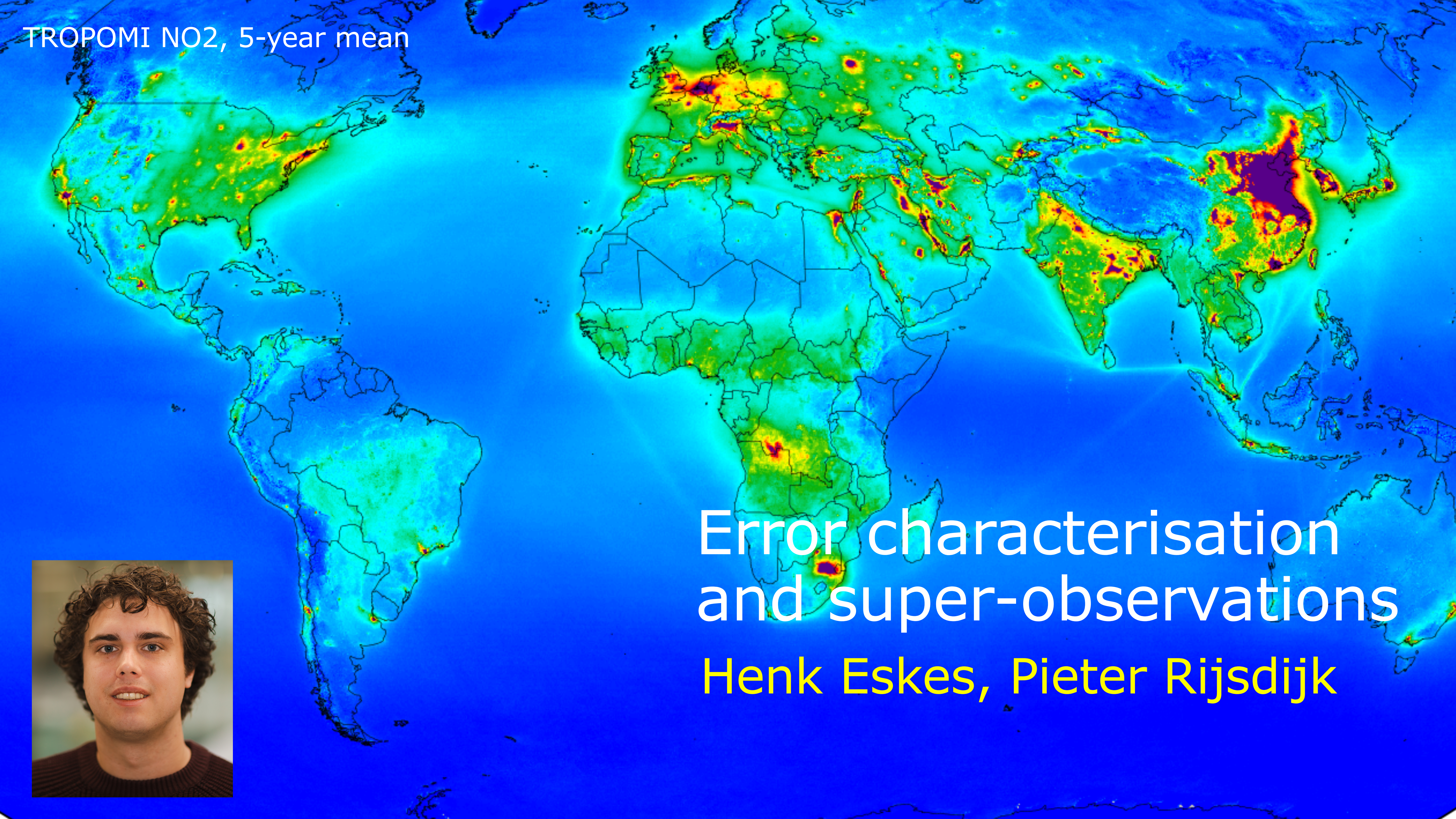


TROPOMI NO2, 5-year mean



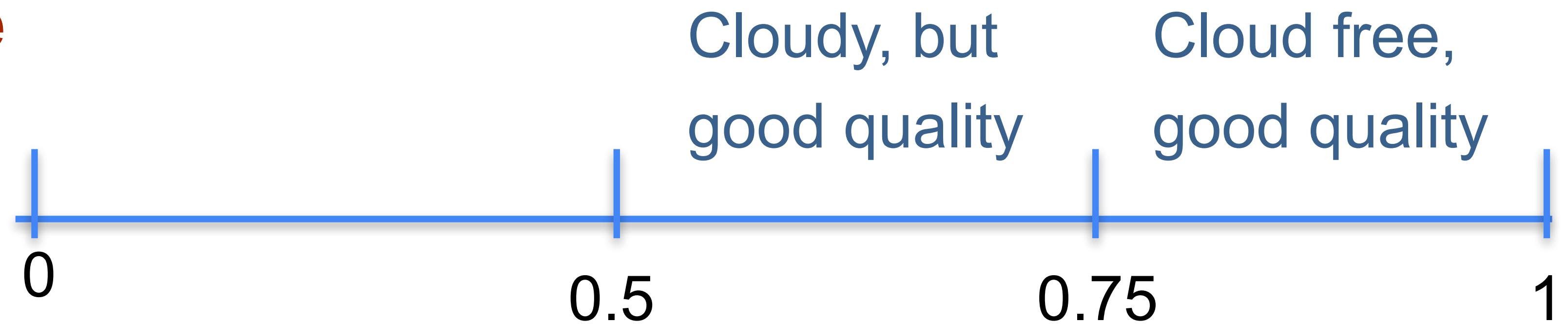
Error characterisation
and super-observations

Henk Eskes, Pieter Rijsdijk



TROPOMI NO2: Use of the data (model validation, assimilation)

Filtering: the qa-value



Make use of averaging kernels ...

- This removes the a-priori dependence

... or apply an a-priori replacement.

- Using high-resolution regional model output - see PUM

$$\mathbf{Ax} = \mathbf{y}$$

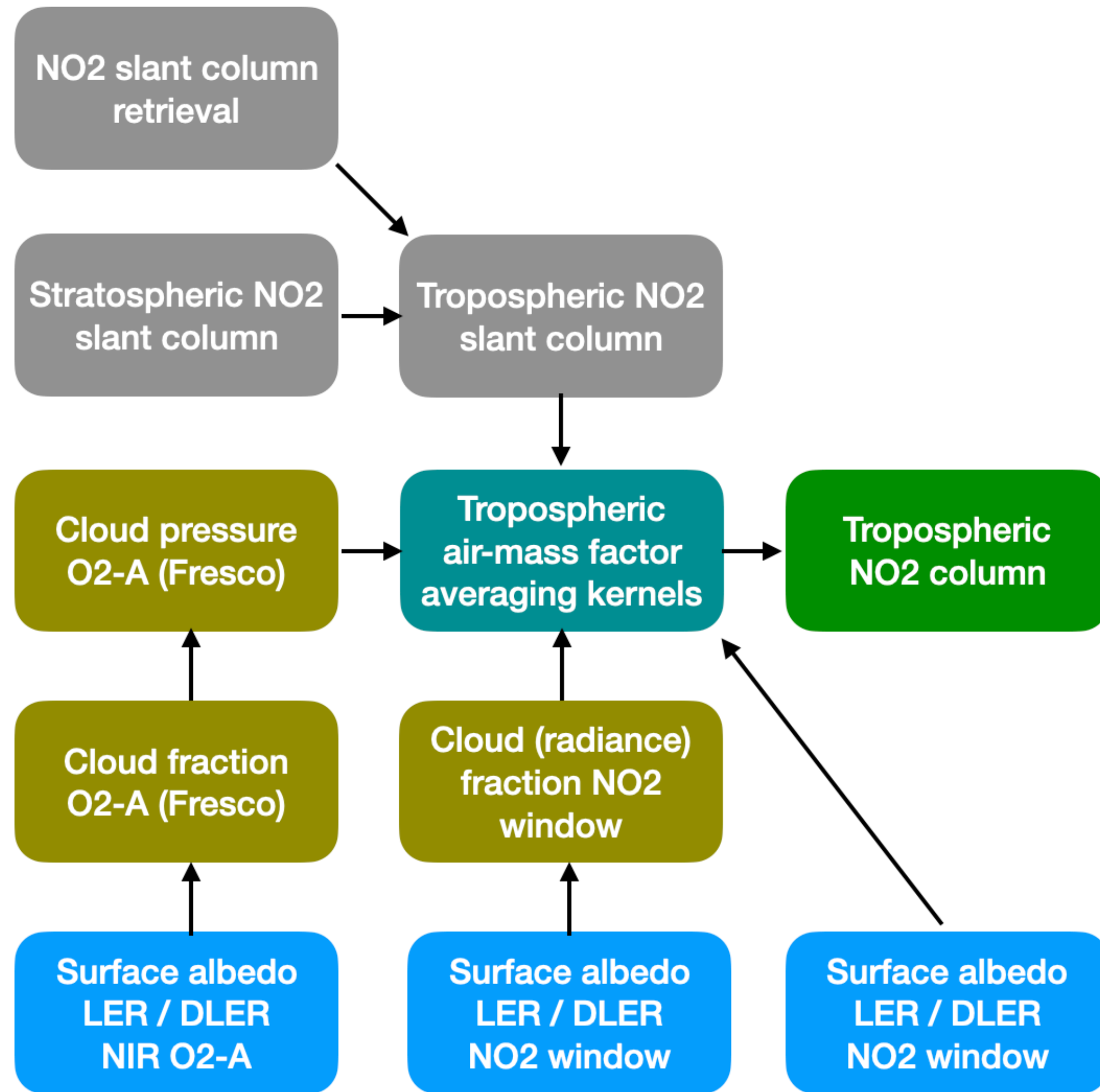
$$N_v^{\text{trop}'} = \frac{M^{\text{trop}}}{M^{\text{trop}'}} N_v^{\text{trop}}$$

$$\mathbf{A}^{\text{trop}'} = \frac{M^{\text{trop}}}{M^{\text{trop}'}} \mathbf{A}^{\text{trop}}$$

$$M^{\text{trop}'} = M^{\text{trop}} \sum_l A_l^{\text{trop}'} x'_{m,l} / \sum_l x'_{m,l}$$

Douros et al., GMD 2023, 10.5194/gmd-16-509-2023

TROPOMI NO₂ retrieval: Error estimate



Contributions to uncertainty from:

- Measurement noise and slant column uncertainty
- Stratosphere/troposphere split
- Surface albedo (UV-Vis, NIR)
- Cloud fraction (aerosol)
- Cloud pressure (aerosol)

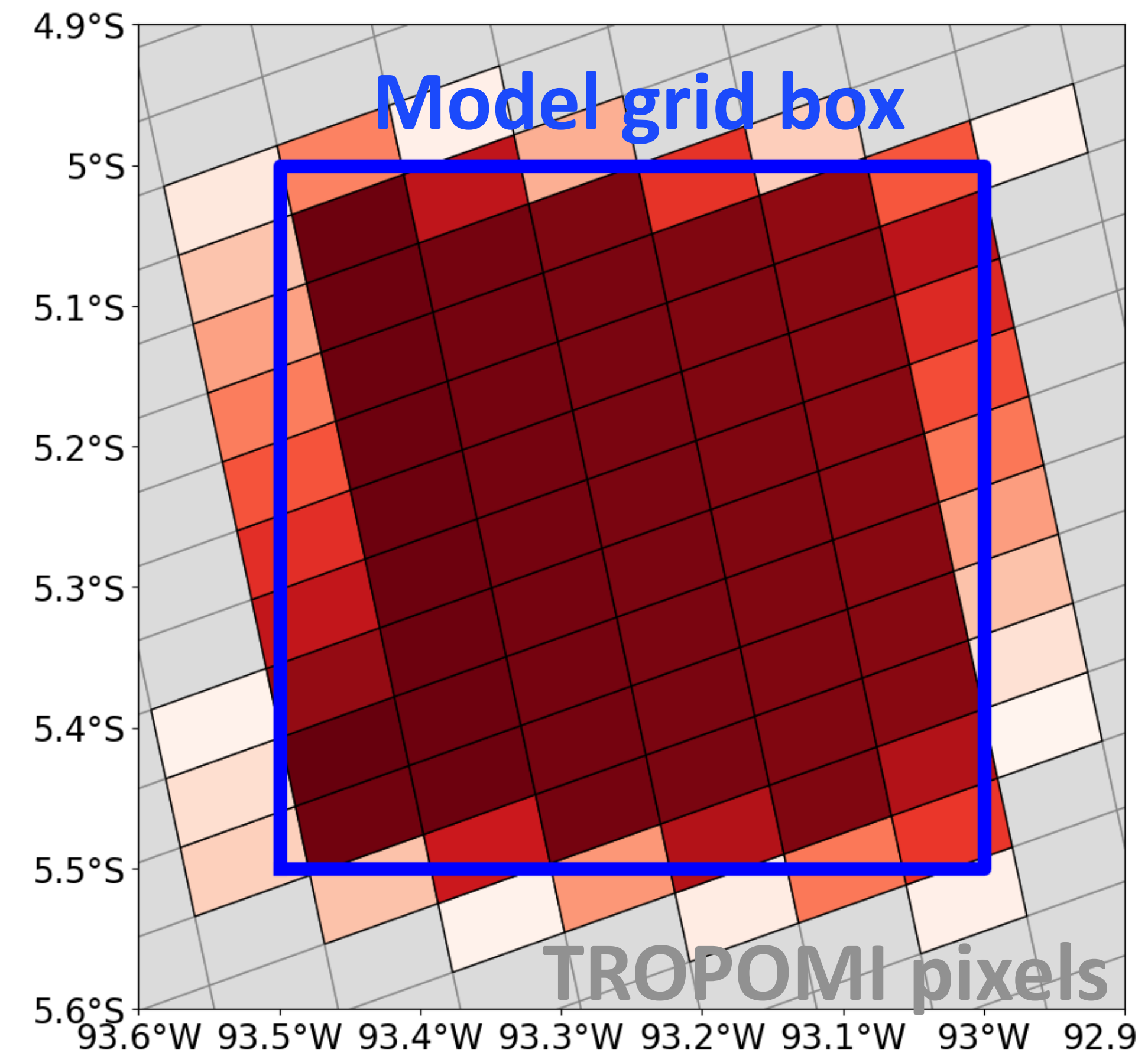
But no information provided on error correlations between (nearby) observations

