



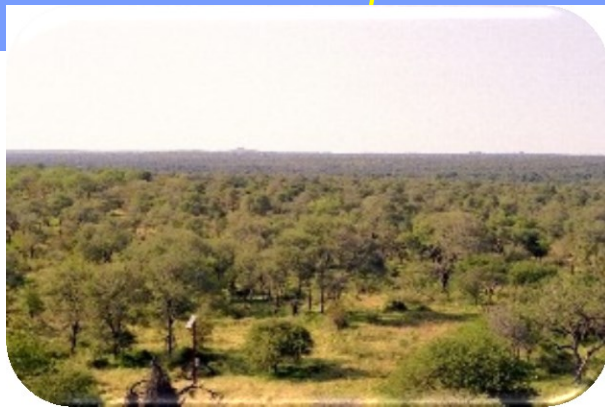
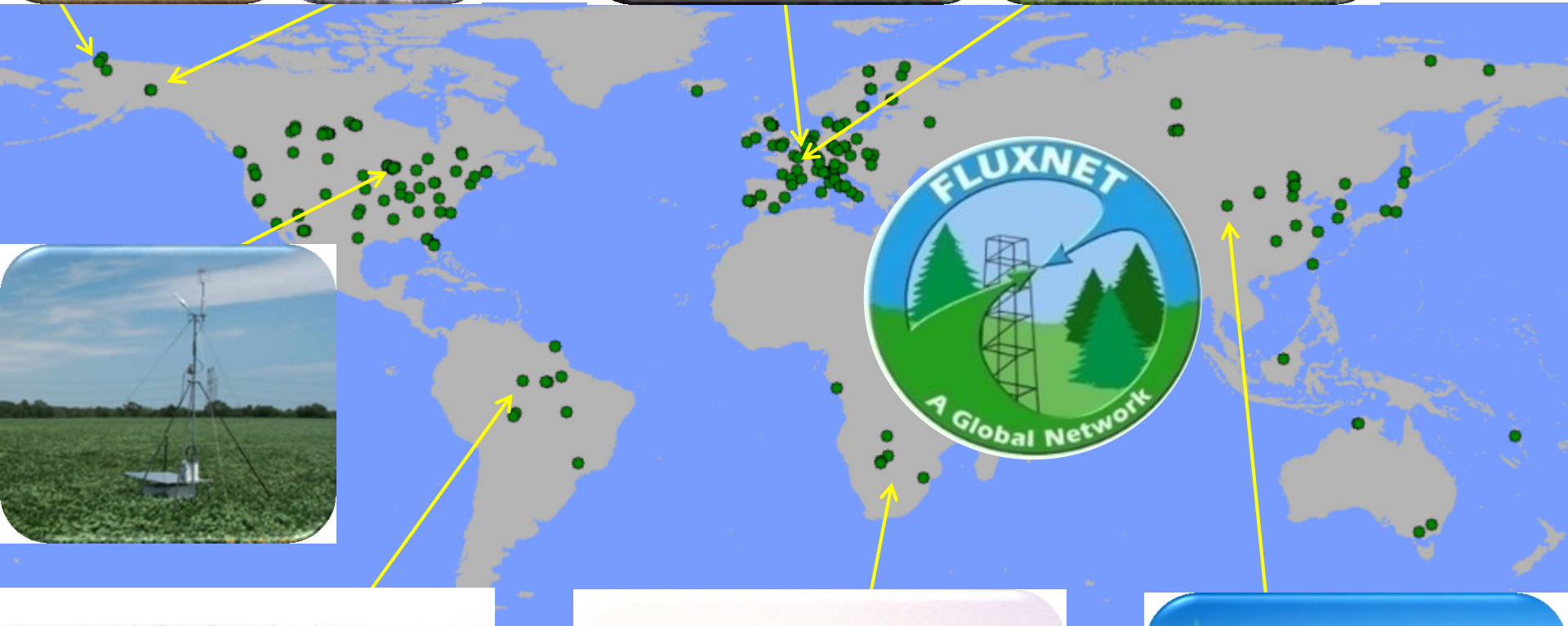
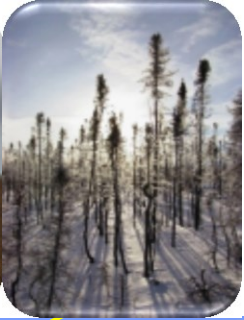
**FLUXNET 2017 Workshop
Berkeley, June 2017**

**FLUXCOM –
from FLUXNET to a global flux picture**

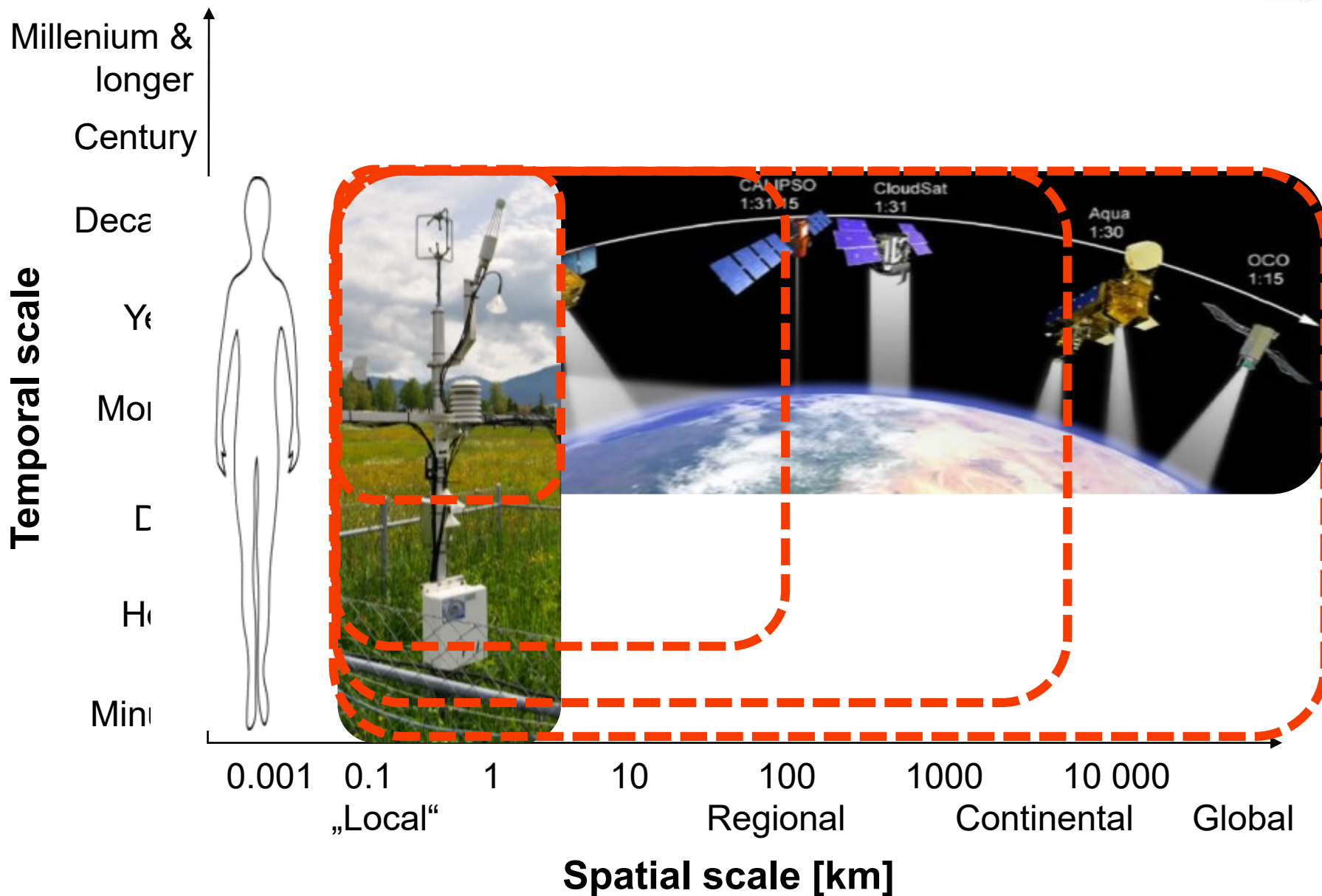
Markus Reichstein, Martin Jung &
FLUXCOM team

