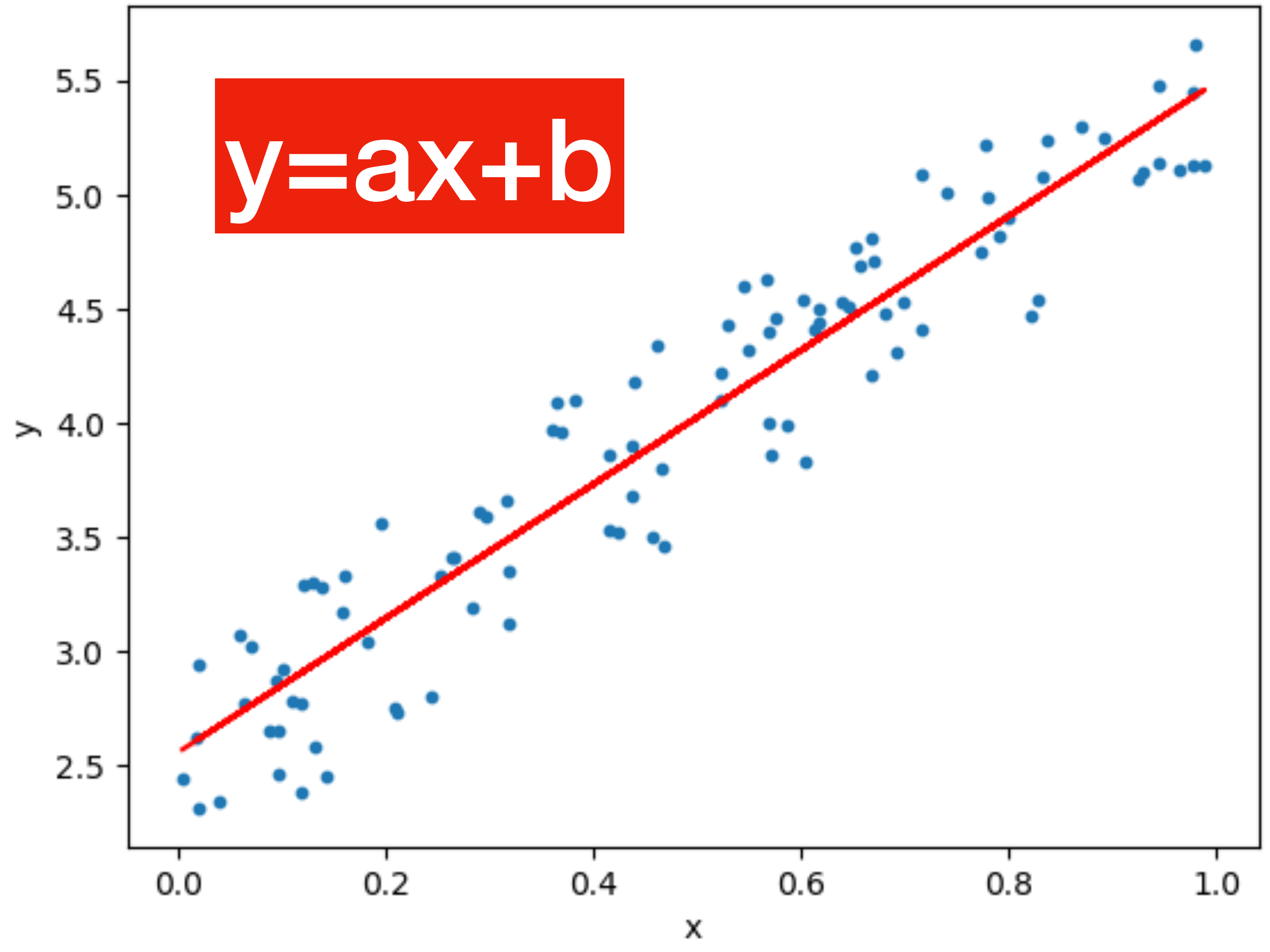
CarbonTracker Europe inverse modeling

update from Wageningen

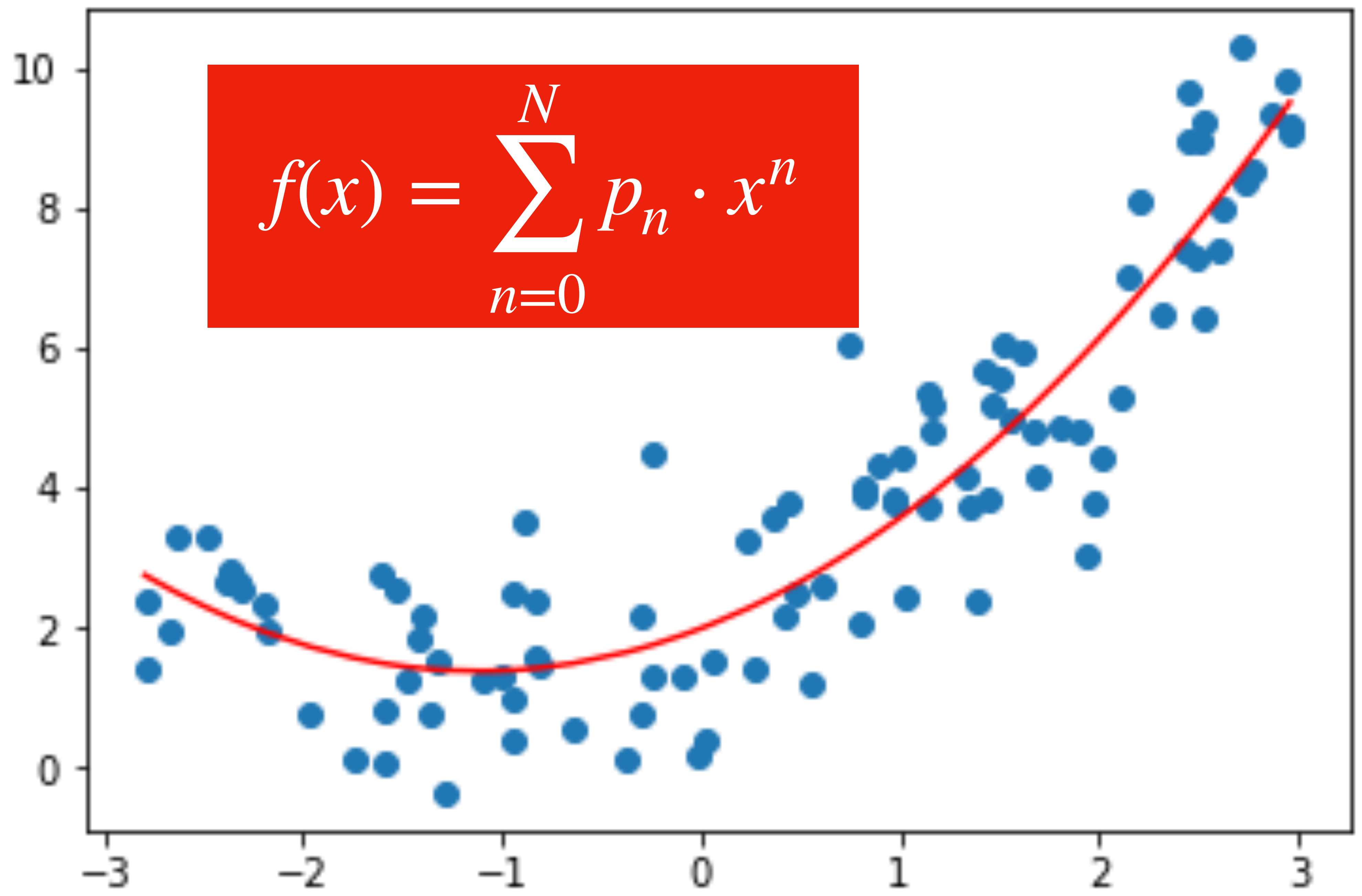
Wouter Peters, Gerbrand Koren, Liesbeth Florentie, Ingrid Luijkx, Remco de Kok, Anne-Wil van den Berg

A statevector in data assimilation



a	b										

A statevector in data assimilation

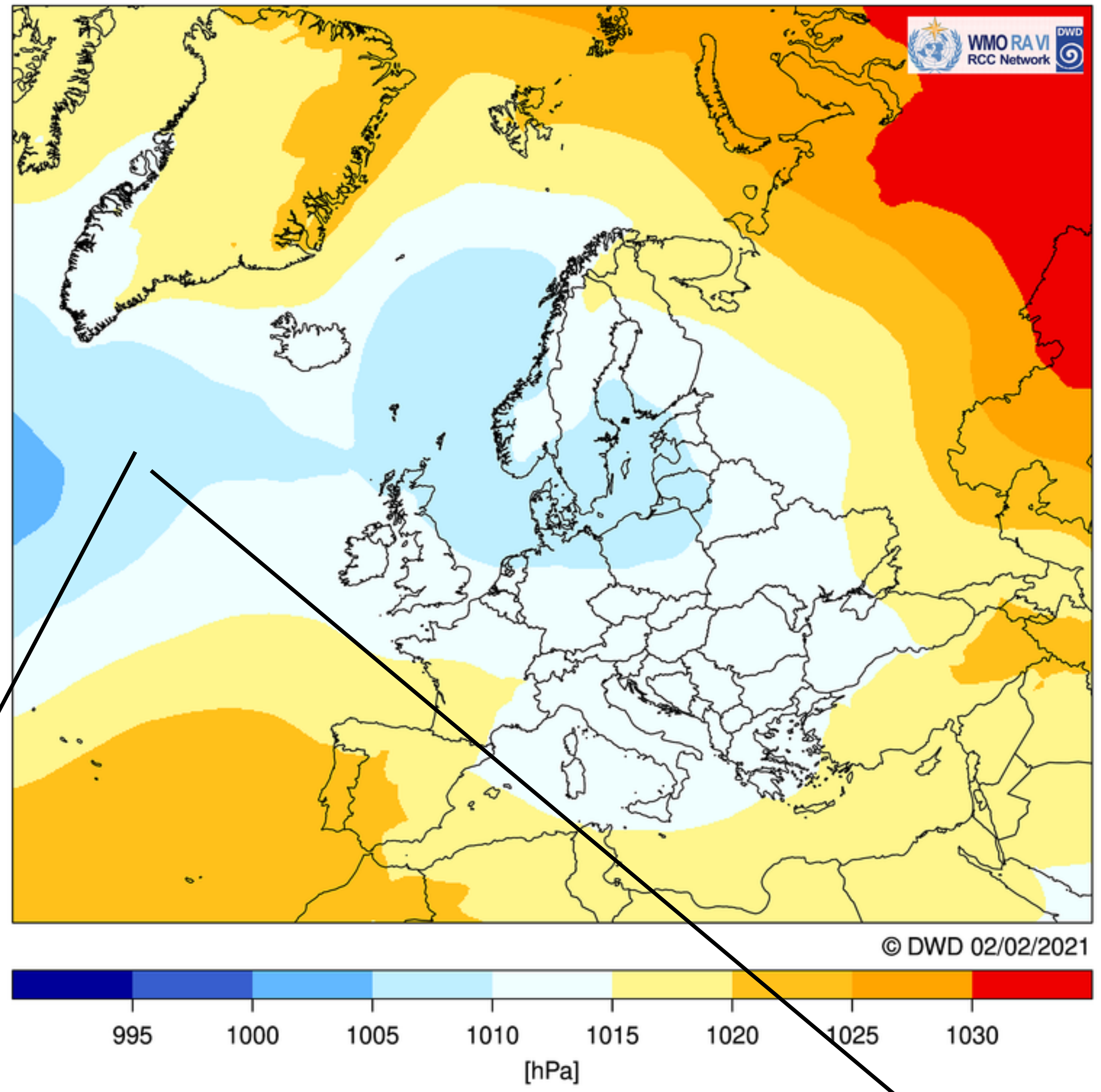


$$f(x) = \sum_{n=0}^{N} p_n \cdot x^n$$

p0	p1	p2	p3	p4	..	..	..	..	..	..	

