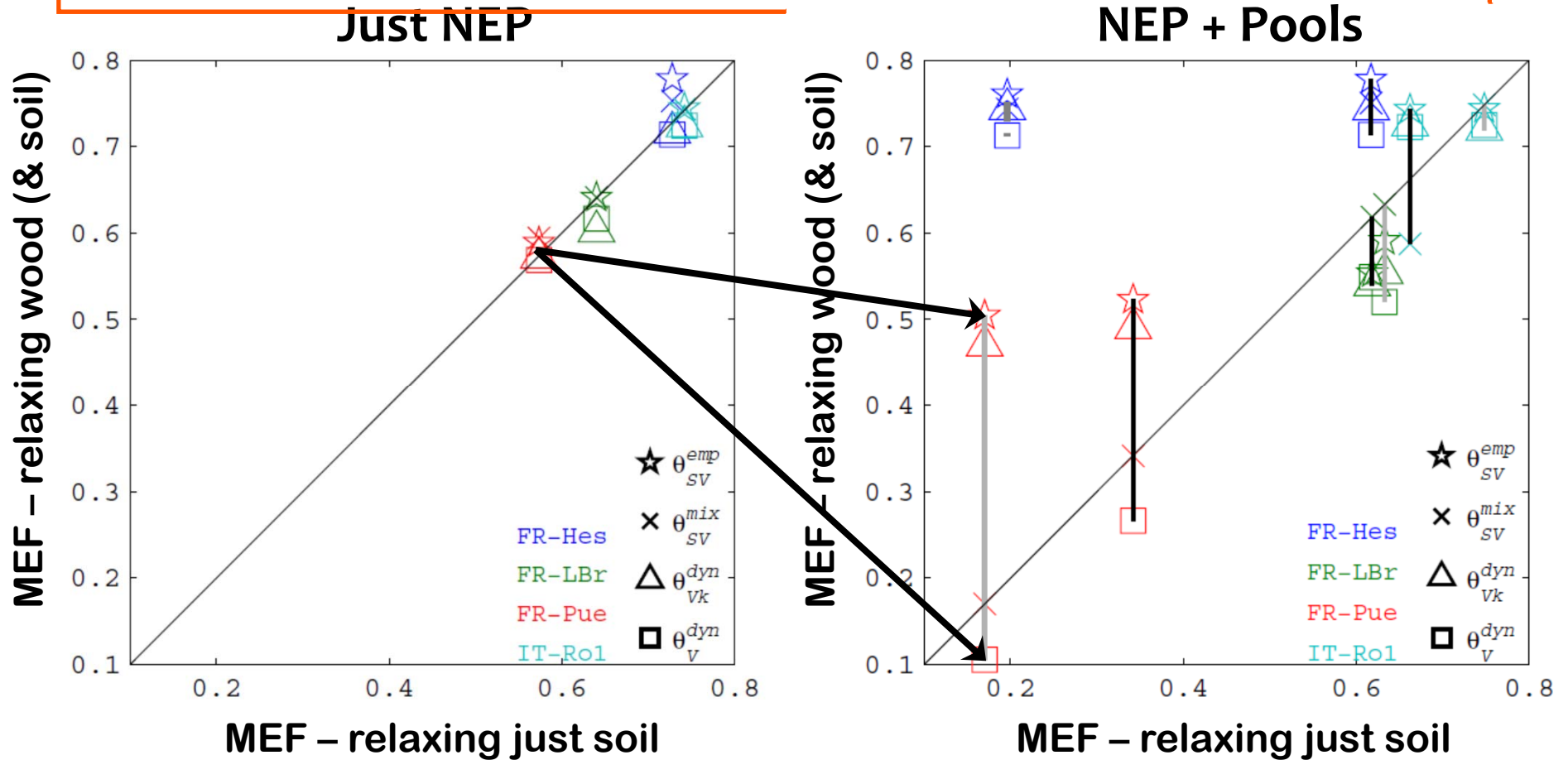
Just NEP



- Despite differences in the initialization routines it is not possible to distinguish between the different “prescribed dynamics”

