Processes, complexity, dynamics and scaling:
using data to tackle these modelling challenges

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Model challenges

Complexity – understanding

Processes – calibration, error

Dynamics – non-steady state, feedbacks

Scaling – using earth observation effectively

Models, Data and Occam's razor

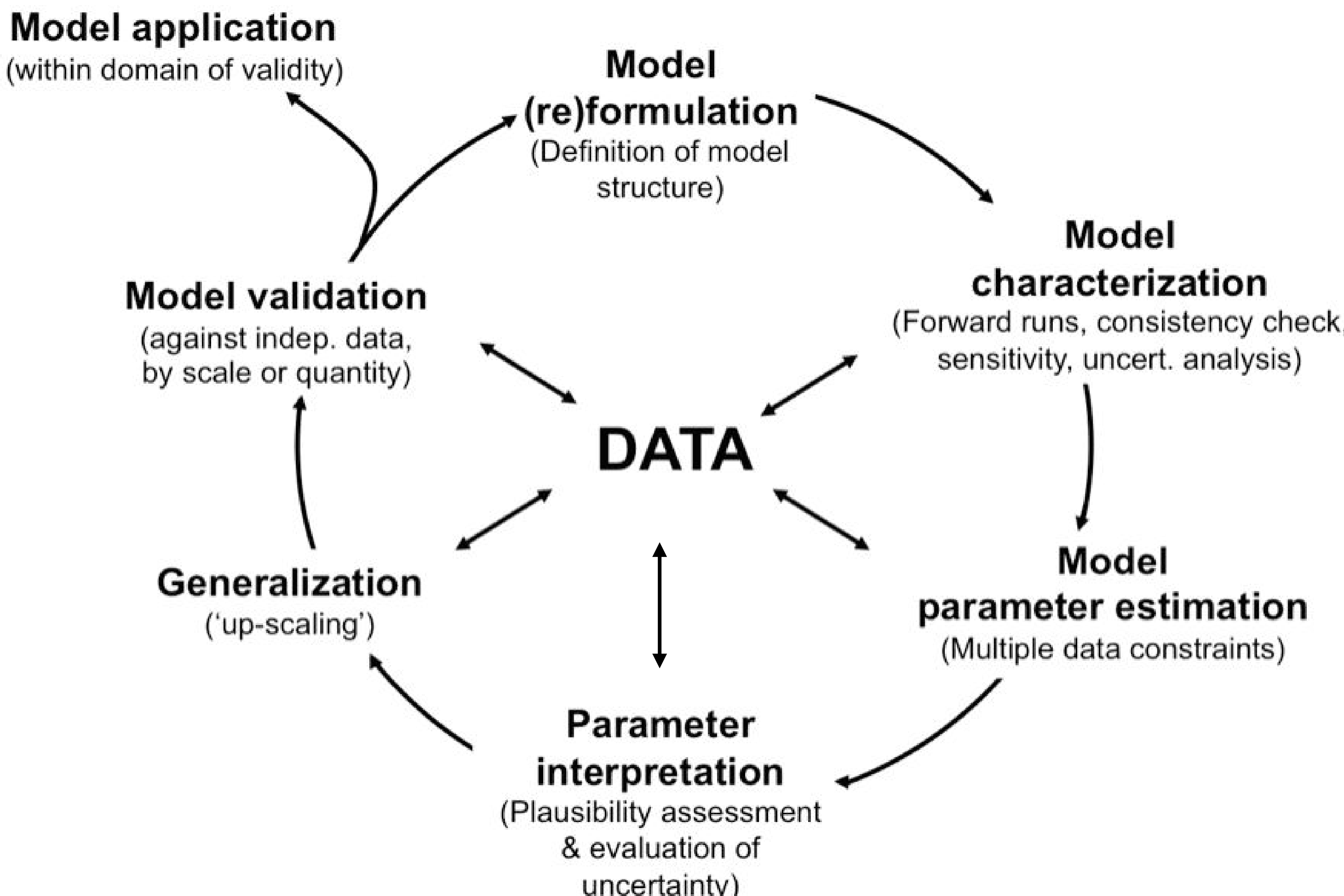
Complexity –simplification of models to represent key factors and interactions

Processes – use data to constrain parameters and study the emergent patterns

Dynamics – use time series data to constrain time constants for transient systems, with explicit uncertainty

Scaling – use multiple orthogonal spatial data to extend knowledge

Combining data with (simple) models



Williams et al. 2009

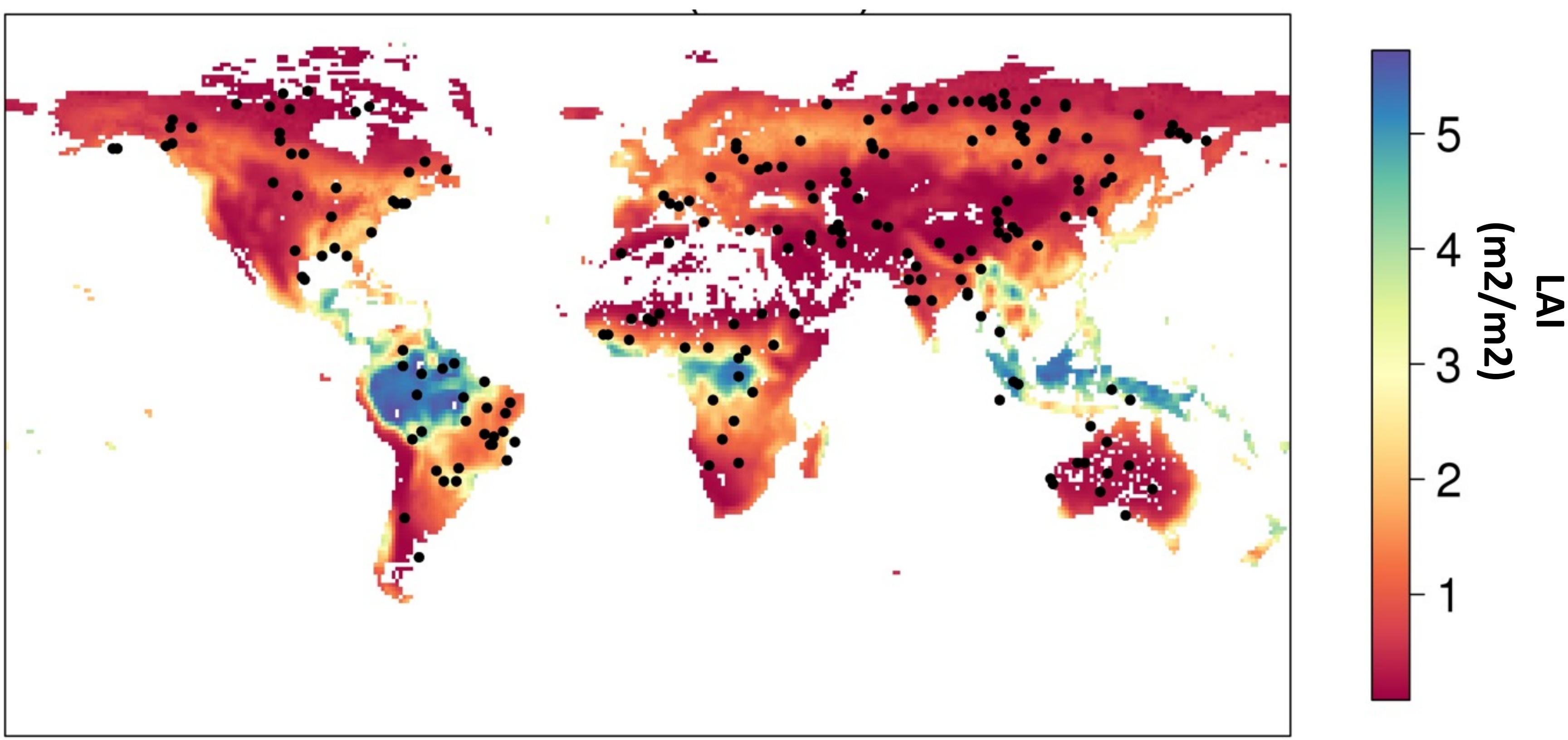
Emulating a complex canopy model

- Multiple canopy layers
- Radiative transfer scheme
- Leaf level energy balance
- Light and dark reactions
- Stomatal model
- Plant water transport
- 30 min time step, 100+ parameters,