A statevector in weather data assimilation

Sea Level Pressure January 2021
Monthly Mean



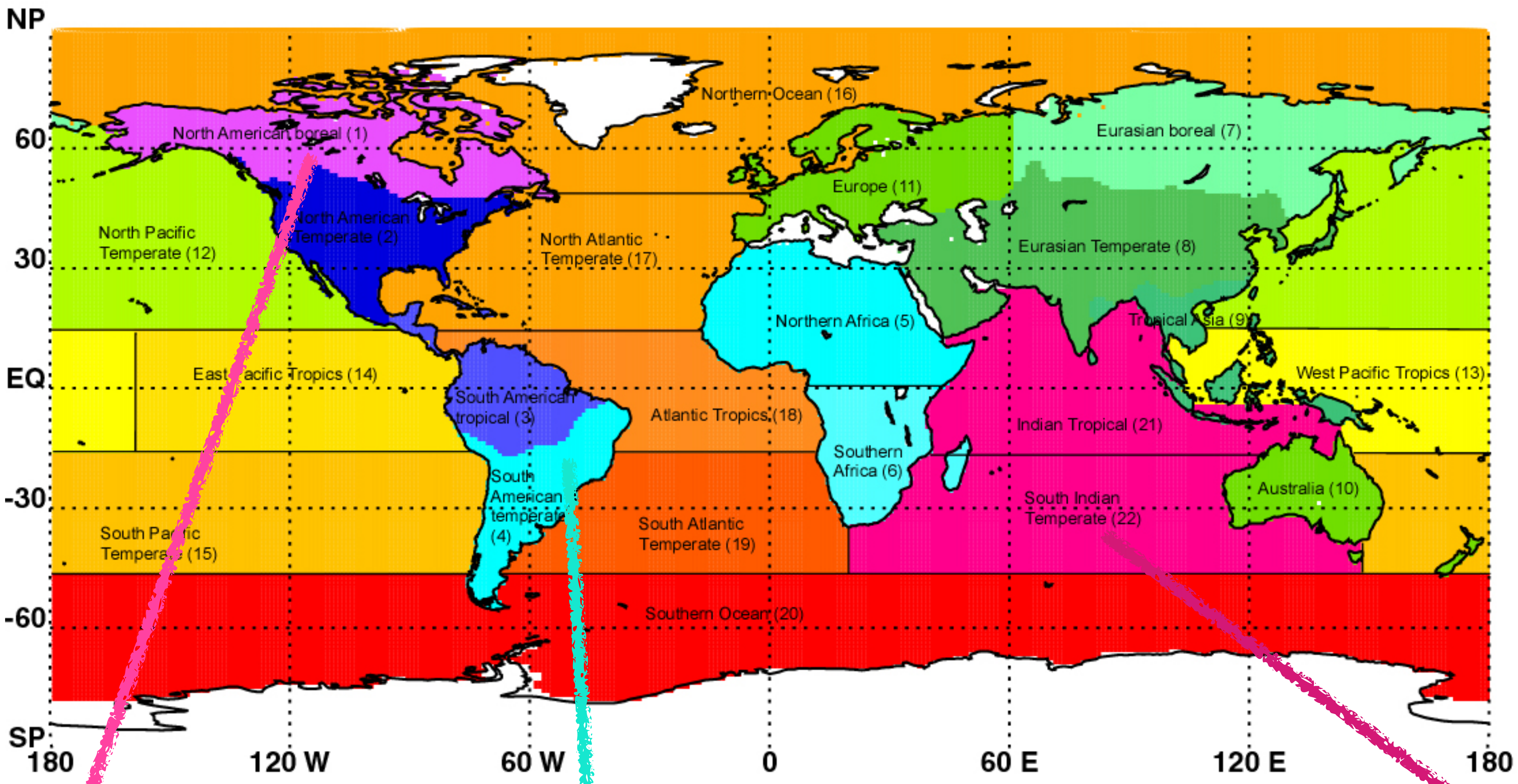
f(x) = IFS model

$$\rho \frac{D\vec{V}}{Dt} = -\nabla p + \rho \vec{g} + \mu \nabla^2 \vec{V}$$

q1	q2	q3	q4	..	..	t1	t2	t3	t4	..

A statevector in CO_2 data assimilation

TRANSCOM



$$f(x) = F_{ff} + F_{fire} + f1 + f2 + \ldots$$

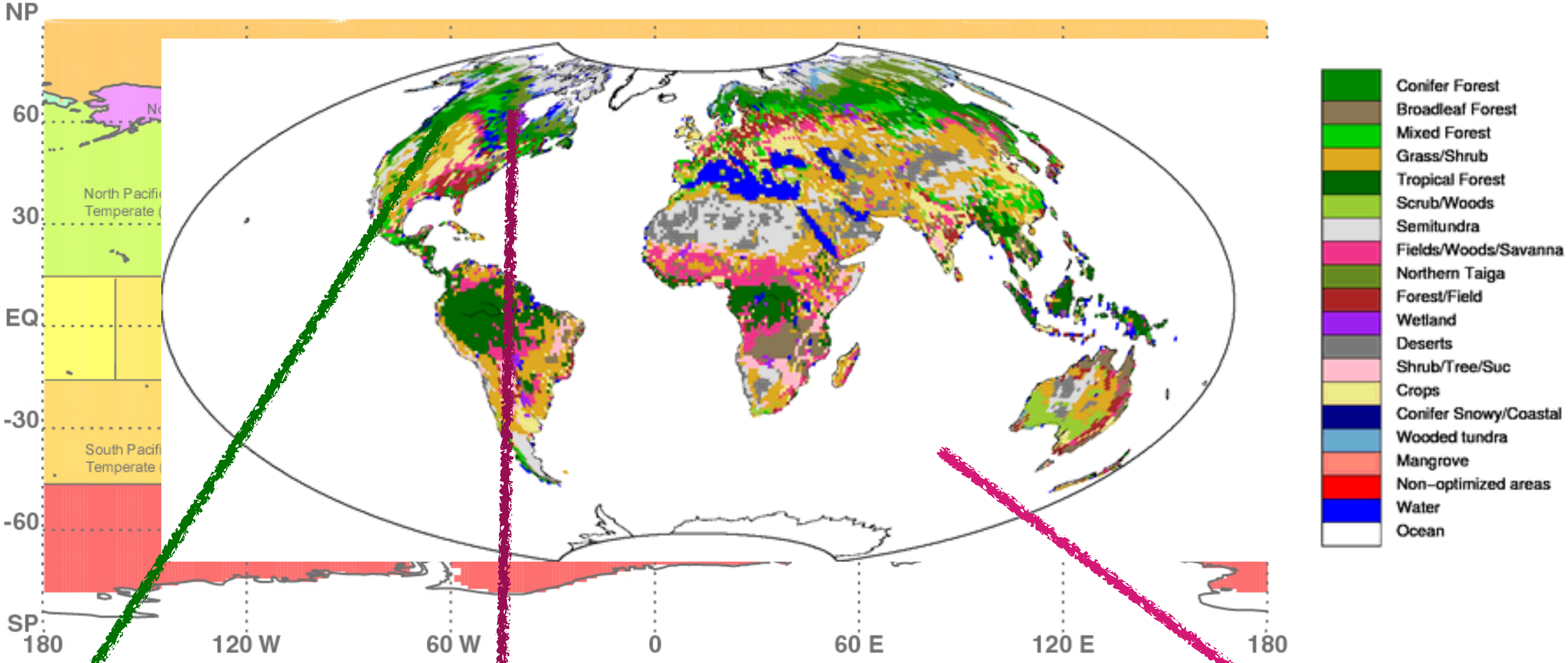
f1	f1	f2	f3	f4	..	..	..	..	..	..	f22

The first CarbonTracker statevector

TRANSCOM

+

OLSON

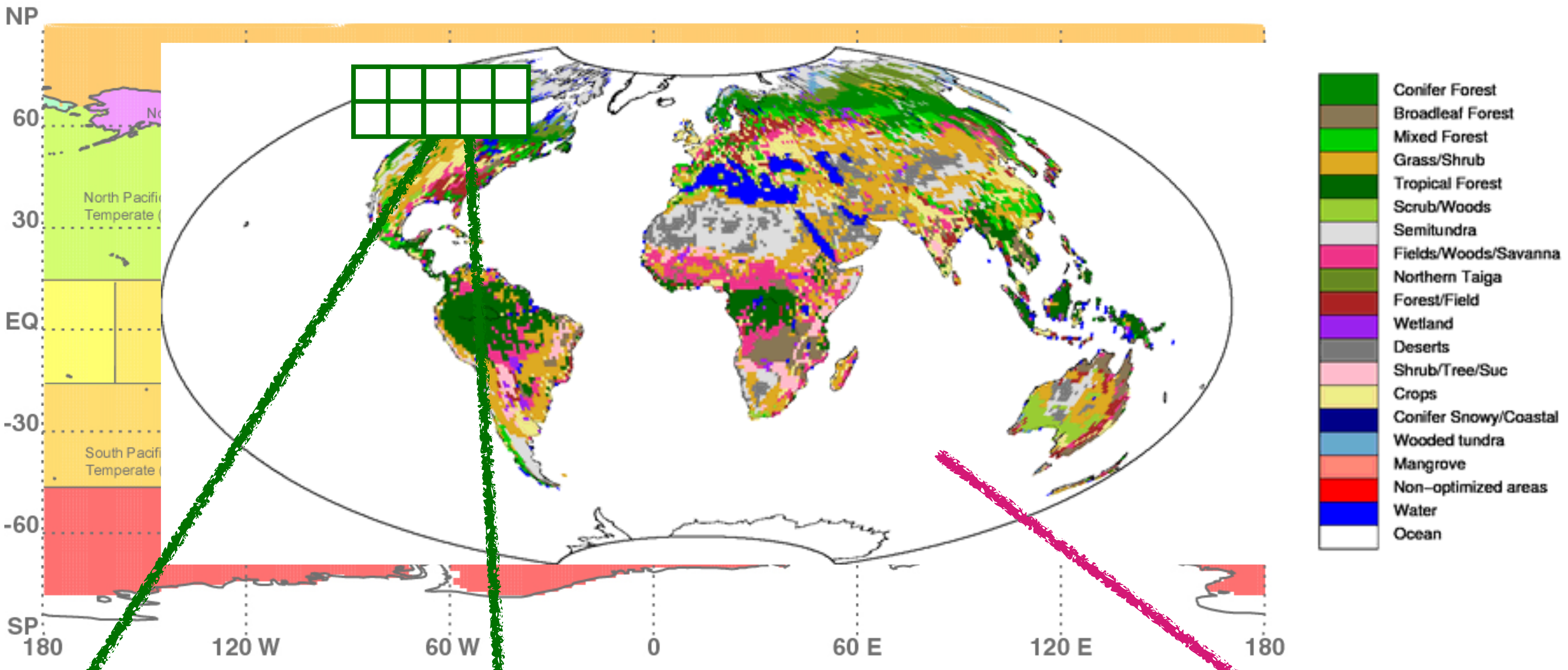


f1	f1	f2	f3	f4	..	..	..	..	..	..	f240

$$f(x) = F_{ff} + F_{fire} + f1 * F_{con}(t) + f2 * F_{broad}(t) + \dots + f240 * F_{oce}$$

The current CarbonTracker statevector

TRANSCOM
+
OLSON
+
NH 1x1

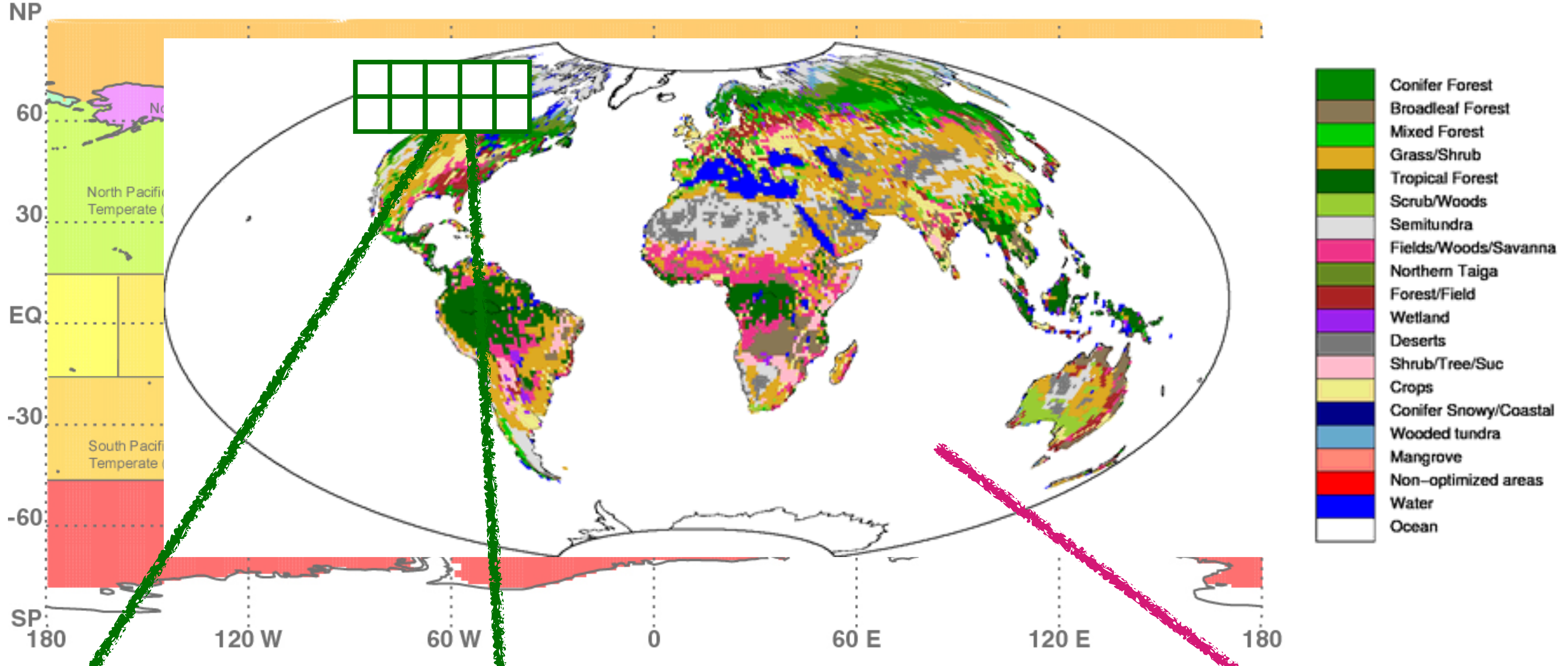


f1	f1	f2	f3	f4	..	..	..	..	..	..	f9835

$$f(x) = F_{ff} + F_{fire} + f1 * F_{con}(1,1,t) + f2 * F_{broad}(1,2,t) + \dots + f9835 * F_{oce}$$

The current CarbonTracker statevector

TRANSCOM
+
OLSON
+
NH 1x1



f1	f1	f2	f3	f4	..	..	..	..	..	..	f9835

Covariances become really important to keep the system well-behaved!