FluxCom

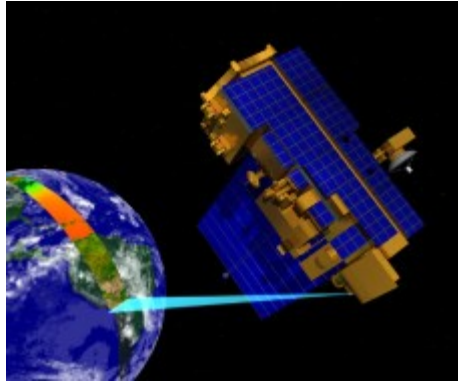




Scaling from flux-towers to globe



Empirical upscaling methodology

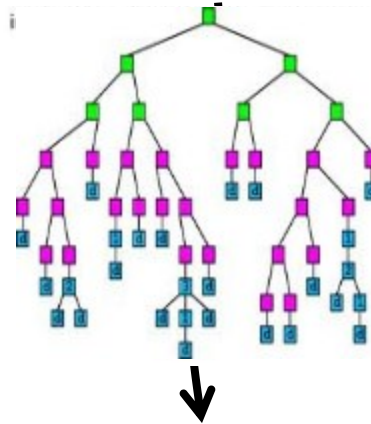


Site-level explanatory variables

- Meteorology
- Vegetation type
- Remote sensing indices

Training

The same gridded explanatory variables

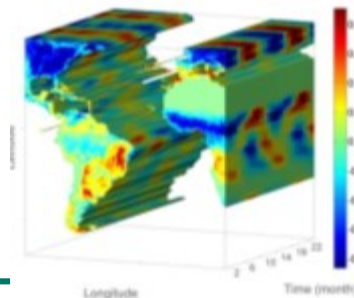


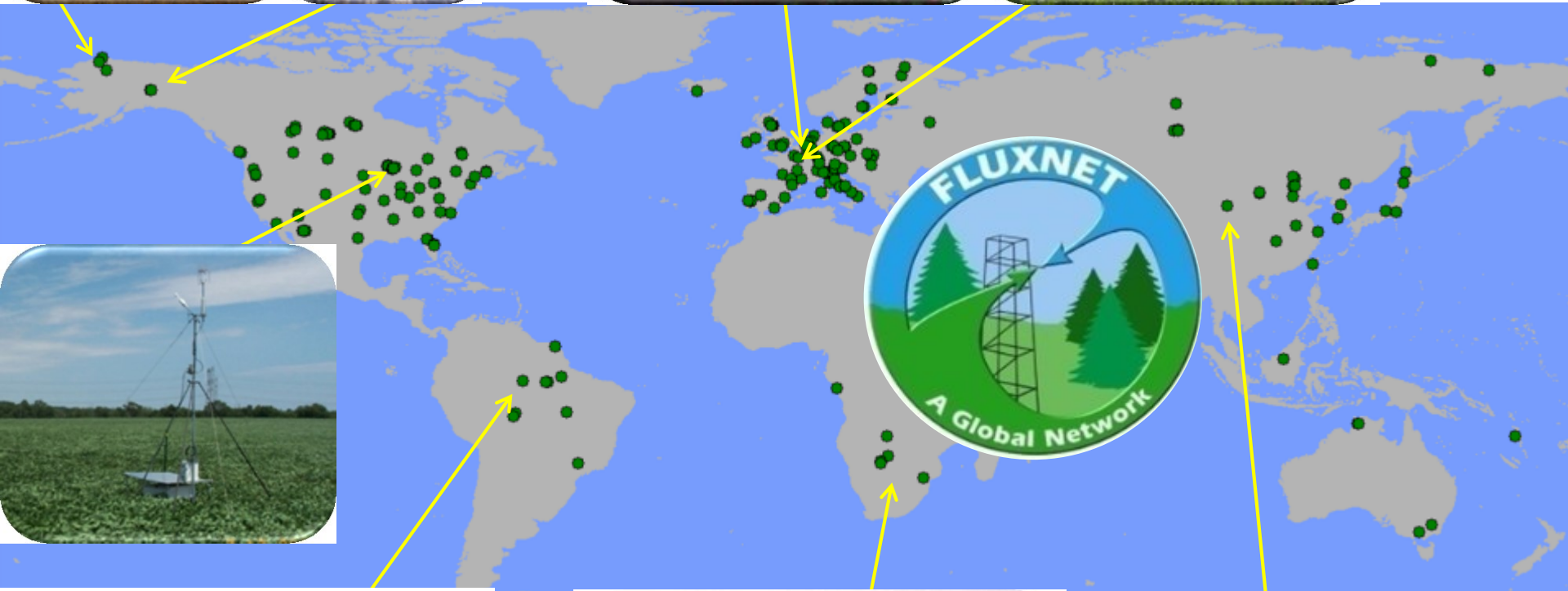
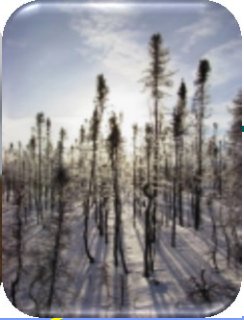
Training