Use process knowledge to guide emulation

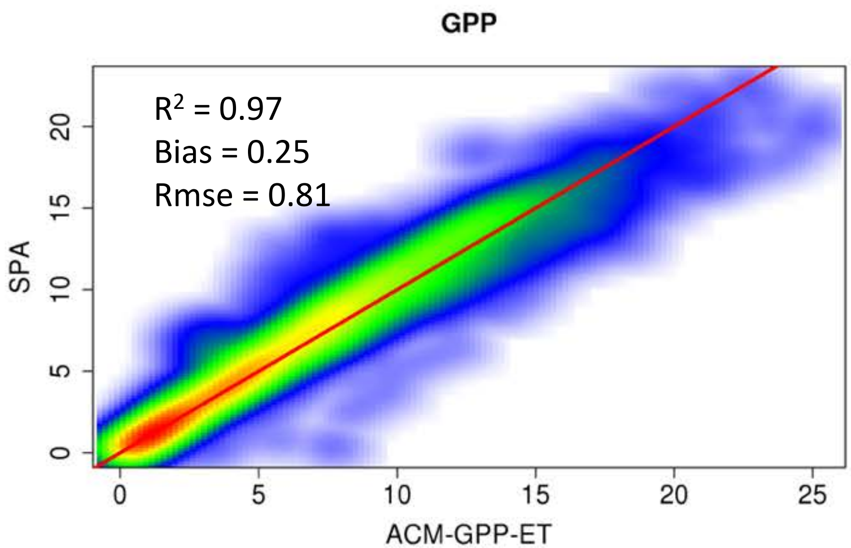
- $p_N = a_1 NL \exp(a_2 T)$
- $p_C = p_N(C_i - \theta)/\ k + (C_i - \theta)$
- $\mathrm{p_D} = \mathrm{g_c}(\mathrm{C_a} - \mathrm{C_i})$
- $\mathrm{g_c}$ = f(soil moisture, T, VPD)
- $\mathrm{p_C} = \mathrm{p_D}$
- $p_l = E_0 I p_D / (E_0 I + p_D)$
- 10 parameters
- 7 daily drivers

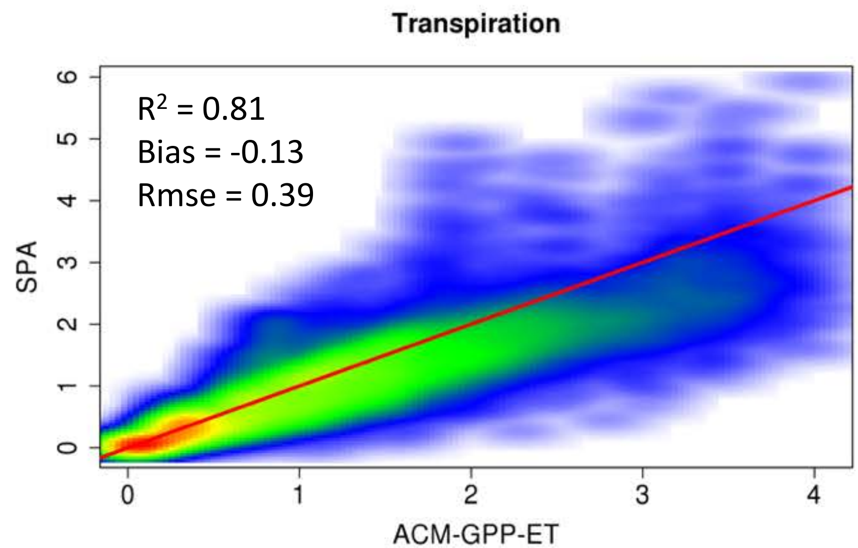
Location of calibration sites selected using stratified random sampling

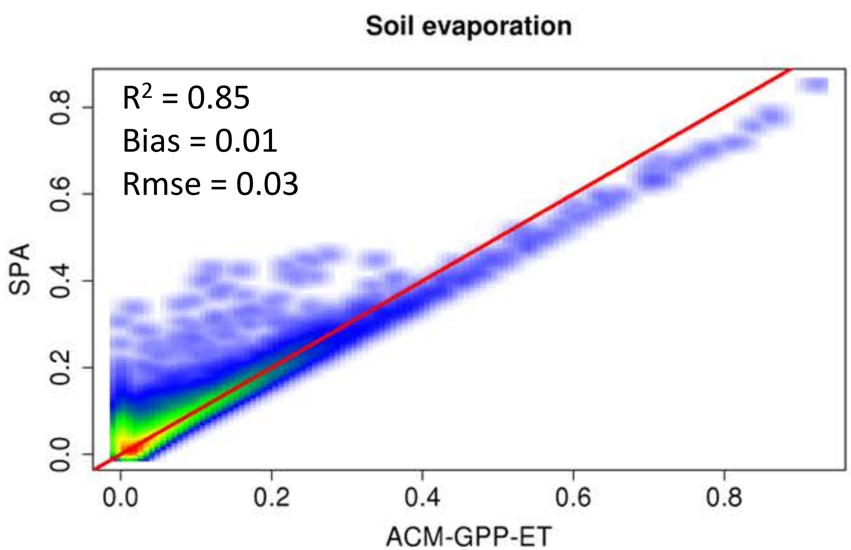


Variation in LAI, day length, temperature, radiation, VPD, CO_2, foliar N, soil moisture

Fit simple model to complex LSM







Smallman et al (in prep)