CarbonTracker Statistical Fit (CTSF): Long-window inversion for biosphere flux

Goals

- Separate long- from short time scales in inversion, and:
  - Better constrain slow processes with CO_2
  - use other proxies and satellite data of XCO2, XNO2, XCO, … for hi-res
  - Detect trends from seasonal to decadal time scales
  - Use direct observations of NEE proxies to capture anomalies
- CTSF framework (long time scales) being developed and applied for CO_2 and $\delta^{13}C$ (Gerbrand, soon Joram), based on initial work by Liesbeth Florentie

How does the terrestrial carbon exchange respond to inter-annual climatic variations? A quantification based on atmospheric CO_2 data

Christian Rödenbeck[1], Sönke Zaehle[1], Ralph Keeling[2], and Martin Heimann[1,3]

A new CarbonTracker statevector

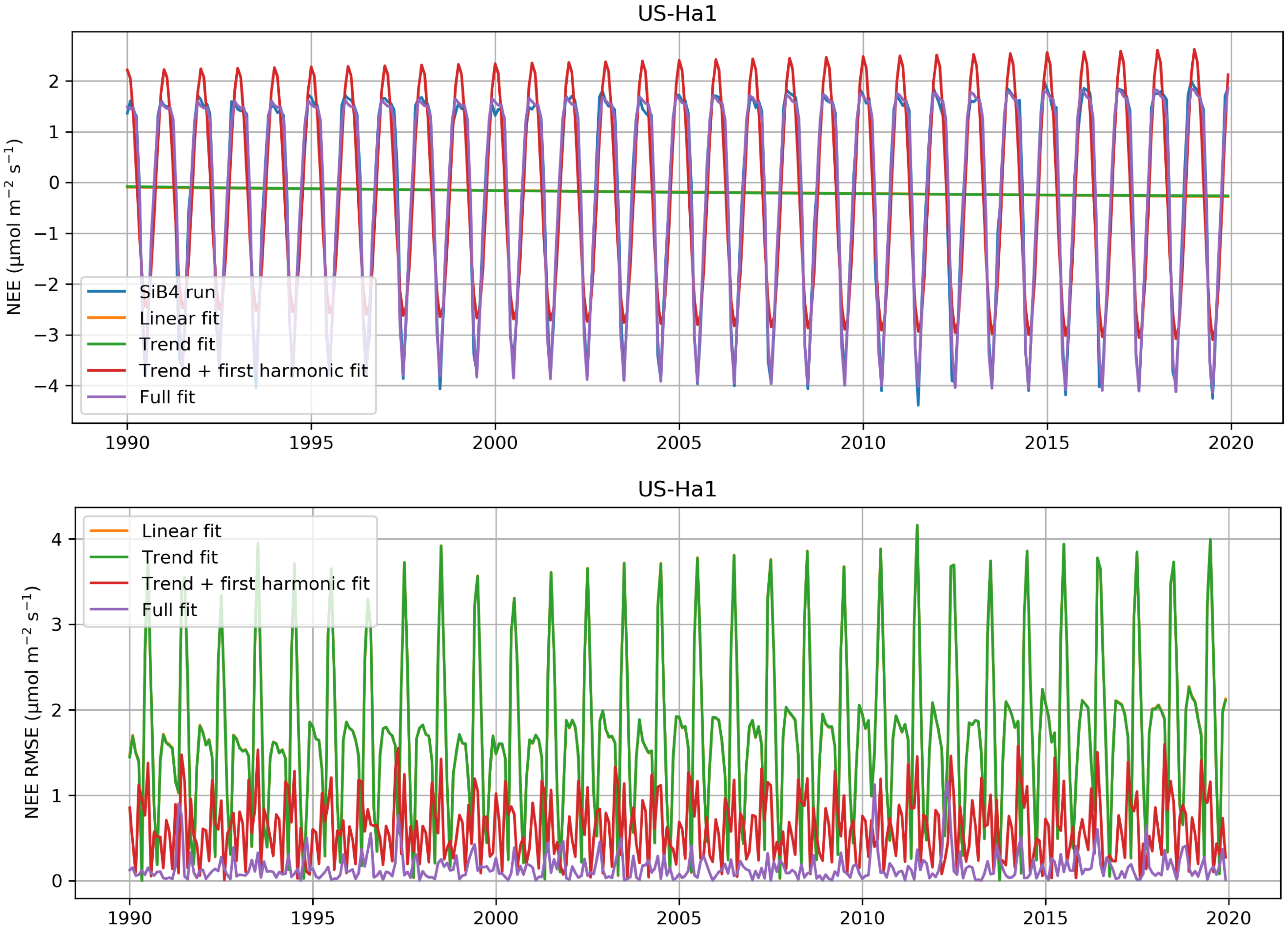
Inspired by Rödenbeck et al., (2019)

Assumptions

- Mean NEE per ecoregion → polynomial function + harmonics of yearly cycle

$$NEE(x,y,t) = \underbrace{x_0 + x_1 t + x_2 t^2 + \sum_{n=1}^{4}\left[\left(a_n + b_n t\right)\sin\left(\frac{2\pi}{T}nt\right) + \left(c_n + d_n t\right)\cos\left(\frac{2\pi}{T}nt\right)\right]}_{\text{Long-term mean, seasonal cycle, temporal trend}}$$

SiB4 output: statistical fit (US-Ha1)



A new CarbonTracker statevector

Inspired by Rödenbeck et al., (2019)

Assumptions

- Mean NEE per ecoregion → polynomial function + harmonics of yearly cycle
- Linear correlation between variations in NEE and a proxy (T, VPD, SIF, or NIR_V)

$$NEE(x, y, t) = \underbrace{x_0 + x_1 t + x_2 t^2 + \sum_{n=1}^{4} \left[(a_n + b_n t) \sin\left(\frac{2\pi}{T} nt\right) + (c_n + d_n t) \cos\left(\frac{2\pi}{T} nt\right) \right]}_{\text{Long-term mean, seasonal cycle, temporal trend}}$$

$$+ \underbrace{\gamma^P \Delta P(x, y, t)}_{\text{spatial \& interannual variability}}$$

Statevector **x**:

- One set of parameters per ecoregion
- Sensitivities (γ) additionally vary per calendar month

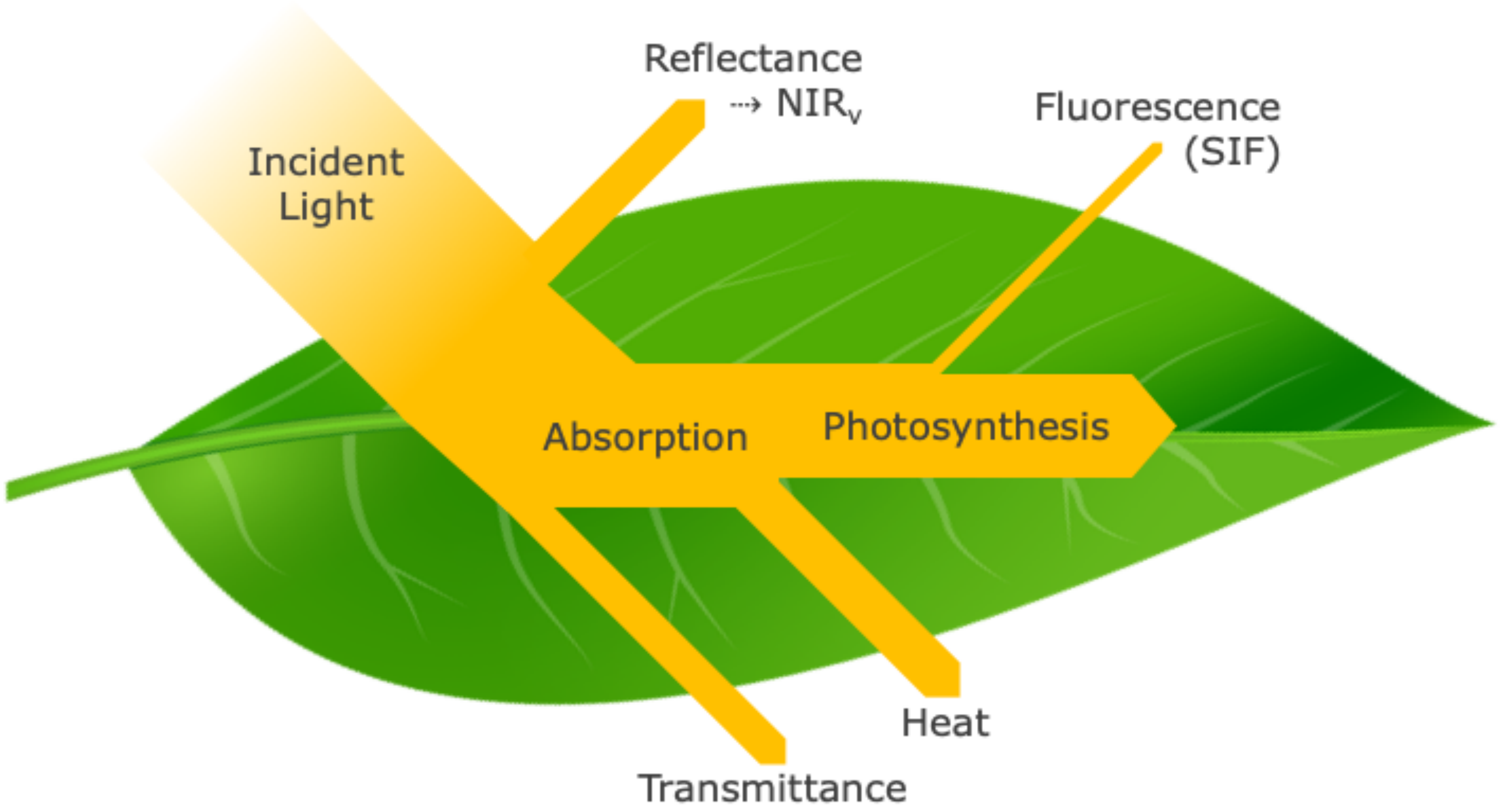
→ For n=4: 31*134 = 4154 parameters

NIR_v and SIF good proxies for photosynthesis

- **Near-infrared reflectance of terrestrial vegetation (NIR_v)**
  = total near-infrared reflectance * NDVI
- **Sun-induced fluorescence (SIF)**
  = re-emission at longer wavelengths of part of the absorbed solar radiation during photosynthesis

↓

Satellite measurements



SIF and NIR_V good proxies for photosynthesis

GPP (FLUXCOM) versus satellite SIF (GOME-2) and NIR_V (MODIS)