Superobservations: mitigate resolution mismatches

Construct one effective observation from all individual satellite pixels overlapping a model grid cell
(Instead of comparing with individual obs)

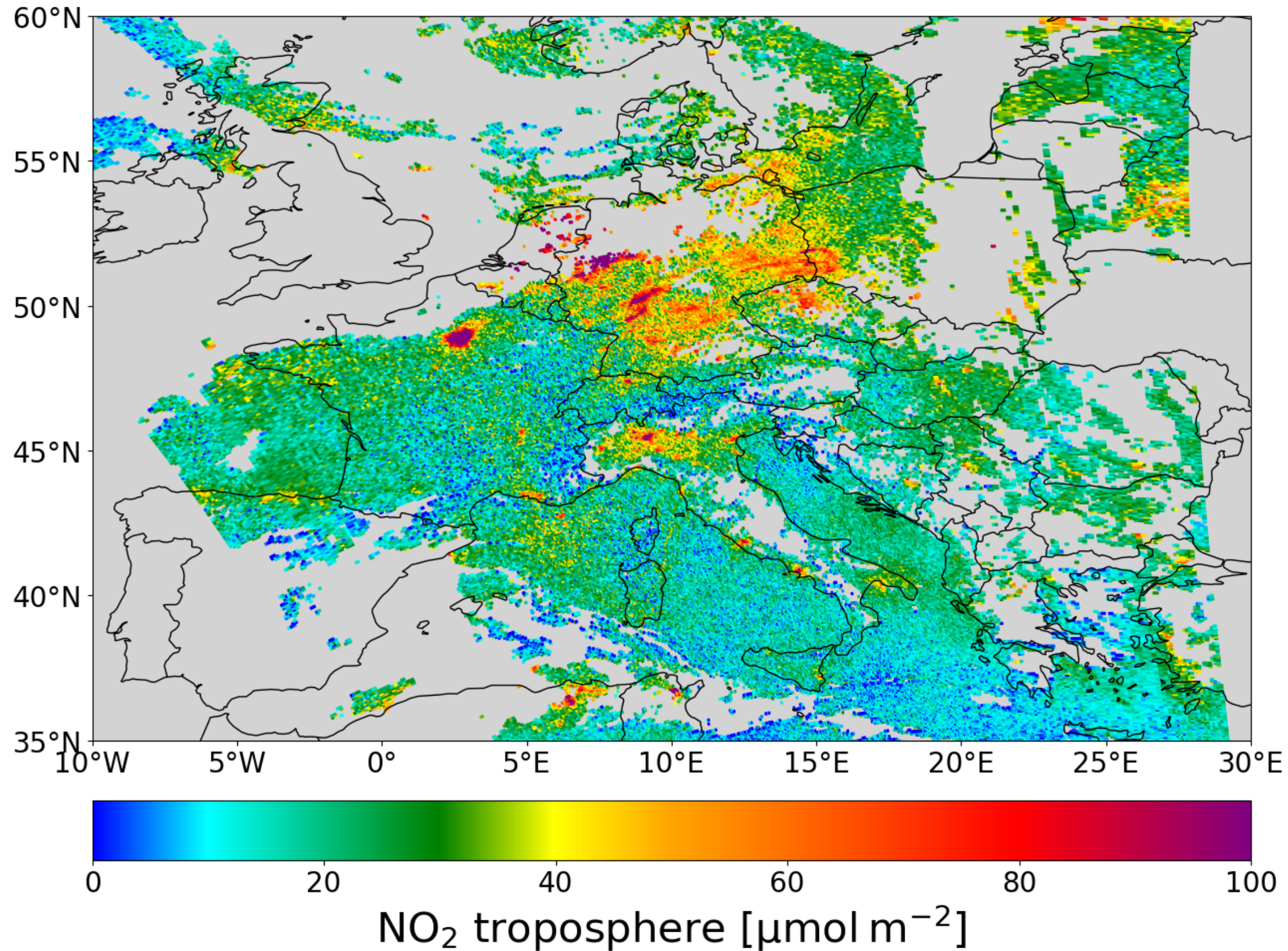
Advantages:

- Computationally very efficient
- Use all satellite information at model scale
- Avoid biases (sat error scaling with column)
- Allow (partial) treatment of
 - Spatial error correlations between obs
 - Representativity errors

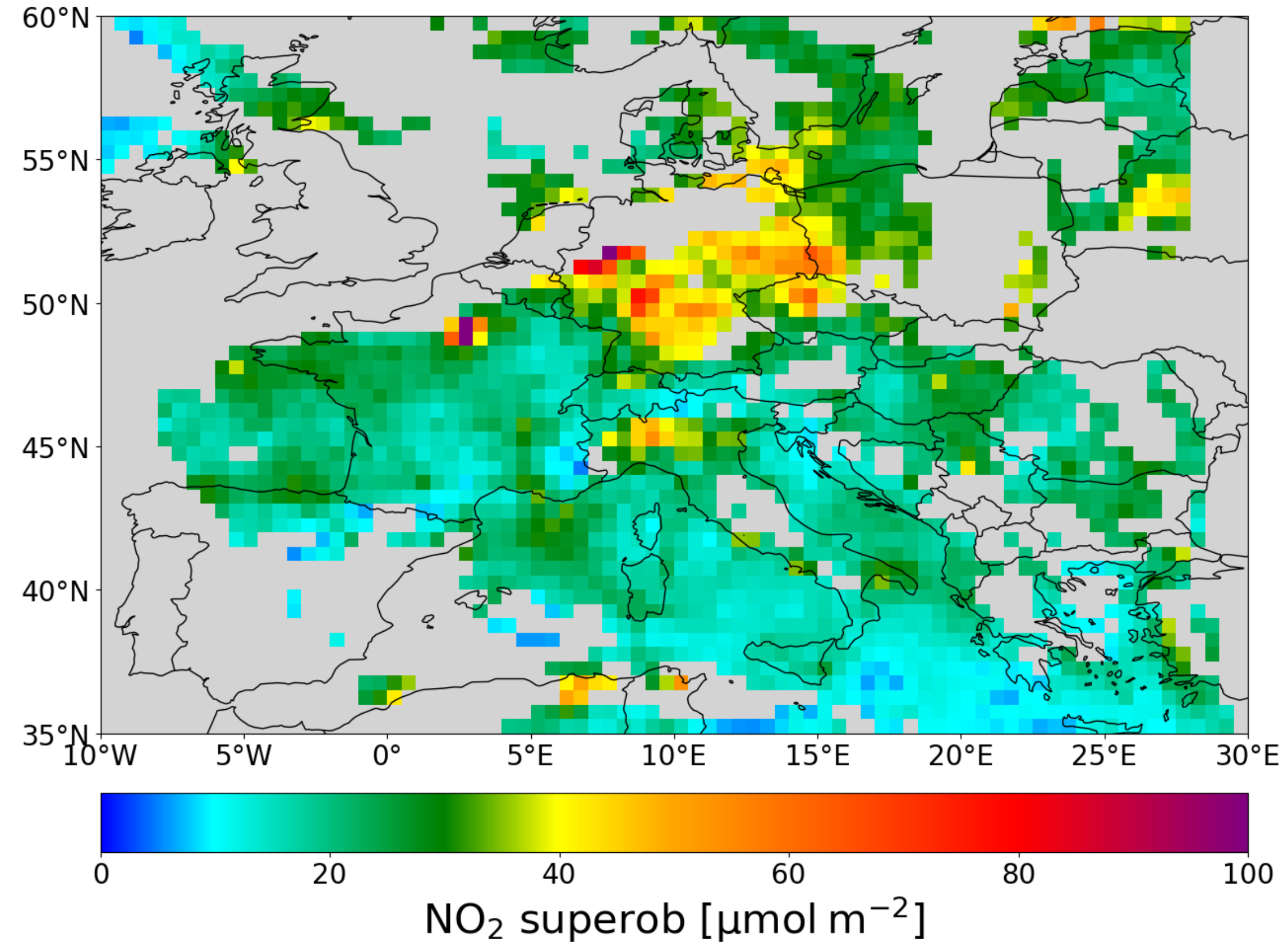
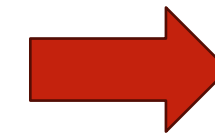


0.5 x 0.5 degree model

Superobservations: mitigate resolution mismatches



TROPOMI NO₂, full resolution



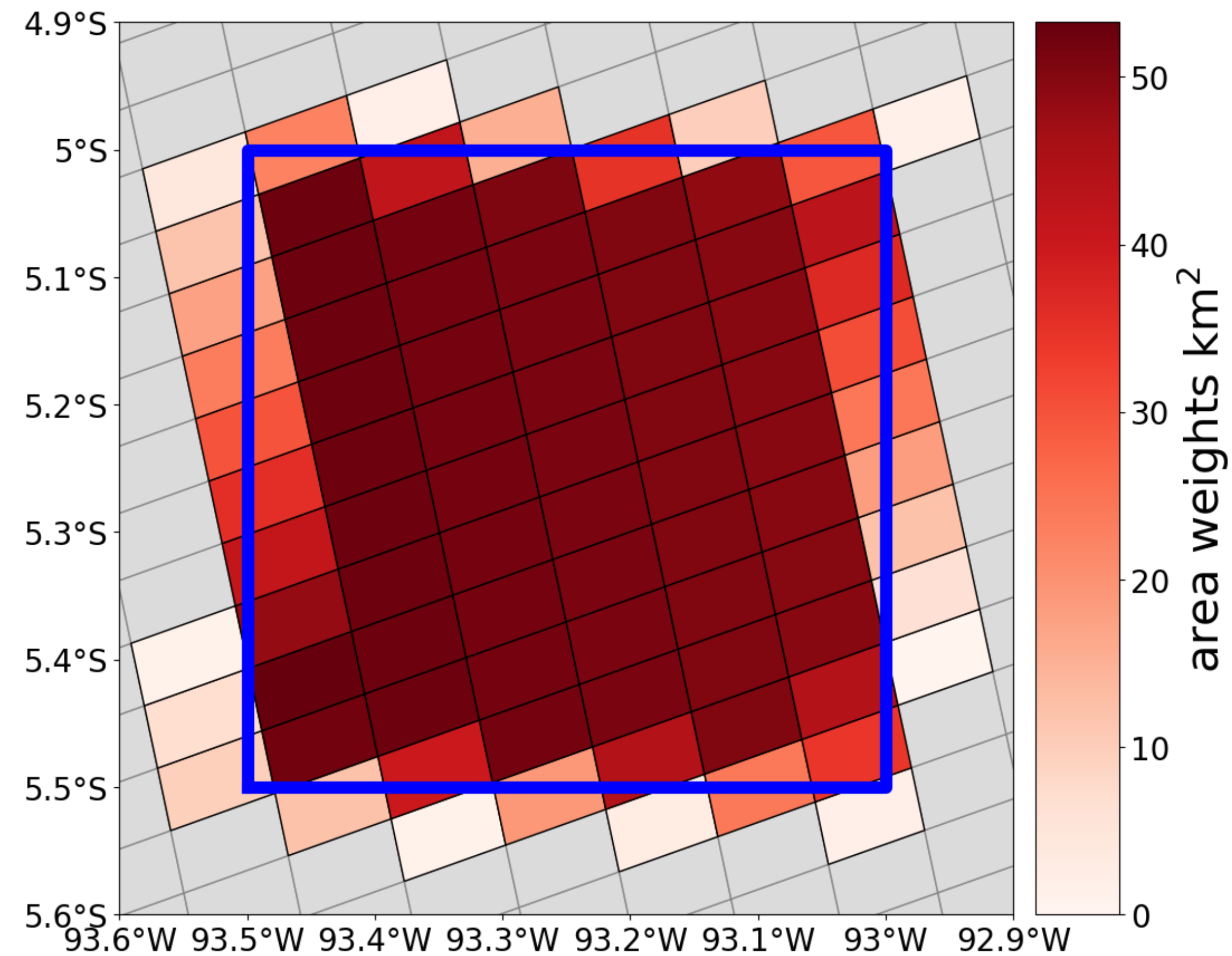
TROPOMI NO₂, superobservations
0.5 x 0.5 degree model