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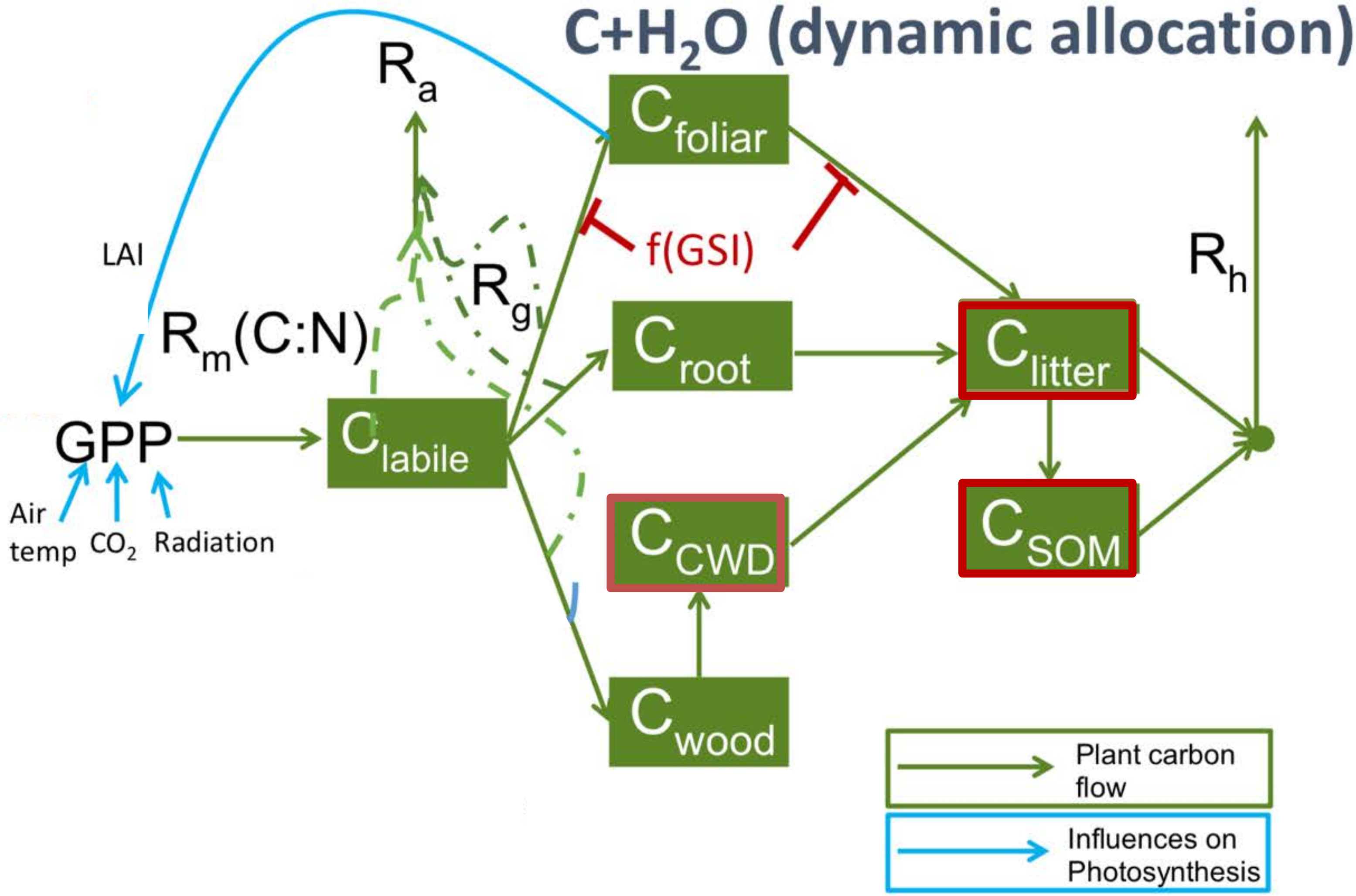
DALEC



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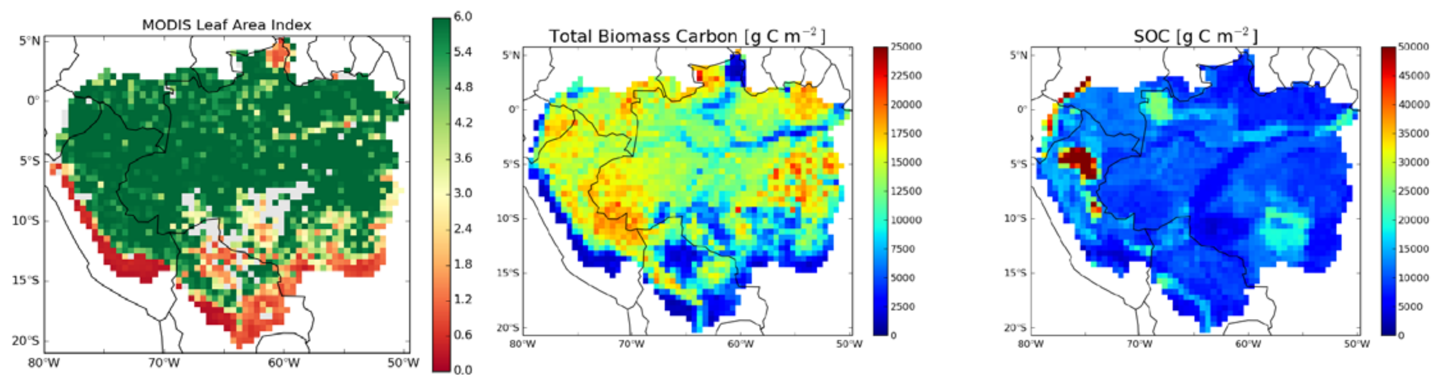
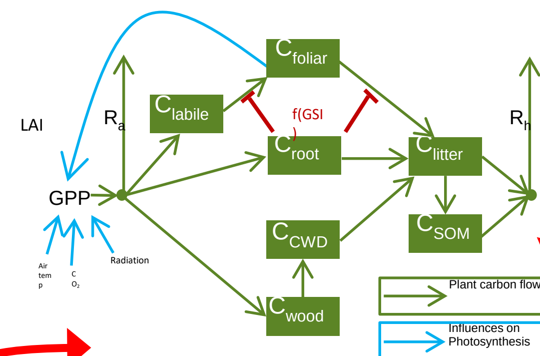
Carbon-Data-Model Framework: CARDAMOM

- DA in each pixel
- No PFTs
- Continuous maps of parameters

Observations – LAI time series, biomass, SOC



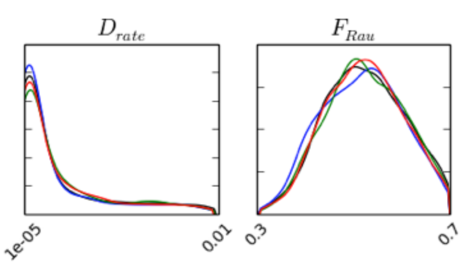


Update

MDF algorithm

OUTPUT

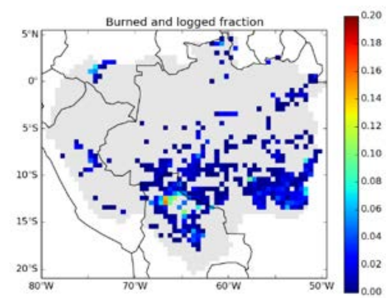
PDFs of parameters, fluxes, pools, etc…



DRIVERS

CRU+NCEP weather

GFED burned area



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Bloom et al (2016)