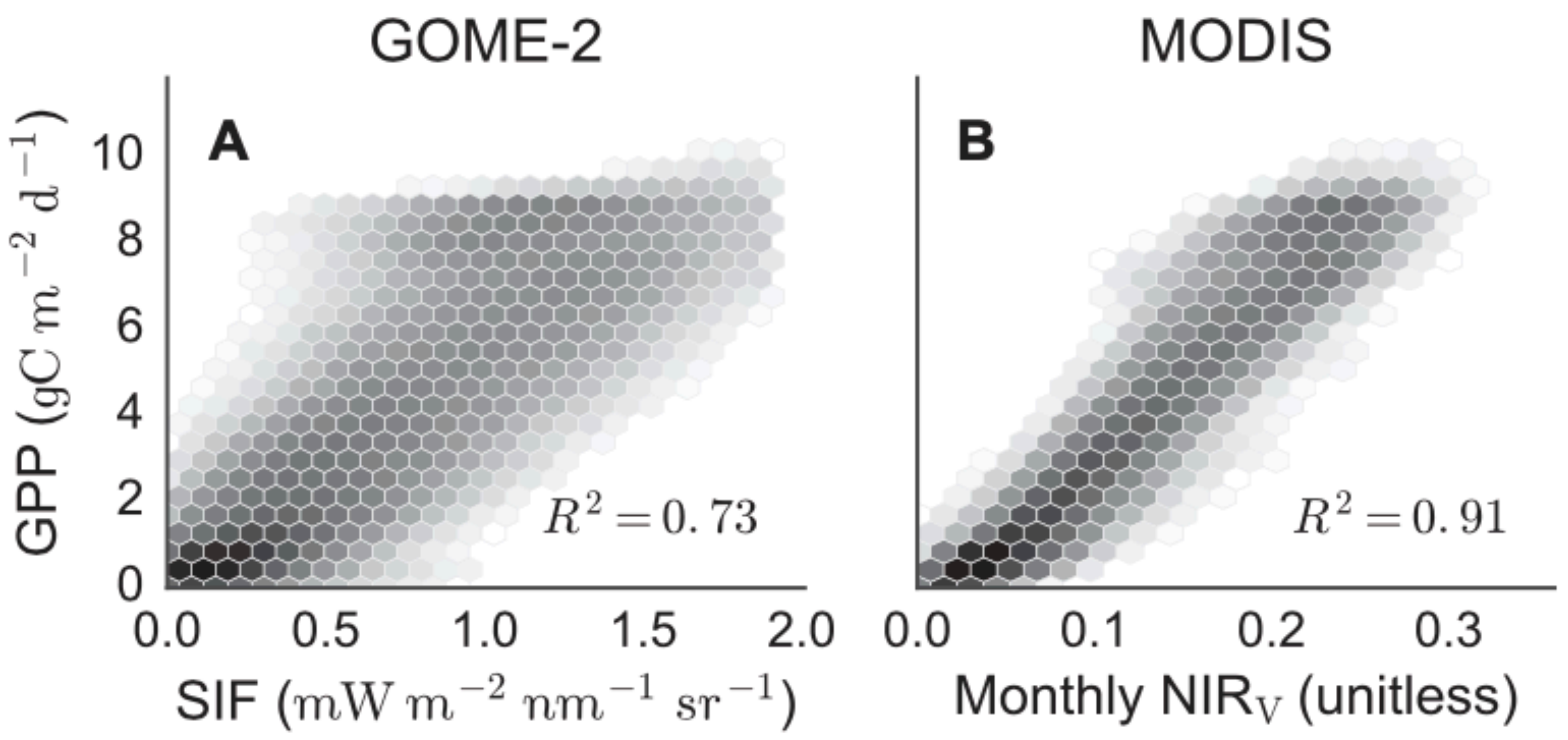
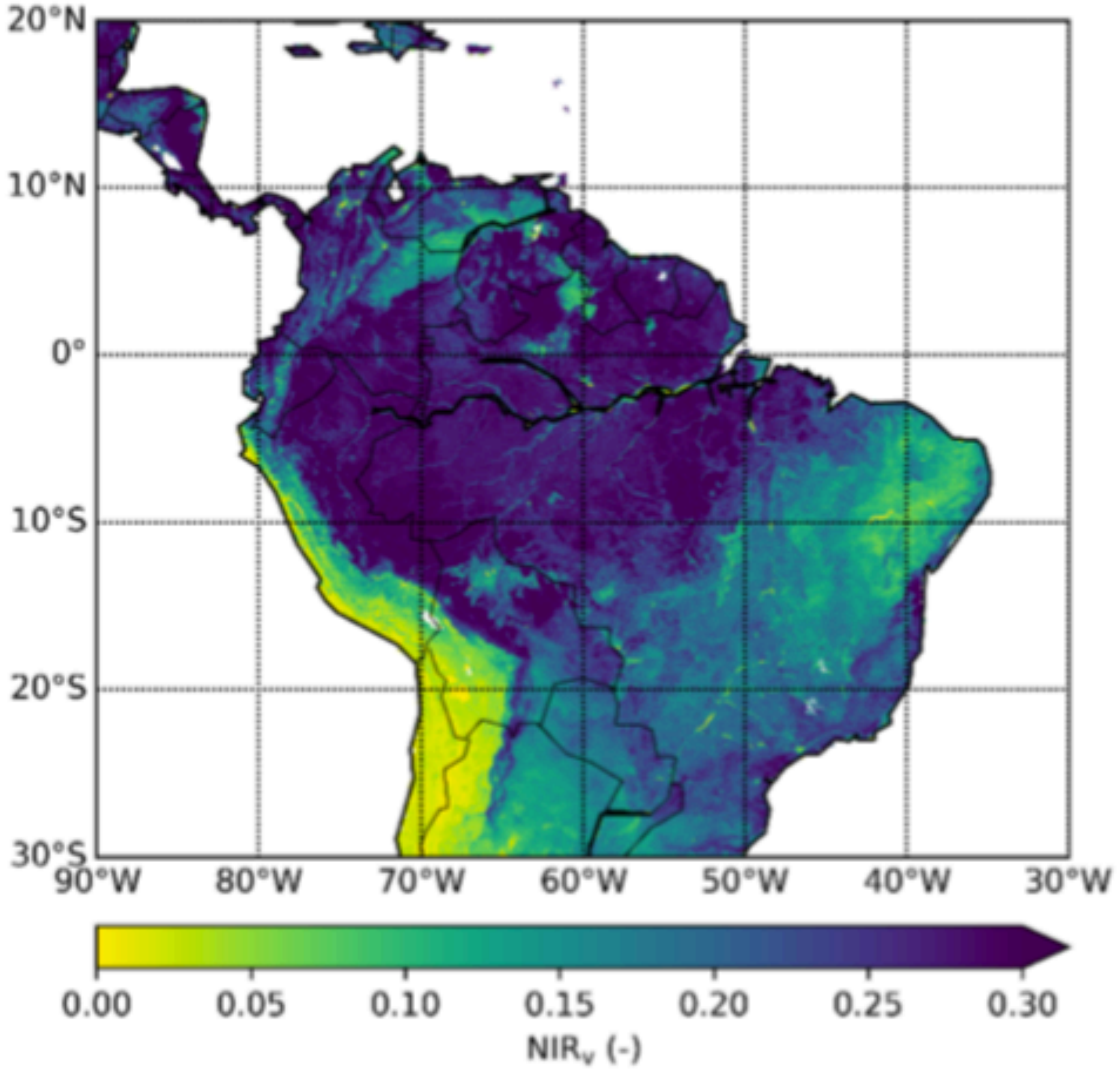


Fig. 2. Comparison of multiyear monthly mean (A) SIF and (B) NIR_V against global data-driven GPP estimates. SIF estimates come from GOME-2 data averaged monthly and regridded to 0.5°. MODIS NIR_V estimates were aggregated to 0.5° from 500-m scenes of BRDF-corrected reflectances. GPP estimates come from the Max Planck Institute upscaling approach (*16*). Shading indicates the logged number of pixels within each bin.

SIF and NIR$_v$ good proxies for photosynthesis

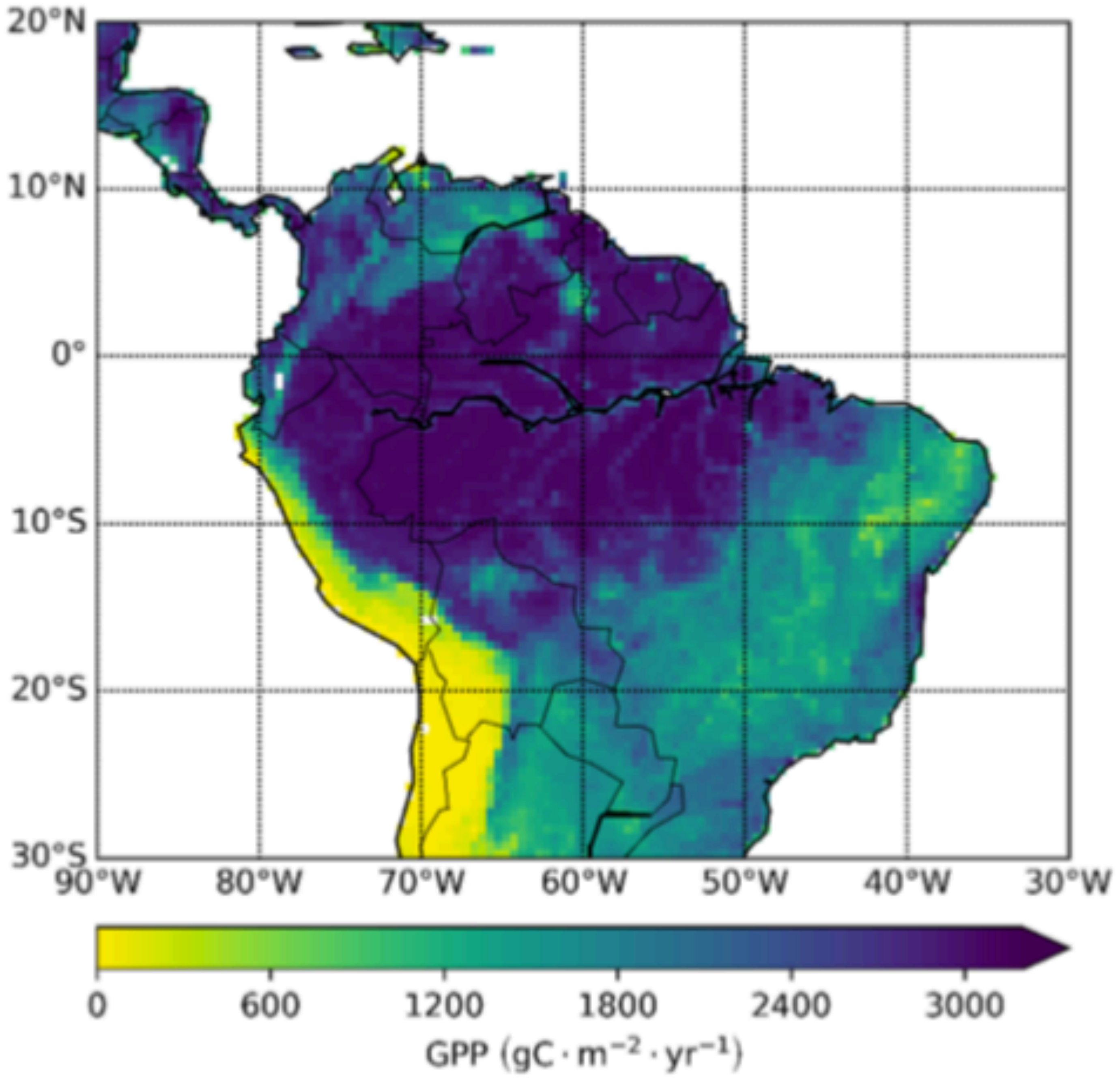
SIF observations

(Koren et al. 2018)



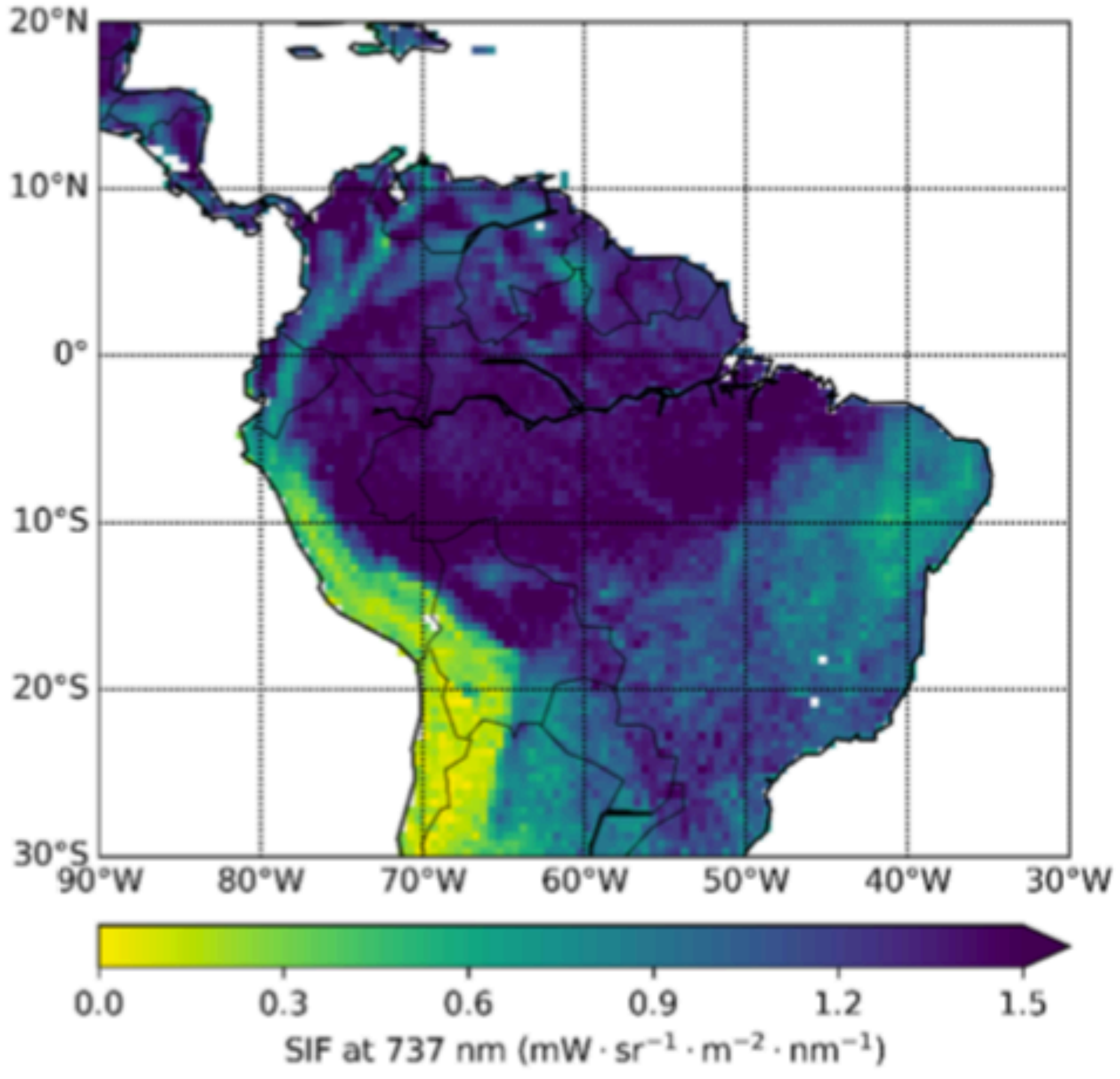
GPP machine learning

(Beer et al. 2010)

