Data-driven bottom-up estimates of biogenic fluxes: An overview

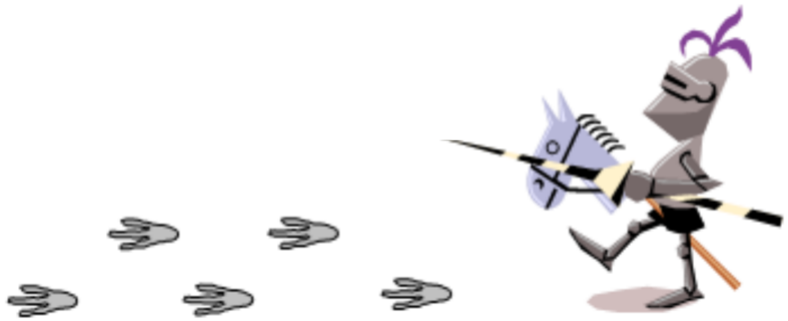
Martin Jung, **Sophia Walther**, Paul Bodesheim, Markus Reichstein and the FLUXCOM team

Annual meeting of CHE and VERIFY

Reading, March 2019

Max Planck Institute
for Biogeochemistry

We're all after the CO_2 signature



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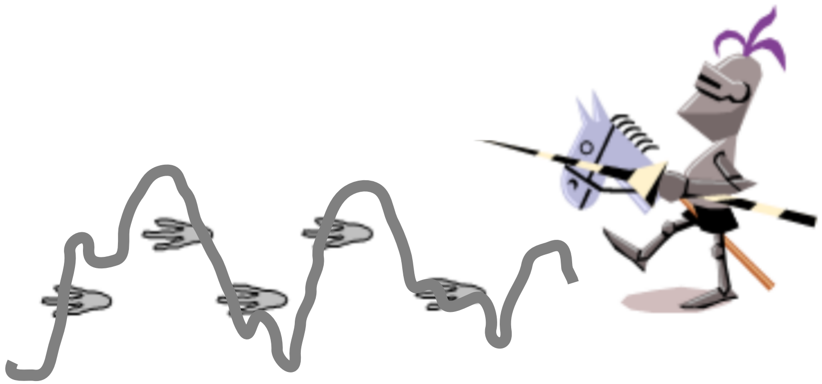
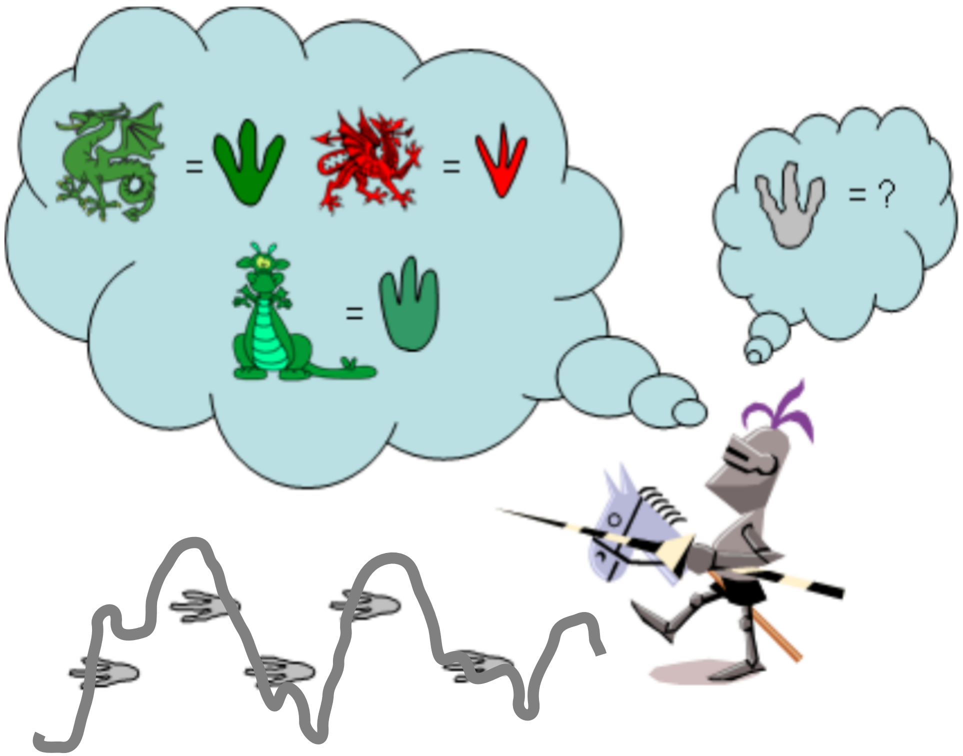


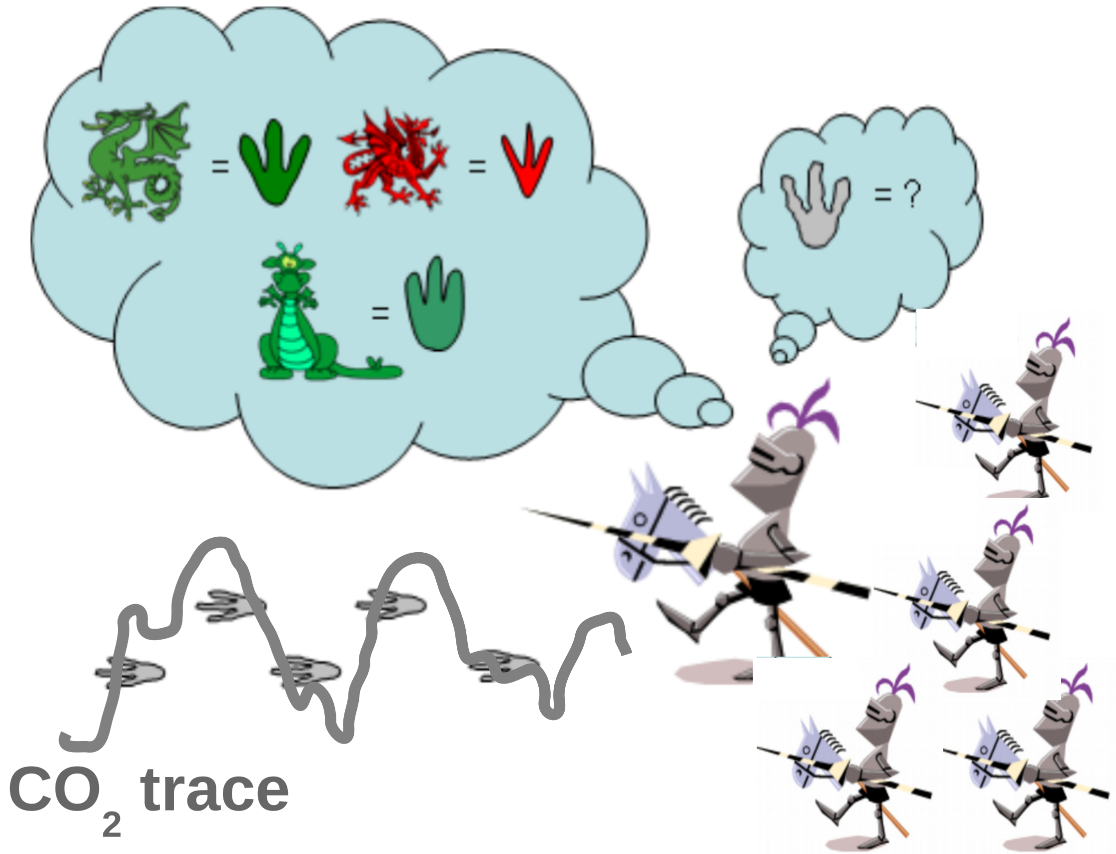
CO_2 trace

We're all after the CO_2 signature

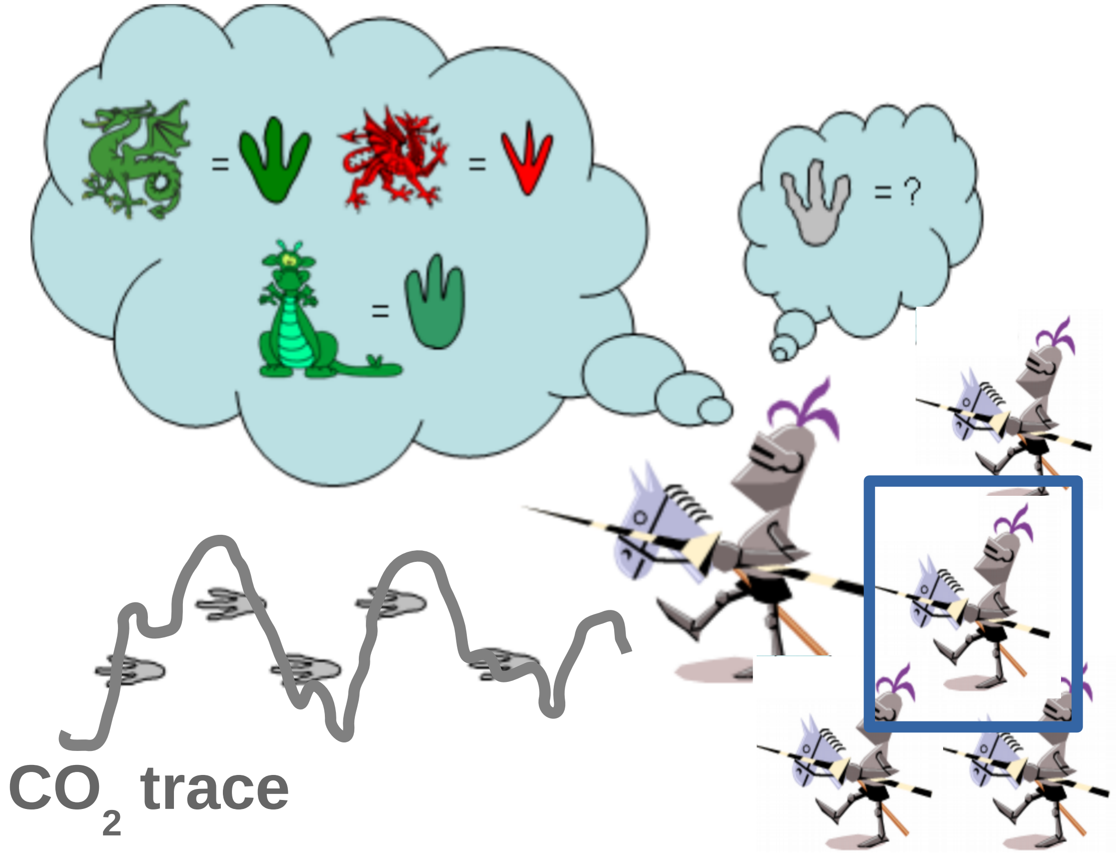


CO_2 trace

We're all after the CO_2 signature

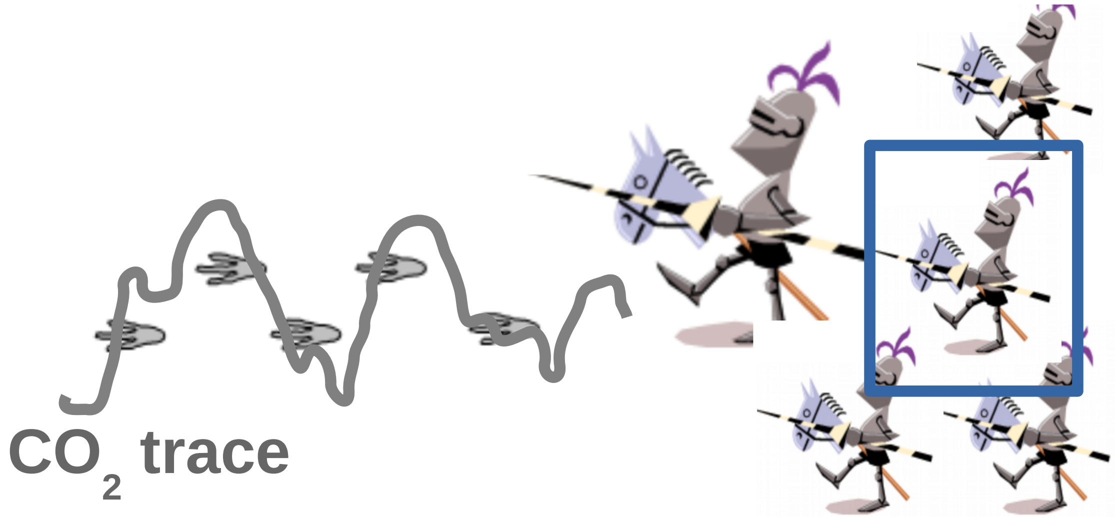


We’re all after the CO_2 signature

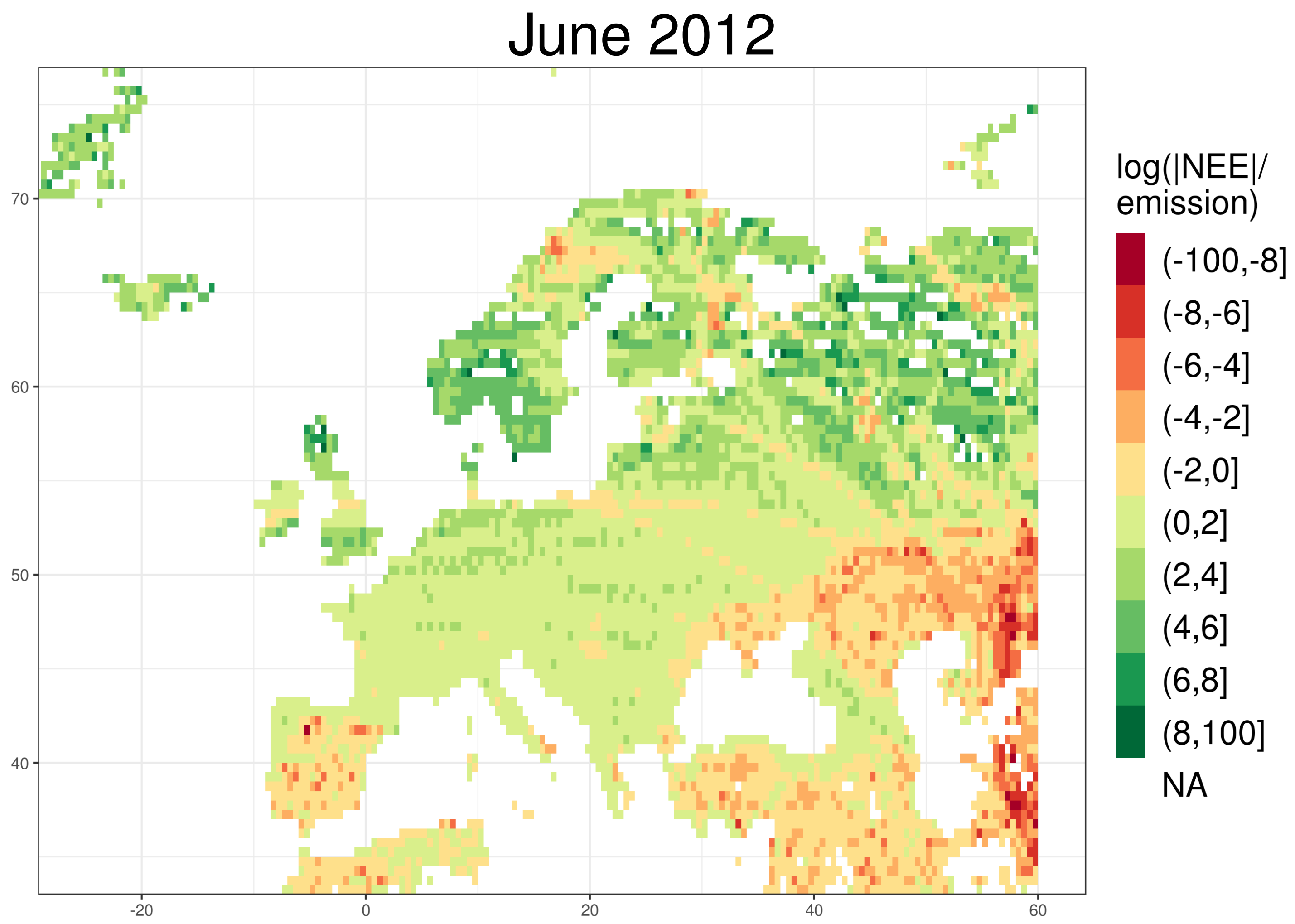


How can this help the other science knights to characterize the unknown dragon?