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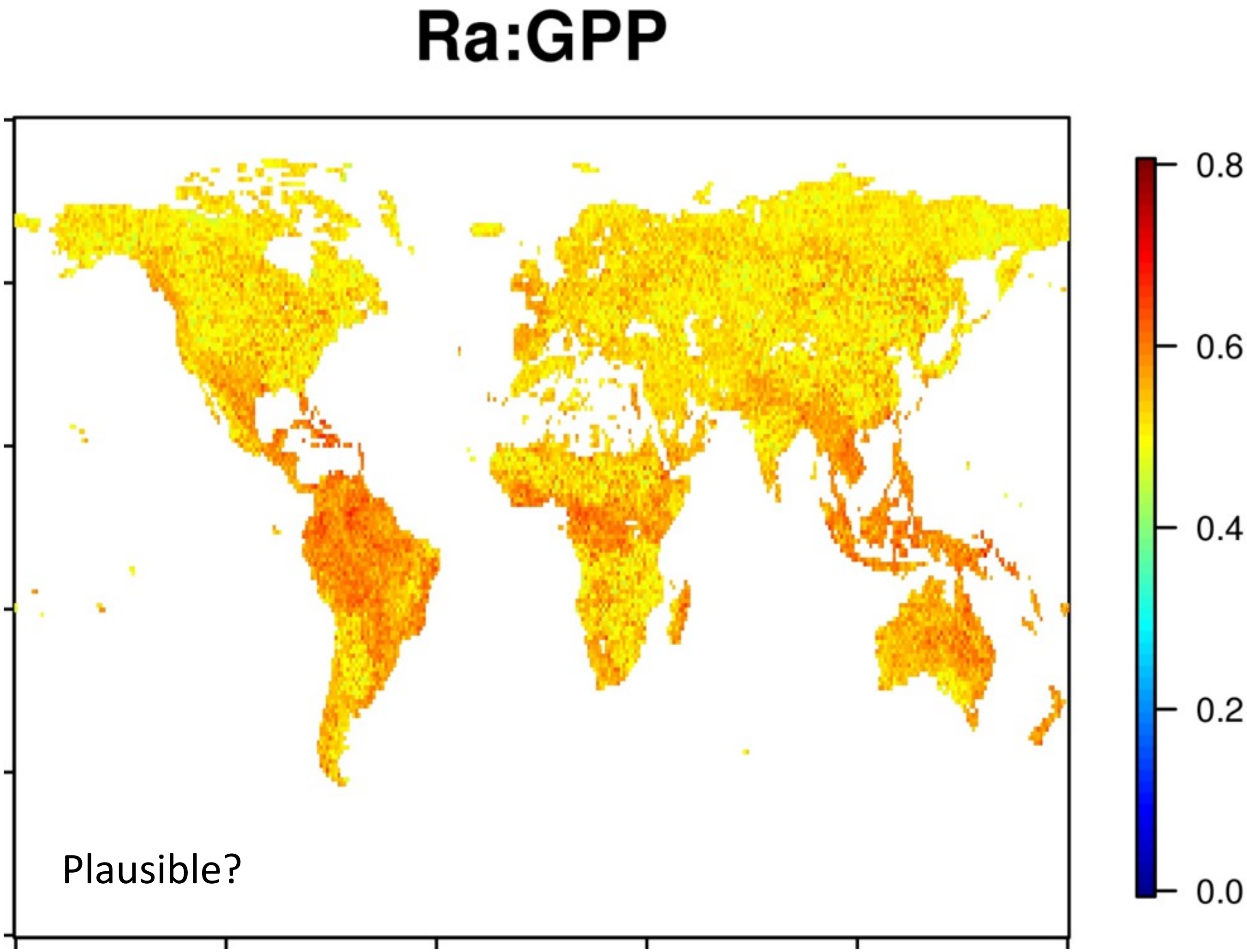
Maps respiration variability



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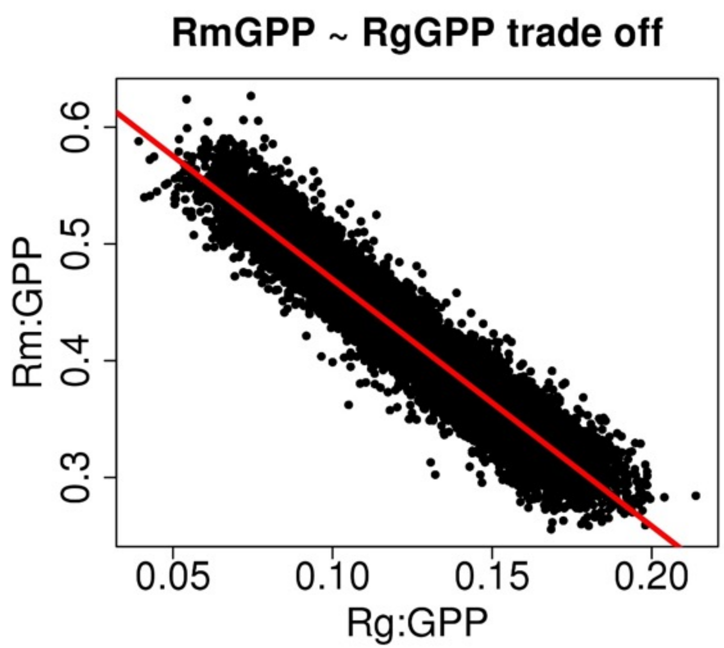
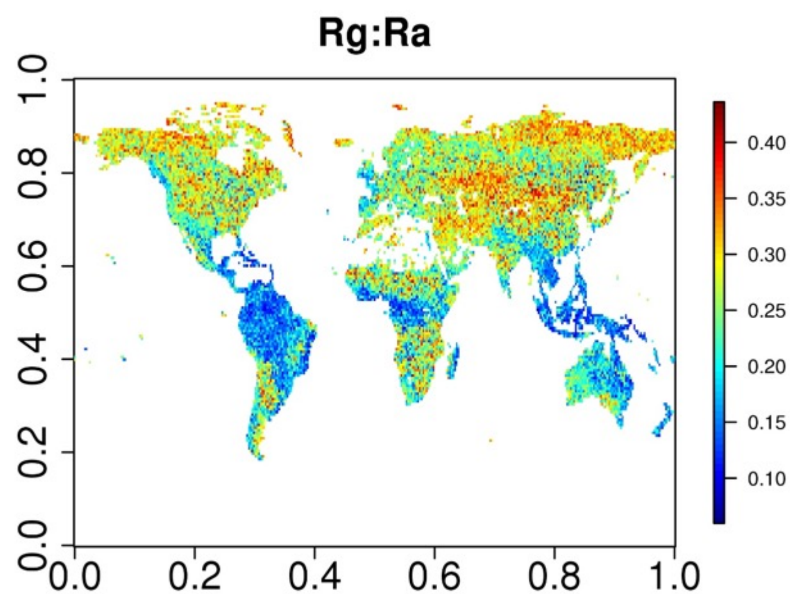
Identifies components of respiration