Target variable ecosystem-atmosphere flux

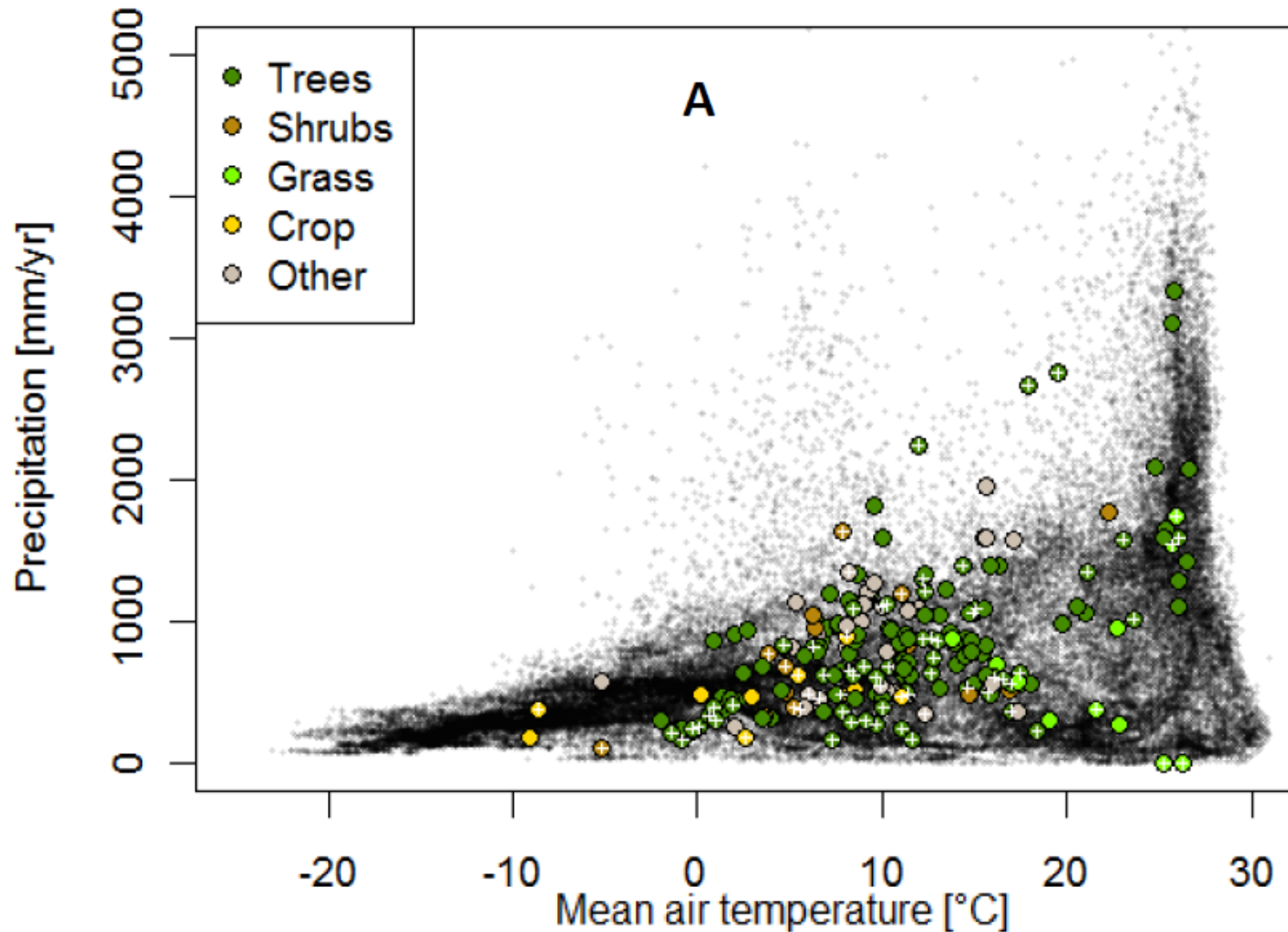


Gridded target variable





Representativeness in climate space



Reichstein et al. (2014), PNAS

After 1st promising results: global effort



D. Papale



M. Reichstein



M. Jung



K. Ichii



G. Camps-Valls



G. Tramontana



C. Schwalm

FluxCom



T. Hilton

MDF



N. Carvalhais



A. Bloom



T. Keenan

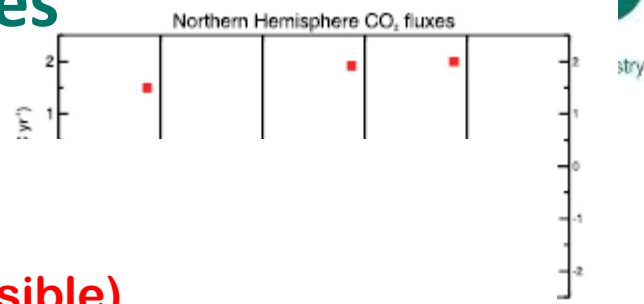
1st idea: RECCAP ws, Tuscia

Consolidation: Berkeley 2012 ws

Inferring fluxes: complementary strategies

Key assets and challenges of bottom-up:

- + Flux predicted from flux (→ crossvalidation possible)
- + Spatially explicit at potentially high resolution
- + High-temporal resolution possible (incl. diurnal)
- Not all predictors needed for NEE readily available
- No global constraint (→ can be globally “off”)



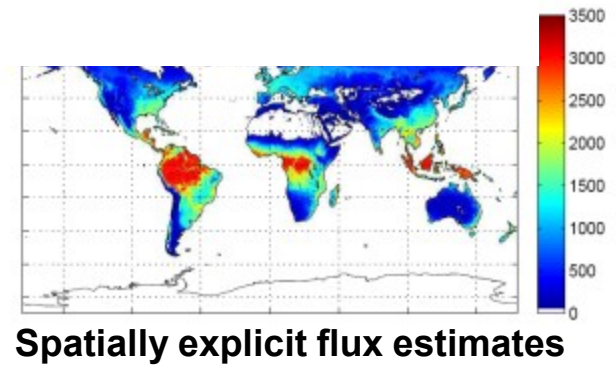
Eddy covariance

- Knowledge of fluxes
- Fluxes at multiple time scales (10²-10⁷)
- Carbon and water, and energy fluxes
- Biogeochemistry and Ecosystems
- Diurnal fluxes
- Stochastic data gaps
- Biases (fluxing out/in)
- Combined land/sea

Bio-Atm flux network

Ameriflux, CarboAfrica, Afriflux, Ozflux, USCC, NECC, GARD, FLUXNET, LBA, ChinaFLUX, AfriFlux, OzFlux, USCC, NECC, GARD, FLUXNET, LBA, ChinaFLUX, AfriFlux, OzFlux

Remote sensing and meteo fields, „Biosphere“ modelling



Global Products: all Fluxes - Rn, NEE, LE, H, GPP, TER

Driven only by remote sensing data

8 daily temporal, 0.0833° spatial, 2001-2012

Driven by climate data & remote sensing
mean seasonal cycles

daily temporal, 0.5° spatial tiled by PFT, 1982-2010

Cross-validation & Training

Tree ensembles

Random Forests
Model Tree Ensembles (3 variants)
Multivariate Adaptive Regression
Splines

Kernel methods

Support Vector Machines
Kernel Ridge Regression
Gaussian Process Regression
GP Regression + Random Forests

Neural Networks

(2 variants)

Feature Selection

Guided Hybrid Genetic Algorithm

FLUXNET

Quality control

Explanatory variables (~200)

Satellite

Vegetation Indices
(LAI, FPAR, EVI, NDVI, NDWI, LSWI)
Land Surface Temperature (day, night)
Reflectances (7 Bands)