- find a split from anthropogenic emissions
- prior for atmospheric inversions
- cross-consistency checks for NEE from other approaches
- sensitivity of atm. CO_2 to different kinds of uncertainties in NEE at variety of scales
- process understanding through factorial experiments



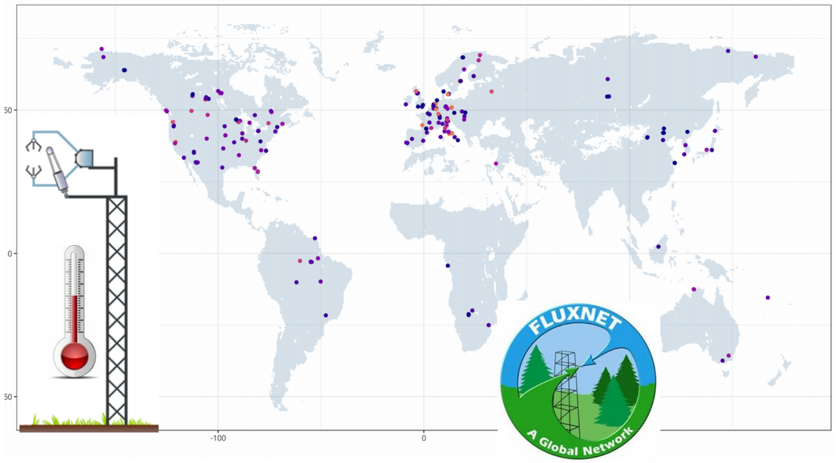
Biogenic fluxes dominate fossil fuel signal (in growing season)



Fuel CO_2 emission: monthly, Peking University, Wang et al., 2013
NEE: hourly, MPI-BGC Jena

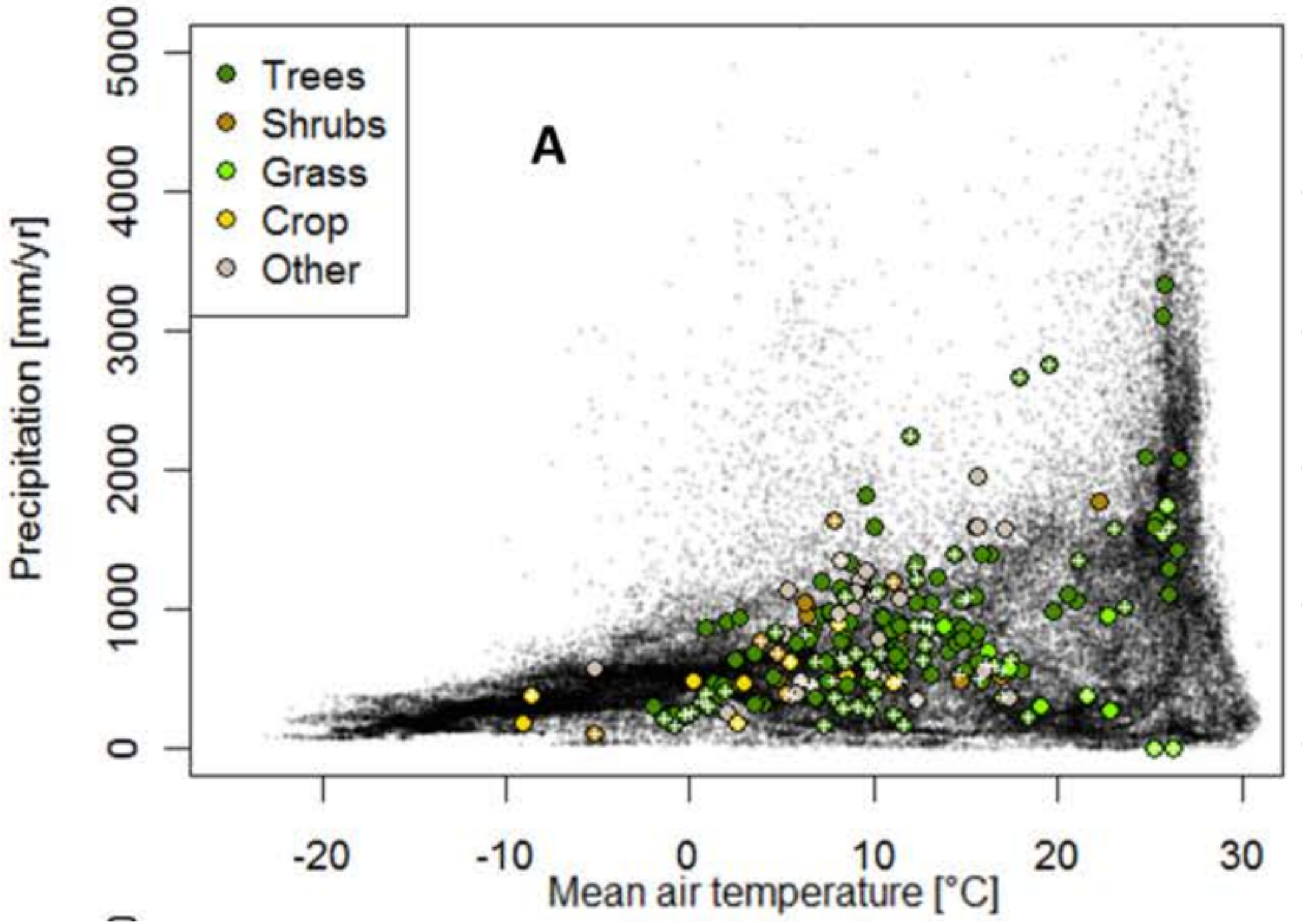
Our approach to modelling the biospheric trace

Our approach to modelling the biospheric trace



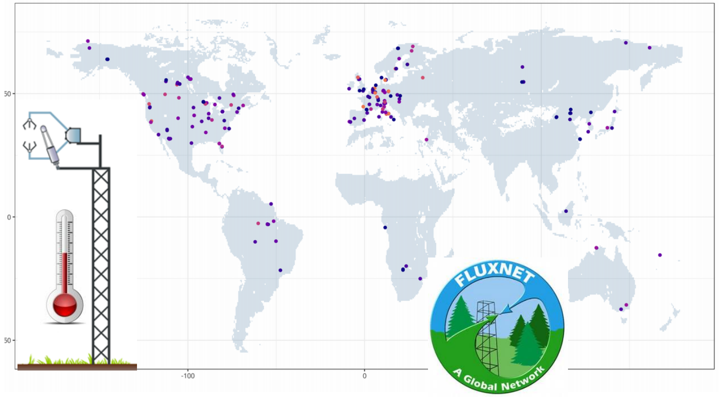
In-situ eddy-covariance carbon fluxes & meteorology

In-situ obs cover large part of the climate space



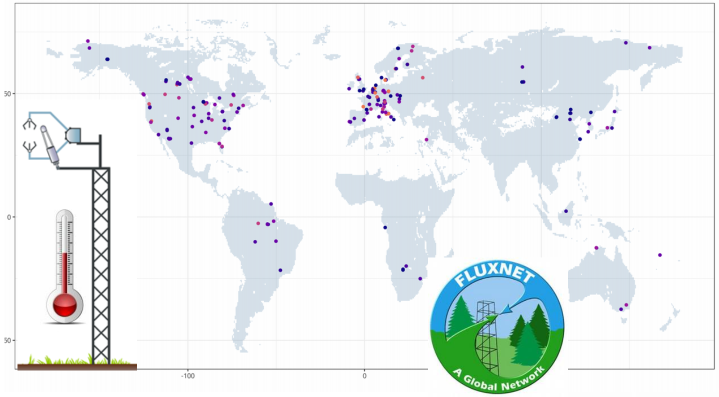
Reichstein et al. 2014

Our approach to modelling the biospheric trace



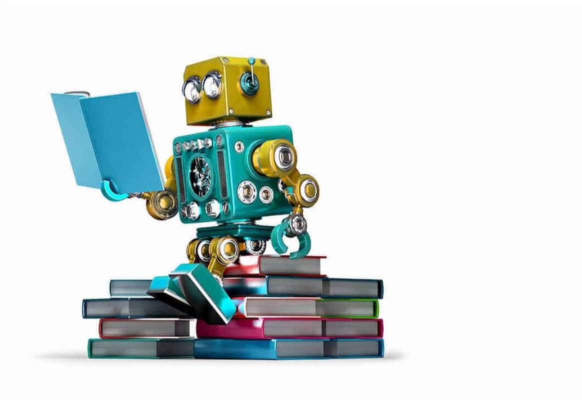
In-situ eddy-covariance carbon fluxes & meteorology

Our approach to modelling the biospheric trace



In-situ eddy-covariance carbon fluxes & meteorology

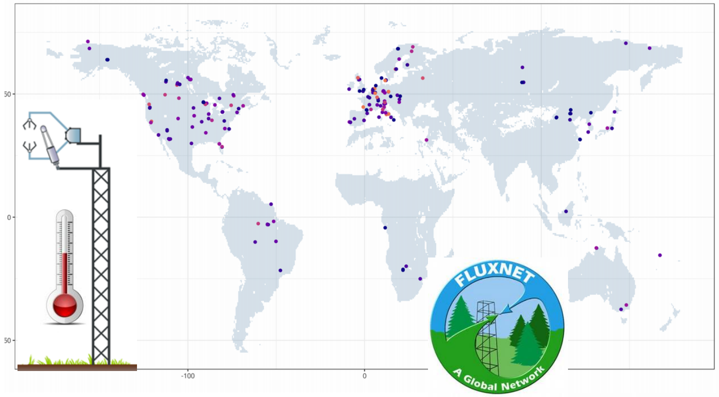
+



machine learning

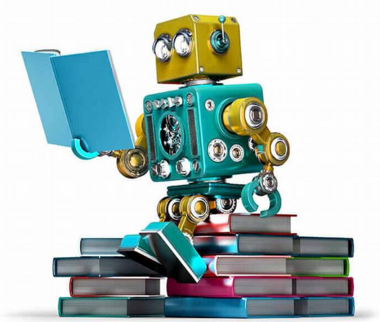
+

Our approach to modelling the biospheric trace



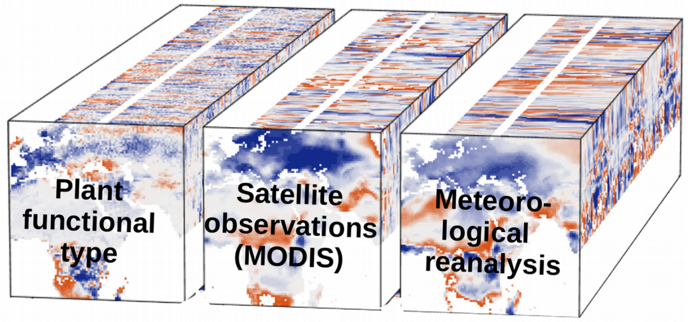
In-situ eddy-covariance carbon fluxes & meteorology

+



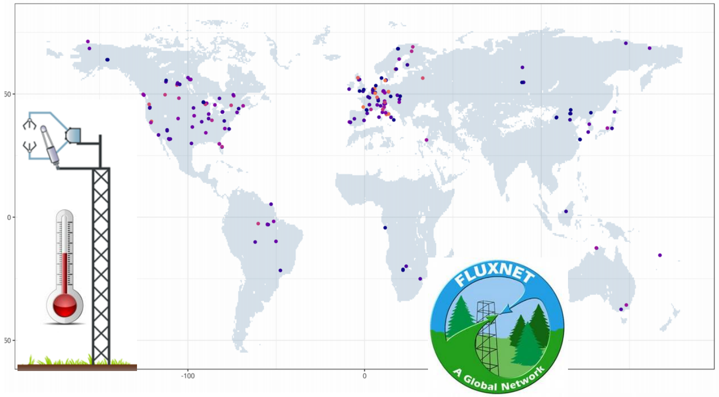
machine learning

+



global gridded data sets of predictors

Our approach to modelling the biospheric trace



In-situ eddy-covariance carbon fluxes & meteorology

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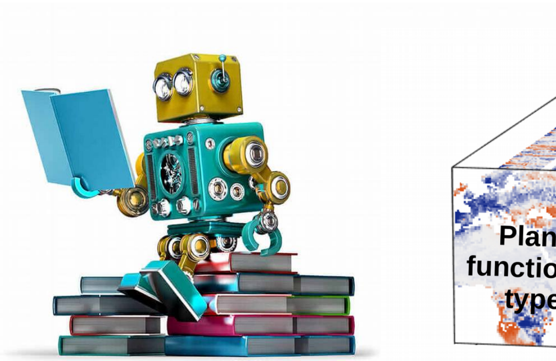
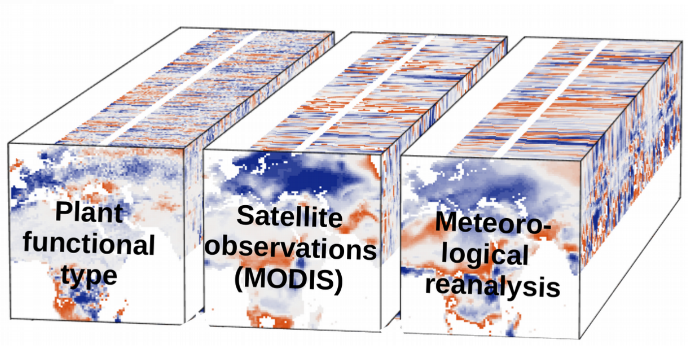