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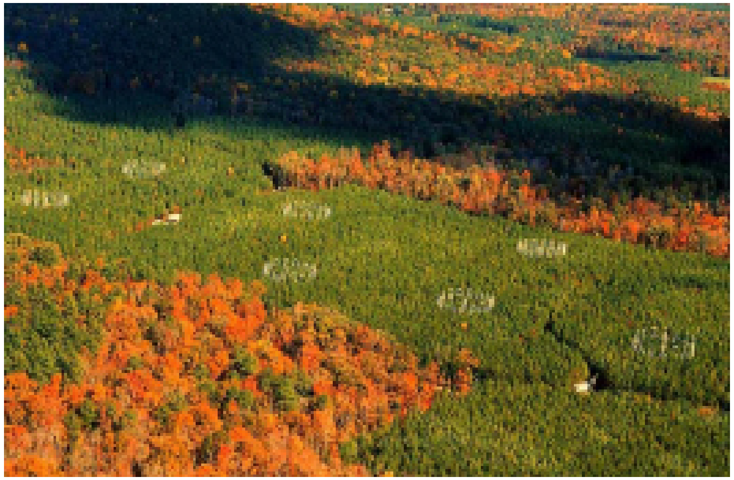
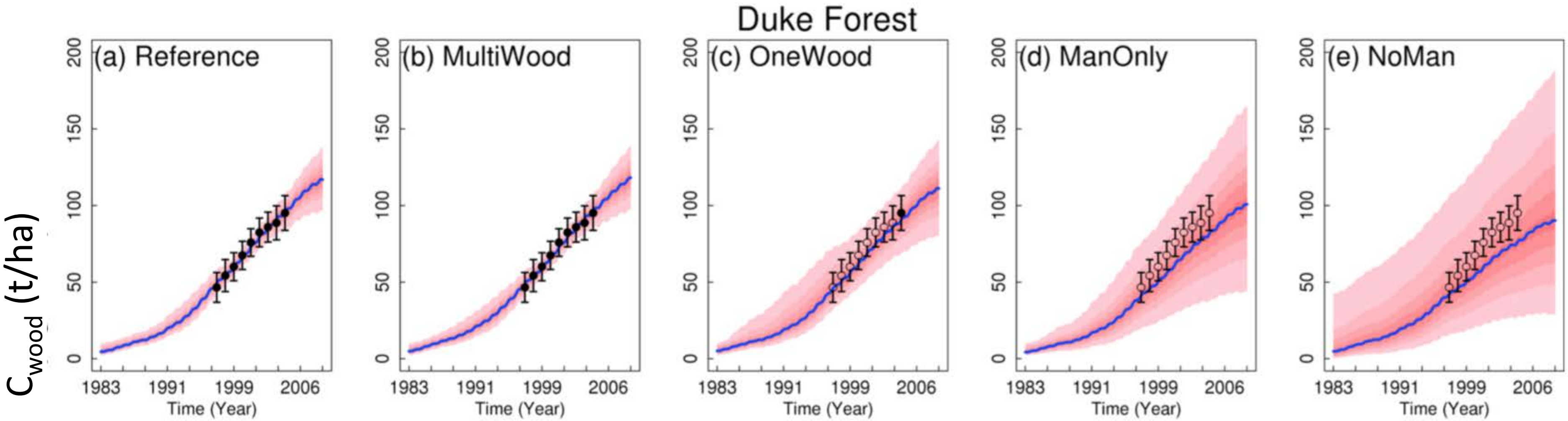
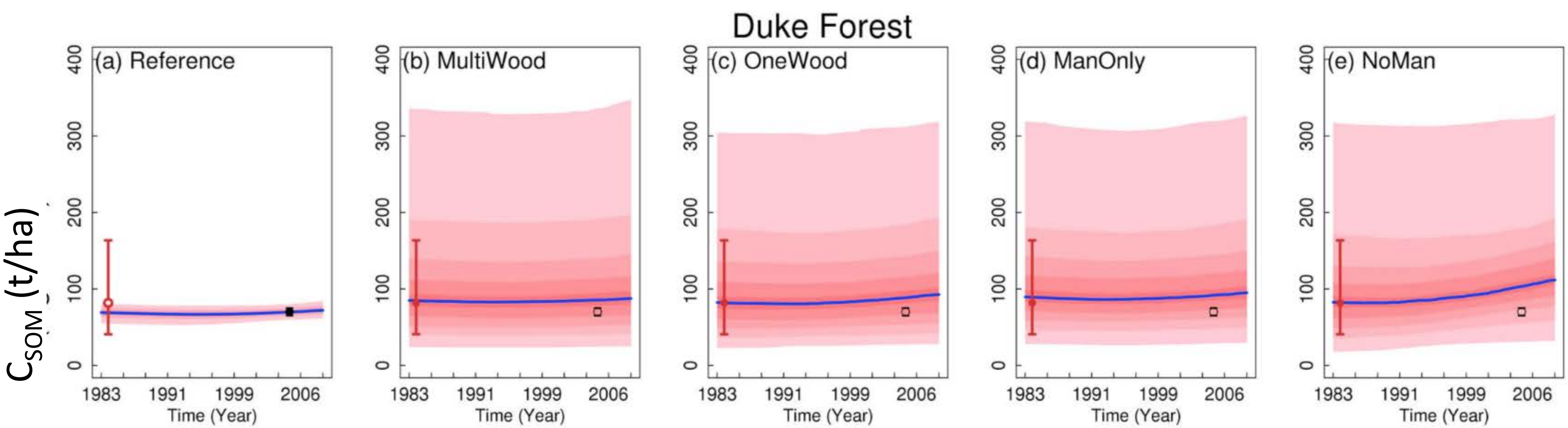
Constraining dynamics

- Aggrading forest, non steady-state
- Duke Forest, NC (Loblolly Pine planted in 1983)
- What information is required to constrain model parameters?







Smallman et al (2017)

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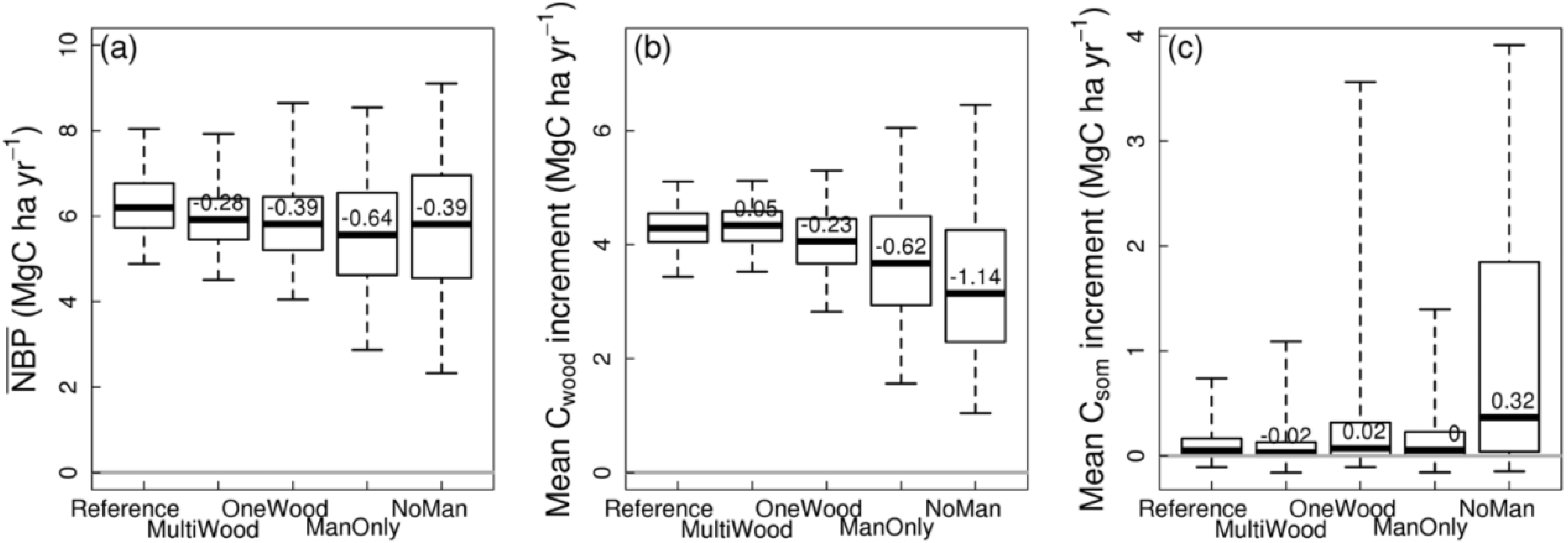
Biomass information can constrain NBP, soil dynamics