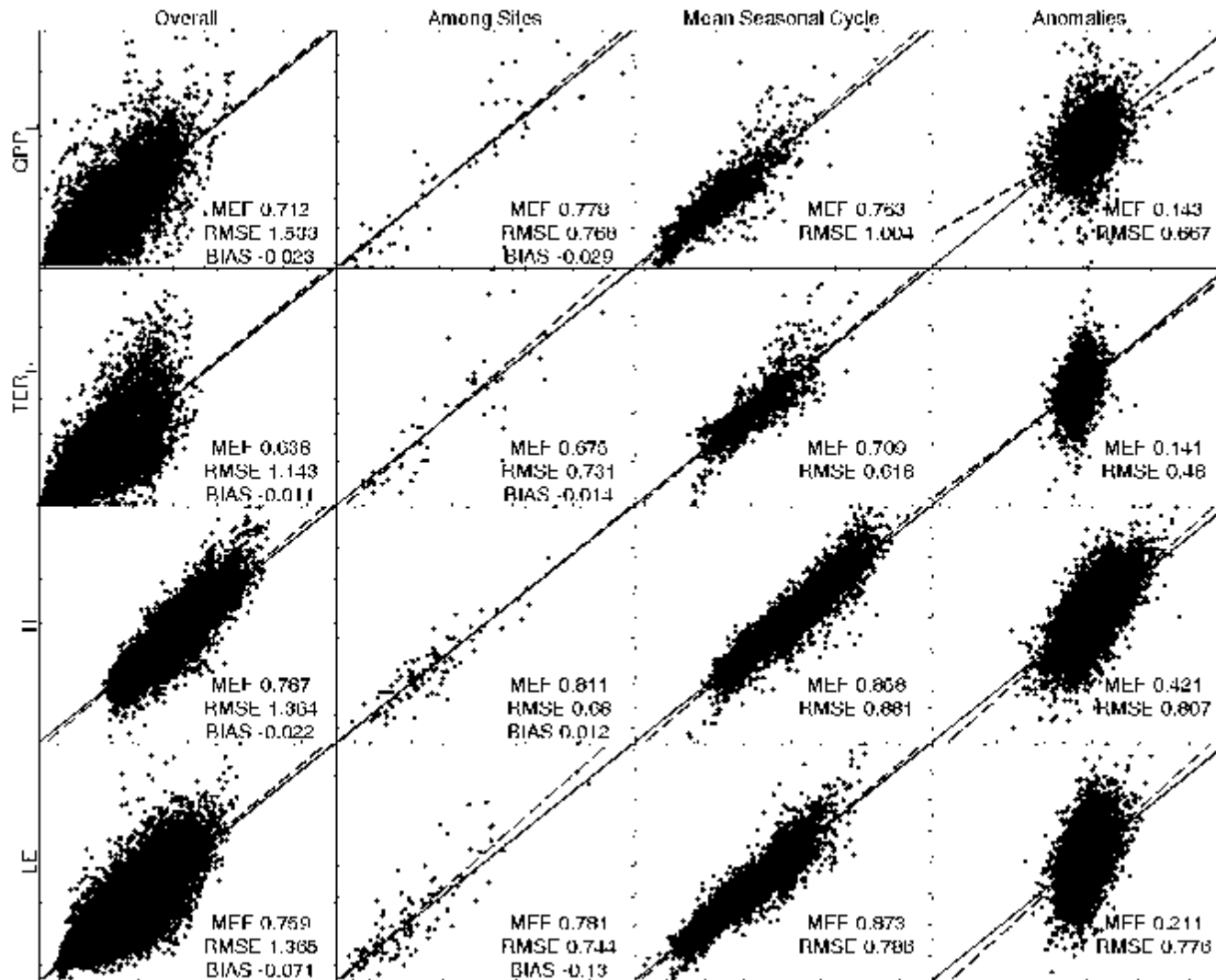
Mean seasonal cycles

Mean, Max, Min,
Amplitude

Climate

Temperature (Tair, Tmin, Tmax)
Radiation (Rg, Rpot, Rg/Rpot)
Humidity (Rh, VPD)
Moisture (precip, WAI1, WAI2, IWA)

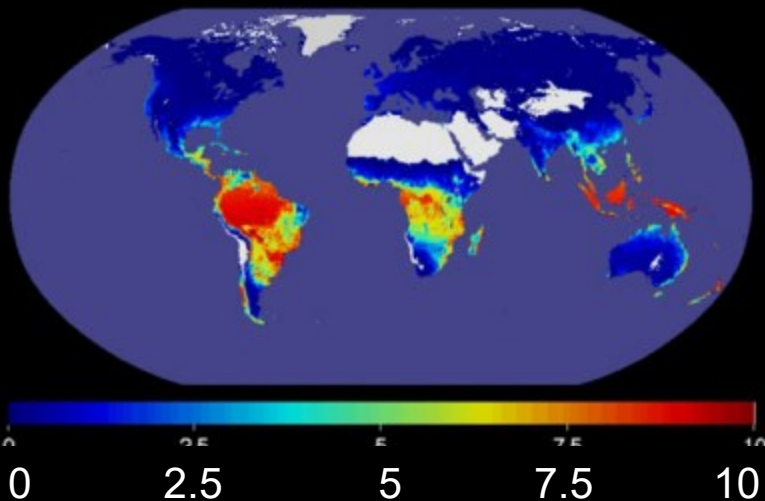
Cross-validation (leave-one-site-out)



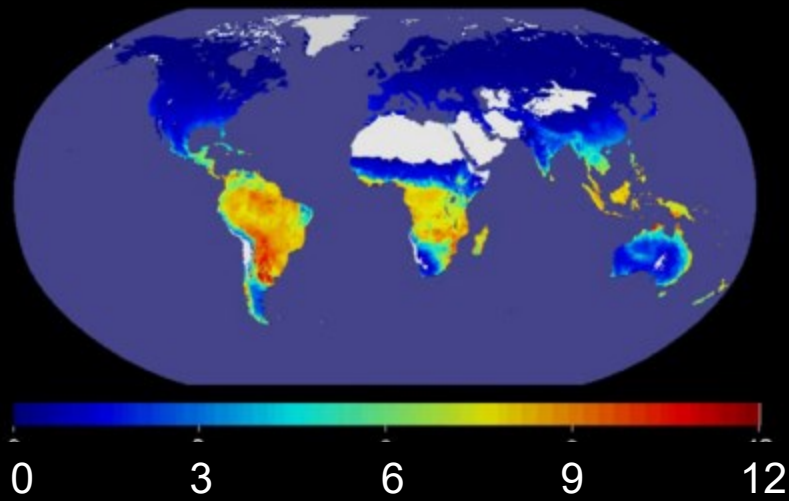
Tramontana et al. (2016), BG

Data-driven view on dynamic Biosphere-Atmosphere Exchange

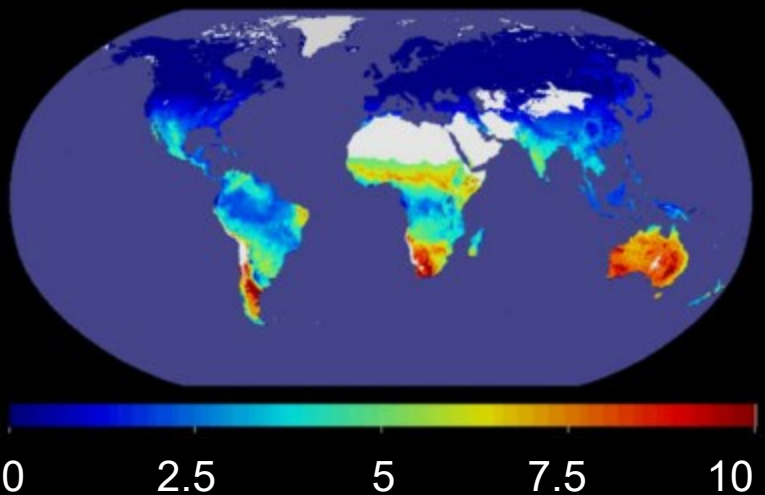
Primary production (GPP) [$\text{g m}^{-2} \text{ day}^{-1}$]



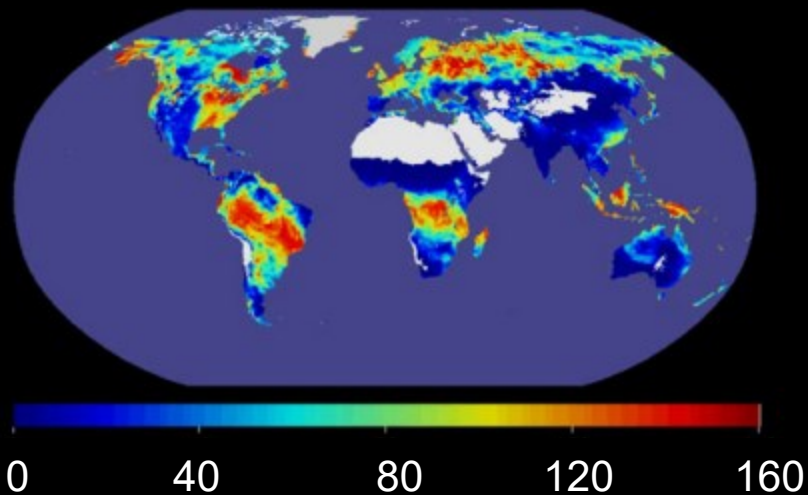
Evapotranspiration [$\text{MJ m}^{-2} \text{ day}^{-1}$]