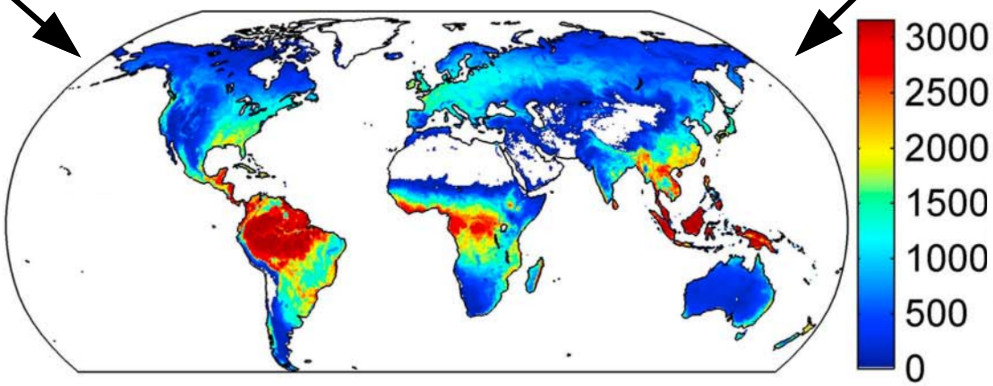
machine learning

+



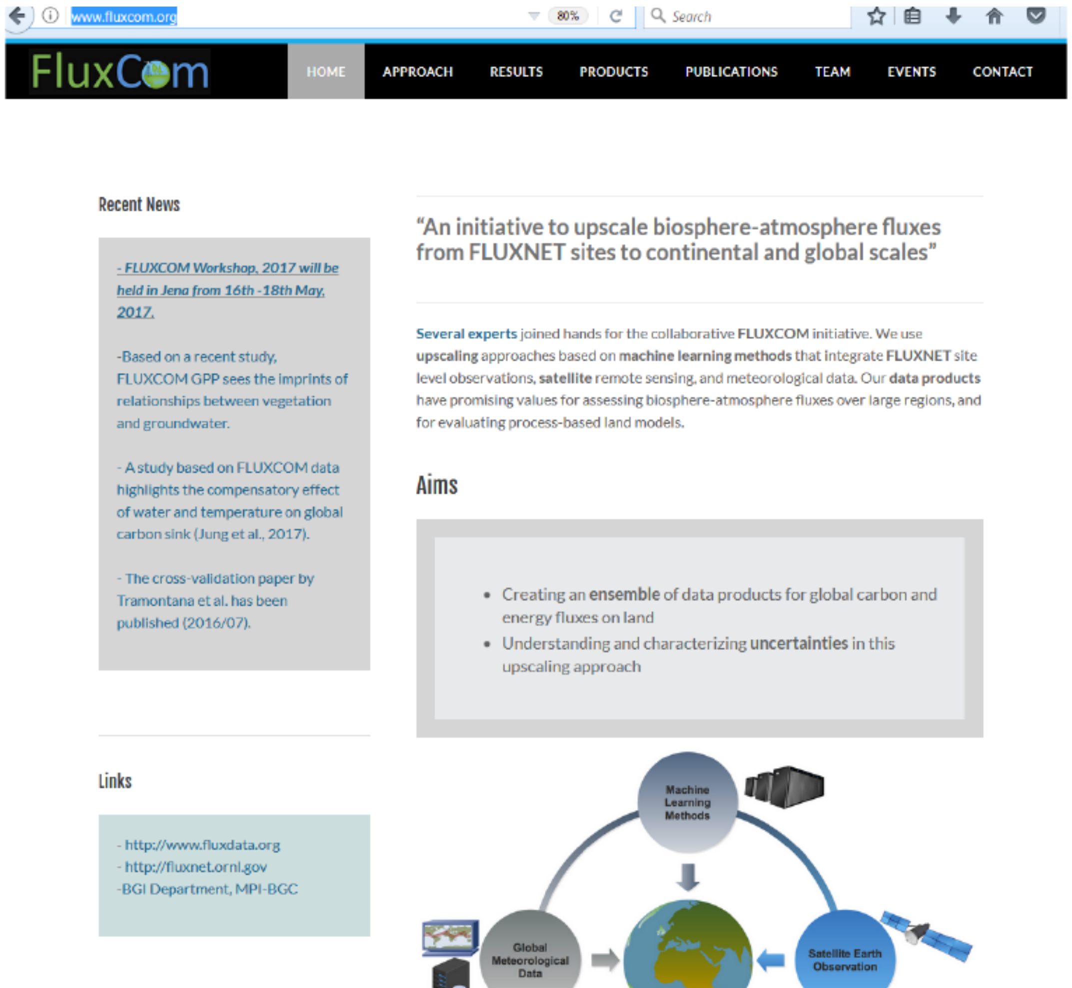
global gridded data sets of predictors

GPP [gC/m2/yr]



Global gridded flux estimates of NEE, GPP, TER

FluxCom



www.fluxcom.org

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G.Camps-Valls

F.Gans

U.Weber

S.Koirala

Two complementary set-ups creating ensembles

		RS
effective drivers		only temporally resolved satellite data
spatial res.		0.083deg
temporal res.		8-daily
years		2001-2015
ML methods		9
meteo forcing		-

Two complementary set-ups creating ensembles

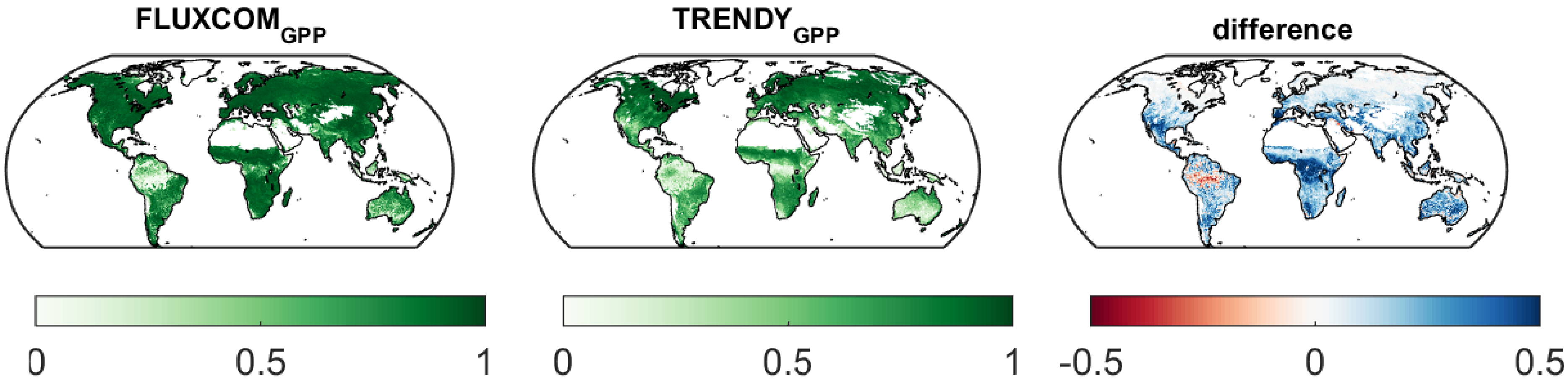
	RS+Meteo	RS
effective drivers	mean seasonality of satellite data and temporally resolved meteorology	only temporally resolved satellite data
spatial res.	0.5deg	0.083deg
temporal res.	daily	8-daily
years	1950-2017	2001-2015
ML methods	3	9
meteo forcing	4(6)	-

Two complementary set-ups

	RS+Meteo	RS
effective drivers	mean seasonality of satellite data and temporally resolved meteorology	only temporally resolved satellite data
R^2 between NEE/GPP_R/GPP_L and observations		
spatially ✓	0.46/ 0.77/ 0.79	0.48/ 0.78/ 0.78
seasonally ✓	0.59/ 0.77/ 0.77	0.61/ 0.76/ 0.77
anomalies !	0.13/ 0.12/ 0.11	0.13/ 0.18/ 0.16

Tramontana et al. 2016

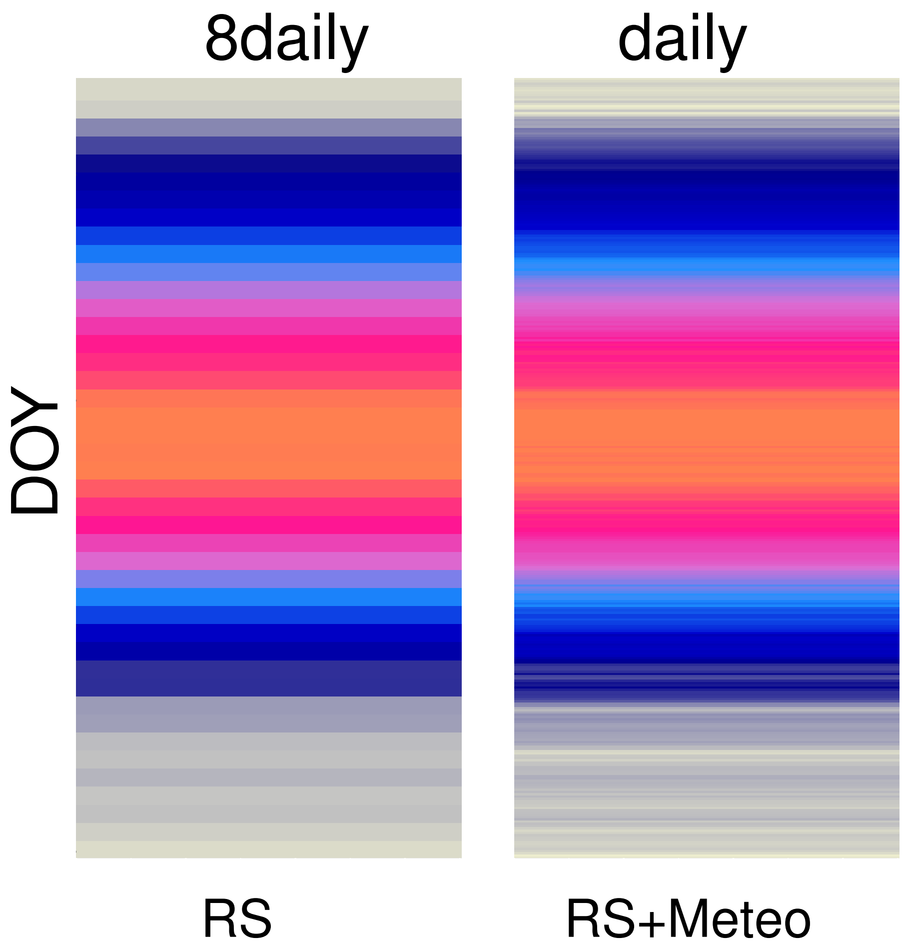
Higher consistency in seasonality with SIF than TRENDY



Jung et al. 2017

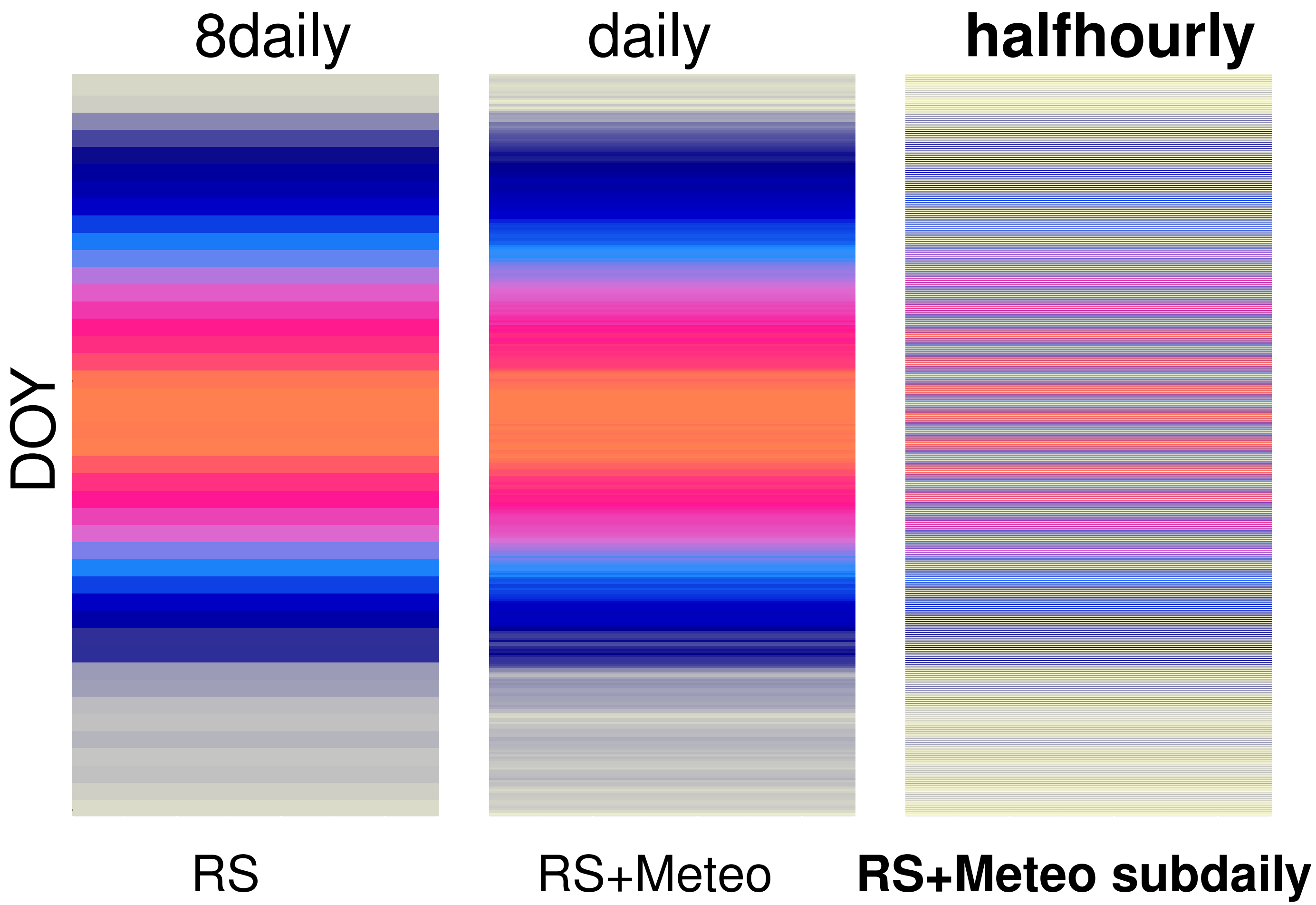
R^2 of monthly mean seasonal GPP with SIF for Trendy and Fluxcom (RS+meteo, only CRUNCEPv6)