NBP

Wood increment

SOM increment

Less assimilated information

Smallman et al., (201

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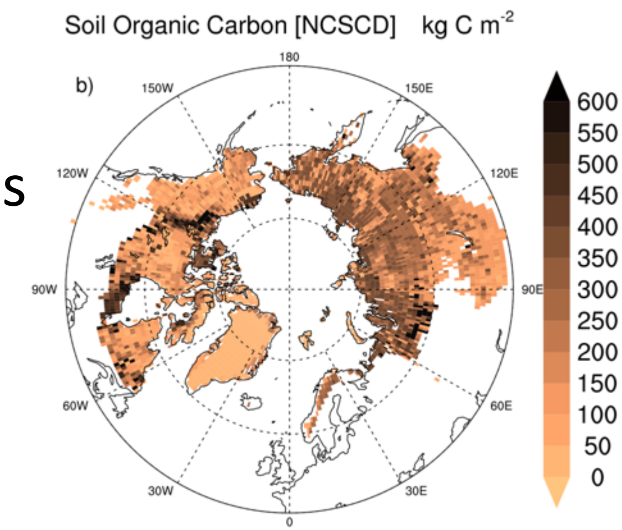
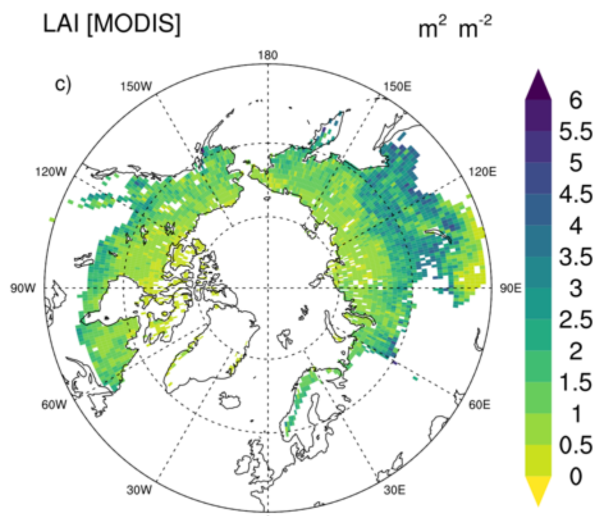
Scaling Up – Pan Arctic

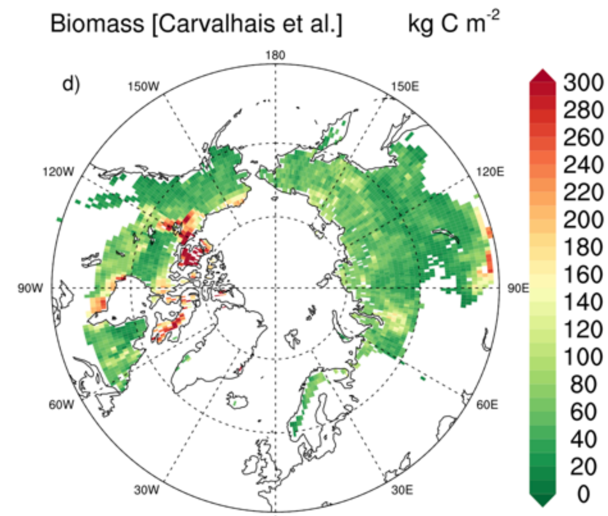
Satellite derived LAI and Biomass
Soil sampling for soil C