Constructing superobservations

Tiling principle

Weight equal to the **overlap** between satellite footprint and model grid cell

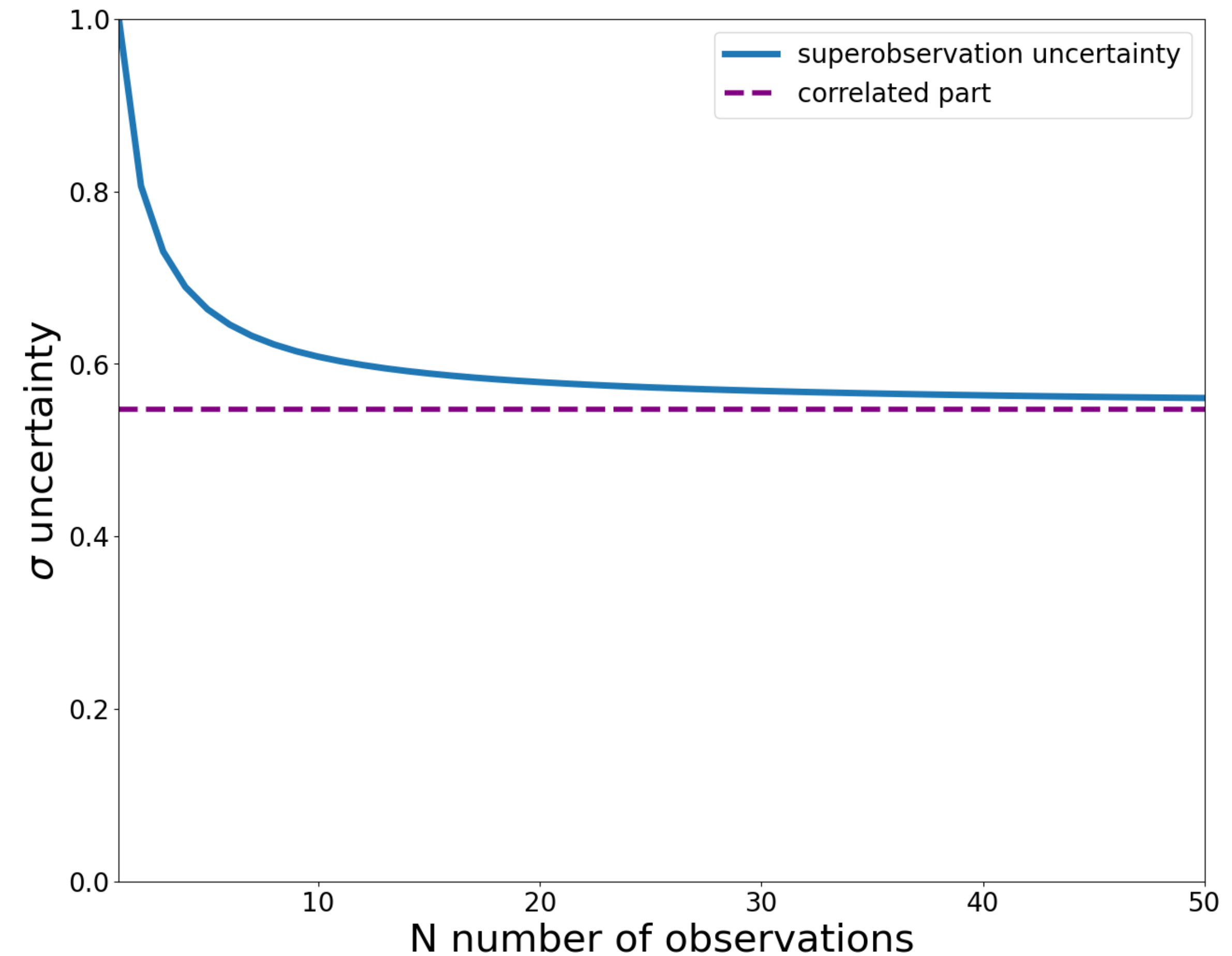
Averaging kernel is averaged with same weights






Superobservation error: Inter-pixel error correlations

Superobservation error as sum of uncorrelated and correlated part, modelled with single correlation factor “c”

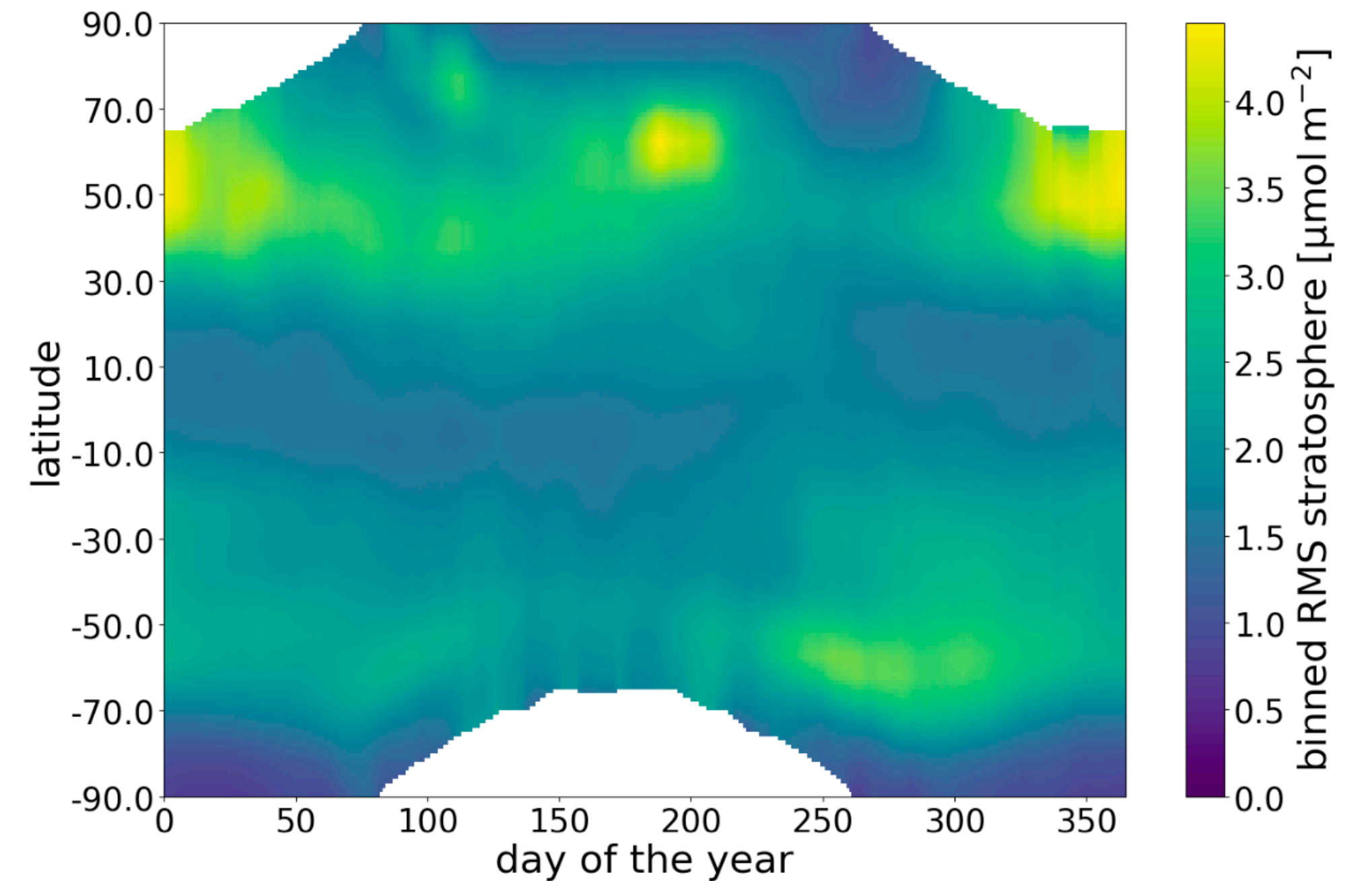
$$\sigma_{obs}^2 = (1 - c) \sum_{i=1}^N \tilde{w}_i^2 \sigma_i^2 + c \left(\sum_{i=1}^N \tilde{w}_i \sigma_i \right)^2$$



Inter-pixel error correlations

Error contribution	Correlation
Stratosphere-troposphere separation	
Air-mass factor (cloud fraction, pressure, albedo, aerosol)	
Slant column	