Sensible heat flux [$\text{MJ m}^{-2} \text{ day}^{-1}$]



Soil water availability [index]

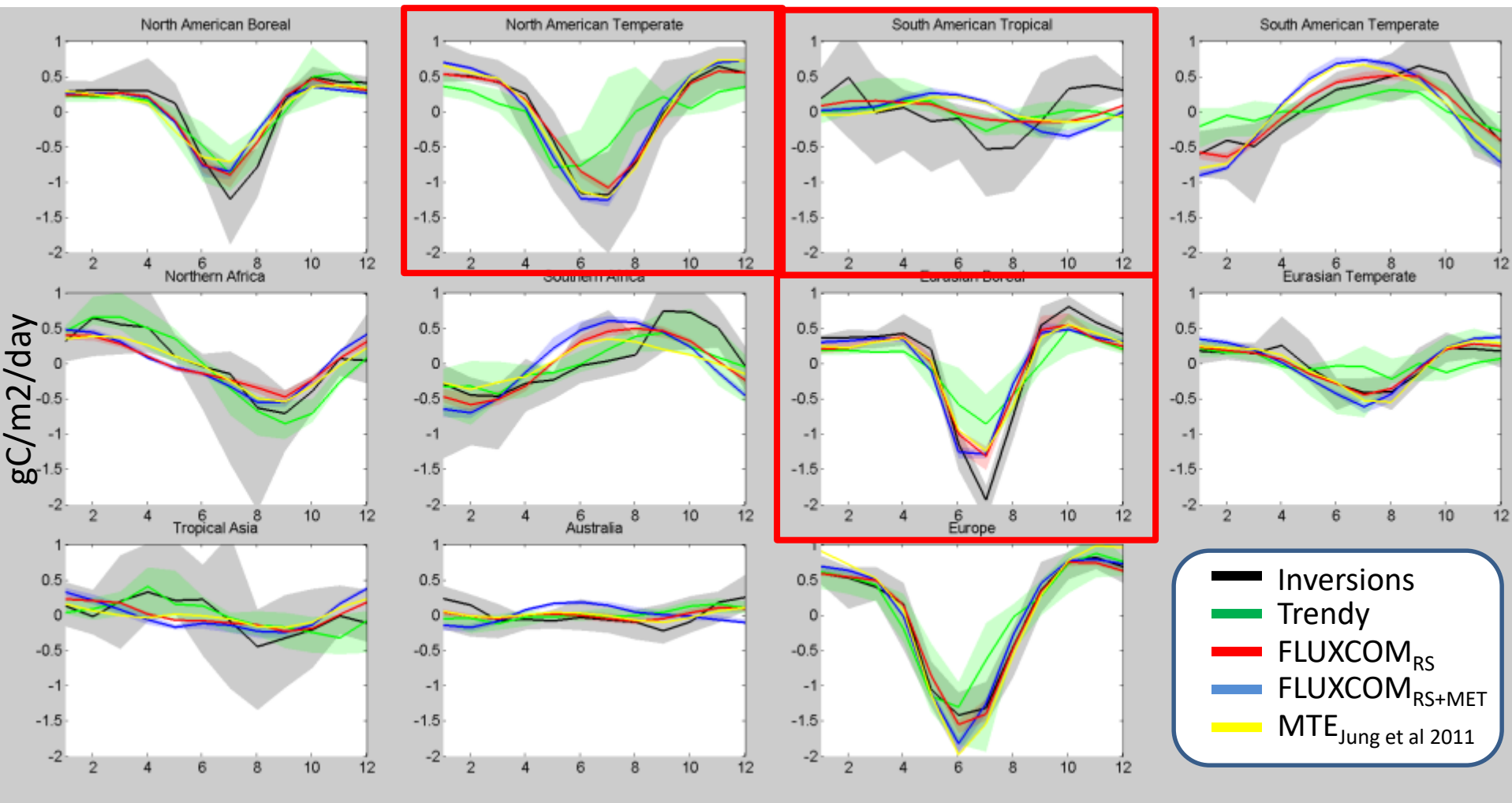


How to evaluate? How to analyse?

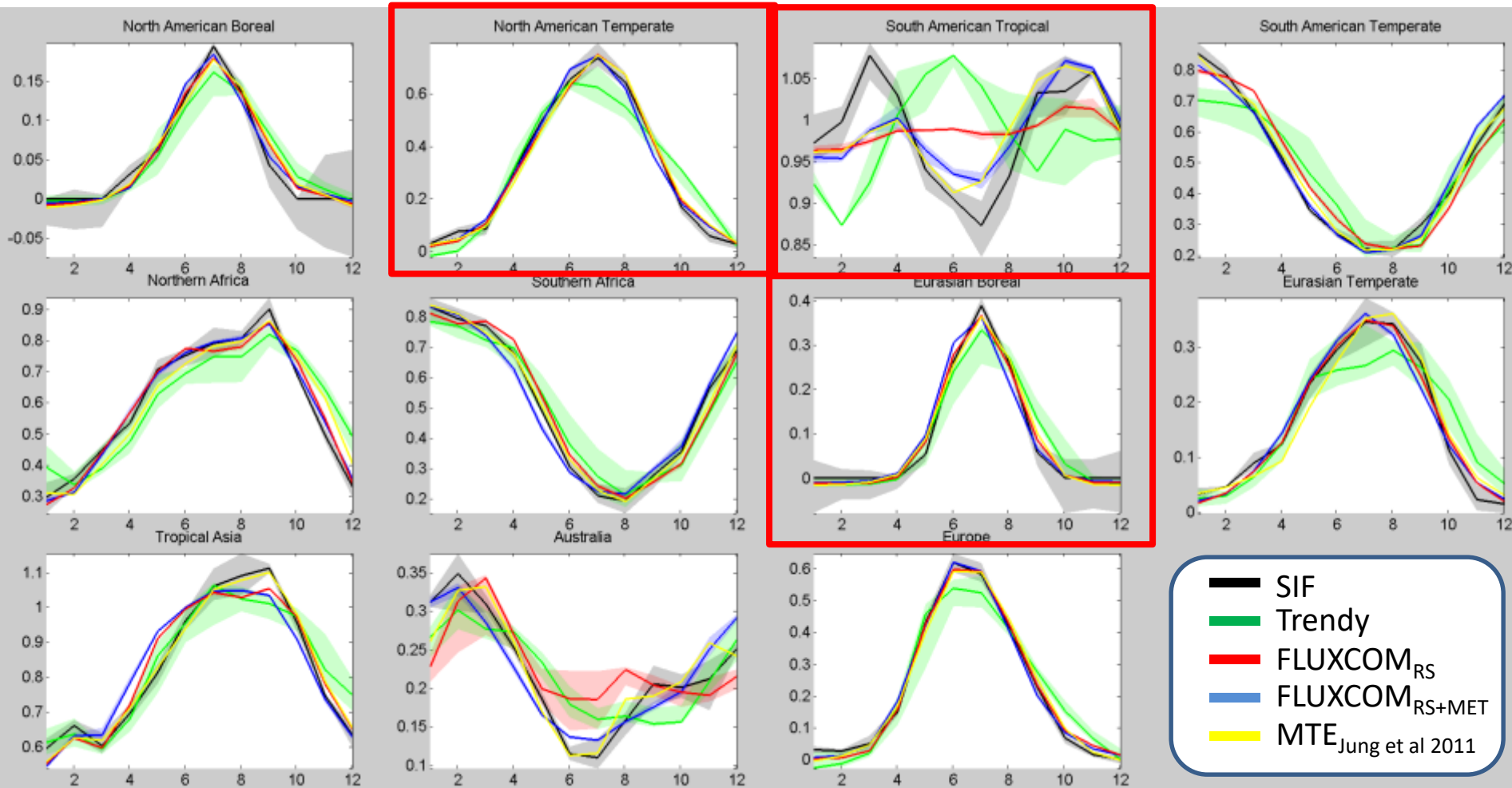
Different answers for carbon fluxes
and energy fluxes