Soil C

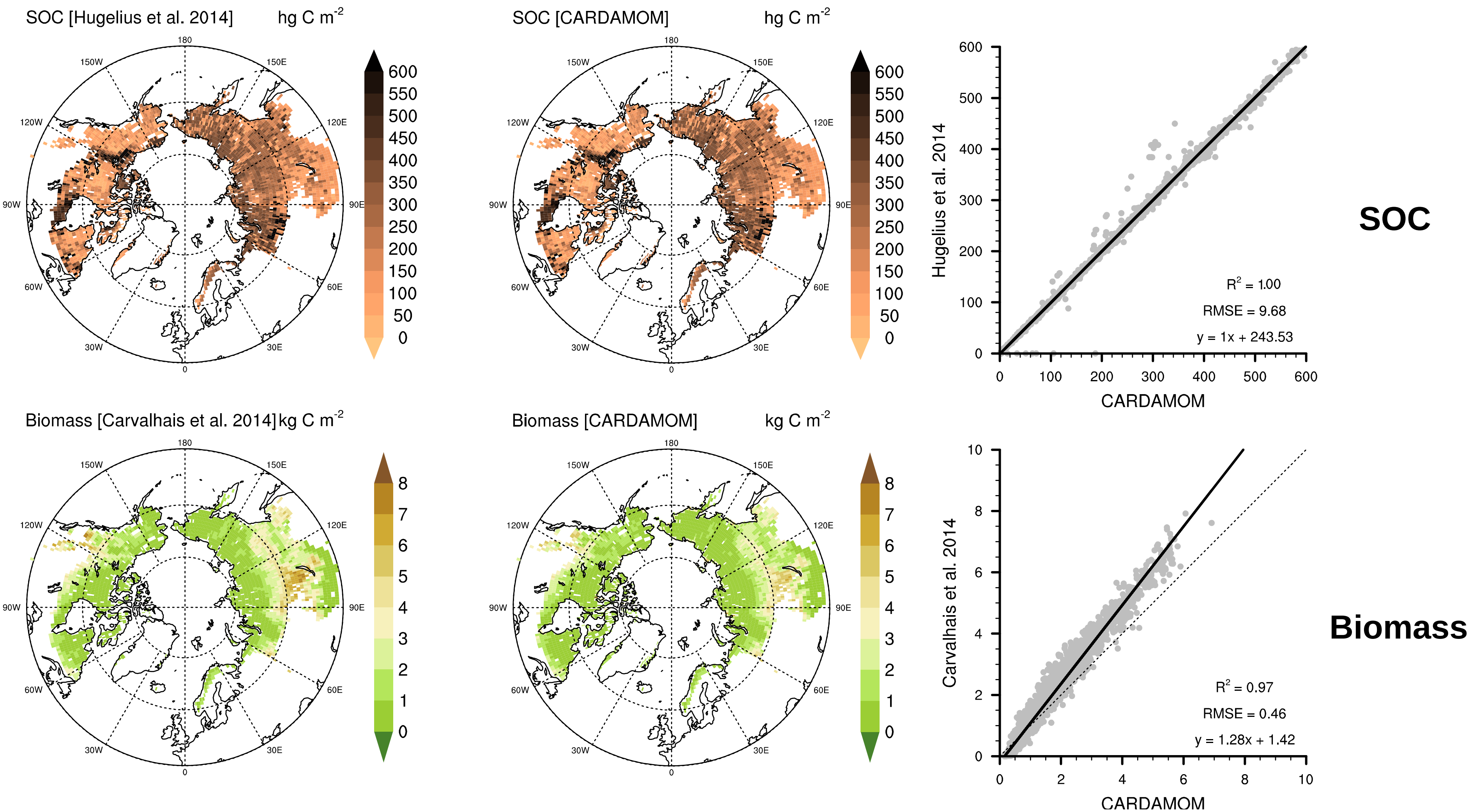
LAI





BIOMASS

Examples of assimilated data



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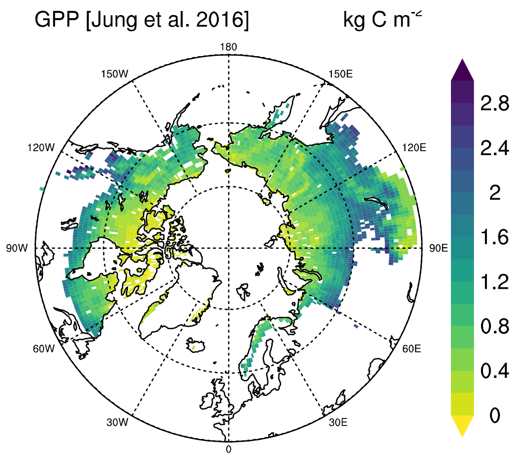
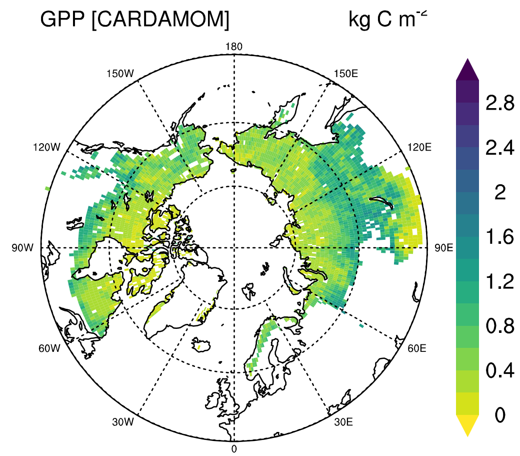
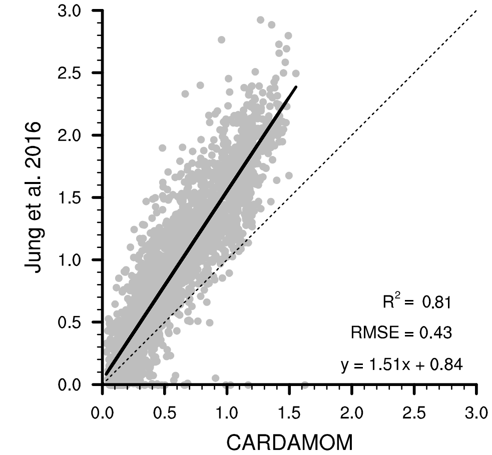
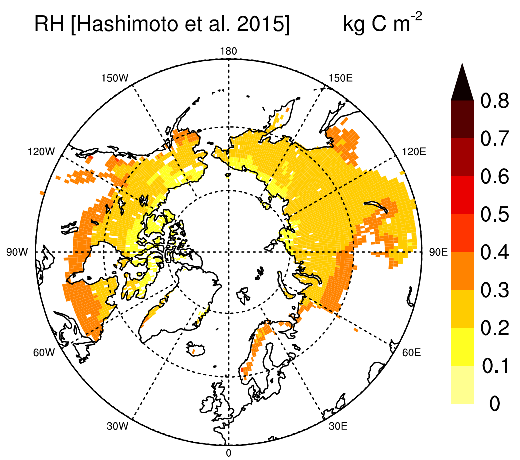
Examples of validated data

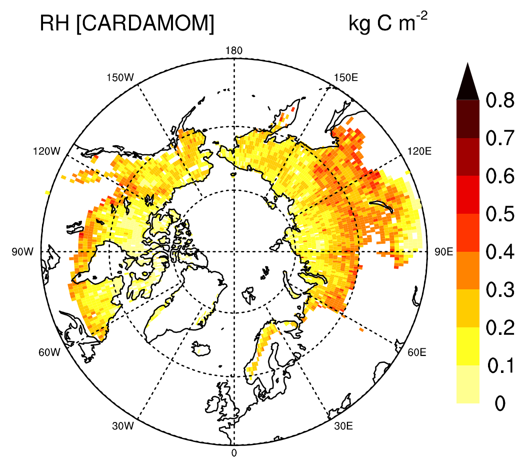


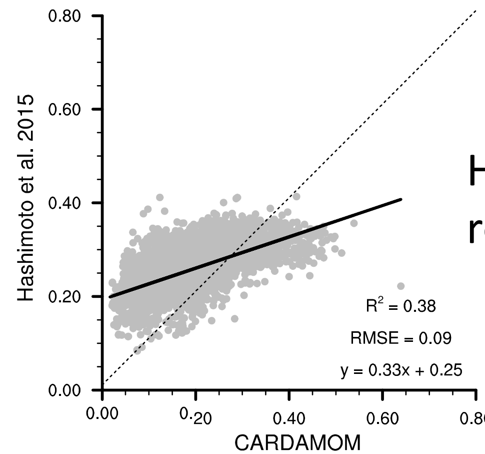




GPP







Heterotrophic respiration

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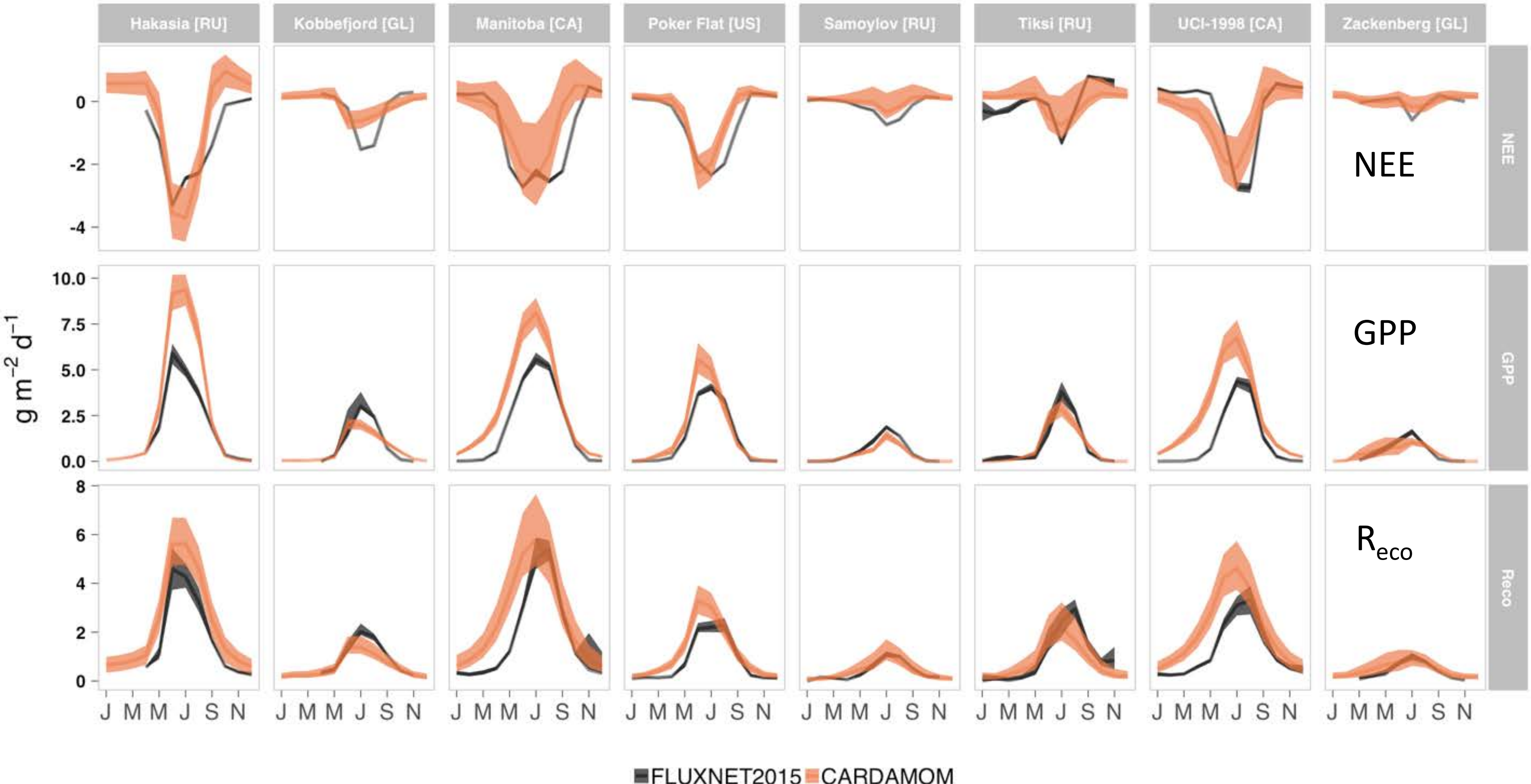
Flux tower data validation – FLUXNET, 2015