Stratospheric error update

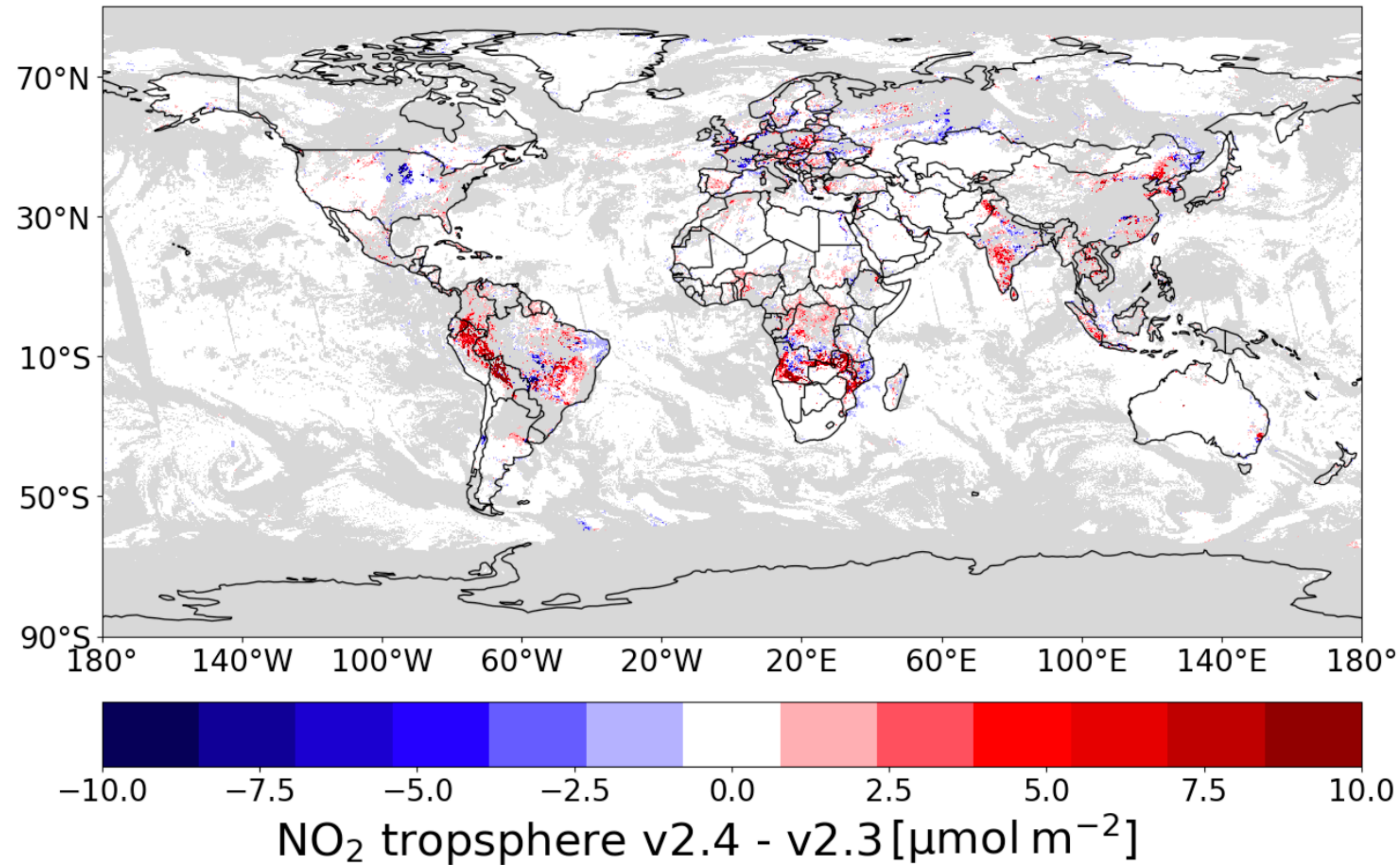


Derived from O-F statistics

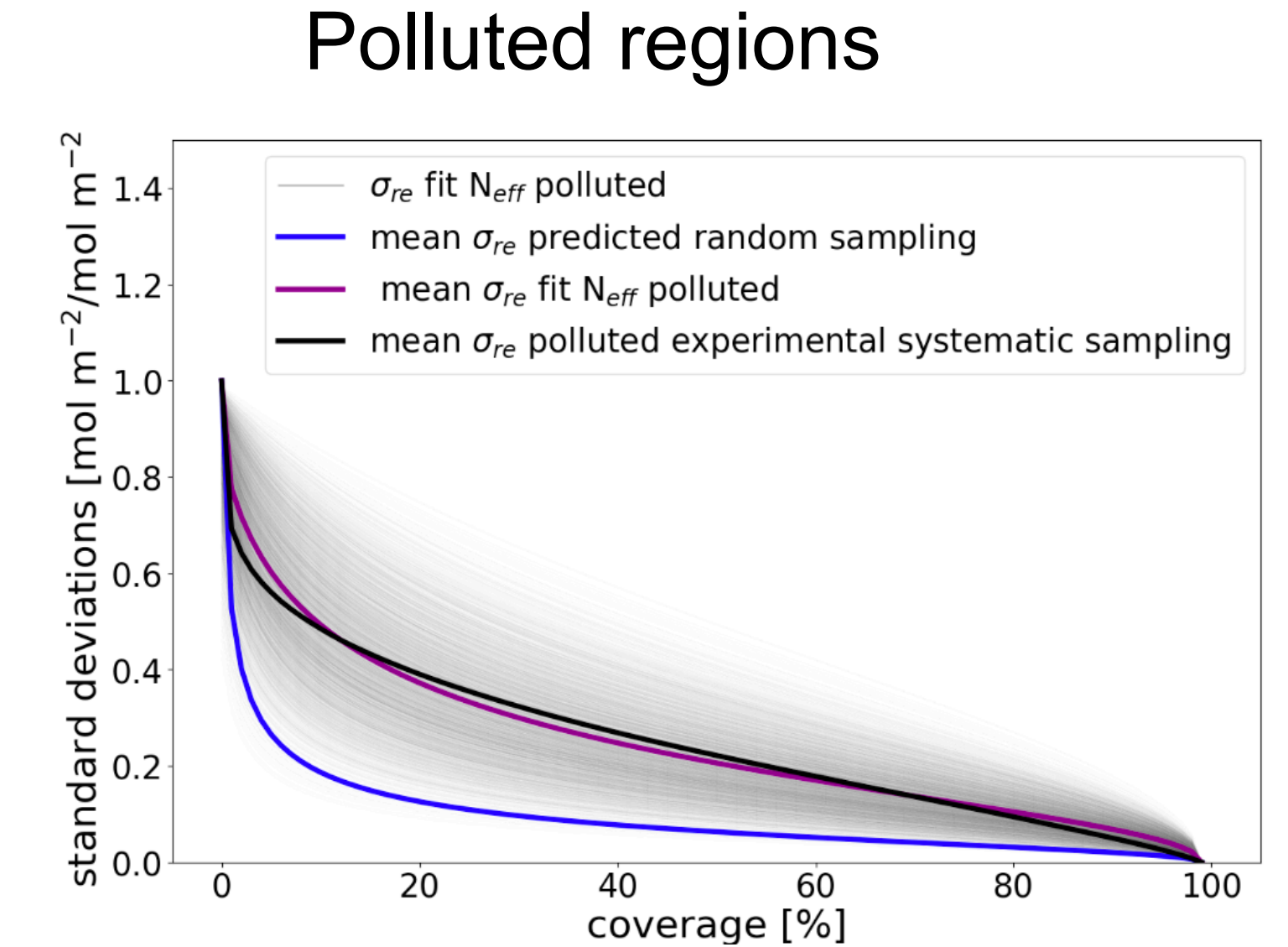
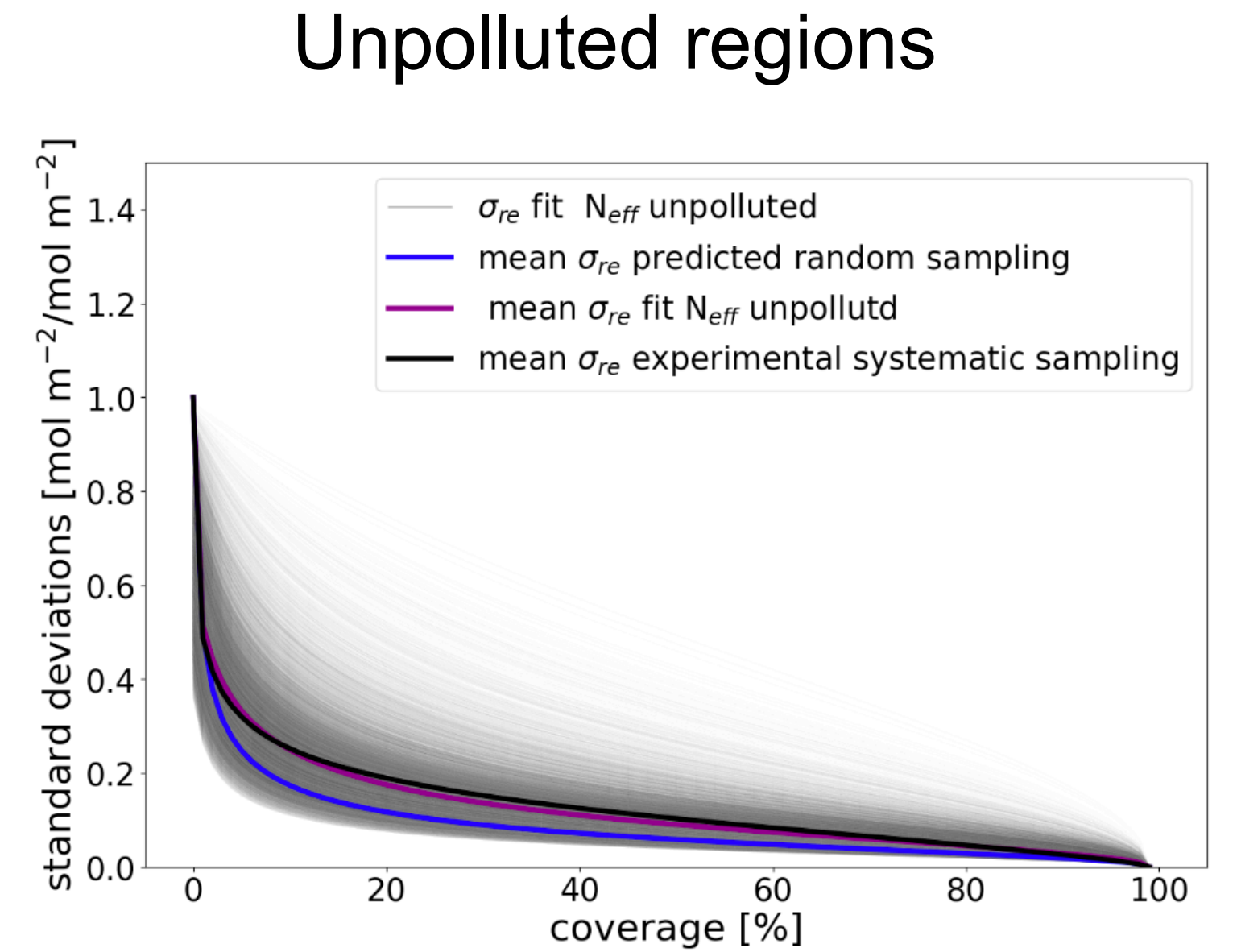
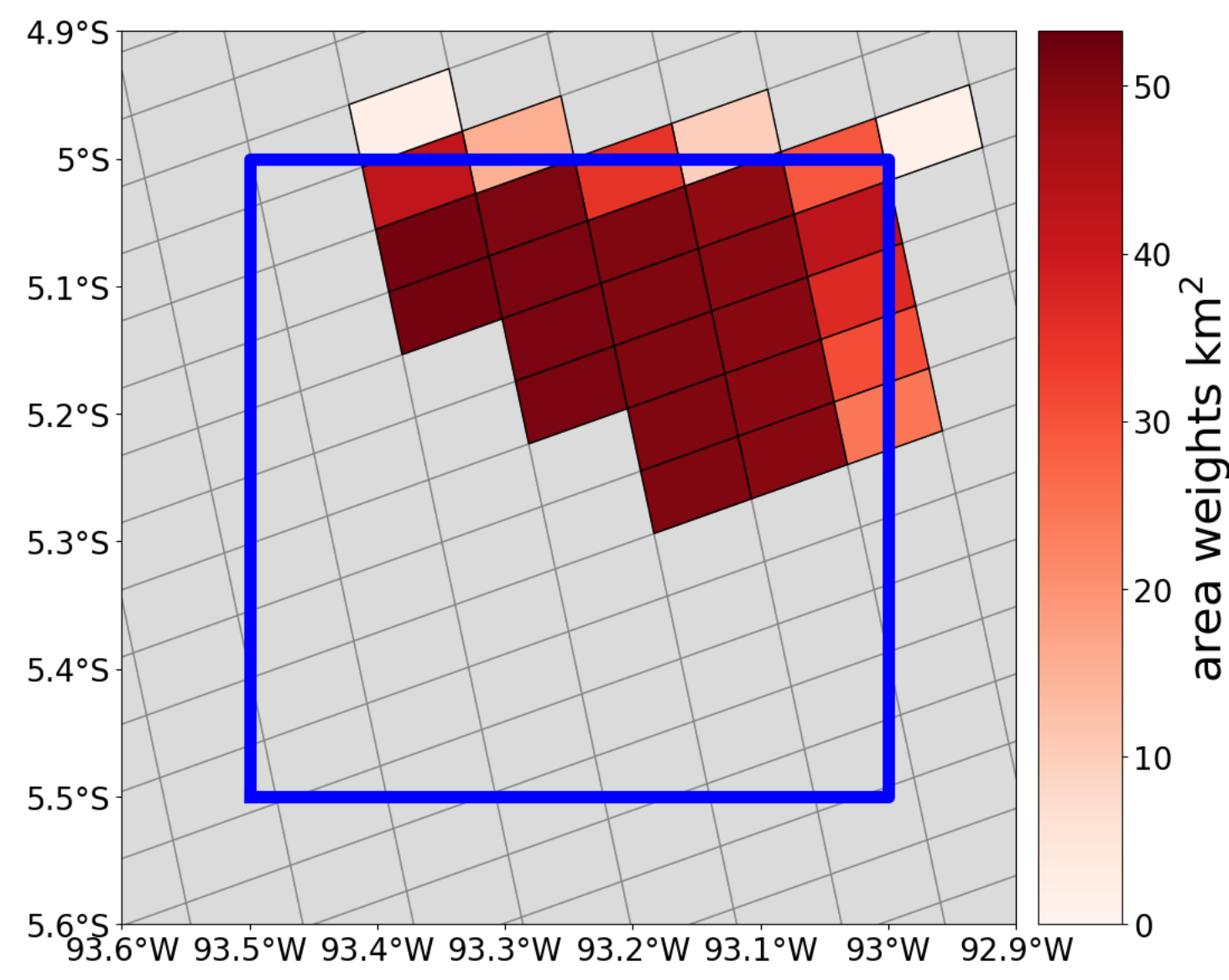
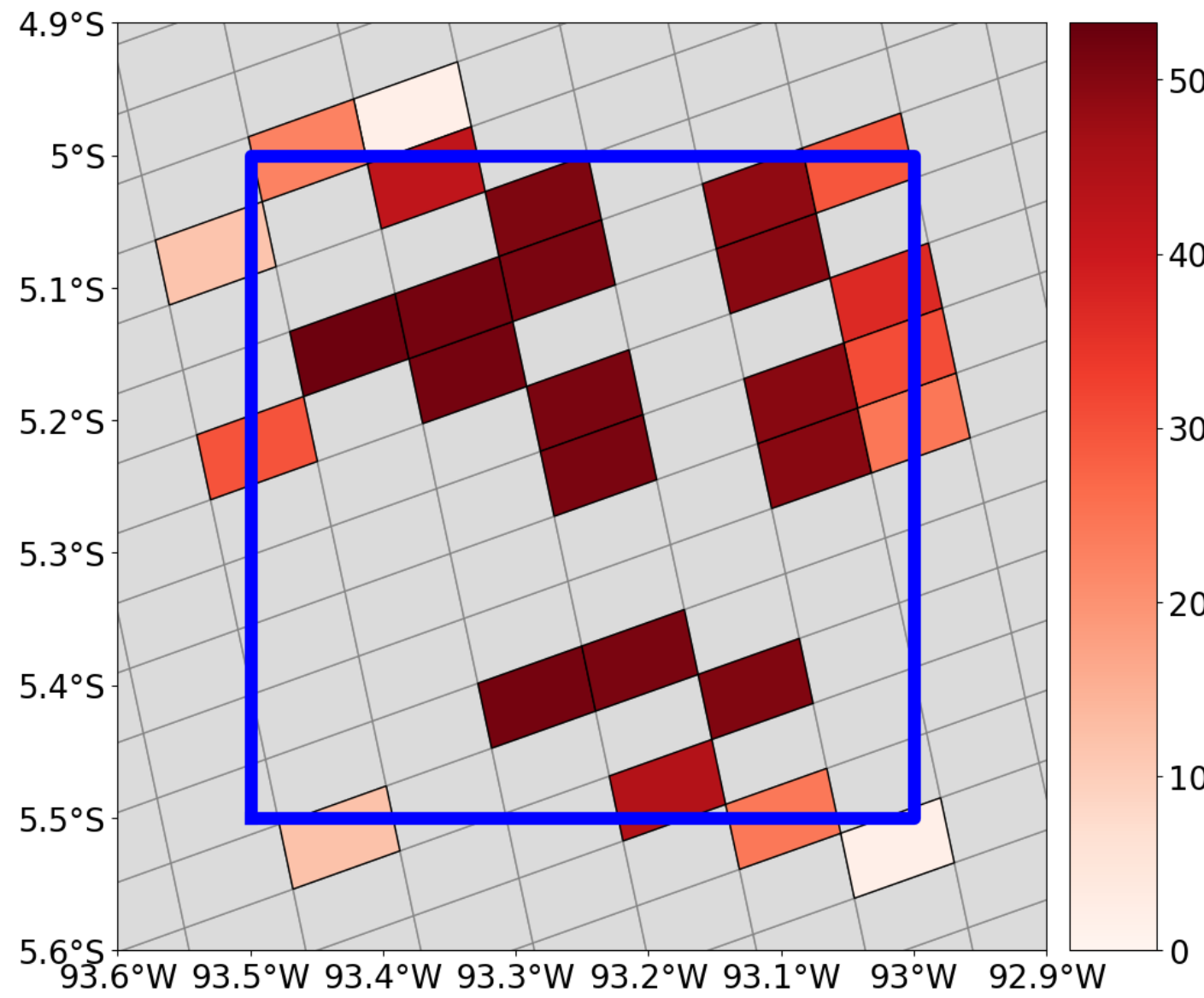
Air-mass factor error correlations

TROPOMI v2.4 and 2.3 differ by the albedo dataset used, influencing cloud fraction, pressure and direct AMF calculation.