Seasonal cycle of NEE against inversion and model

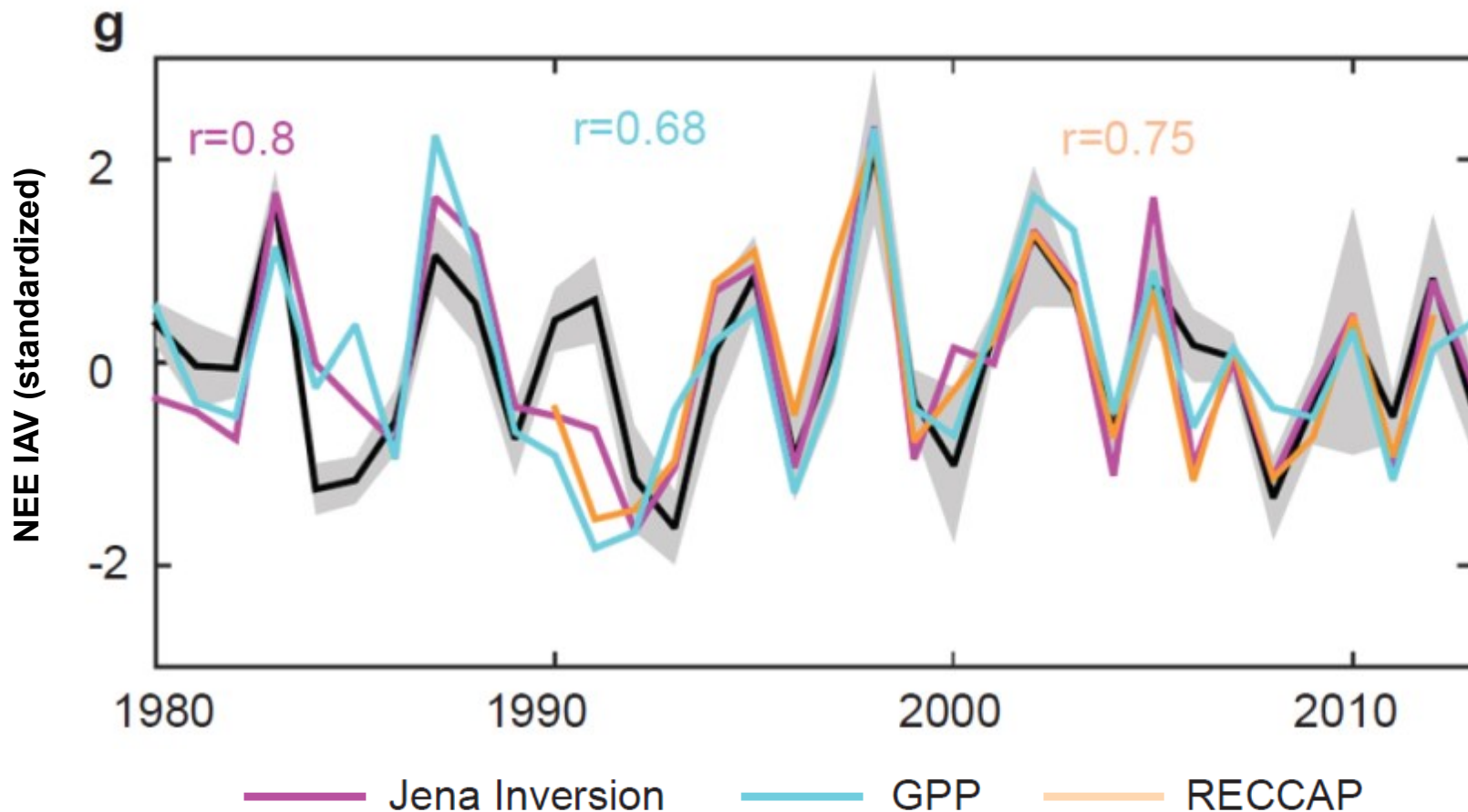
“NEE” (fire subtracted)



Comparison with sun induced fluorescence seasonal cycle (2009-2010)



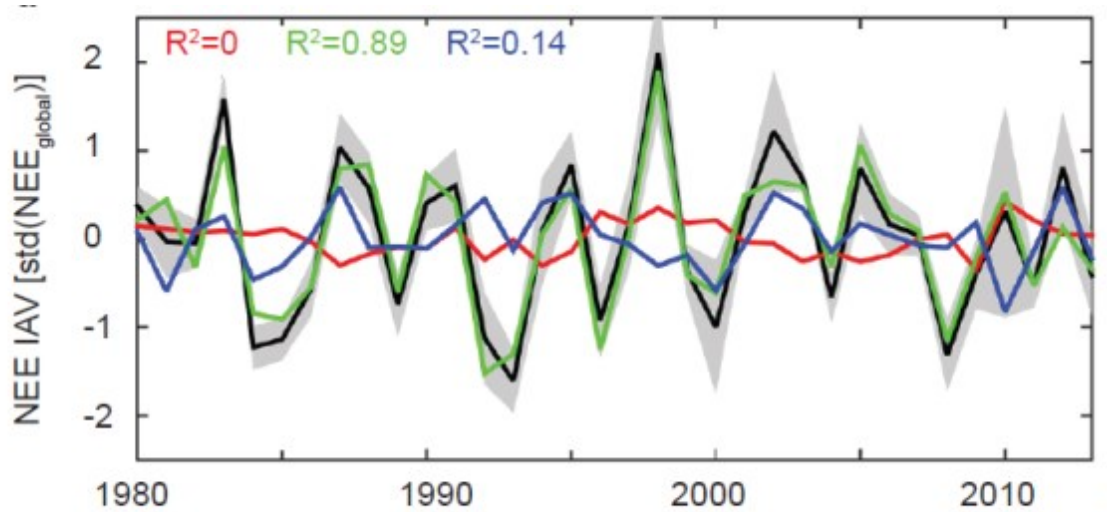
FLUXCOM and atmospheric inversion-based NEE variability correlate well



...as good as state-of-the-art ensemble of vegetation models (“Trendy”)
[but magnitude does not match well!]