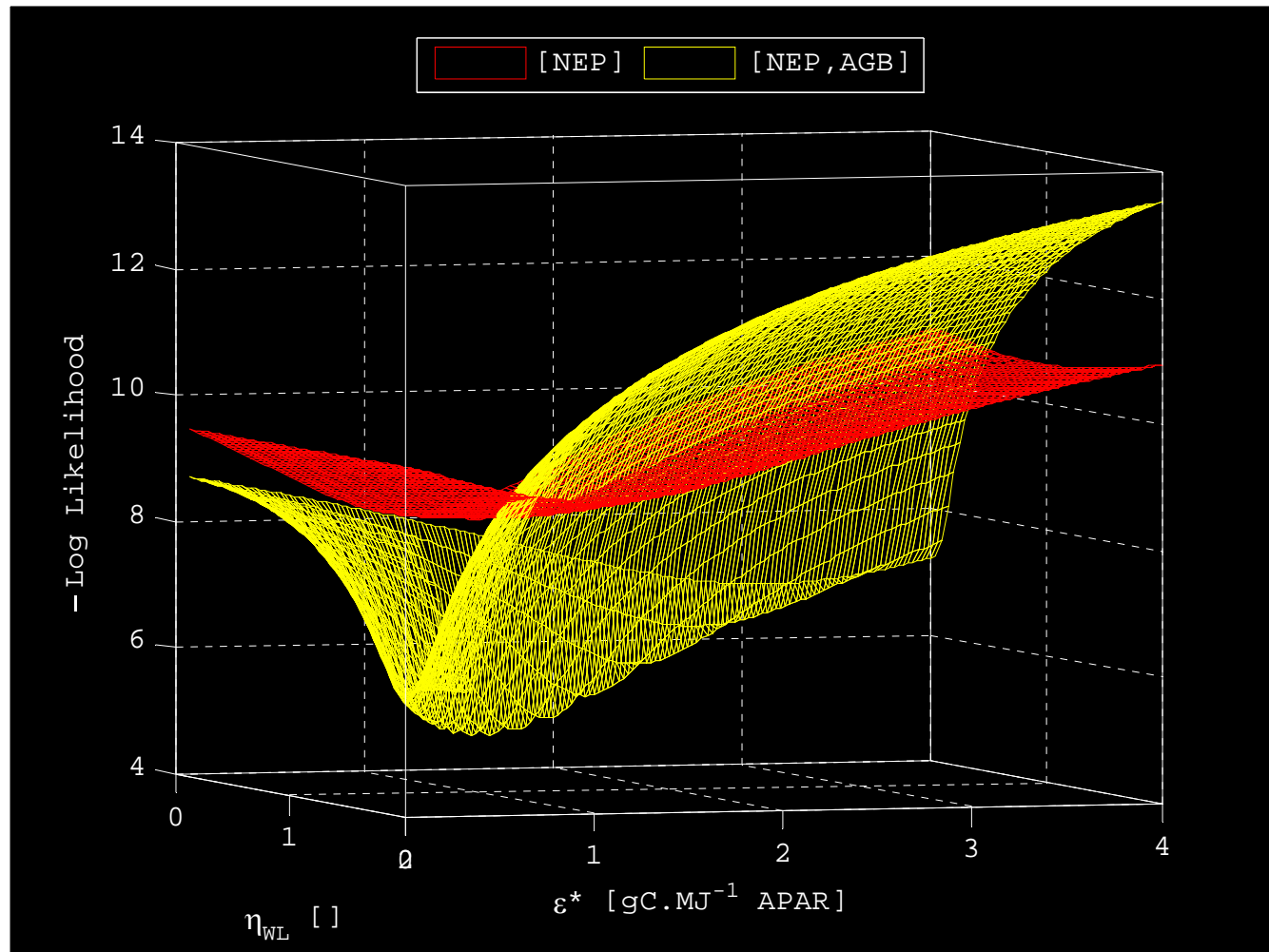
} different scenarios

Scenario differentiation




[Carvalho et al., 2010]