Evolution of resolution of FLUXCOM



Tramontana et al. 2016
Jung et al. 2017

Evolution of resolution of FLUXCOM

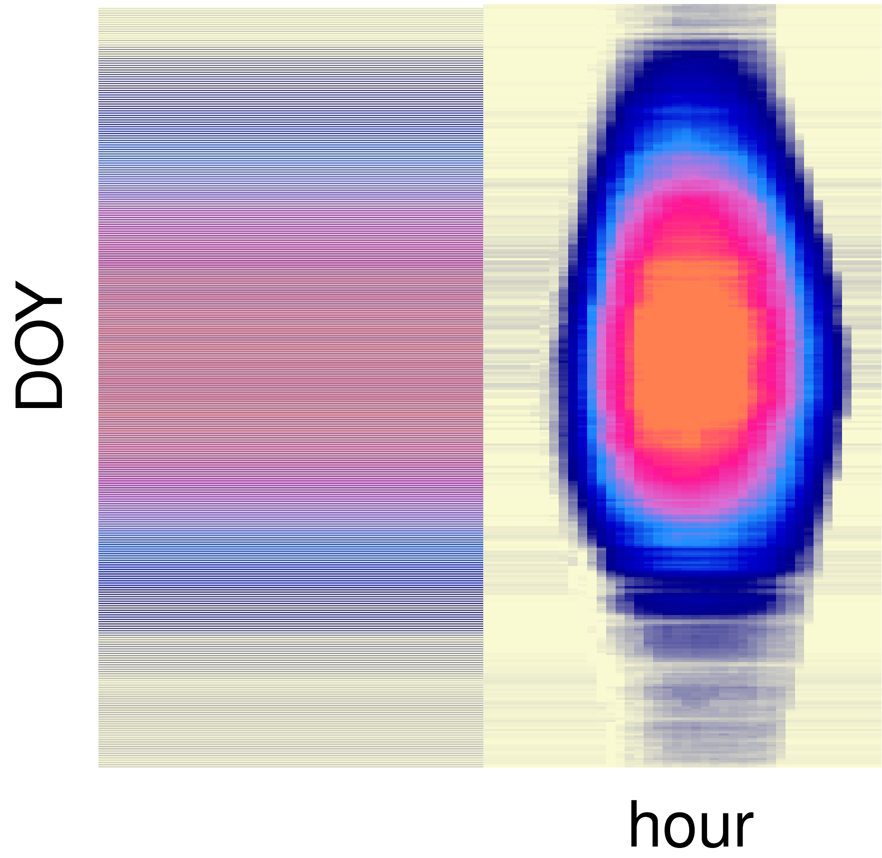


Tramontana et al. 2016
Jung et al. 2017

Bodesheim
et al. 2018

Sub-daily fluxes based on daily meteo

Example: GPP



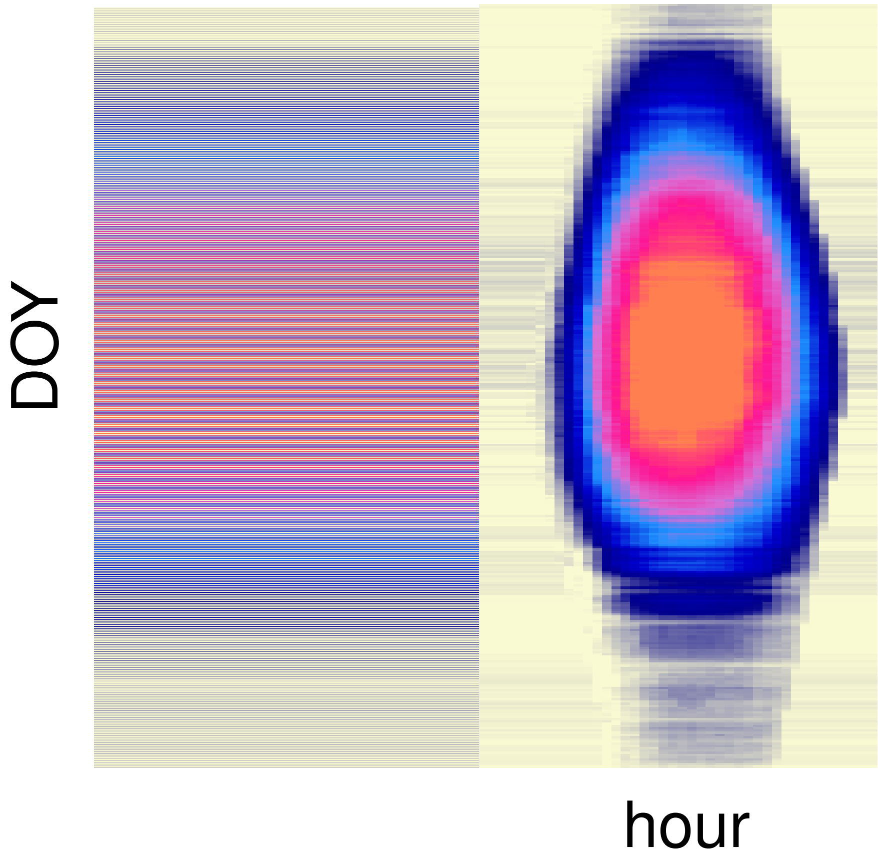
Predictors:

Mean seasonality of RS
+ daily meteo from CRUNCEP
+ half-hourly potential radiation
as the only subdaily predictor

Paul Bodesheim et al. 2018

Sub-daily fluxes based on daily meteo

Example: GPP



Predictors:

Mean seasonality of RS
+ daily meteo from CRUNCEP
+ half-hourly potential radiation
as the only subdaily predictor
+ hourly meteo from ERA5

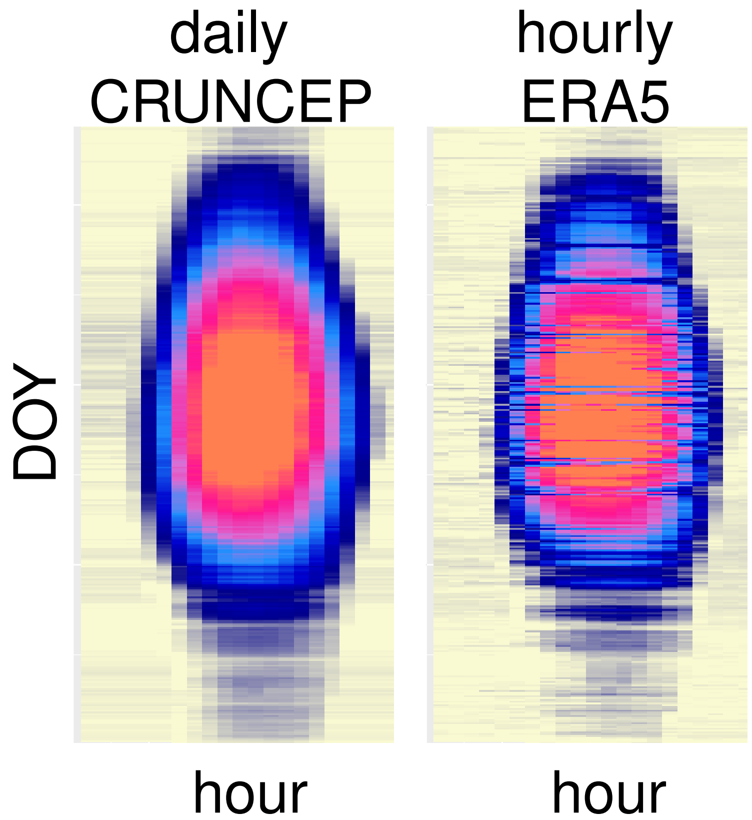
Paul Bodesheim et al. 2018

now **hourly** meteo from ERA5 reanalysis is available

⇒ include additional hourly predictors

first sub-daily fluxes

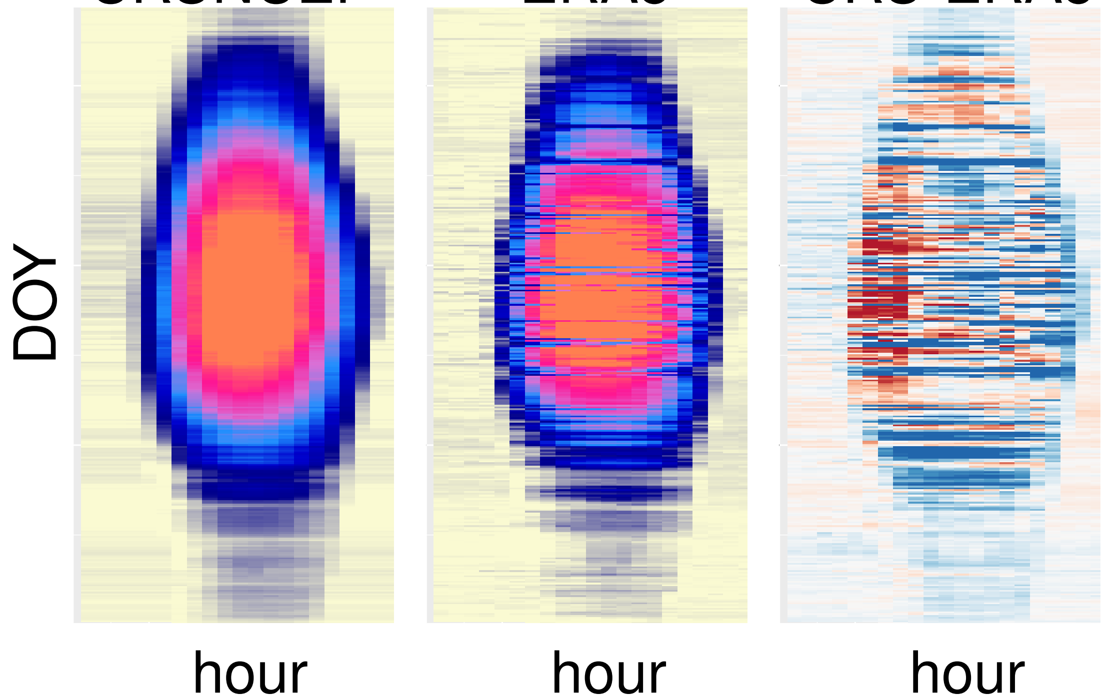
Example: GPP



first sub-daily fluxes

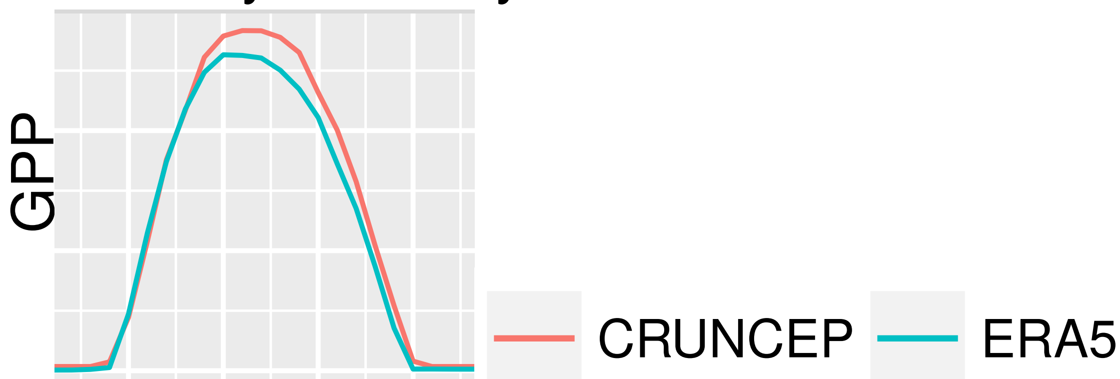
Example: GPP

daily CRUNCEP | hourly ERA5 | CRU-ERA5



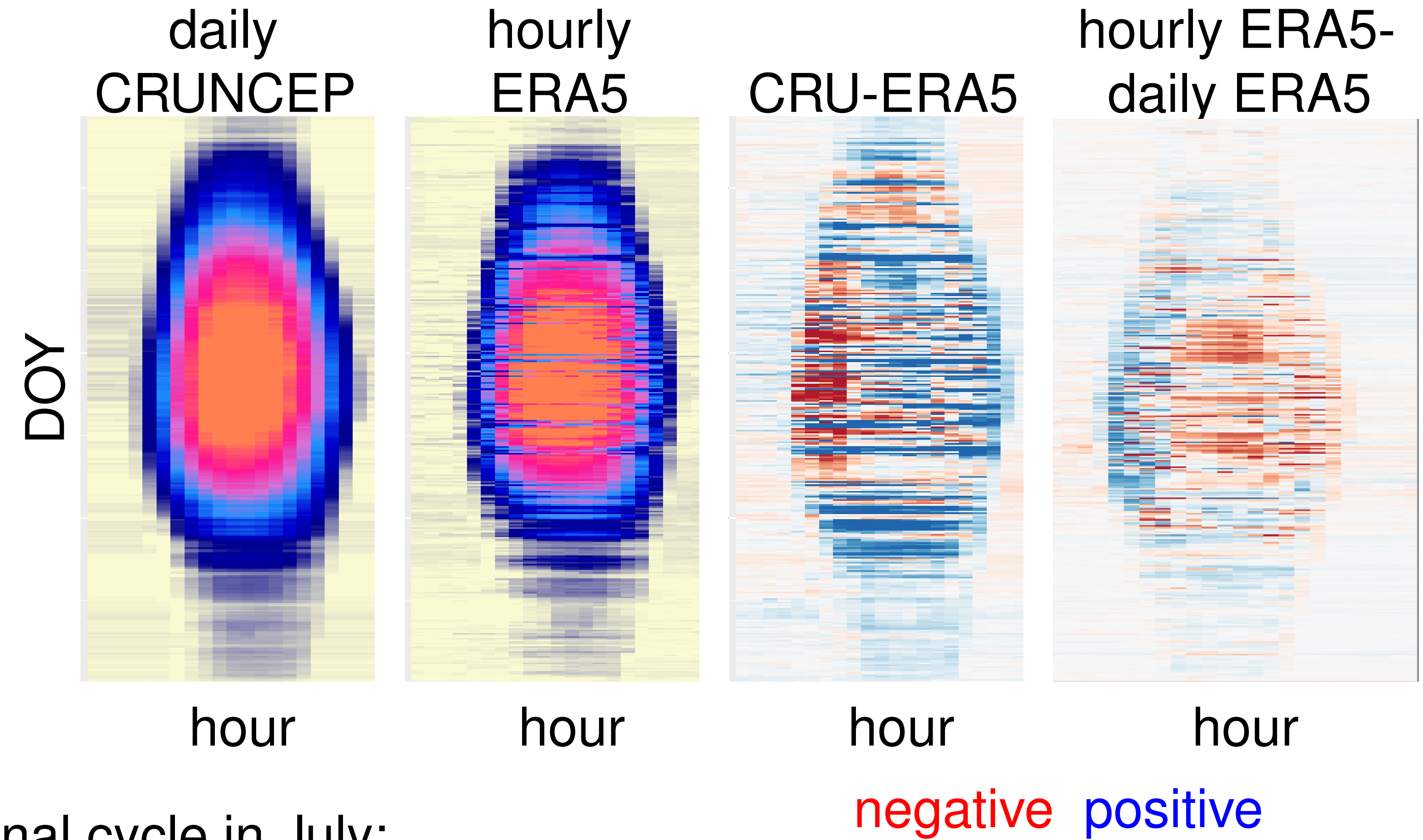
negative positive

Diurnal cycle in July:



first sub-daily fluxes

Example: GPP



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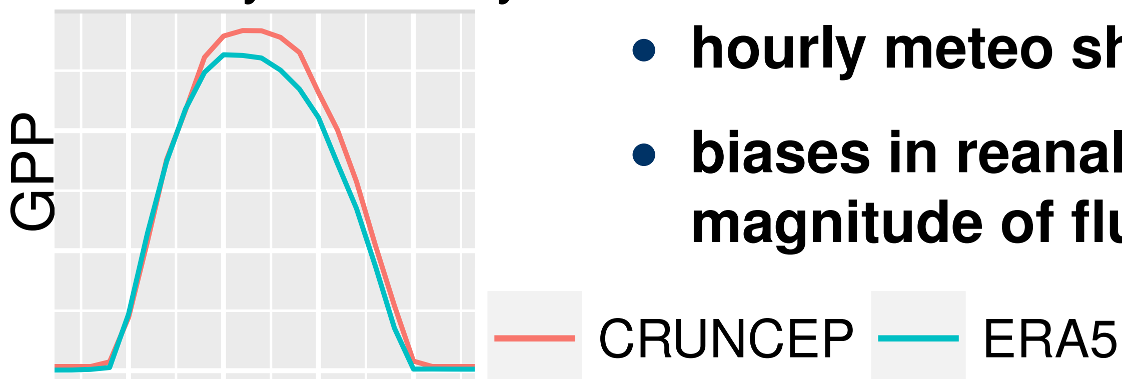
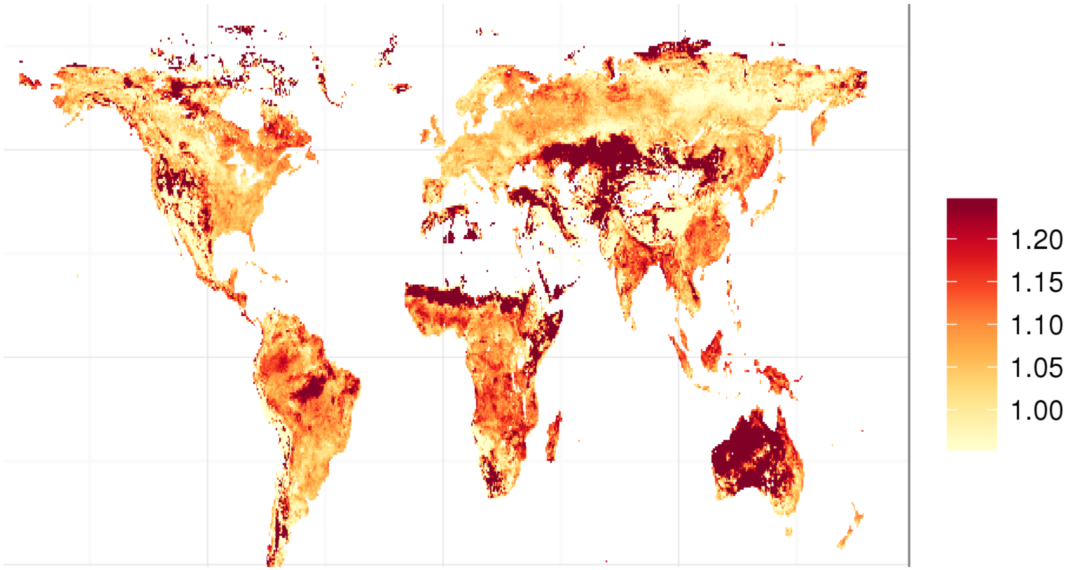


- **hourly meteo shifts diurnal cycle**
- **biases in reanalysis strongly affect magnitude of fluxes**

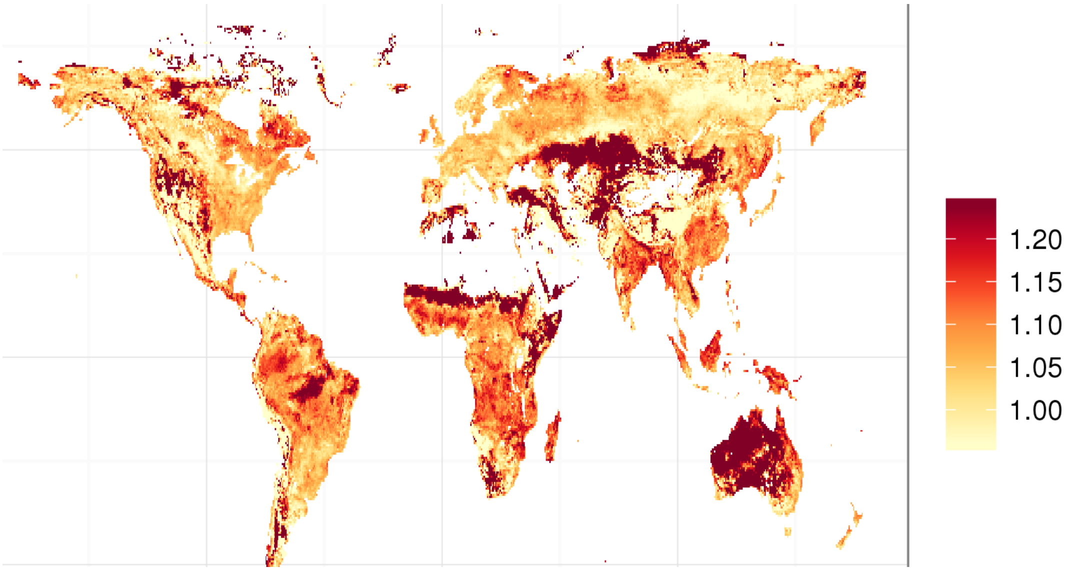
GPP annual sums: choice of meteo. driver is more important than inclusion of subdaily meteo

daily CRUNCEP/hourly ERA

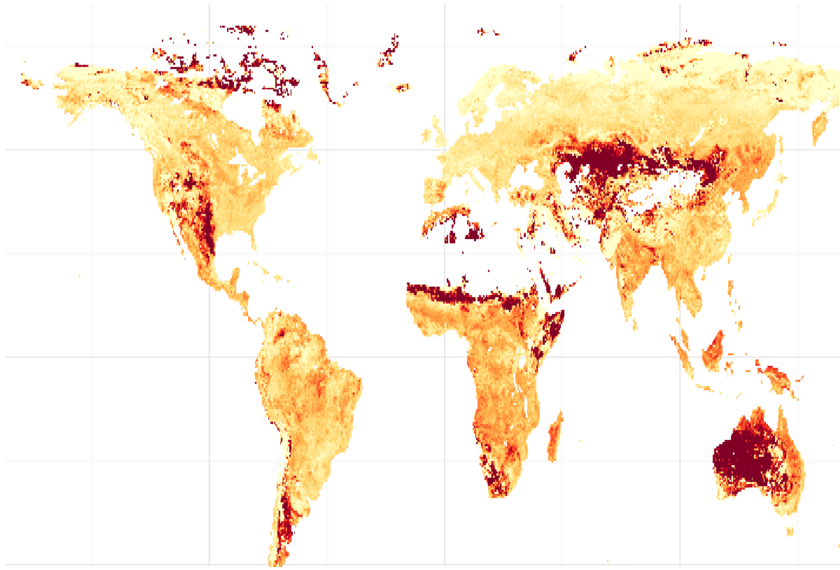


GPP annual sums: choice of meteo. driver is more important than inclusion of subdaily meteo

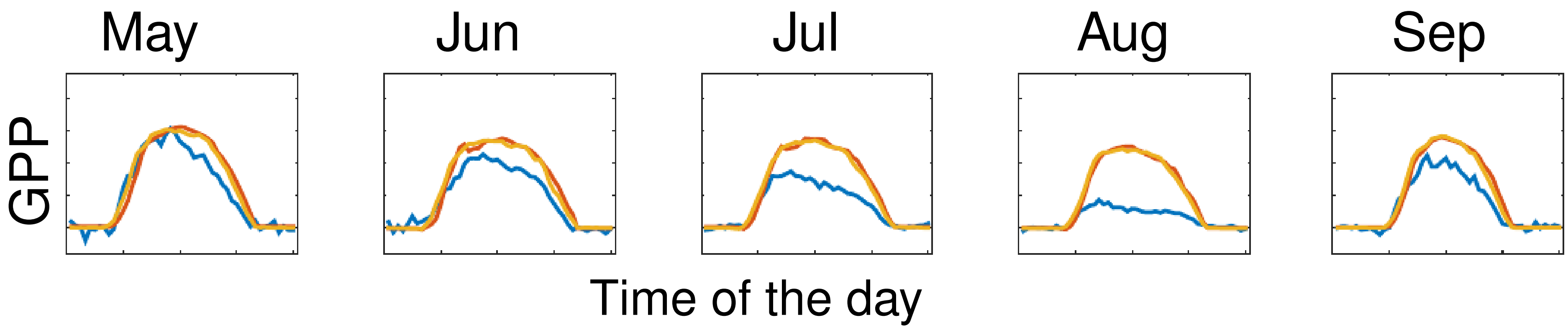
daily CRUNCEP/hourly ERA



daily CRUNCEP/daily ERA



Drought effects not well represented

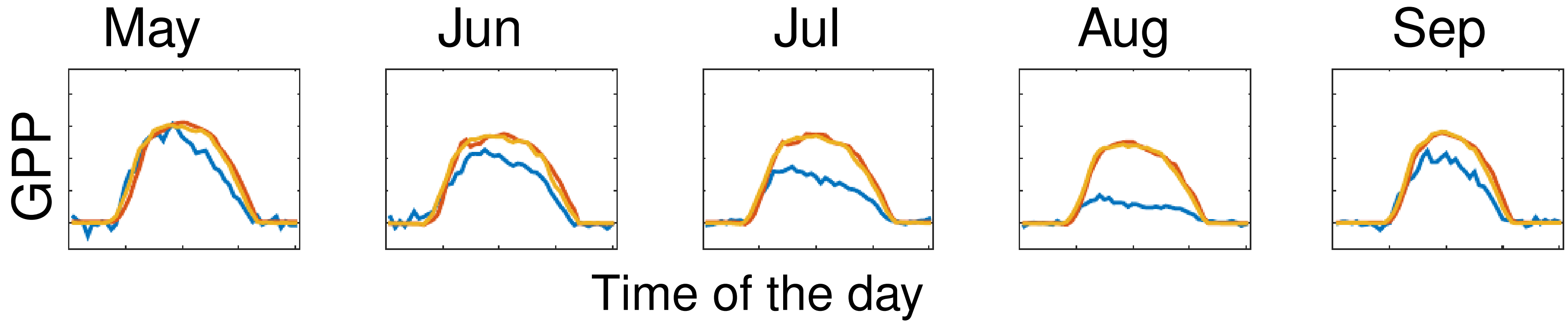


observation
modelled with daily predictors
modelled with daily & halfhourly predictors

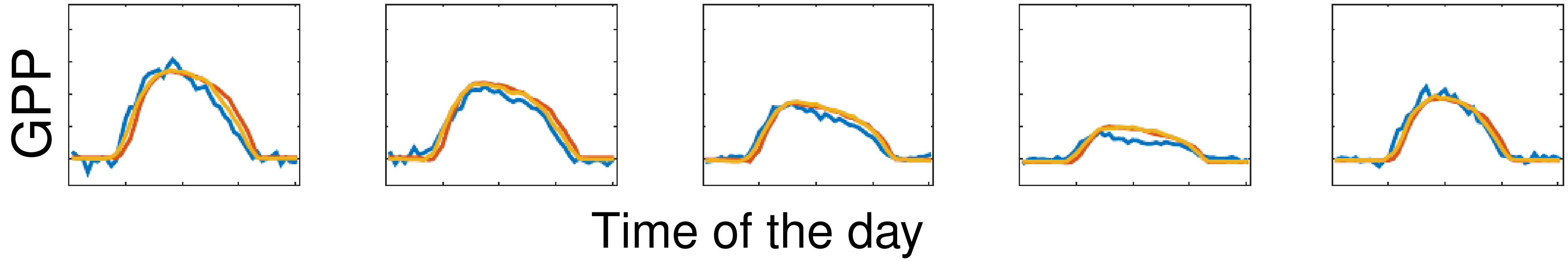
Puechabon

Bodesheim et al. 2018

Drought effects not well represented



Daily GPP as additional daily predictor:



observation
modelled with daily predictors
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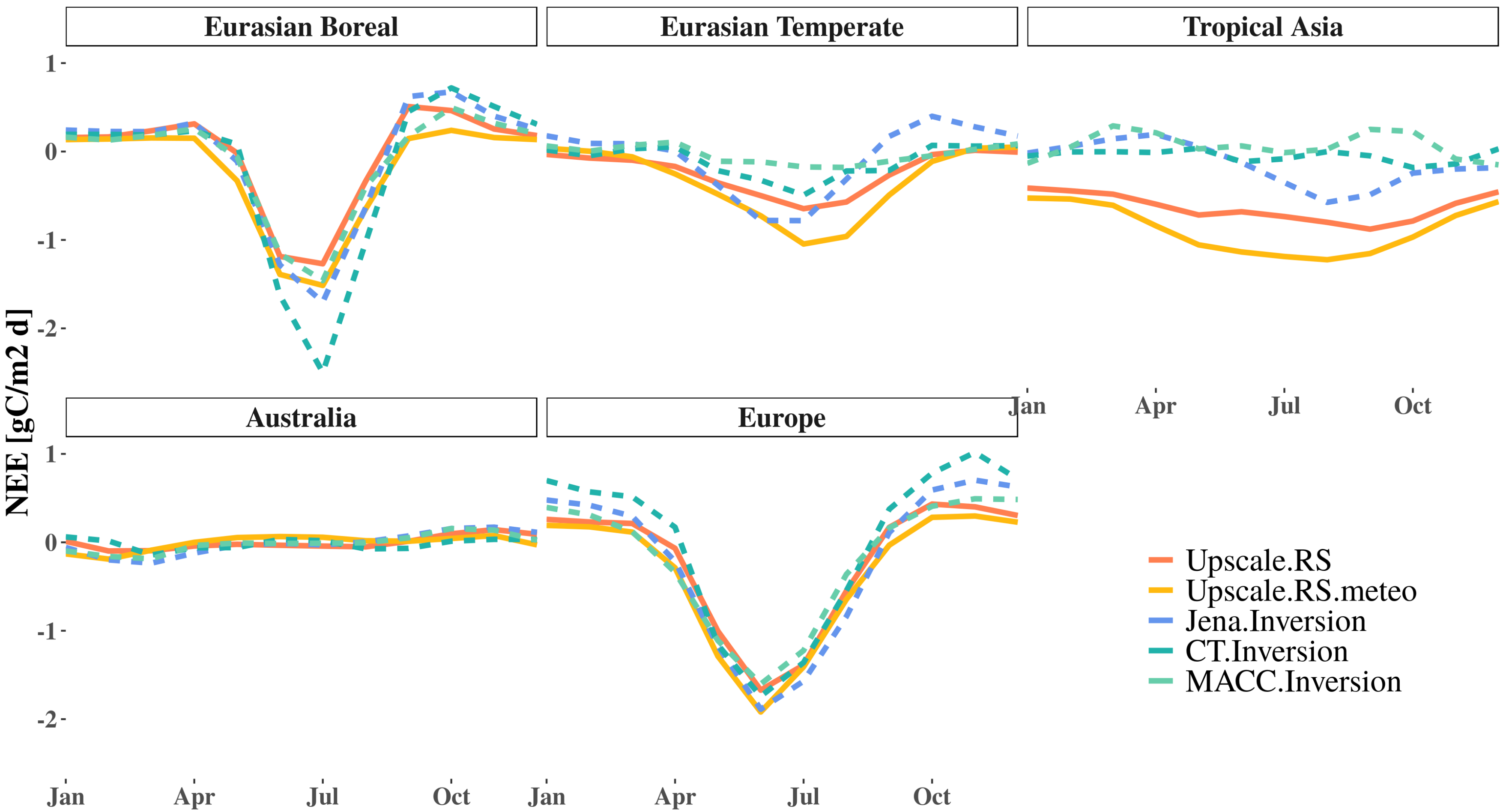
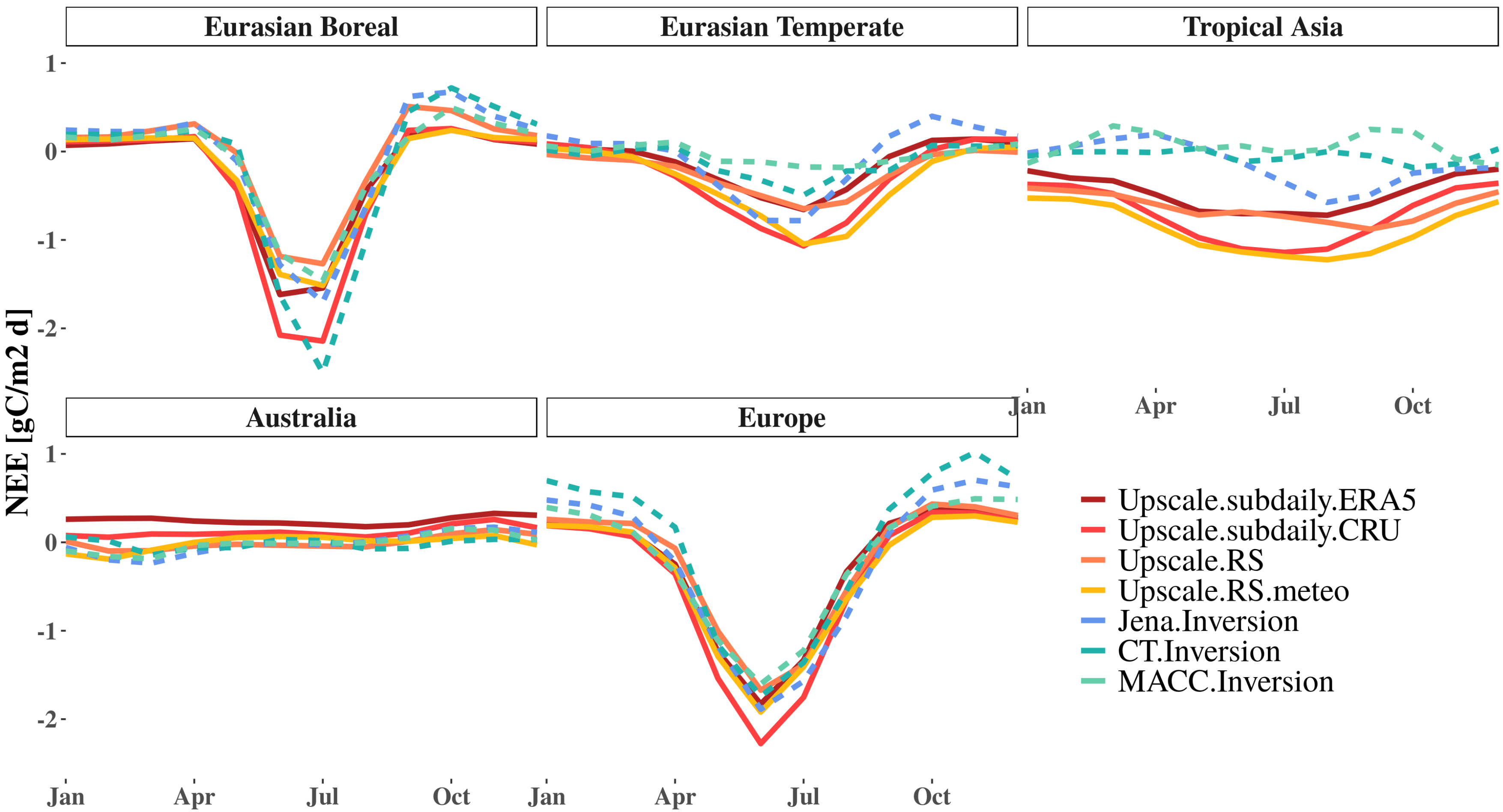
Bodesheim et al. 2018

Seasonal consistency of NEE with inversions

Seasonal consistency of NEE with inversions



Seasonal consistency of NEE with inversions



Towards high spatial AND high temporal resolution

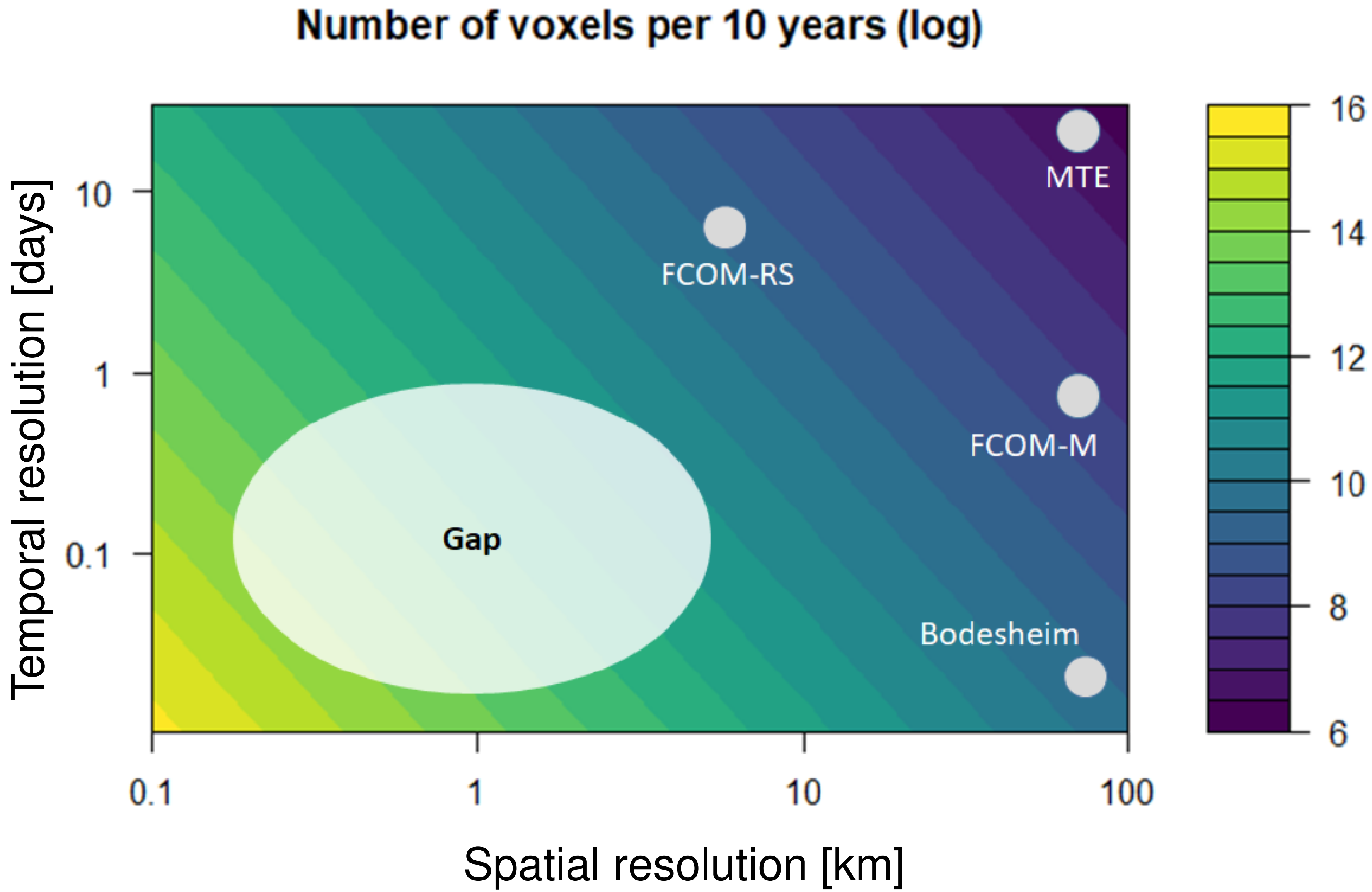


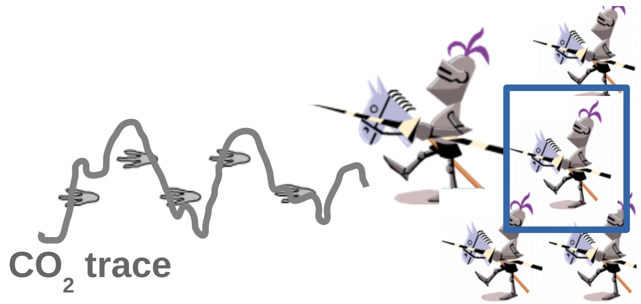
Figure courtesy Martin Jung

Towards dedicated products:

FluxCom2.0

Ongoing efforts for improvements in terms of:

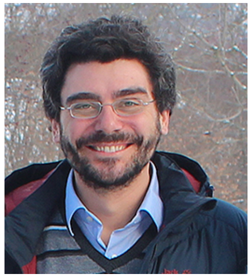
- **Training data:** more sites, more site-years, higher quality
- **spatio-temporal resolution:** ERA5, geostationary
- amount and accuracy of **predictor variables:** extensive QC, additional predictors (SIF, VOD, forest age, management on forests and crops,...)
- **machine learning methods** (e.g. memory effects, transfer learning)
- better **uncertainty** characterization
- **semi-operational** set-up



Acknowledgements

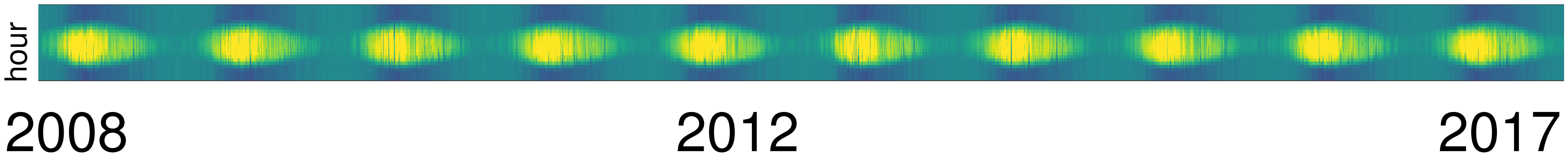
Ongoing efforts by Martin Jung, Sophia Walther, Jake Nelson, Ulrich Weber, Mirco Migliavacca, Nuno Carvalhais, Simon Besnard, Dario Papale






and others...

NEE in the pixel containing Jena:



Mean NEE in Neustift/Austria: Effects of topography and management

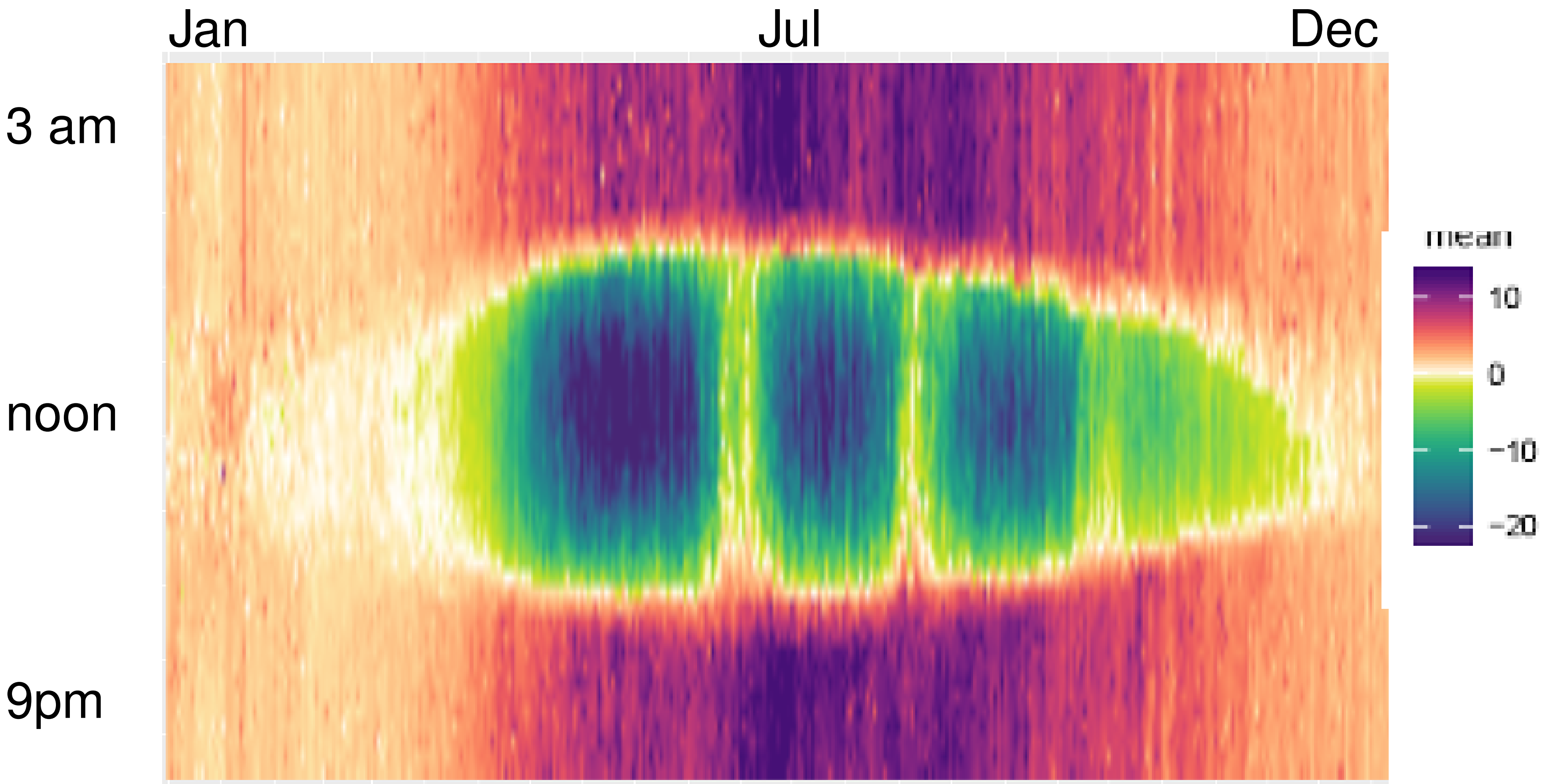
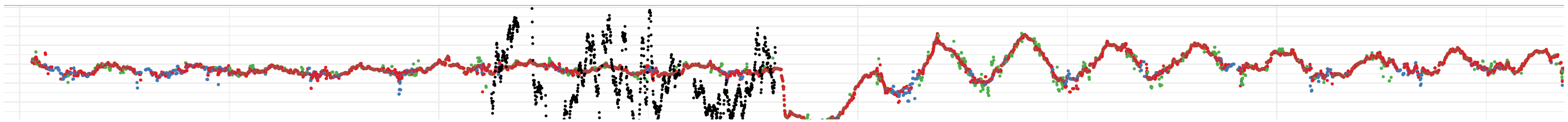