Jung et al. (2017), Nature

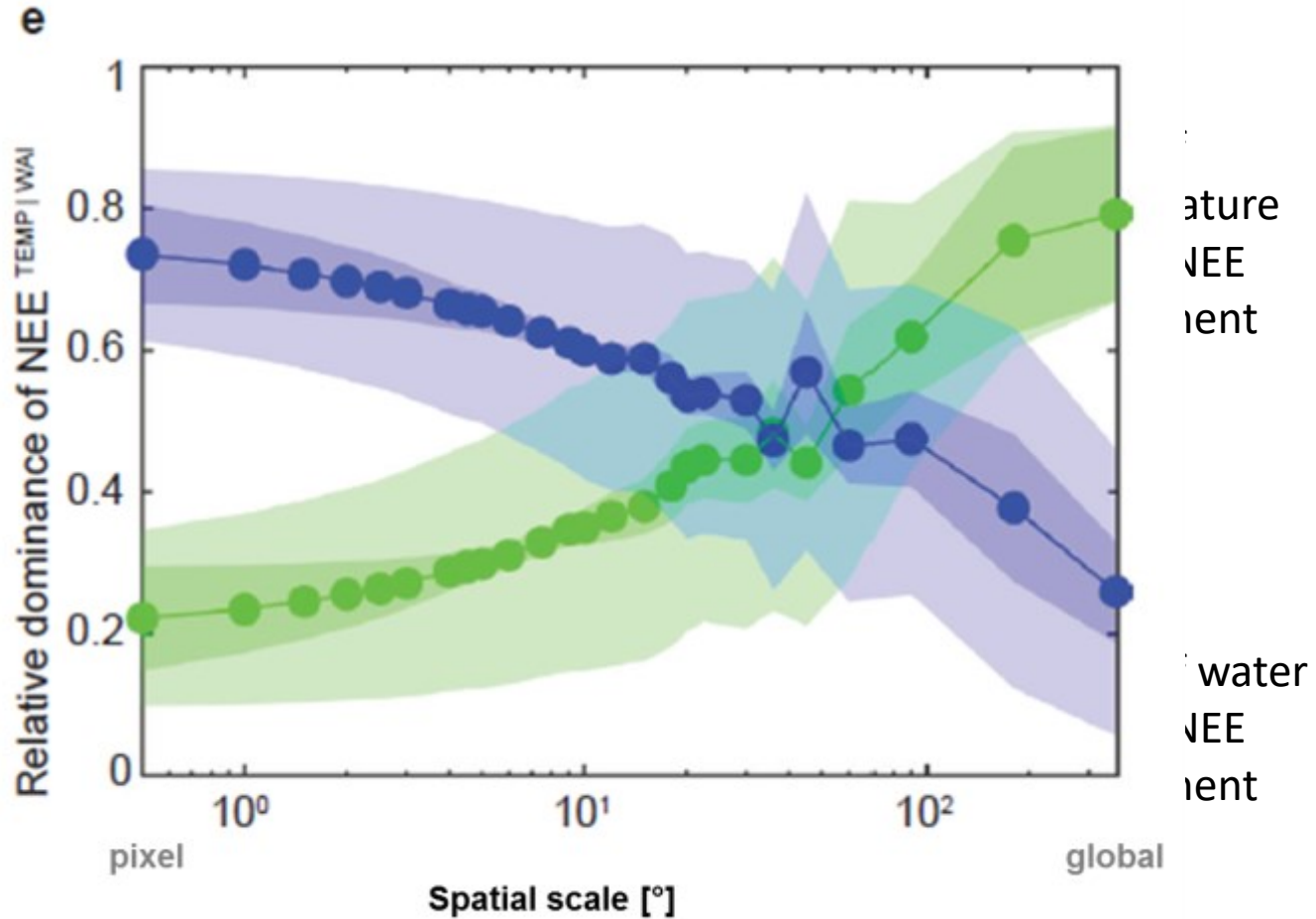
Global signal related to temperature, local signal to water



„global“

Temperature driven
Water driven
Radiation driven
Total signal

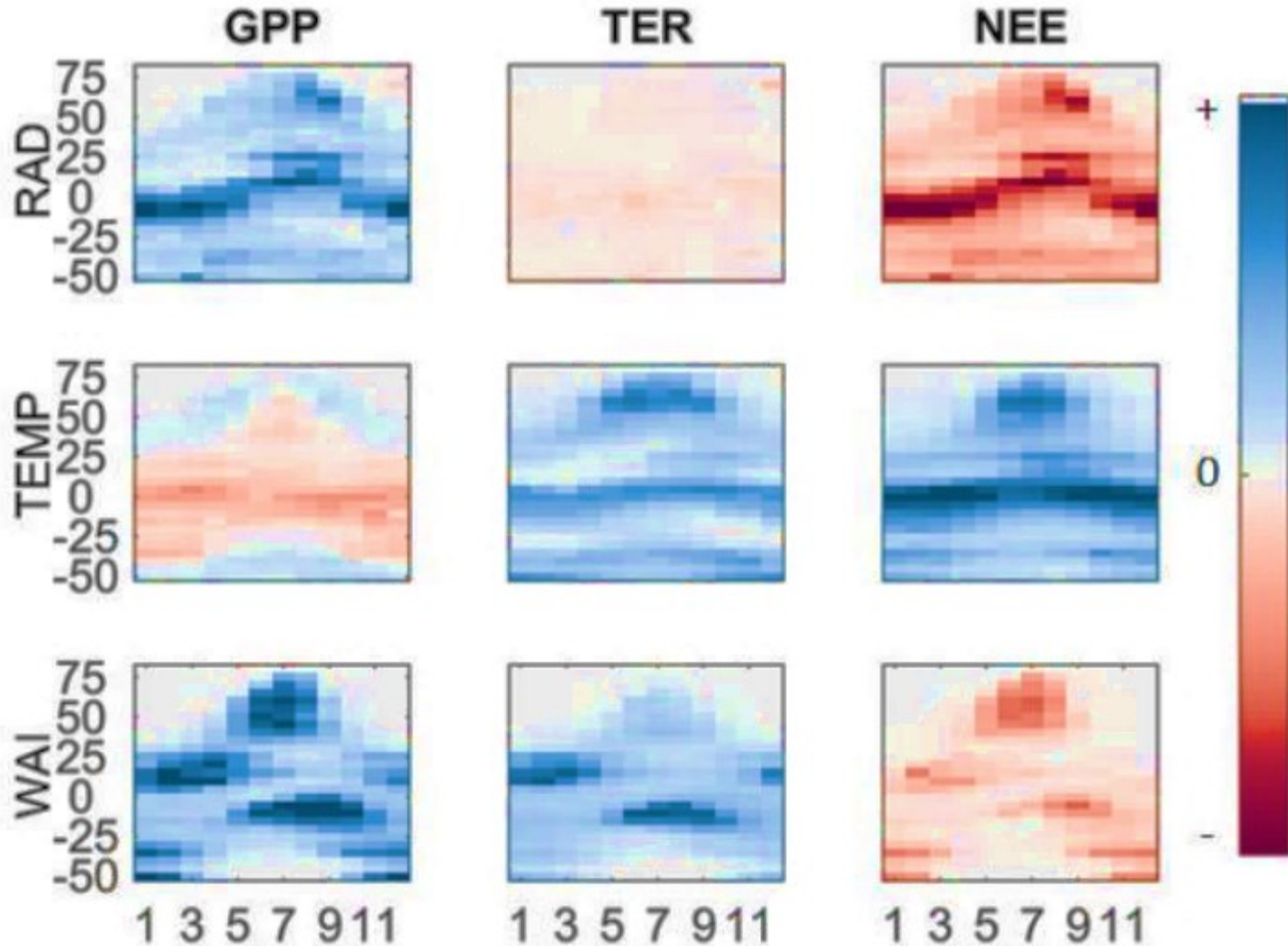
Global C-Cycle-temperature relation demystified