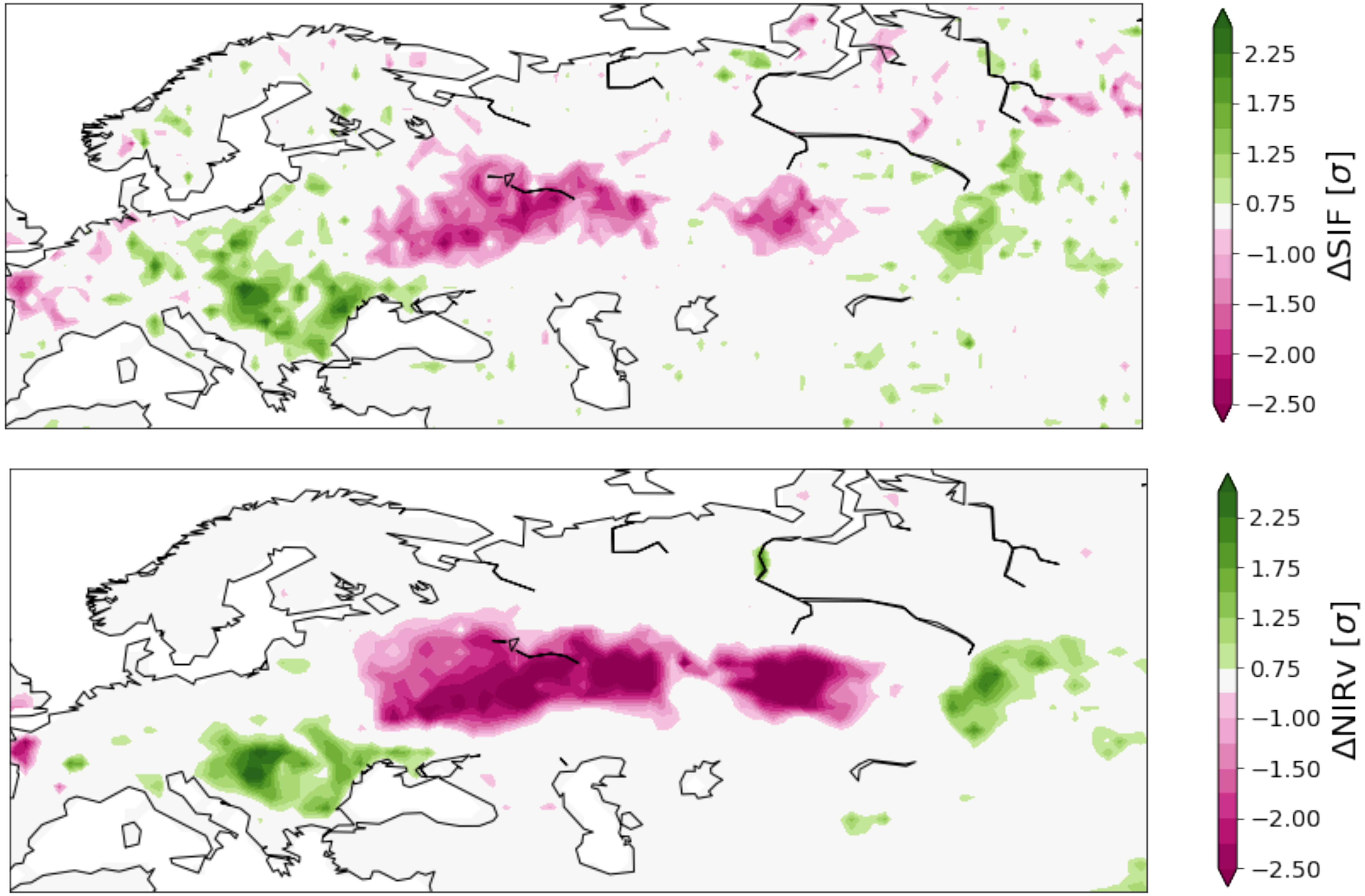


NIRv observations

(Koren et al. 2021)



SIF and NIR$_v$ good proxies for photosynthesis



Large negative anomalies in SIF and NIR$_V$
during Russian drought, July 2010

Proxy datasets

SIF:

- GOME-2A
  (SIFTER v2, KNMI)
- Monthly averages, 2007-2017
- 0.5 x 0.5 deg

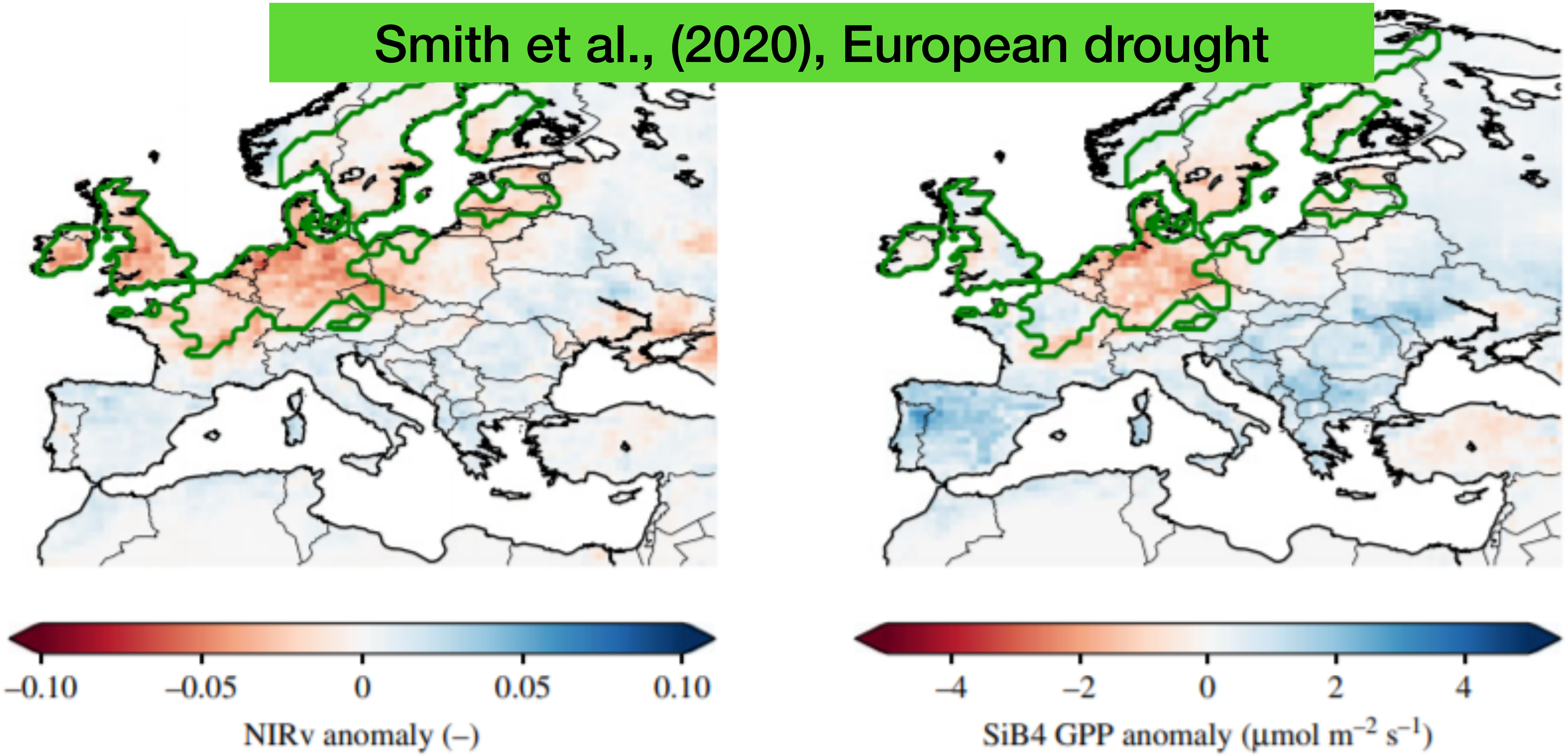
NIR_V:

- MODIS surface reflectance
  (Schaaf and Wang 2015)
- Monthly averages, 2000-2018
- 0.05 x 0.05 deg

Anomalies:

- Grid cell deviation from ecoregion mean seasonal cycle
- Downscaled to 1 x 1 deg

Smith et al., (2020), European drought



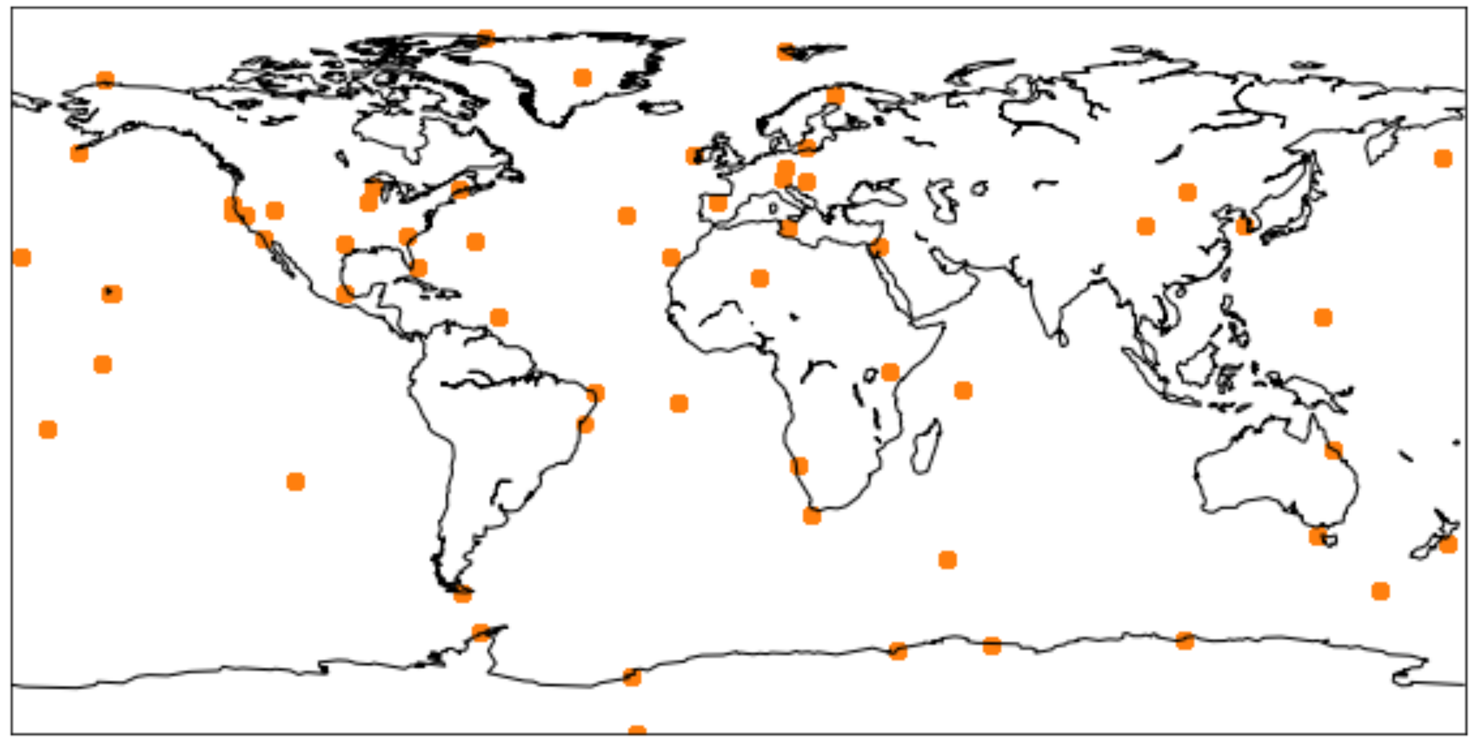
Statistical model as basis for long-window CO_2 inversion

Inspired by Rödenbeck et al., (2019)