different convergence / stronger constraints

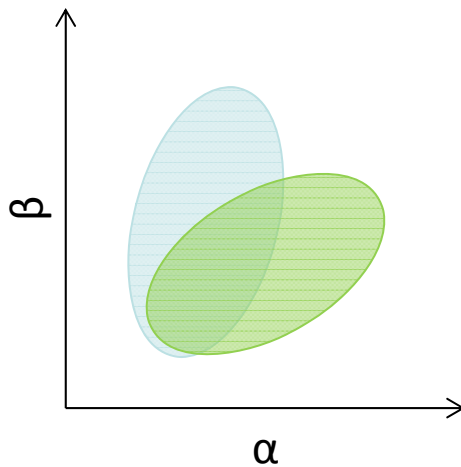


[Carvalhais et al., 2010]

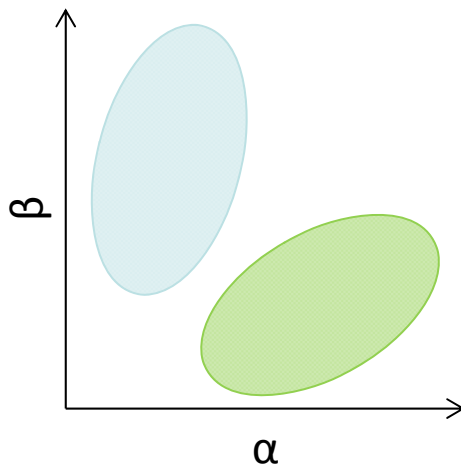
Relevance of multiple constraints

 95% LL for data stream 1

 95% LL for data stream 2



- model structure consistent with observations
- multiple constraints reduces parametric uncertainty



Challenges: Equifinality, Over-parameterisation
(e.g. Knorr et al. 2005, Reichstein et al. 2005)

- model structure inconsistent with both datastreams
- (due) inflation of parameter uncertainty/multimodality

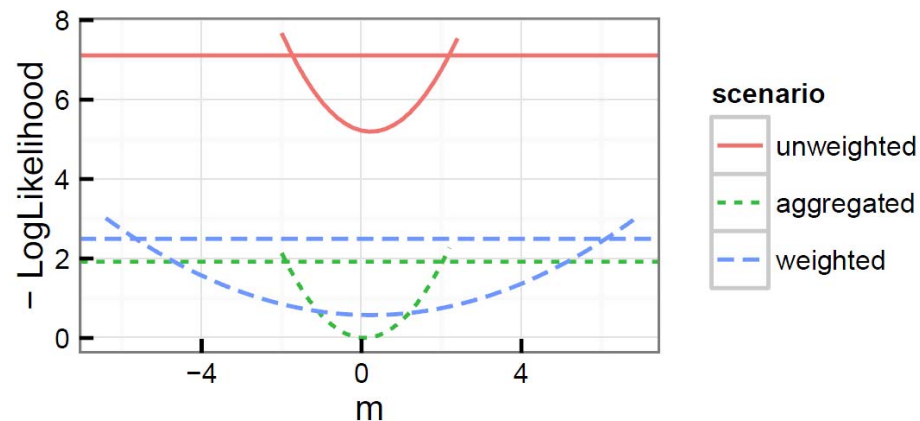
**COMBINING DATASETS WITH SUBSTANTIALLY
DIFFERENT STATISTICAL PROPERTIES**

Wutzler and Carvalhais, in rev.

Particular challenge of multiple constraints approaches

Highly imbalanced dimensions in data streams:

- for a perfect model, different alternative cost functions do not affect the achievement of optimum, but weighted approaches inflate posterior uncertainties.



Particular challenge of multiple constraints approaches

$$\hat{y}_{i,\text{rich}}(a, b, c) = a x_{1,\text{sparse}} + b (x_{i,\text{rich}} - c)$$

$$\hat{y}_{i,\text{sparse}}(a, b) = a x_{i,\text{sparse}} + b \bar{x}_{\text{rich}}/10$$