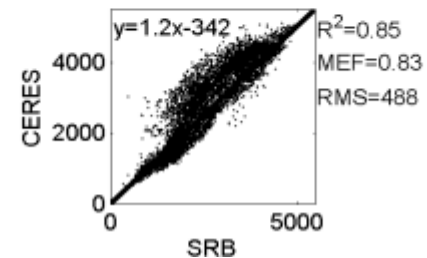
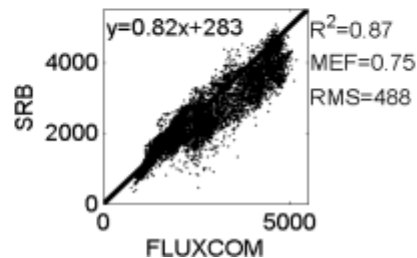
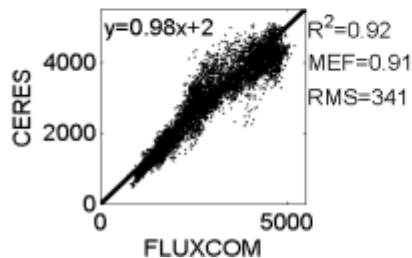
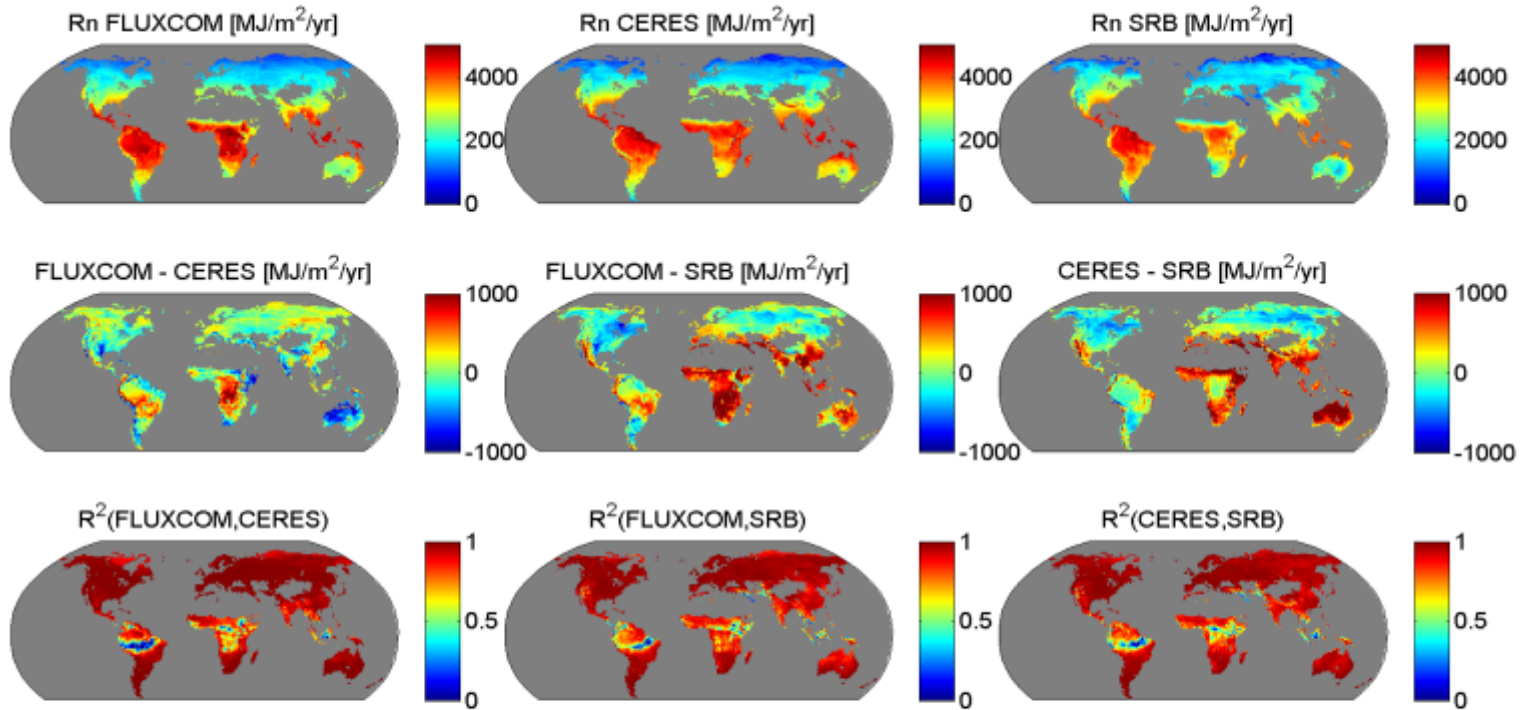
Jung et al. (2017)

Monthly-latitudinal sensitivities: water effects on GPP and TER compensate

Based on: $\delta Flux = a_{Temp} * \delta Temp + a_{WAI} * \delta WAI + a_{RAD} * \delta Rad$, for each month



Evaluation of upscaled Rn

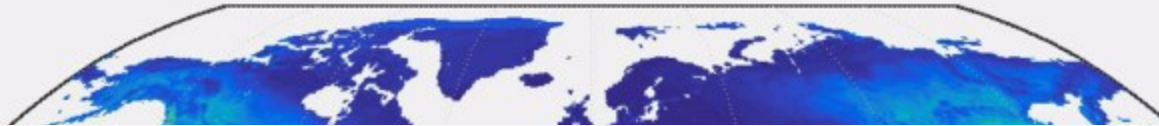


Half-hourly data-driven flux estimates

Year: 2001

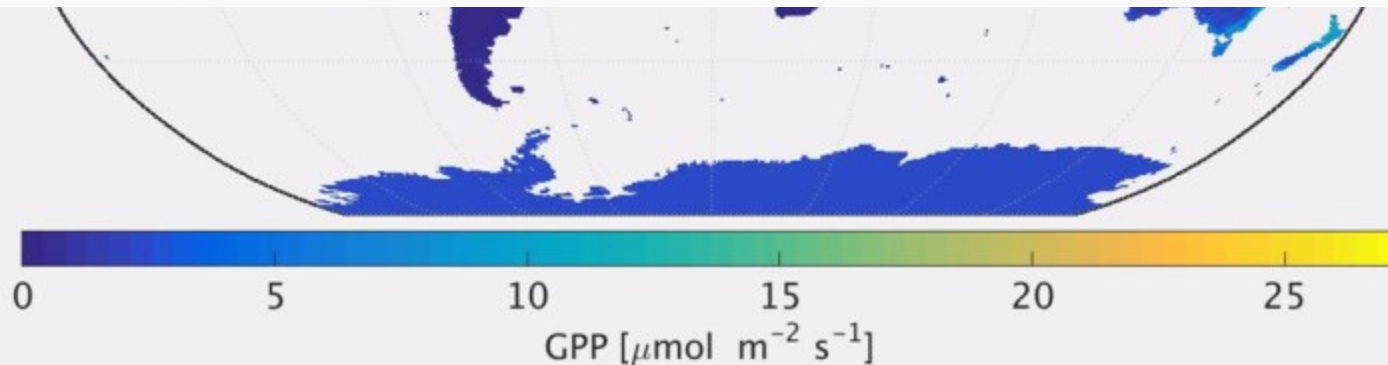
DOY: 150

Time: 00:30



Relevant for:

- Land-atmosphere coupling (energy fluxes, convection, cloud formation)
- Higher-resolution atmospheric inversions (CO₂ net exchange)
- Detection of extreme conditions
- Global functional biogeography (e.g. derivation of A_{max})



Bodesheim, Jung, Mahecha et al.

Some of the next steps

- Tackling global NEP (Simon Besnard)
- Global partitioning of $ET = T + E$ (Jacob Nelson)
- Incorporate dynamic effects (cf. my AGU talk)
- FLUXCOM-MDF (Nuno Carvalhais, Anthony Bloom)
- Incorporating CO_2 effect
- Updating:
 - using FLUXNET2015
 - Using MODIS Collection 6
- So many more things