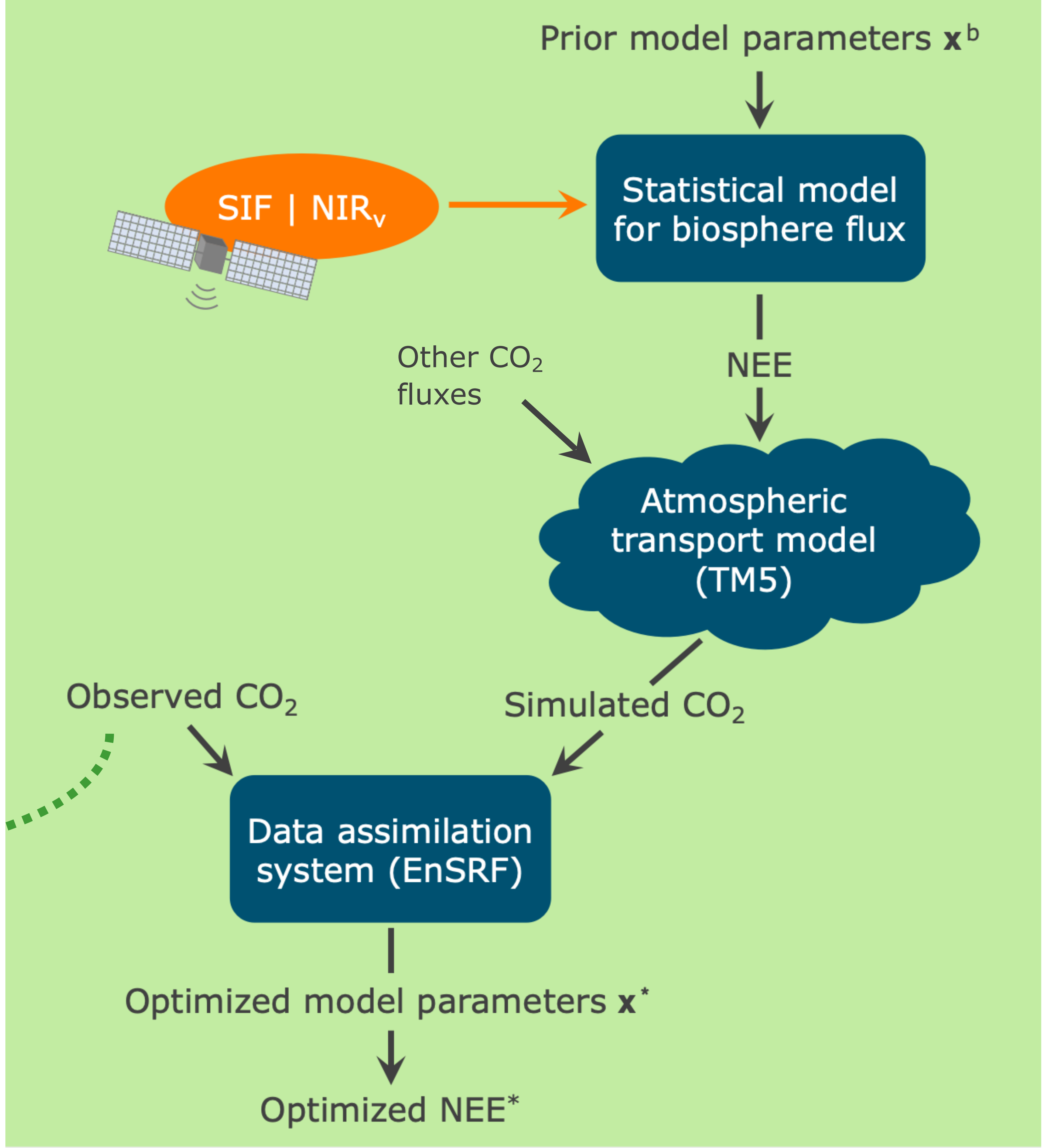
Implementation: New statevector and observation operator in CTE code

First test of system:

- 5-year run: 2009 – 2015 (SIF, NIRv proxy)
  10-year run: 2007 - 2016 (SIF, NIRv proxy)
- 20-year run: 2000 - 2018 (T-proxy)
- 100 ensemble members
- Atmospheric transport on 6x4 deg grid
- Fossil fuel, fire & ocean flux as CTE2018
- Flask measurements, 64 locations:



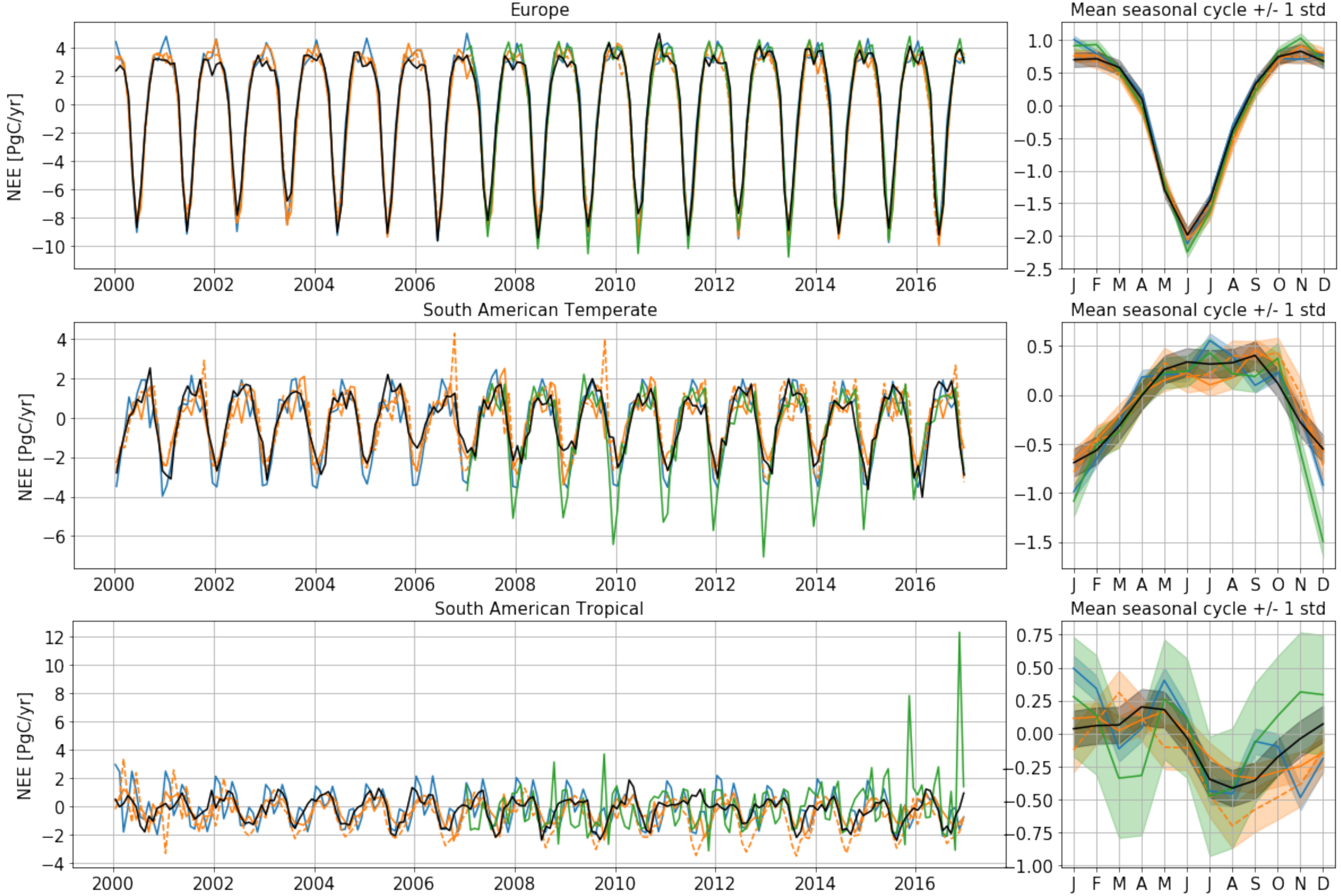
Gerbrand and Liesbeth's work



residuals of CTSF vs CTE

- RMSE of CTSF a bit higher than CTE, but mean bias a bit lower

Good seasonality on TransCom level



Proxy:
Temperature
SIF
NIRv

Preliminary conclusions

Goal: Long-window CO_2 inversion with observed spatiotemporal patterns NEE

New inversion set-up:

- Large reduction computational cost for long-window runs
- Mean seasonal cycle & temporal trend per ecoregion can be approximated with simple statistical function
- T, SIF and NIR_V data can add physical spatiotemporal patterns in NEE field
- Flexible enough to optimize model parameters based on limited set of CO_2 observations

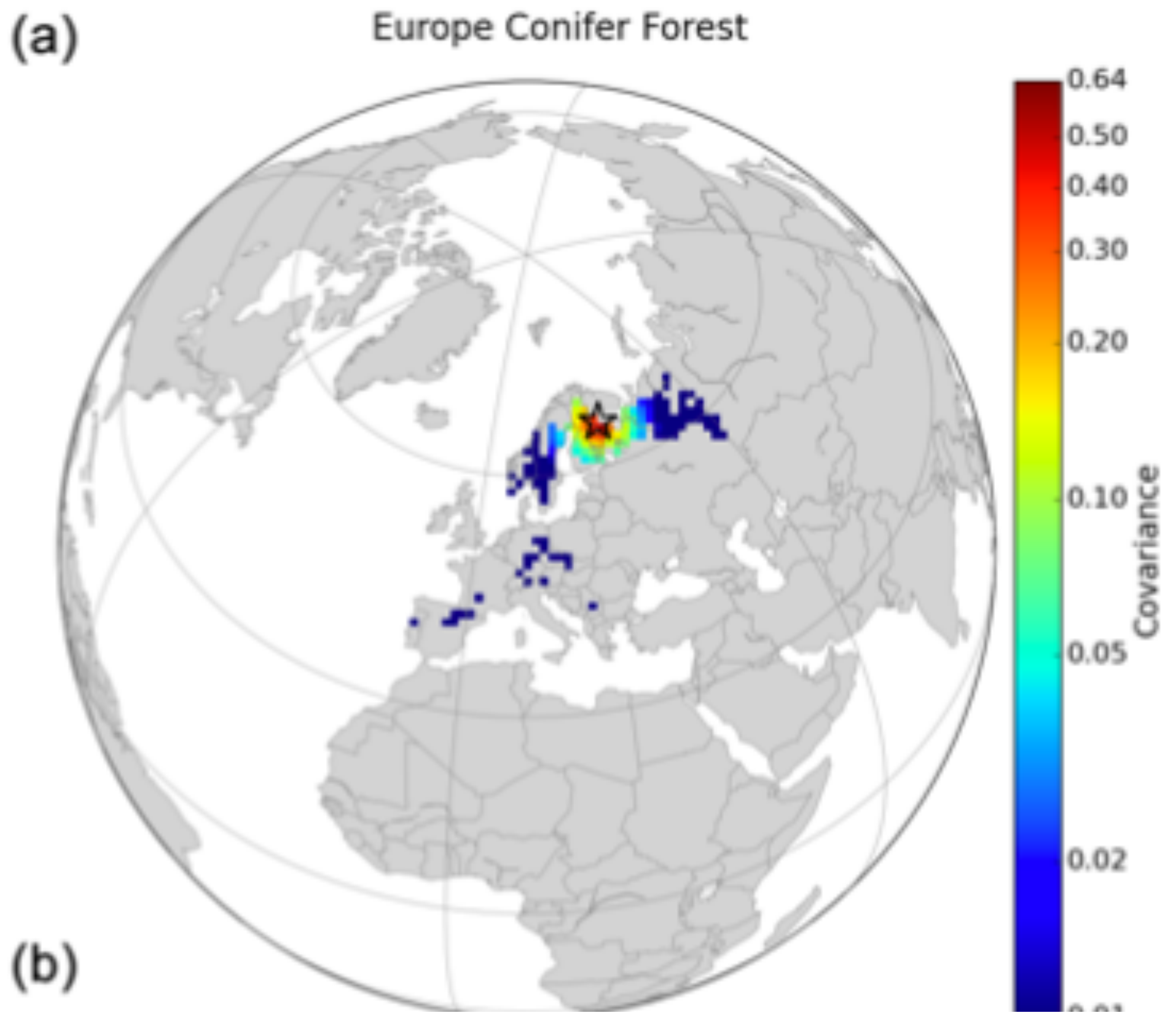
Work in progress:

- Long temporal window runs required to really test potential of approach
- Improve proxy datasets, also test vapor pressure deficit?
- Work on short-window inversions, starting from CTSF posterior