Assumption:
spatial correlation v2.4 - v2.3
representative of
spatial error
correlation length scale



Representation error

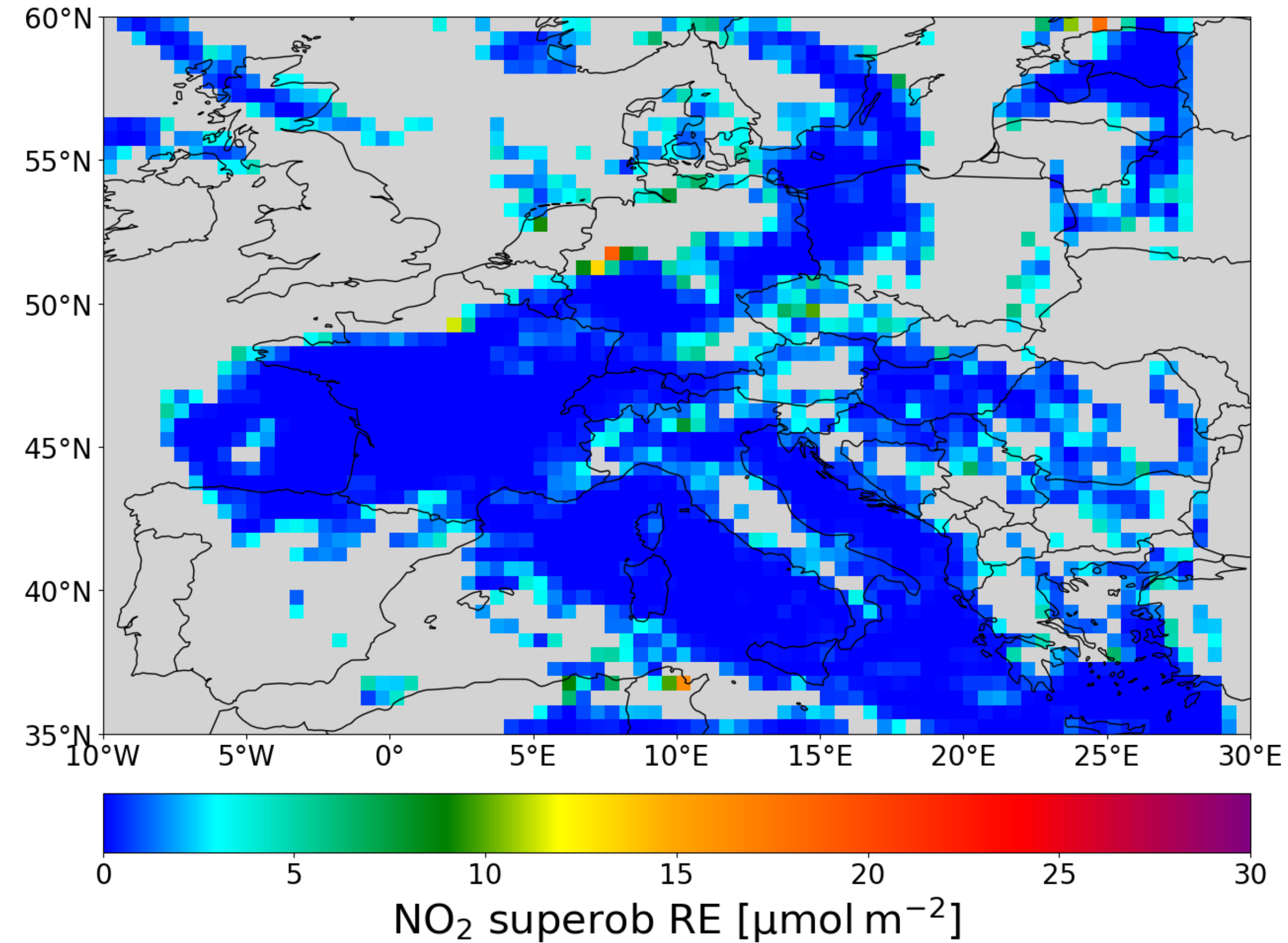


Detailed study of effect of partial cloud cover

- Random cloud cover vs cloud field (latter implemented)
- Polluted regions show larger relative error than unpolluted regions
- Representation error = variability within gridcell * coverage-dependent factor

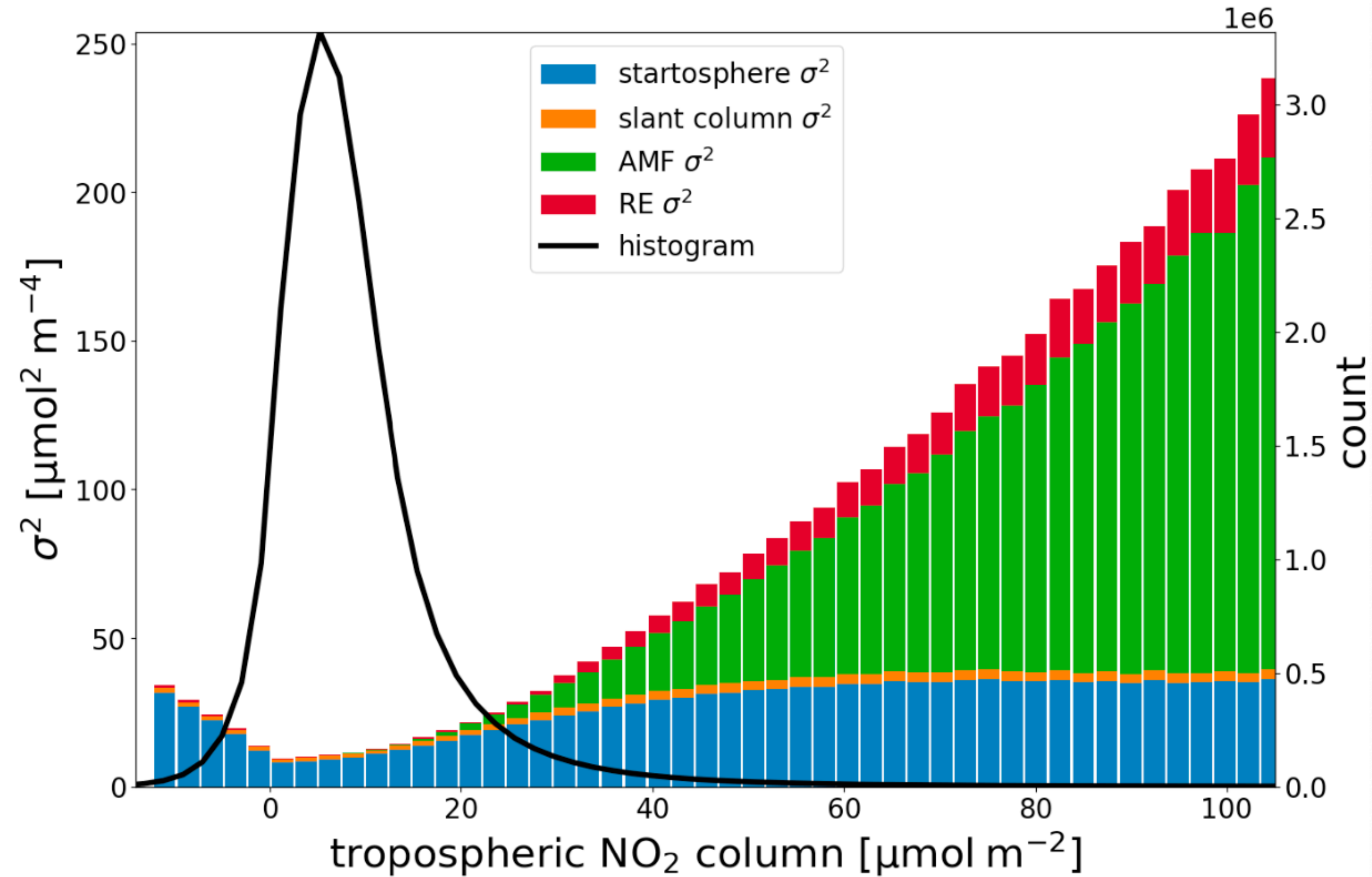
Representation error

Especially important / large
at the edges of the cloud fields



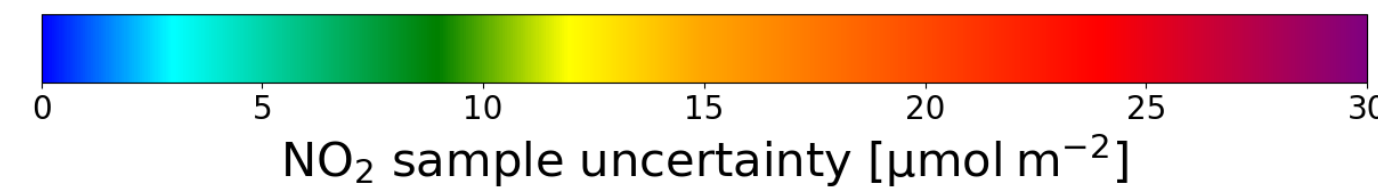
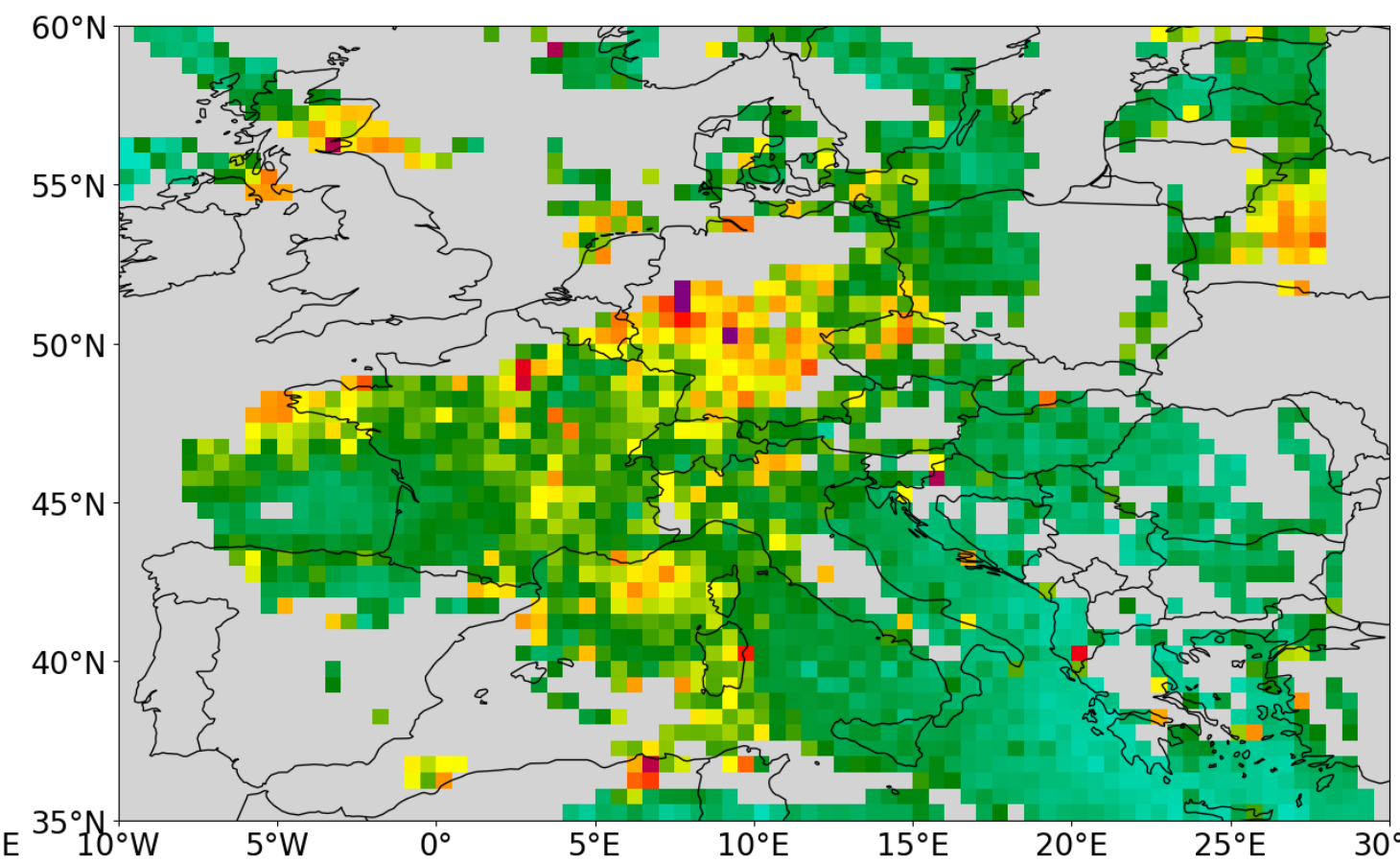
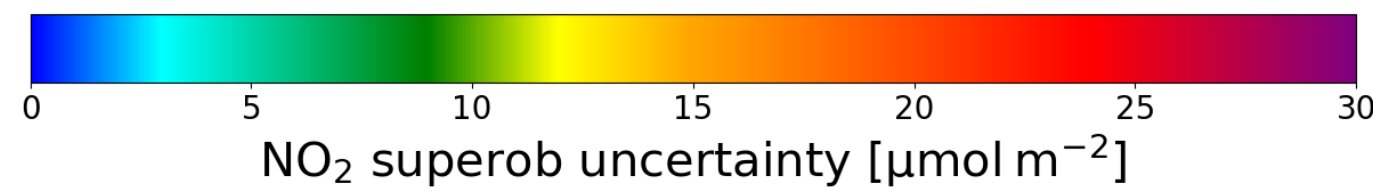
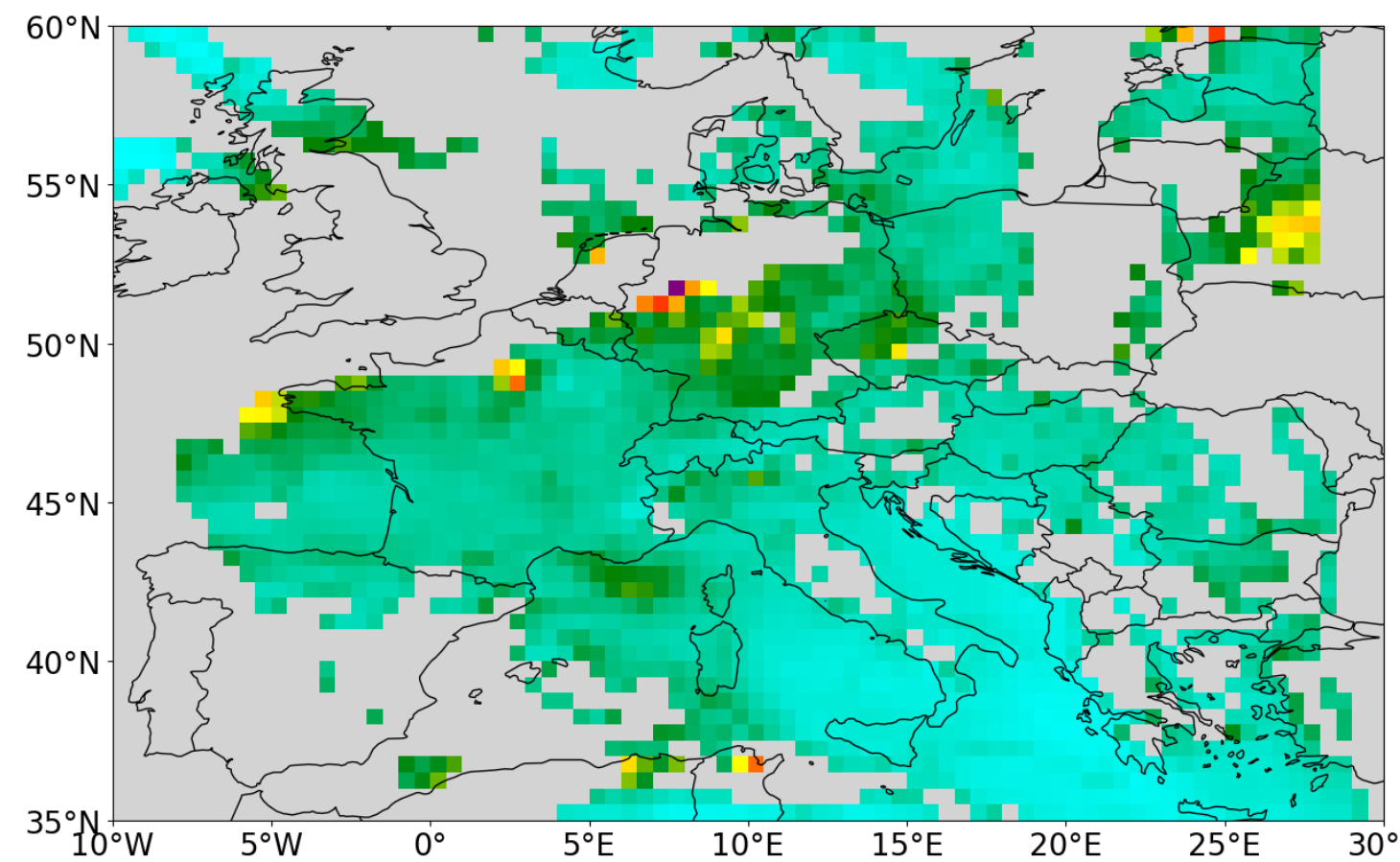
Combined error