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Conclusions

- Simplify models to allow fast running, and focus on emulating key processes
- Use multiple time series data to constrain dynamics (LAI, biomass) and propagate information into SOM
- Incorporate uncertainty into calibration process, and into predictions
- Use data from recent historical period to evaluate models in space and time

Thanks

- Acknowledgements:
  - NERC
  - FLUXNET, MPI
  - Duke Forest team
  - HWSD, NCSCD

Global gross primary productivity remains poorly constrained

CMIP5
GPP 1999-2009

Data Set	Mean (Pg C yr^{-1})	IAV (Pg C yr^{-1})
MTE	119	1.3
MODIS	112	0.8
CARBONES	148	2.45
CLM4CN	147	2.87
CESM1-BGC	130	2.44
NorESM1-ME	131	1.76
JULES	149	4.4
HadGEM2-ES	140	3.89
ORCHIDEE	153	3.23
IPSL-CM5A-MR	169	3.26

Anav et al., (2015) *Reviews in Geophysics*

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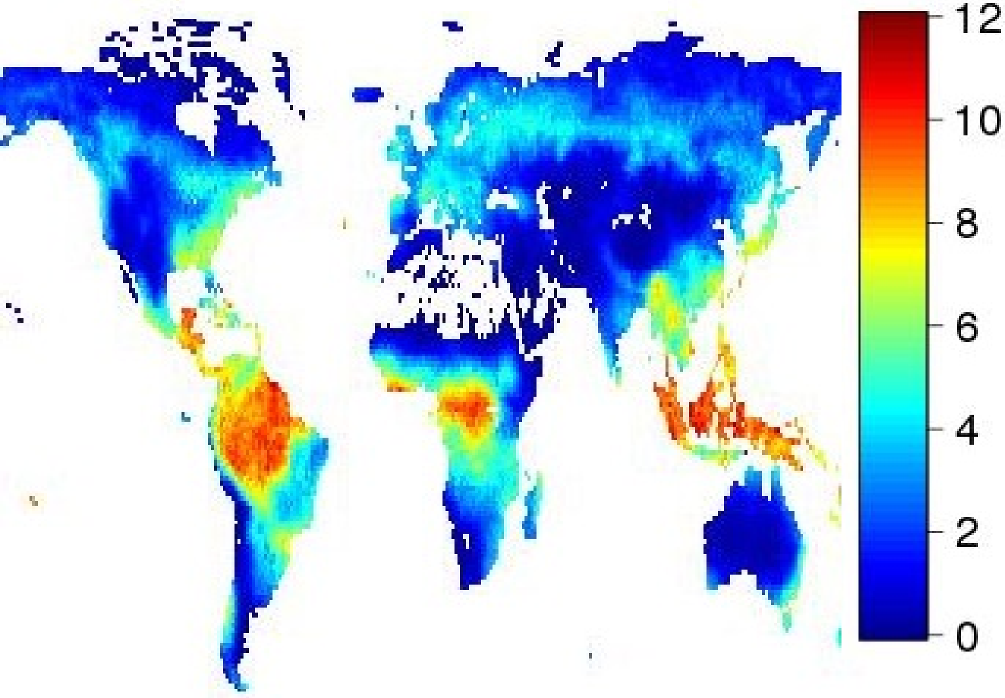
No uncertainty estimate

CARDAMOM

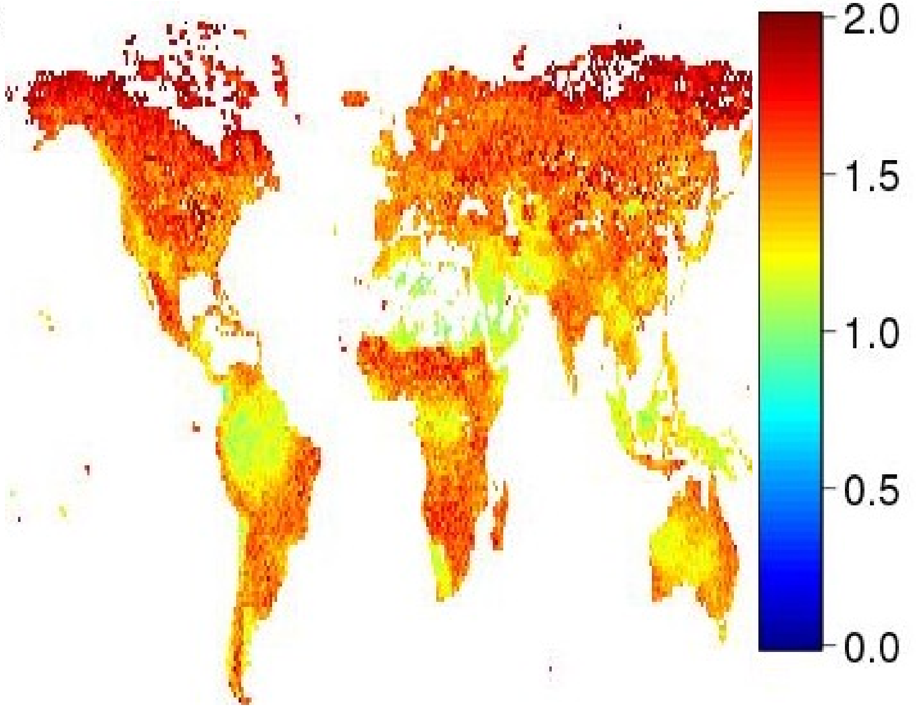
GPP (2010-2015) = 125 (85/181) PgC yr^{-1}

Uncertainty in GPP analysis

Absolute 95% CI Range



Relative 95% CI Range



Managing complexity

- Tendency to add parameters to model
- Increased demand for high resolution forcing
- Computational load
- Harder to understand sensitivity
- Difficult to determine uncertainty