Figure courtesy Markus Reichstein

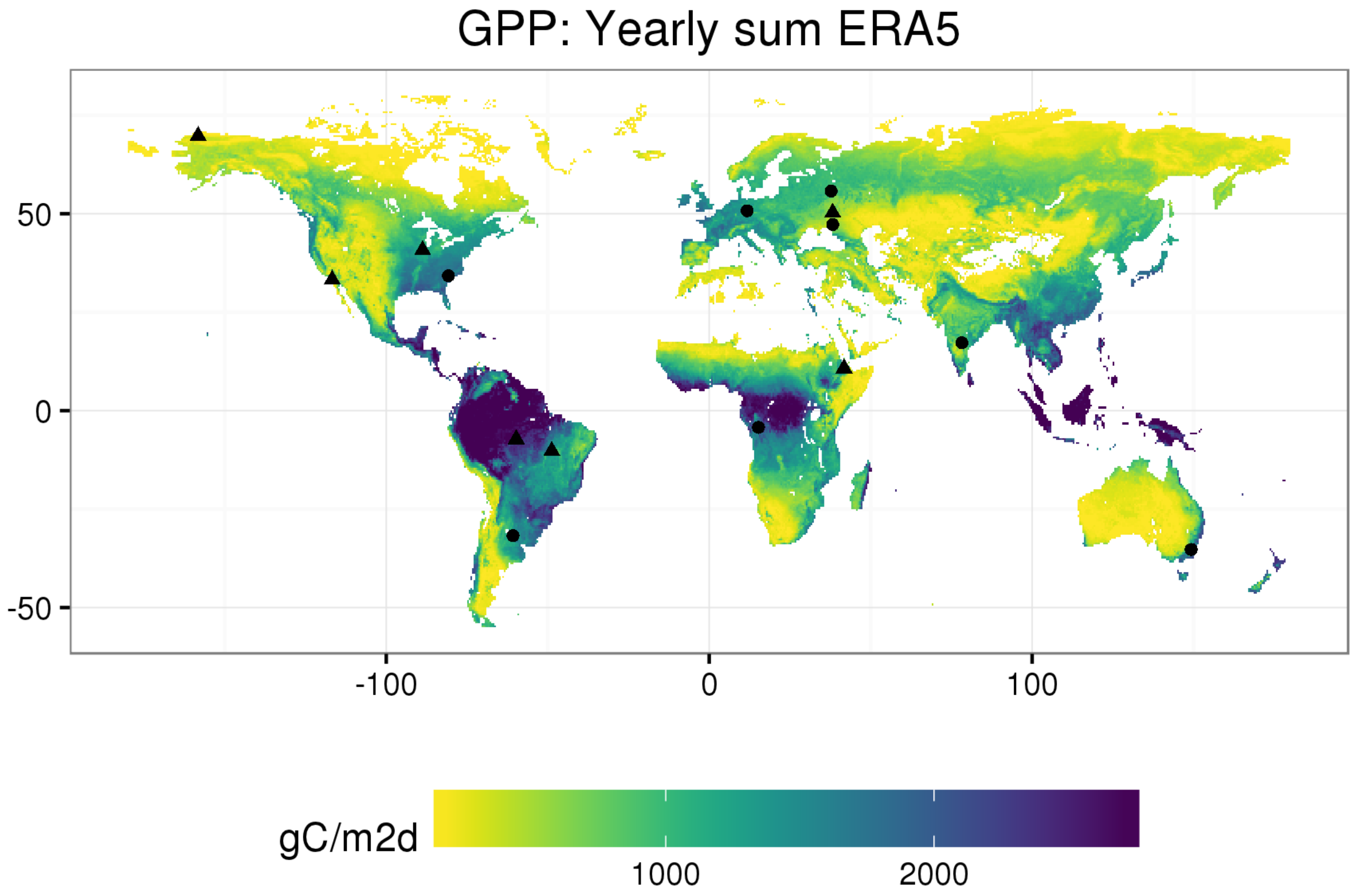
Wallaby Creek - Australia: disturbances and data-availability

EVI from MODIS (colour) and EC (black):

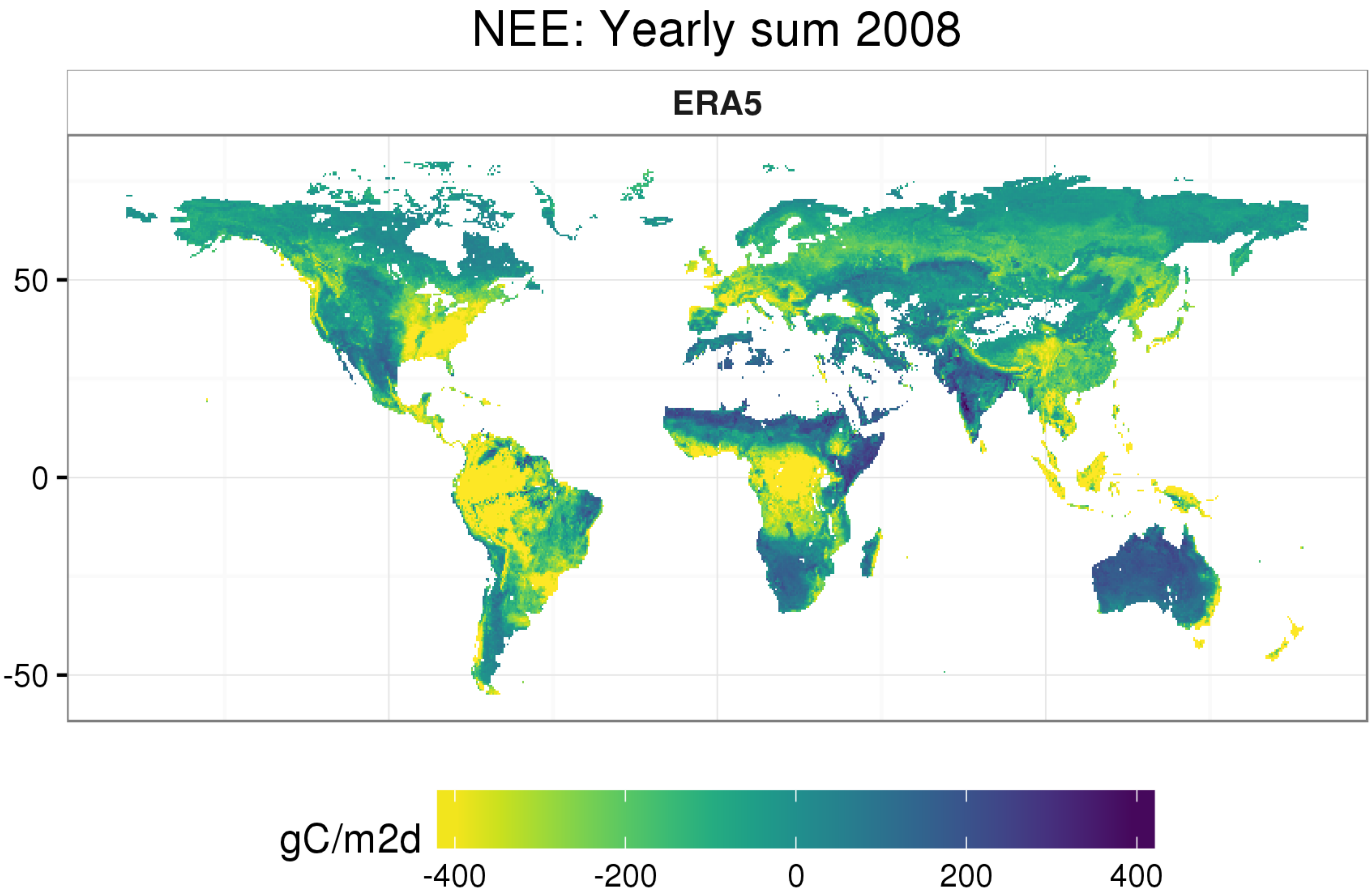


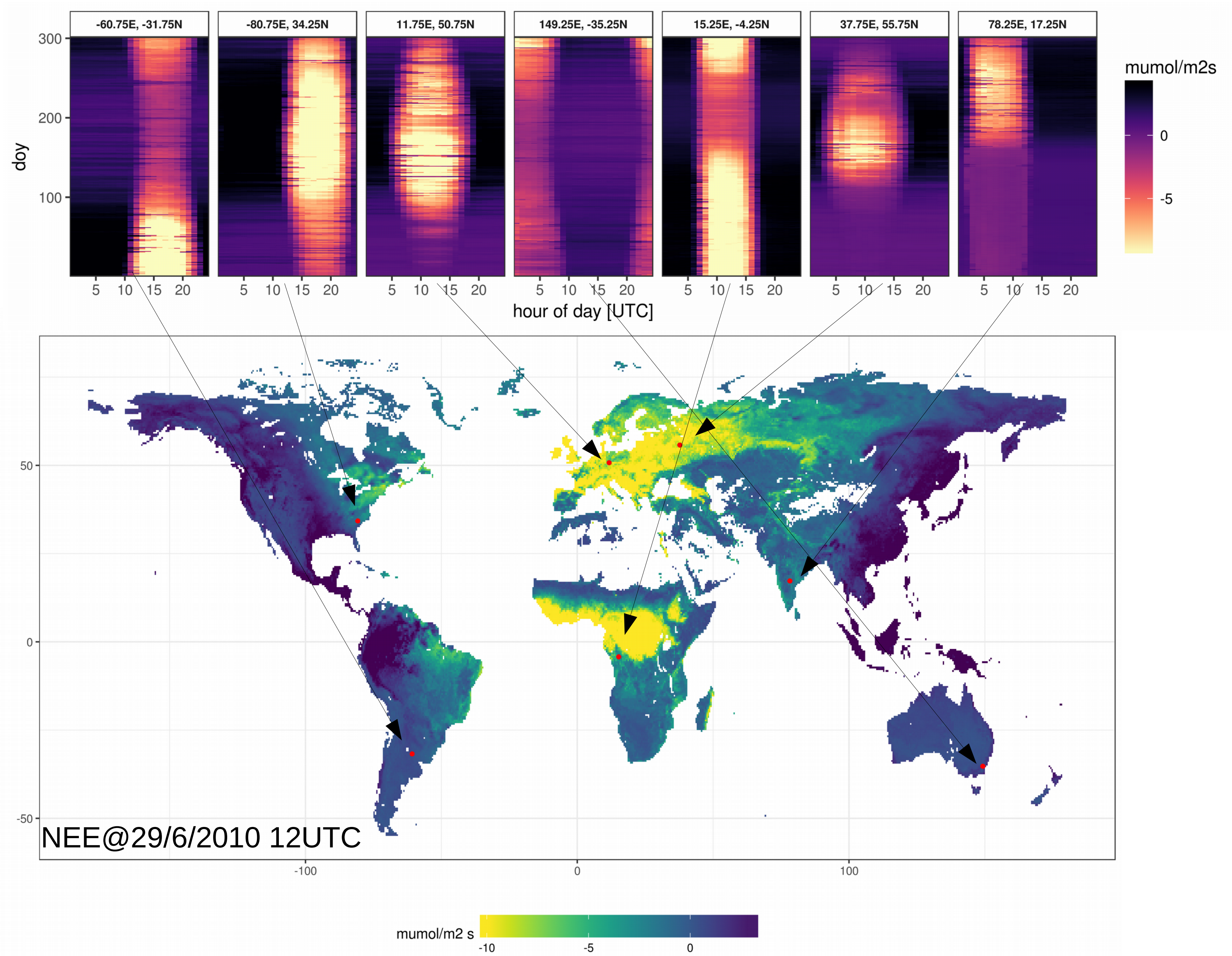
“Bushfires swept through the region in January 2009 destroying the tower. Data from the site was recorded from May 2010 to 2016. The post fire instrumentation was not as diverse when compared to the pre fire instrumentation.”