Superobservations:
Relative importance
stratospheric error
large!



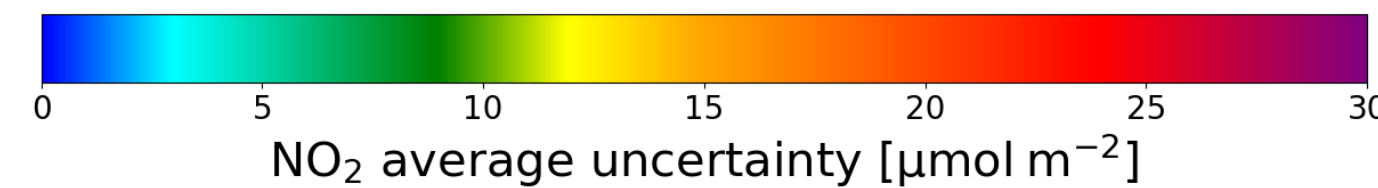
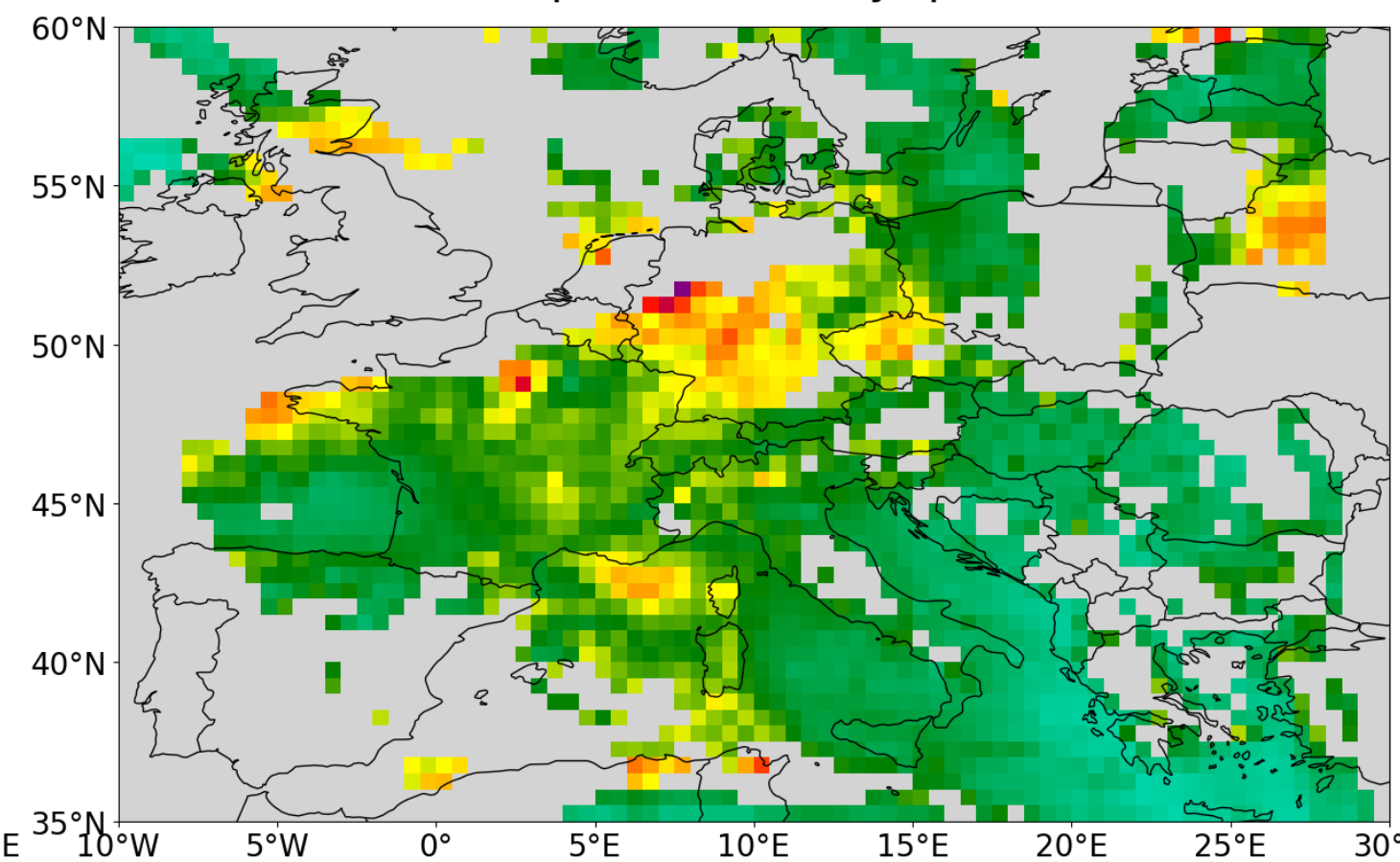
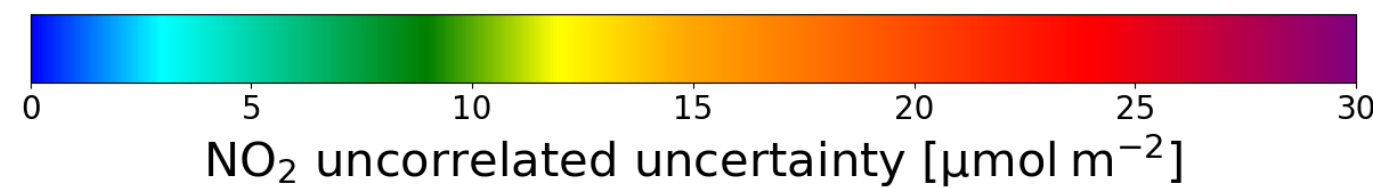
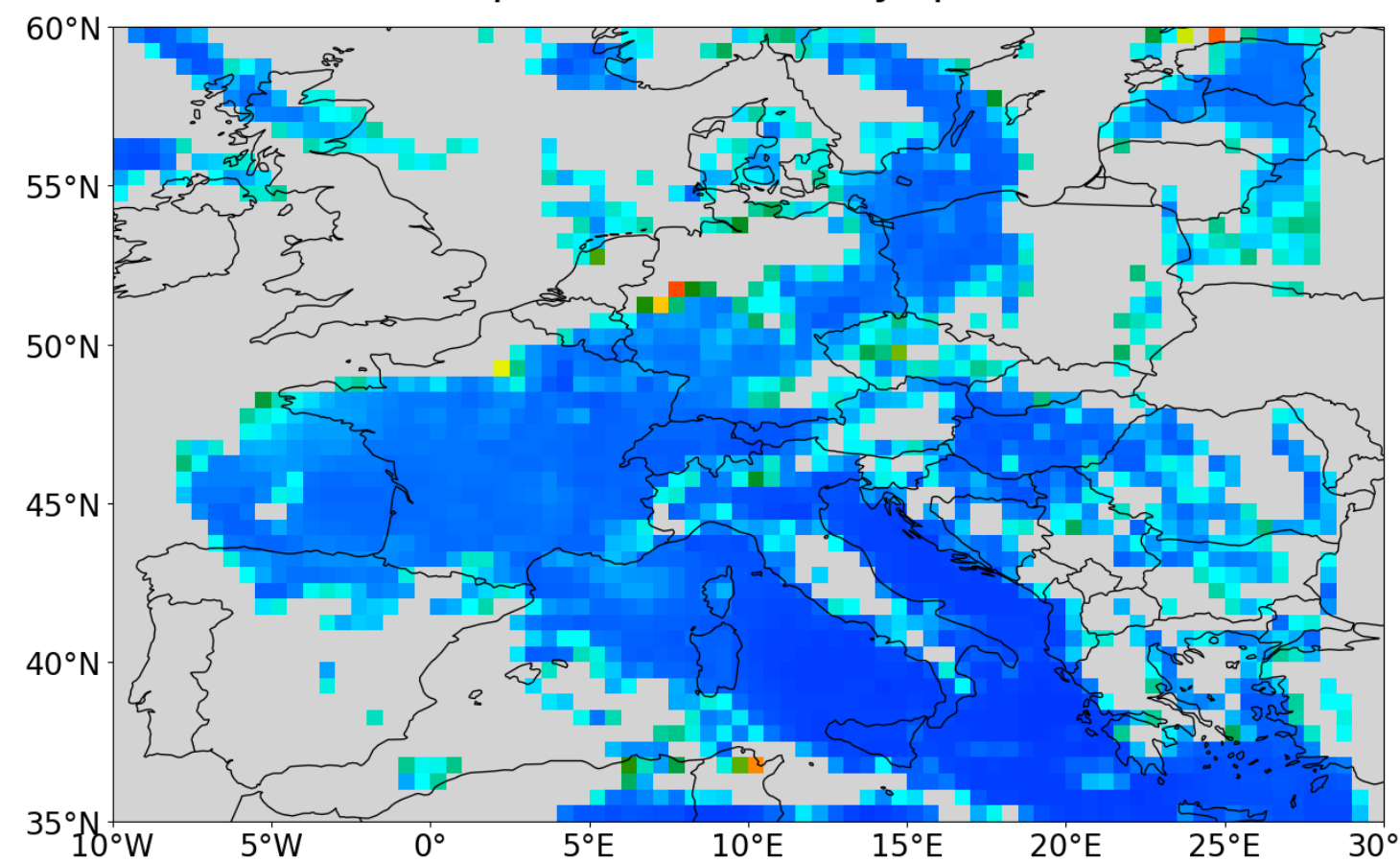
Superobservations: Tests with JAMSTEC assimilation system