The current CarbonTracker statevector

Correlation between 1x1 grids

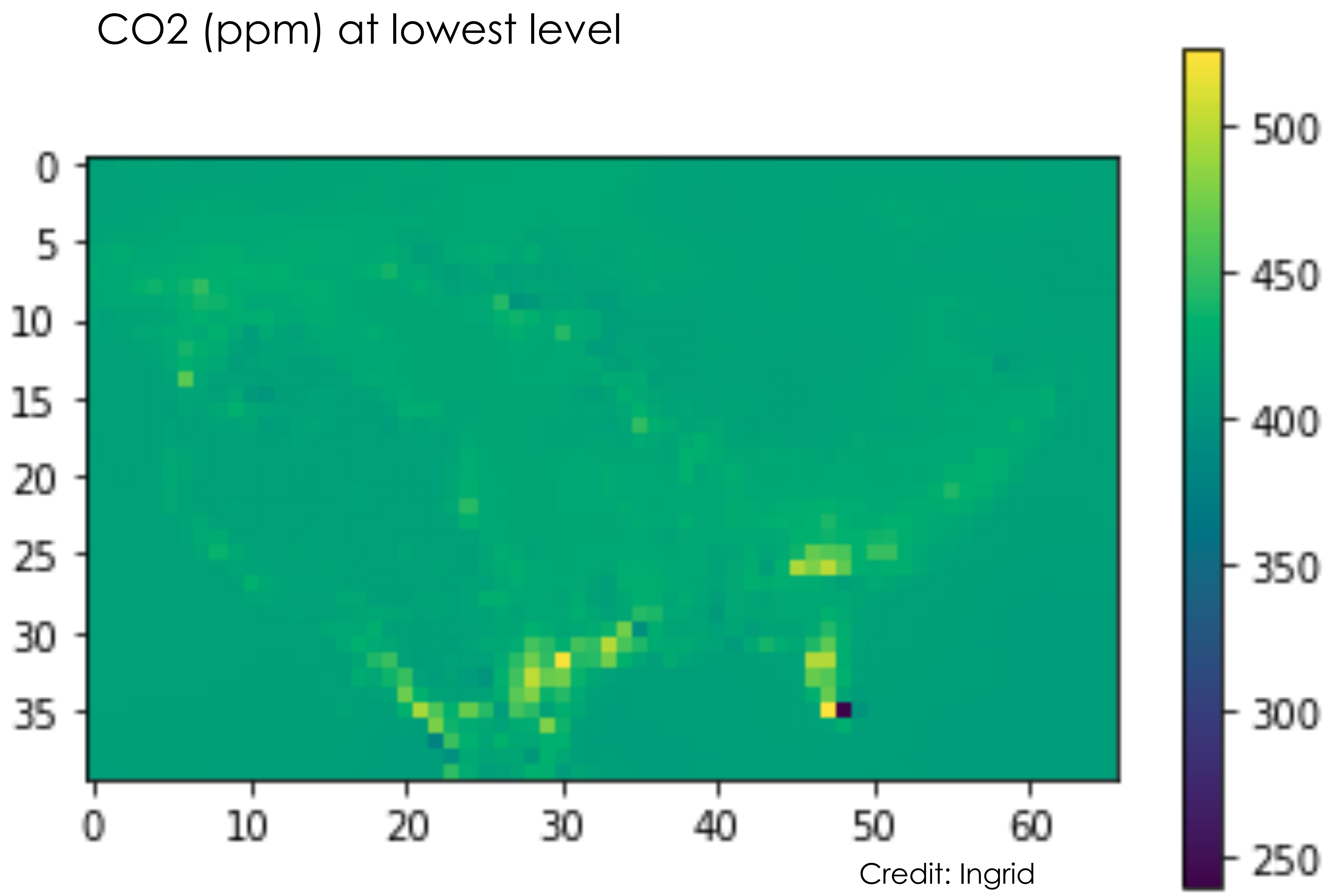
- Per TransCom region, per ecoregion, exponential decay with L=100 km



Van der Laan – Luijkx et al. (2017)

The “Problem”

- Past inspection found unphysical CO2 fields and fluxes
- Large variations on small spatial and temporal scales



Credit: Ingrid

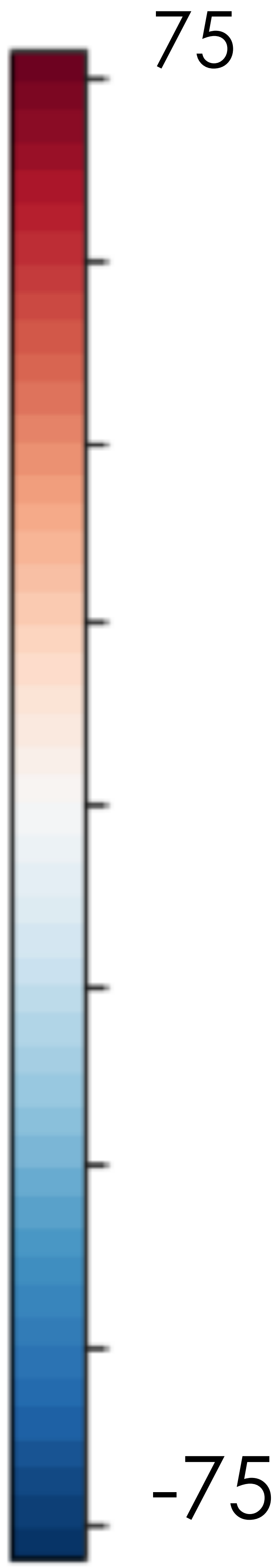
Extreme fluxes get transported vertically

- Now: average bottom 3 layers

Level 0

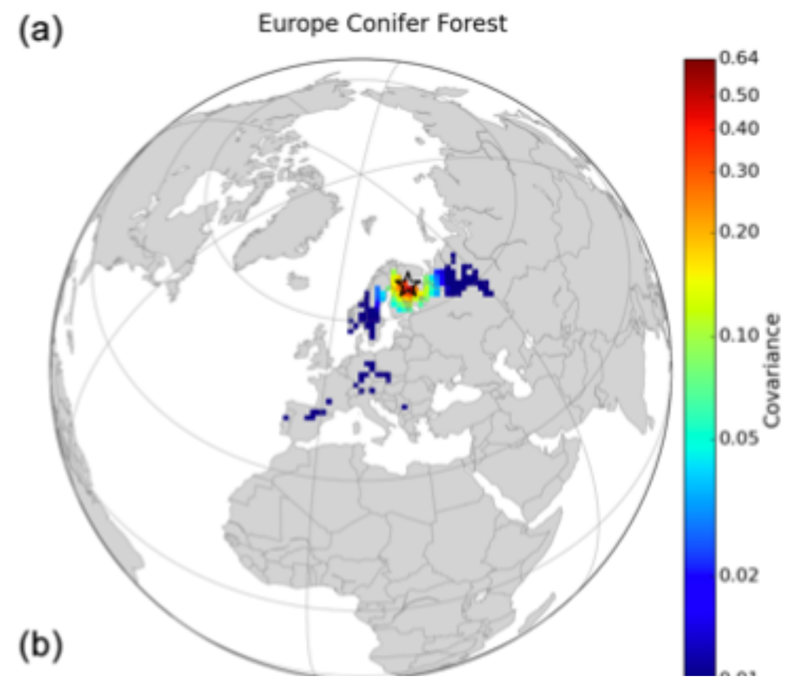
Level 3

CO2_bio (ppm)



Initial idea: smooth fluxes as correlations

- Doesn't change extremes. Why?

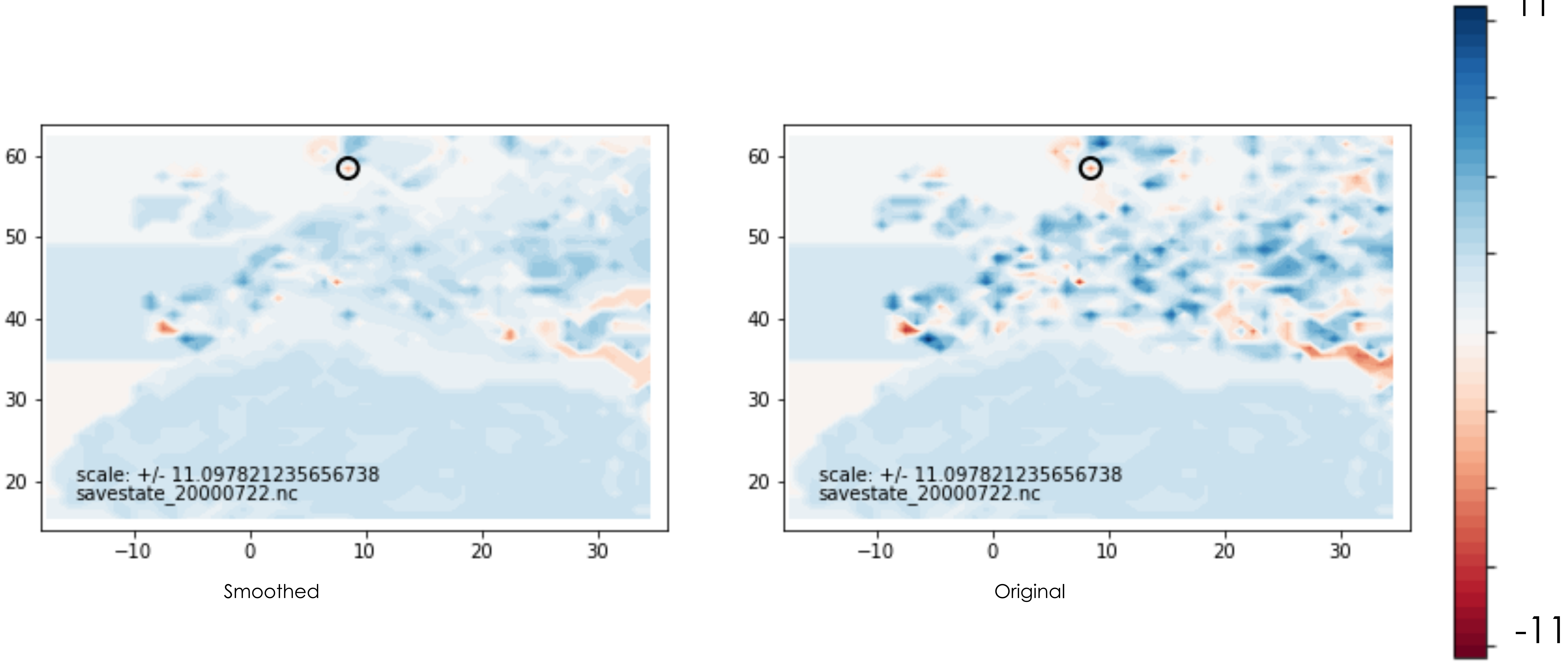


Level 0

Level 3

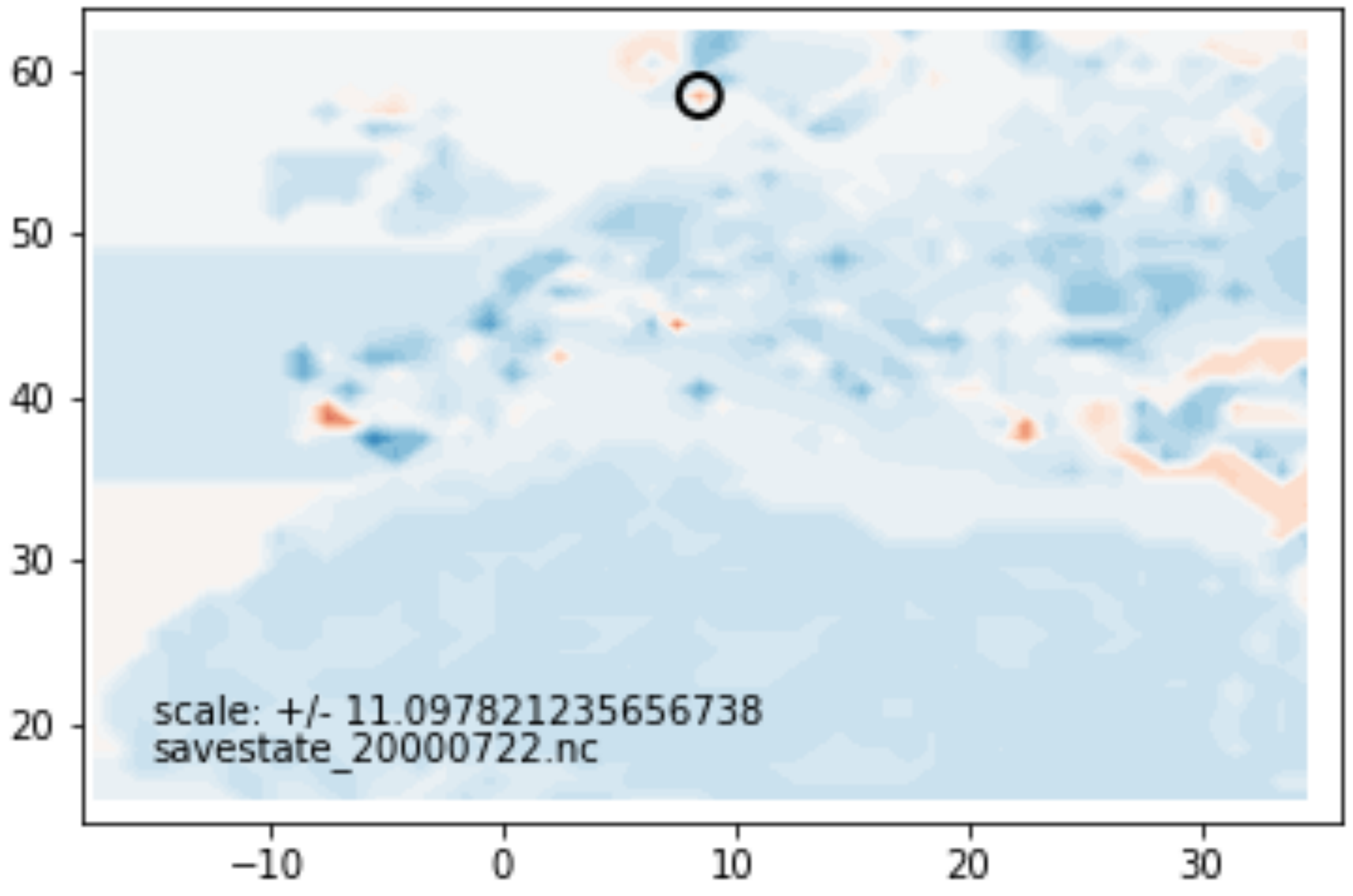
CO2_bio (ppm)