http://www.ozflux.org.au/monitoringsites/wallabycreek/wallabyck_description.html

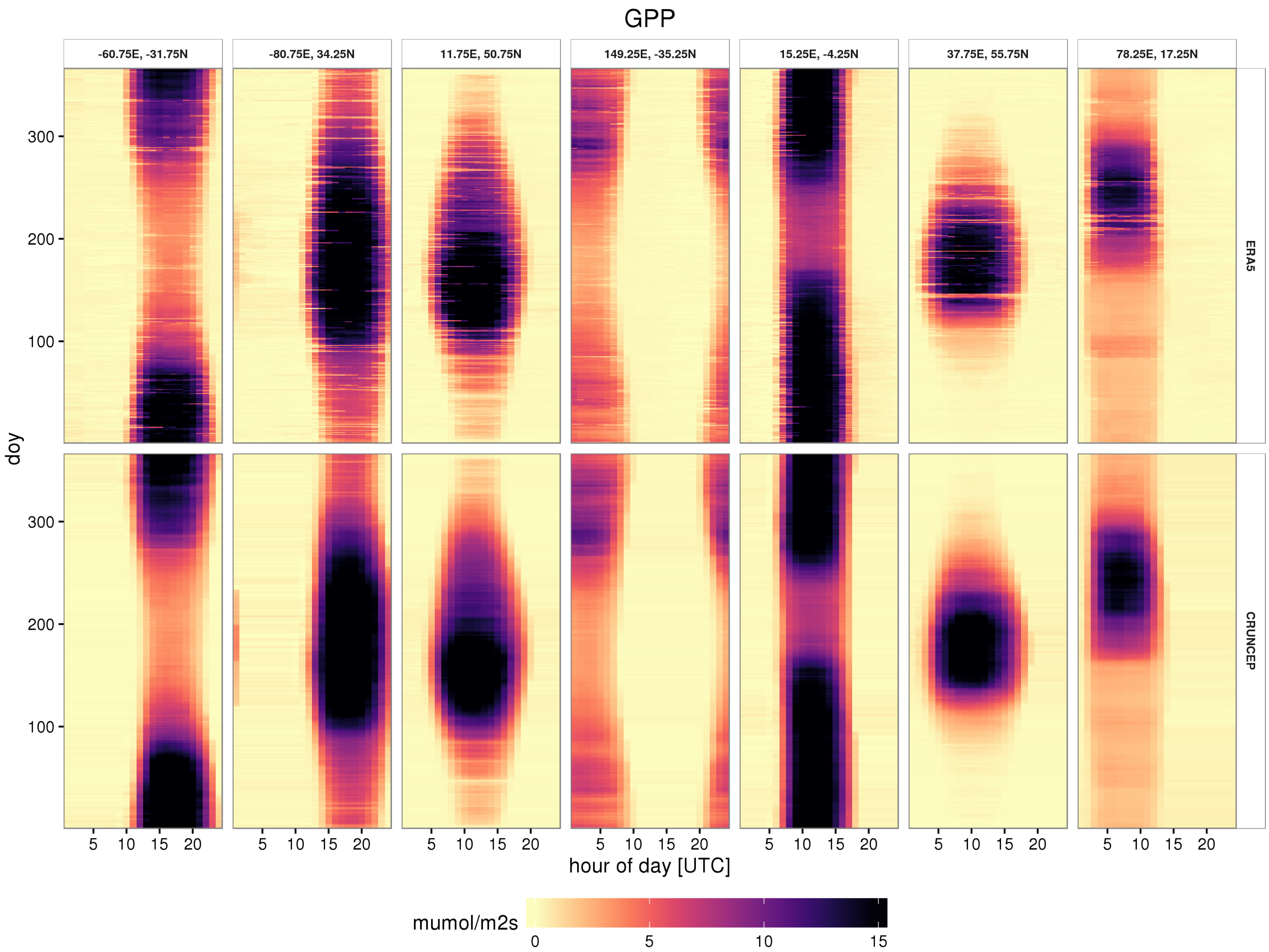


GPP: Yearly sum ERA5
50
0
-50
-100
0
100
gC/m2d
1000
2000

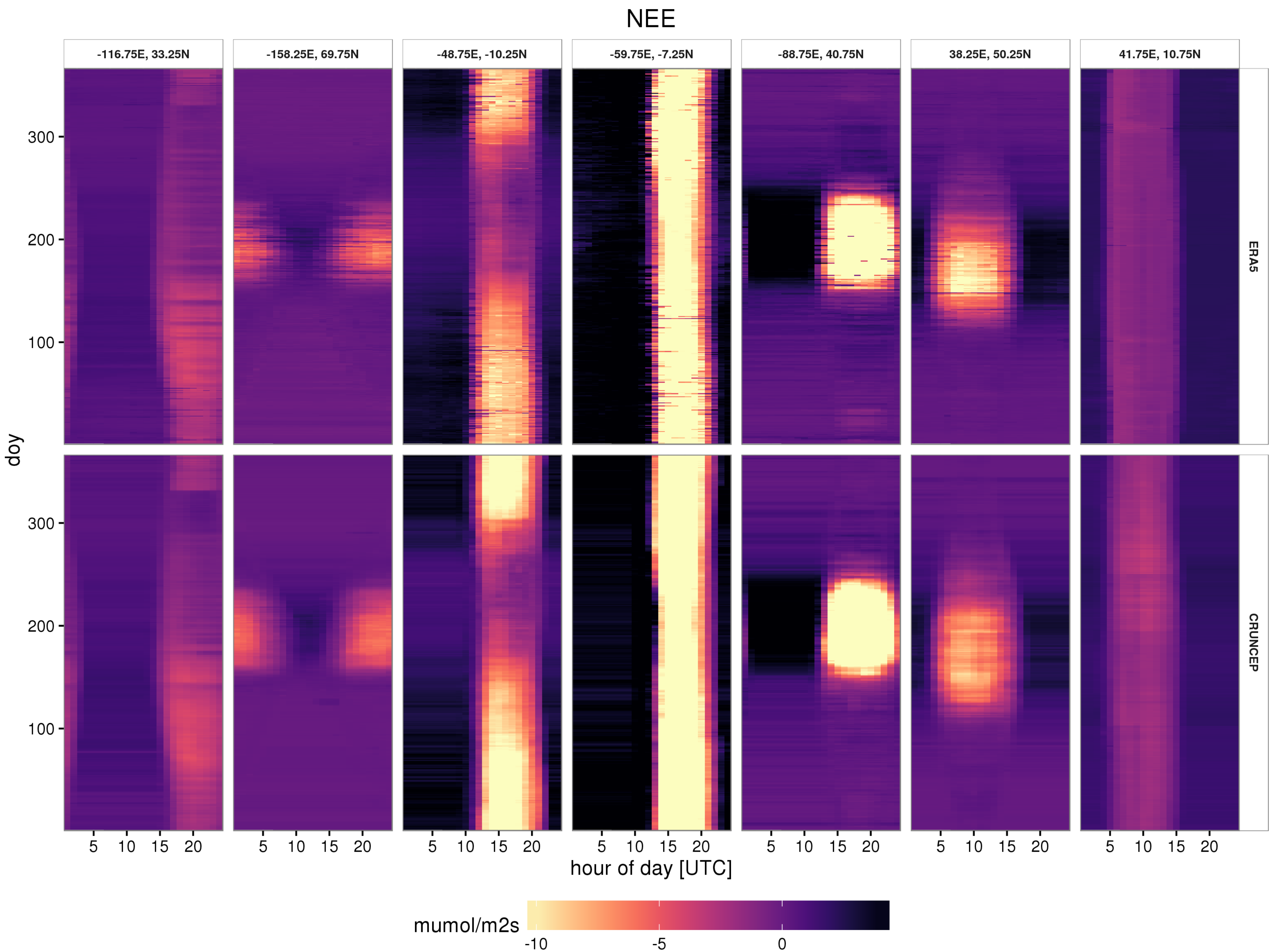

NEE: Yearly sum 2008
ERA5
50
0
-50
gC/m2d
-400
-200
0
200
400



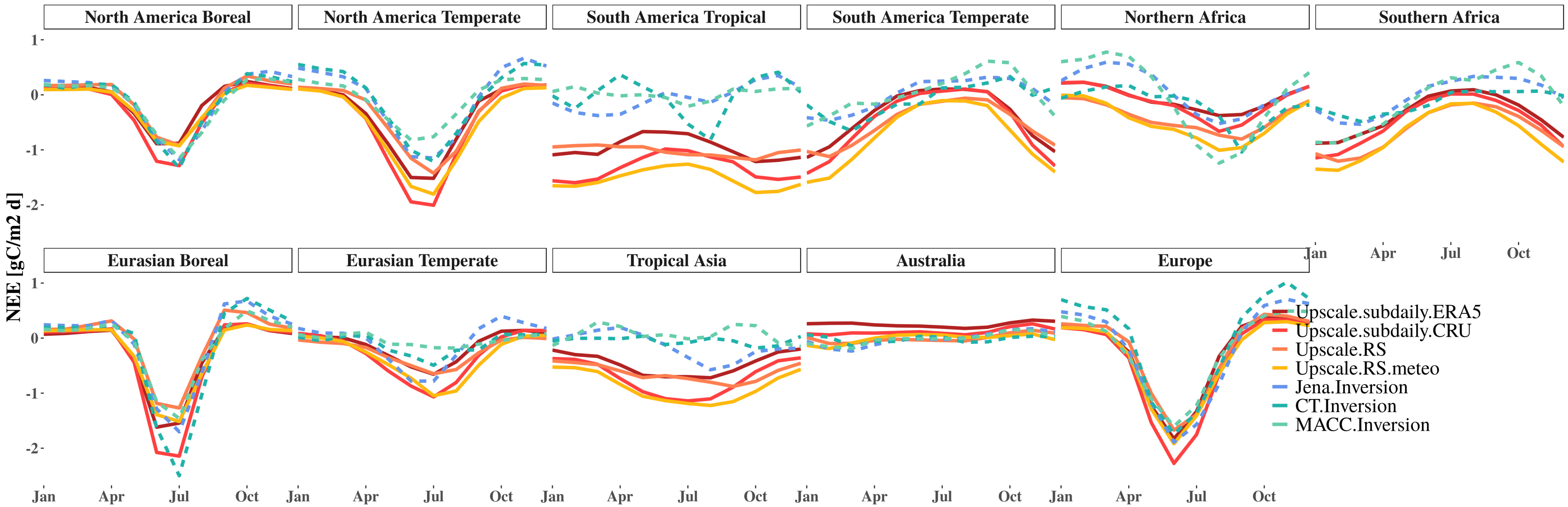
-60.75E, -31.75N
-80.75E, 34.25N
11.75E, 50.75N
149.25E, -35.25N
15.25E, -4.25N
37.75E, 55.75N
78.25E, 17.25N
doy
hour of day [UTC]
mumol/m2s
NEE@29/6/2010 12UTC
mumol/m2 s



GPP
-60.75E, -31.75N
-80.75E, 34.25N
11.75E, 50.75N
149.25E, -35.25N
15.25E, -4.25N
37.75E, 55.75N
78.25E, 17.25N
ERA5
CRUNCEP
doy
300
200
100
5 10 15 20
hour of day [UTC]
mumol/m2s
0 5 10 15



NEE
-116.75E, 33.25N
-158.25E, 69.75N
-48.75E, -10.25N
-59.75E, -7.25N
-88.75E, 40.75N
38.25E, 50.25N
41.75E, 10.75N
ERA5
CRUNCEP
doy
300
200
100
5 10 15 20
hour of day [UTC]
mumol/m2s
-10 -5 0


North America Boreal
North America Temperate
South America Tropical
South America Temperate
Northern Africa
Southern Africa
Eurasian Boreal
Eurasian Temperate
Tropical Asia
Australia
Europe
NEE [gC/m2 d]
1
0
-1
-2
Jan
Apr
Jul
Oct
Upscale.subdaily.ERA5
Upscale.subdaily.CRU
Upscale.RS
Upscale.RS.meteo
Jena.Inversion
CT.Inversion
MACC.Inversion

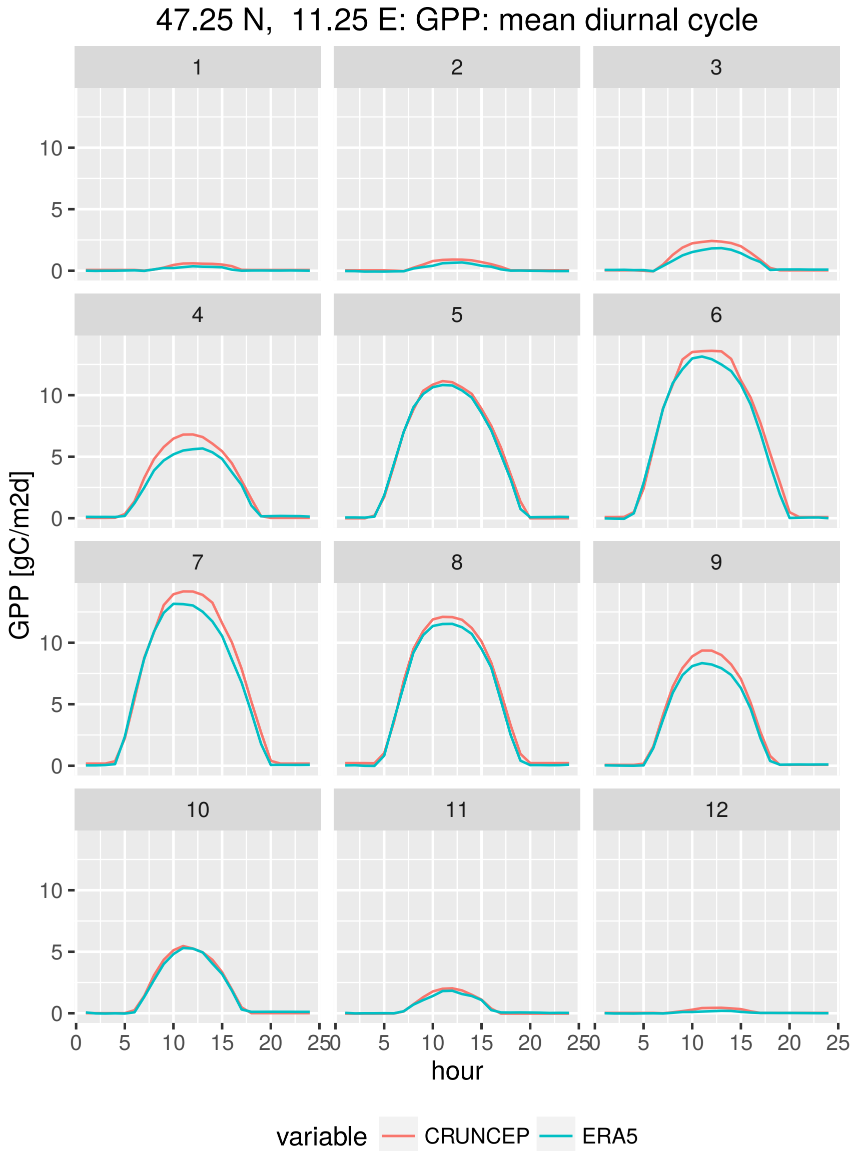
Predictors Fluxcom

Setup	Type of variability	CO_2 fluxes
RS	Spatial	PFT Amplitude of MSC of EVI Amplitude of MSC of MIR[1] Maximum of MSC of LST_{Day}
	Spatial and seasonal	MSC LAI
	Spatial, seasonal and interannual	NDWI LST_{Day} LST_{Night} (NDVI, R_g)
RS + METEO	Spatial	PFT Amplitude of MSC of NDVI Amplitude of MSC of band 4 BRDF reflectance[2] Minimum of MSC of NDWI Amplitude of MSC of WAI_L
	Spatial and seasonal	MSC of LST_{Night} MSC of (fPAR, LST_{Day}) MSC of (EVI, Rpot)
	Spatial and seasonal and interannual	T_{air} (R_g, MSC of NDVI) WAI_L

[1] Derived from the MOD13 product. [2] Derived from the MCD43 product.

- differences in magnitude between CRUNCEP and ERA5 with only daily (ERA5.nh-HHCRU), but rather not clear phase shift, ERA lower values in GPP –> driver differences, ERA up to 30% lower Rg
- including hourly data compared to only daily data using only ERA5 (ERA5.h-ERA5.nh)
    - reduces magnitude everywhere, particularly crops
    - enhances variability (including negative values) at night
    - ehnaces GPP in high lats in summer and in isolated areas in the Amazon, Ethiopia, western India, slightly in midlats in autumn
    - shifts centroids of daily cycles to earlier increase/decrease in some biomes (e.g. not crops) –> phaseshift in the morning (e.g. particularyl in dry season amazon)
    - there is no systematic lagged corr explaining the phaseshift

Shift of diurnal cycle due to hourly meteo info



EC: error sources and magnitude
scale mismatch/ pixel heterogeneity