Estimated
superobservation
error



Thinning:
random
selection of
1 observation

Assuming
errors are
uncorrelated

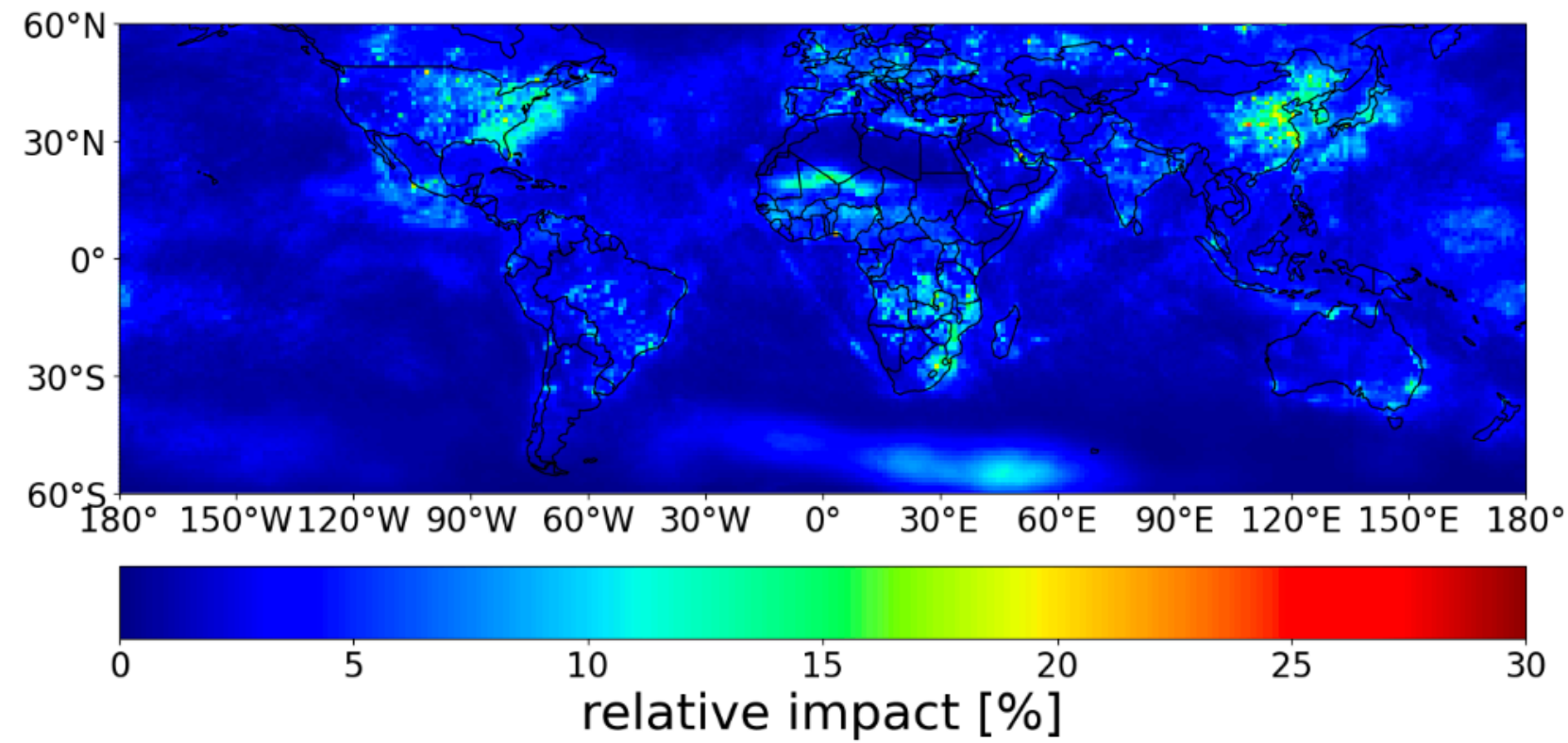


Assuming
errors are
fully
correlated

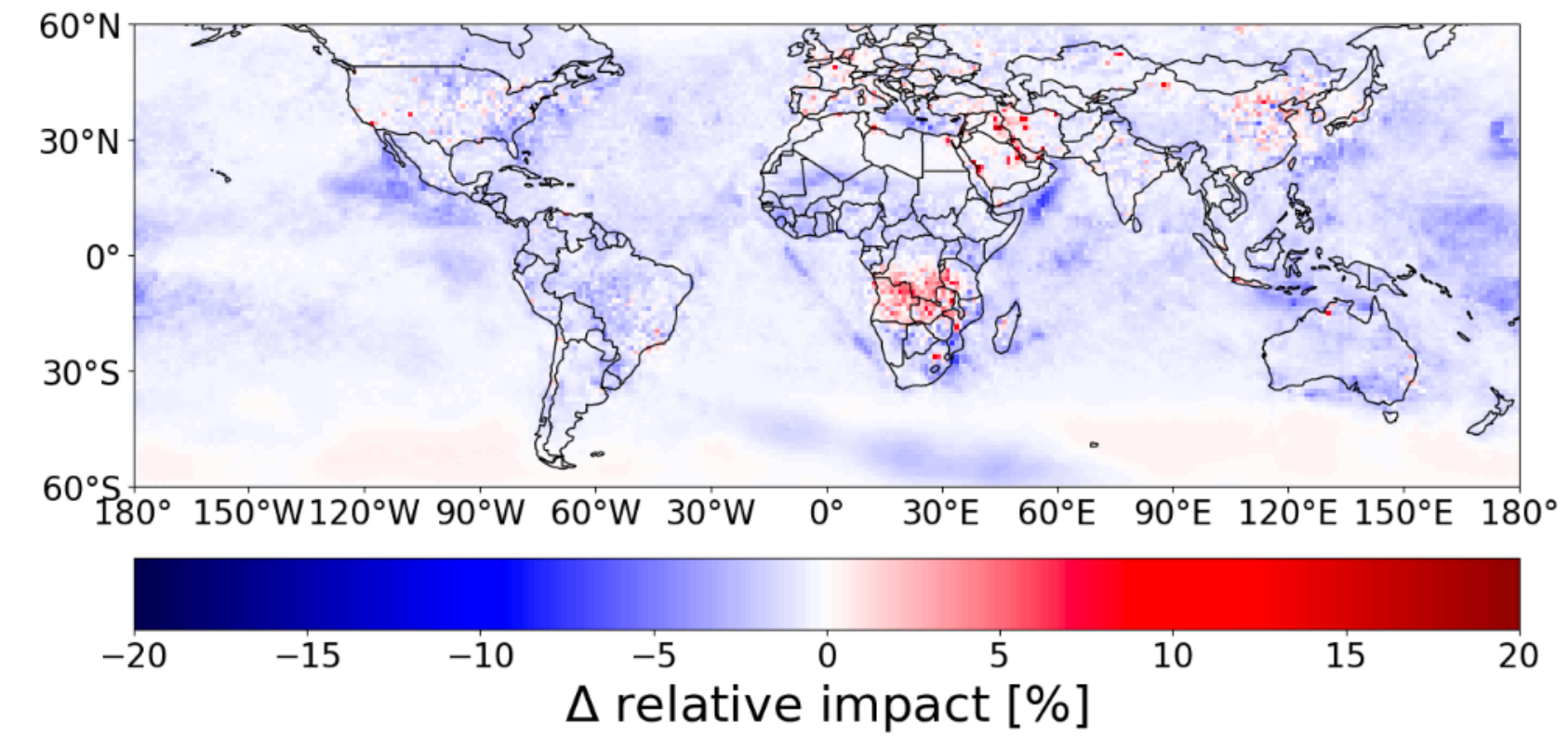
Superobservations: Tests with JAMSTEC assimilation system