Scaling factor

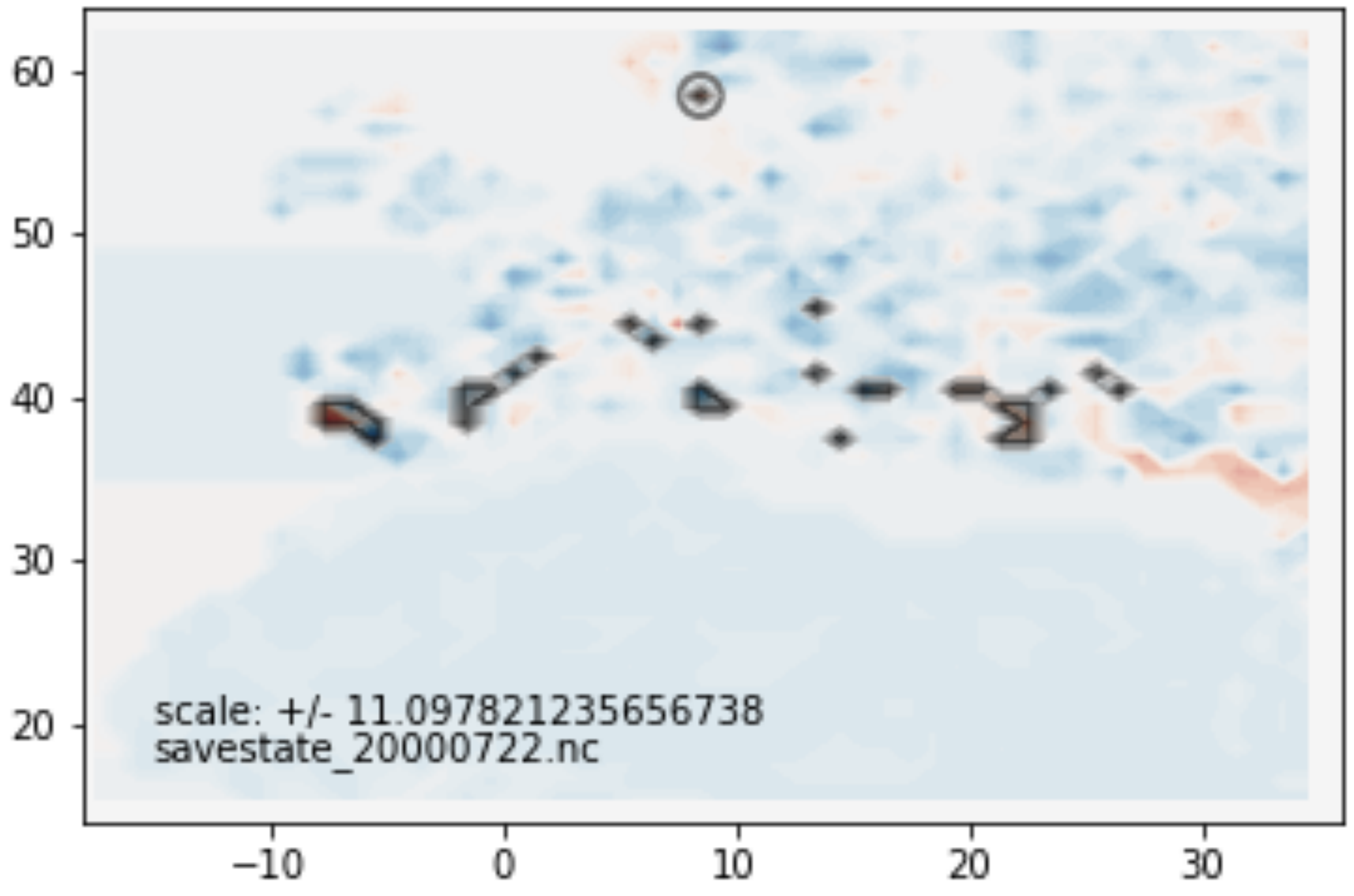


Scaling factor

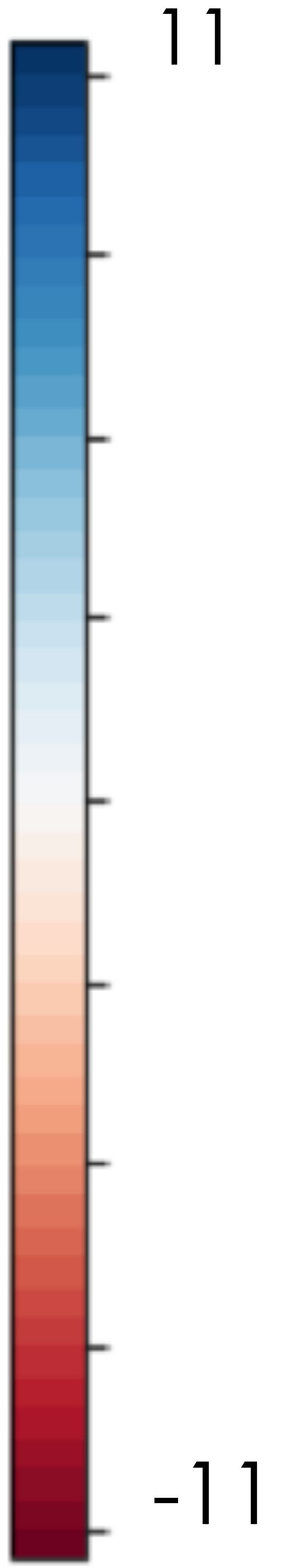
- Small, isolated region



Smoothed



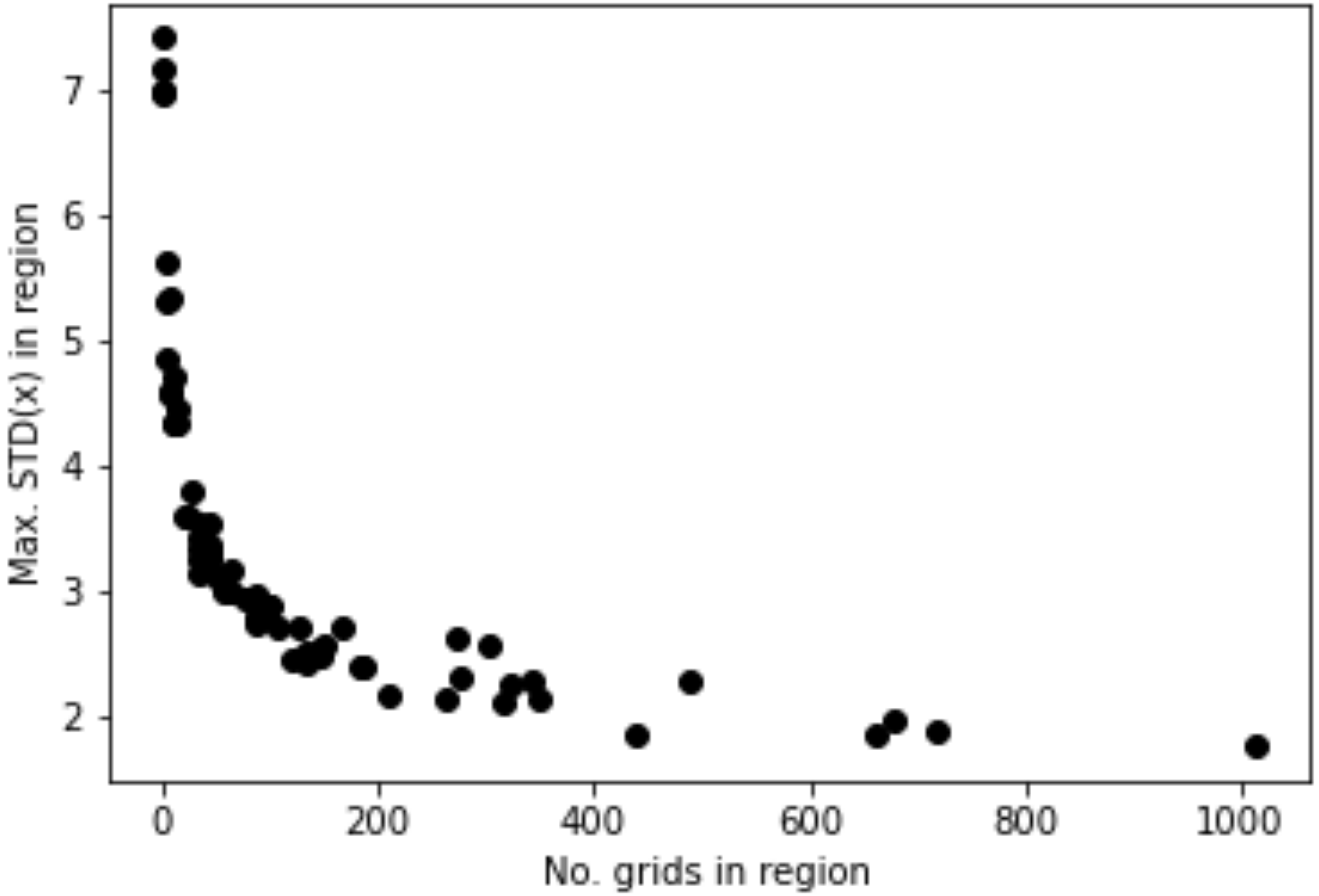
Original



Small regions, high variability

Remco de Kok's work

- Prior errors higher there
- Less constraints from other grid cells
- Smoothing per region will help less here



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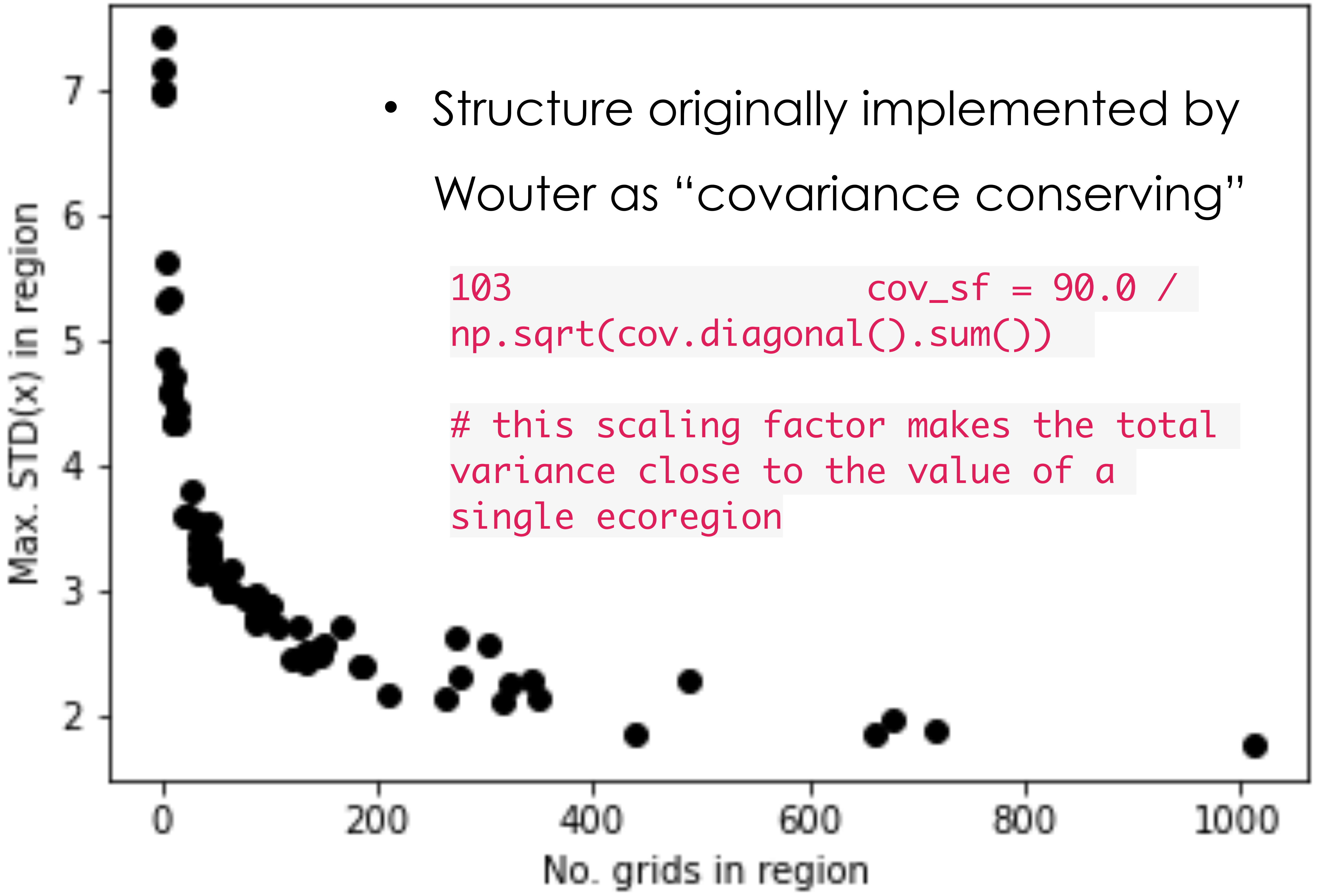

- Structure originally implemented by Wouter as “covariance conserving”

```
103                    cov_sf = 90.0 / np.sqrt(cov.diagonal().sum())

# this scaling factor makes the total variance close to the value of a single ecoregion
```

New inversions (orange)

- Limit prior error for small regions