Impact

(a) Impact superobservations

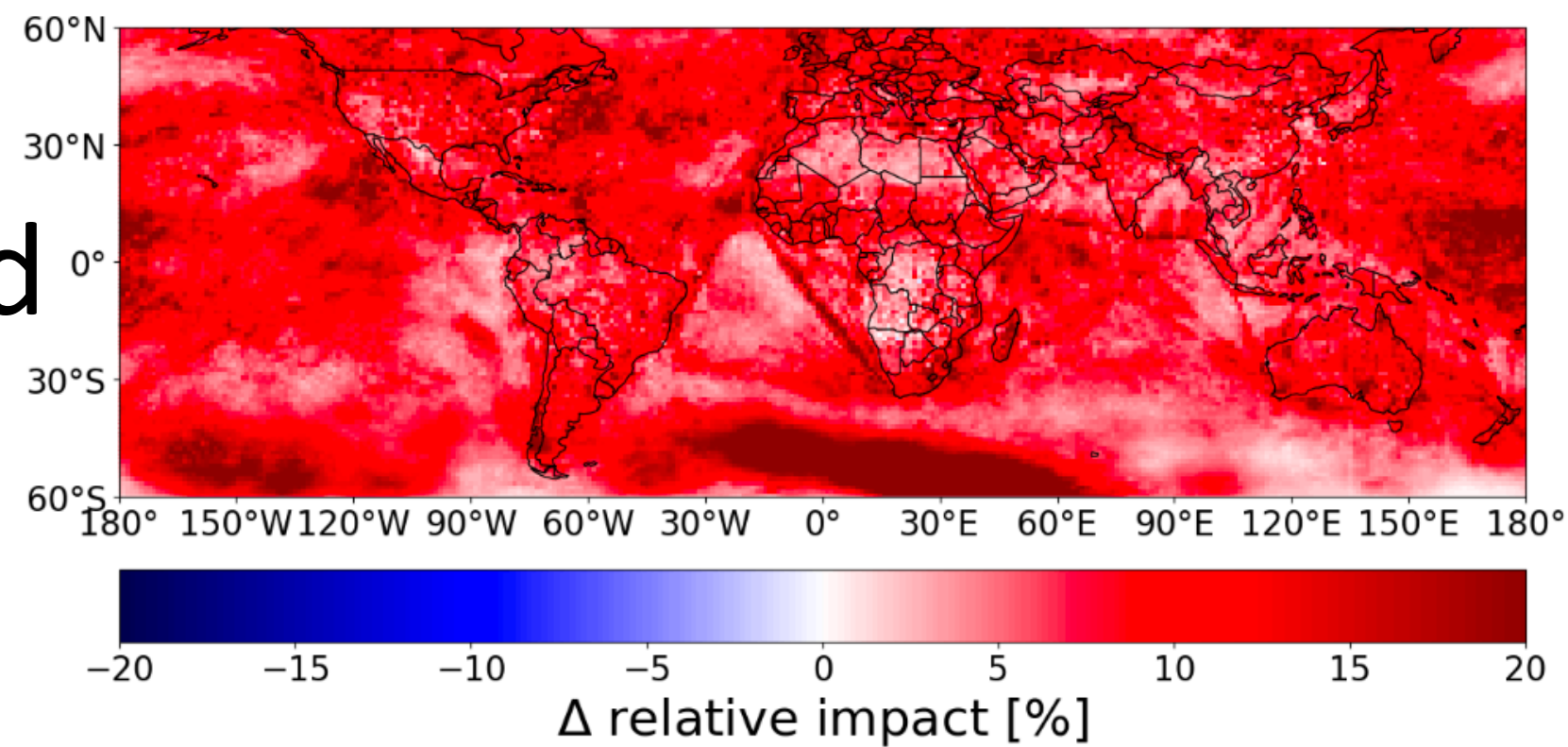


(b) difference thinning - superobservations



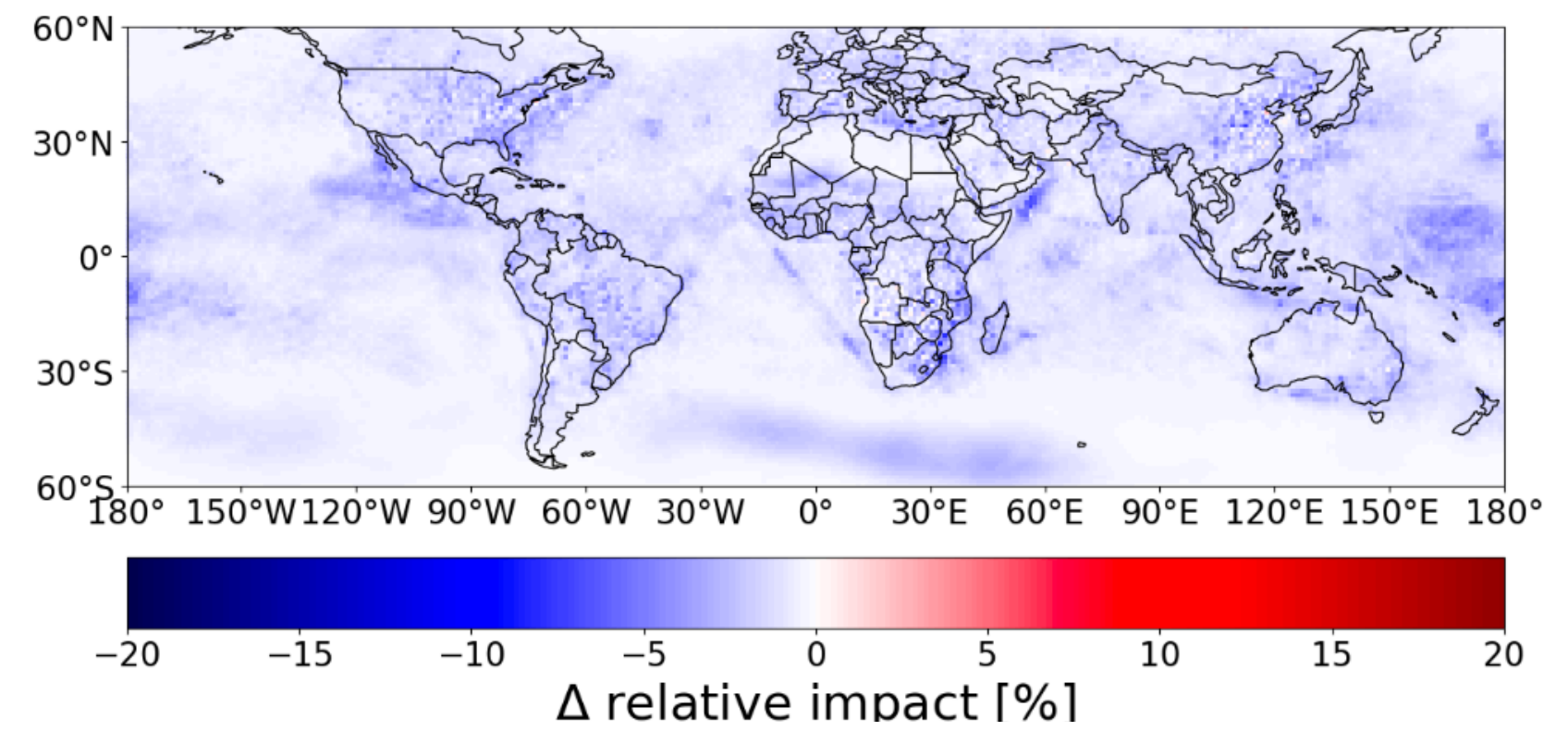
Thinning
bit smaller

(c) difference uncorrelated - superobservations



Un-
correlated
bigger

(d) difference fully correlated - superobservations



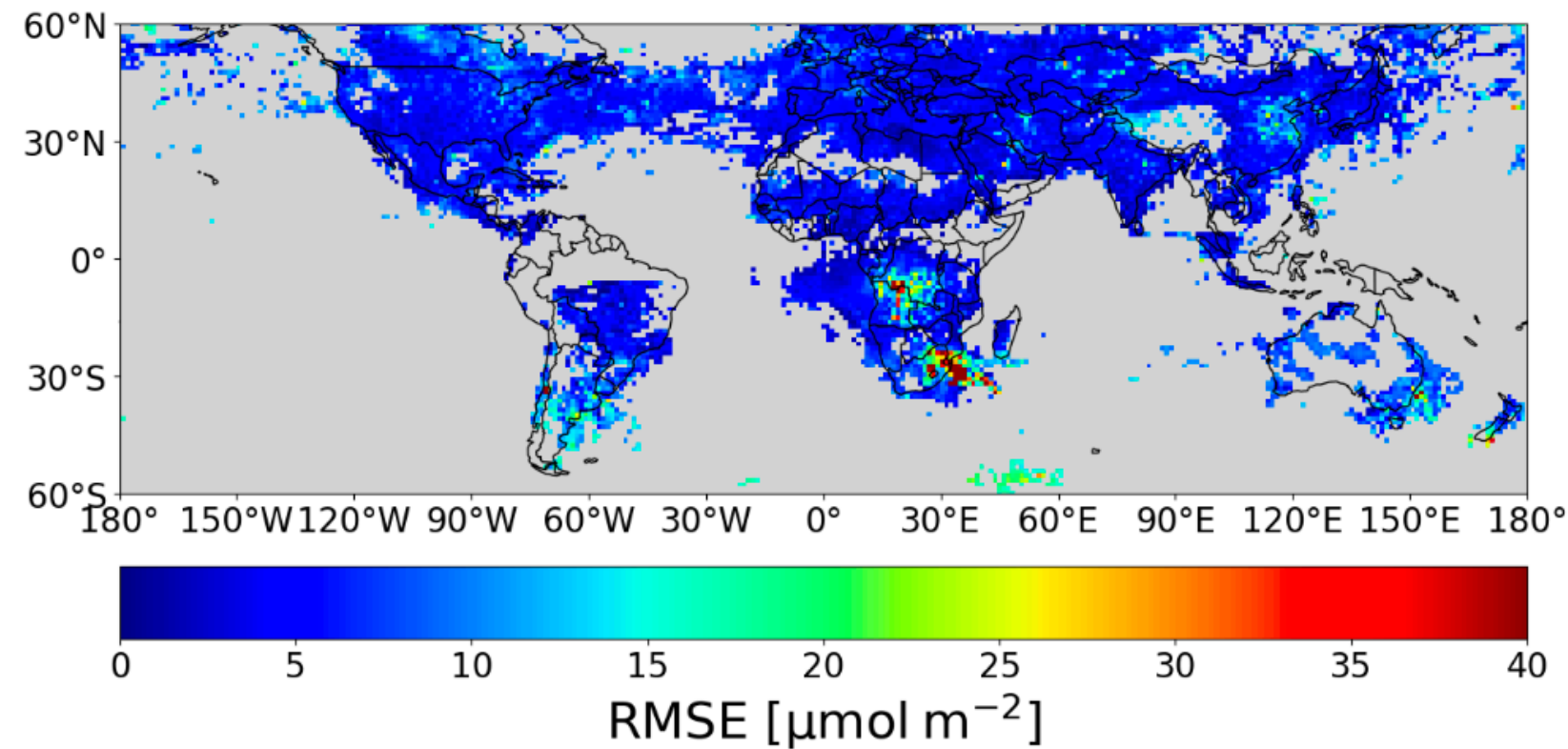
Fully
correlated
smaller

$$Impact[\%] = \frac{1}{t} \sum_1^t \frac{|A_t - F_t|}{F_t} * 100$$

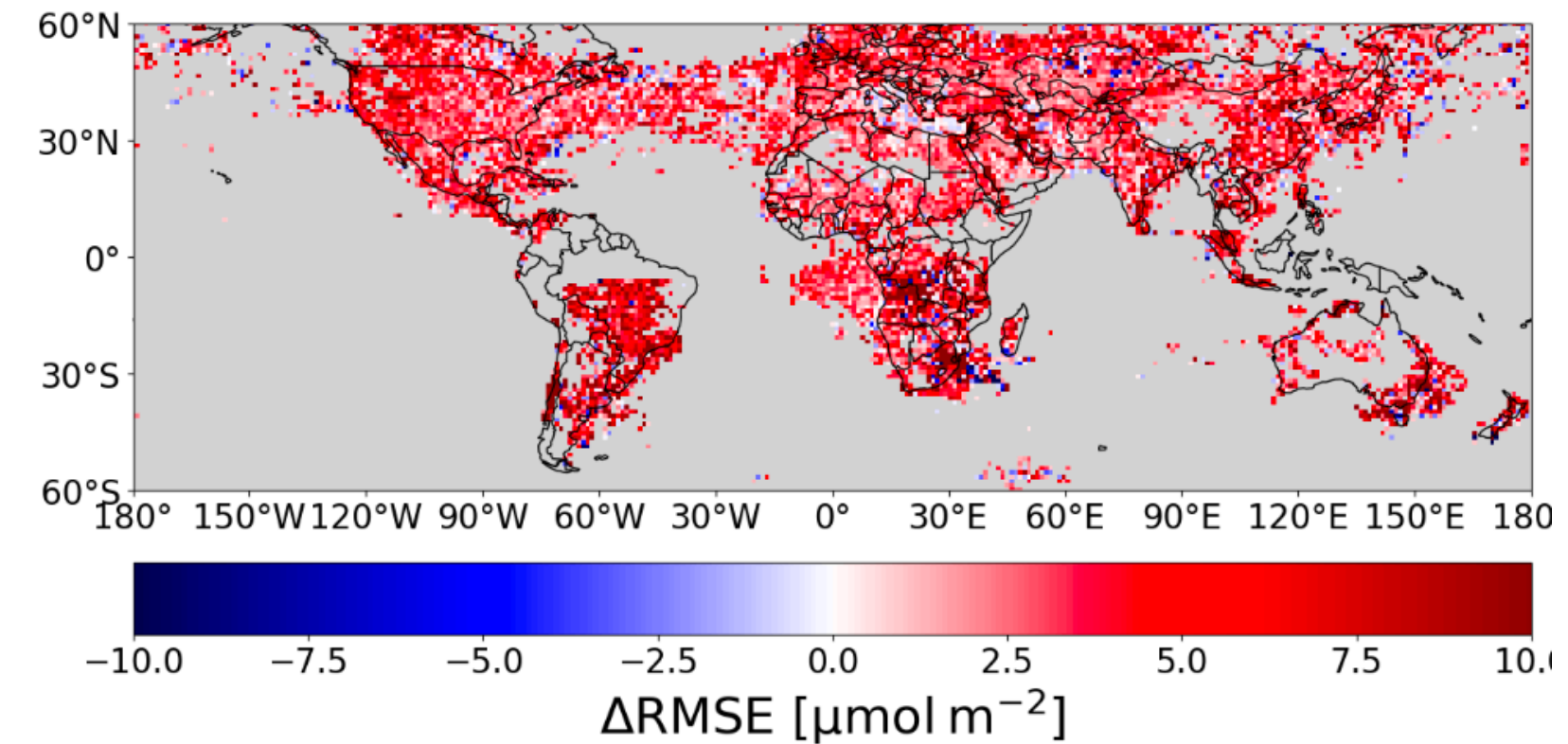
Superobservations: Tests with JAMSTEC assimilation system

Forecast performance

(a) RMSE superobservations

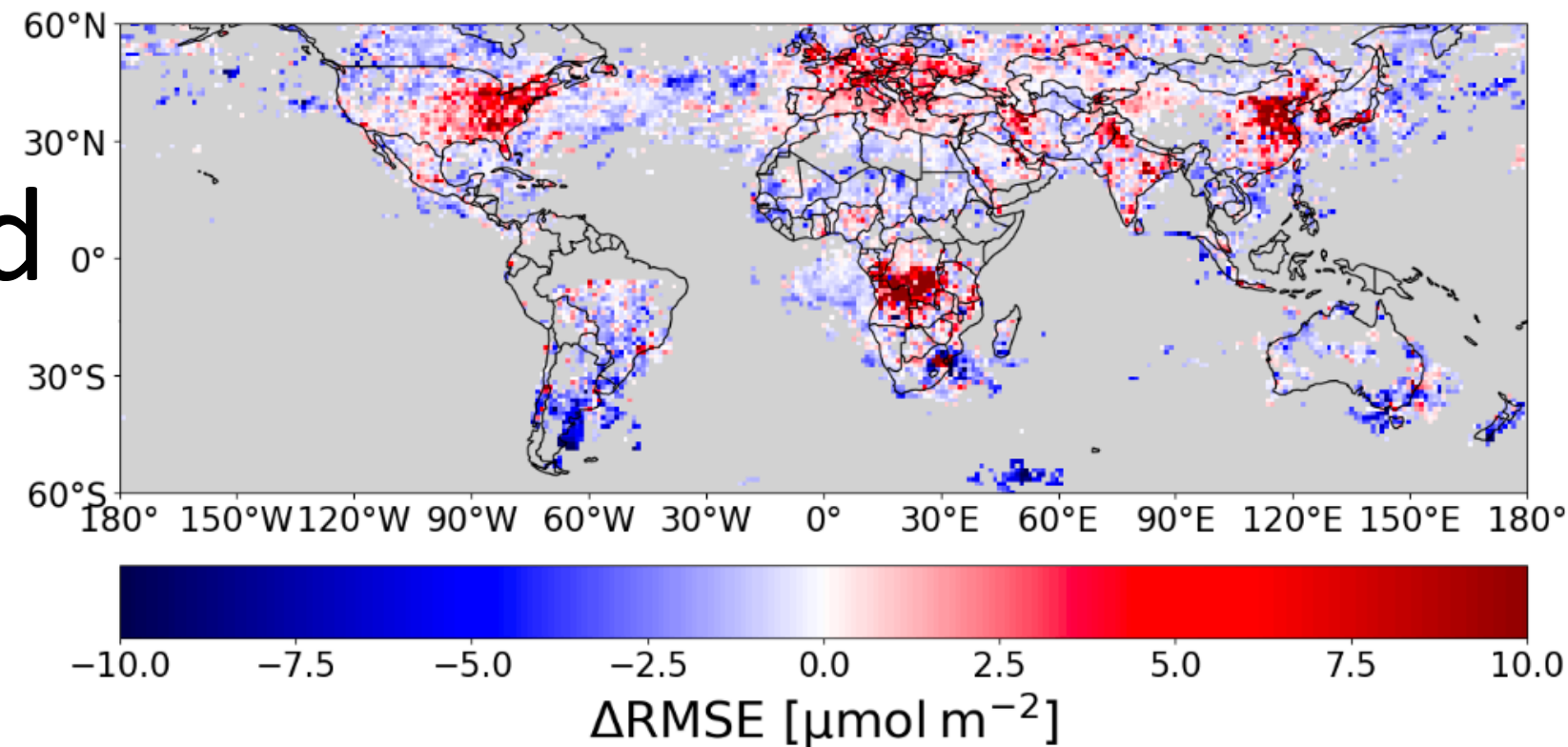


(b) difference thinning - superobservations



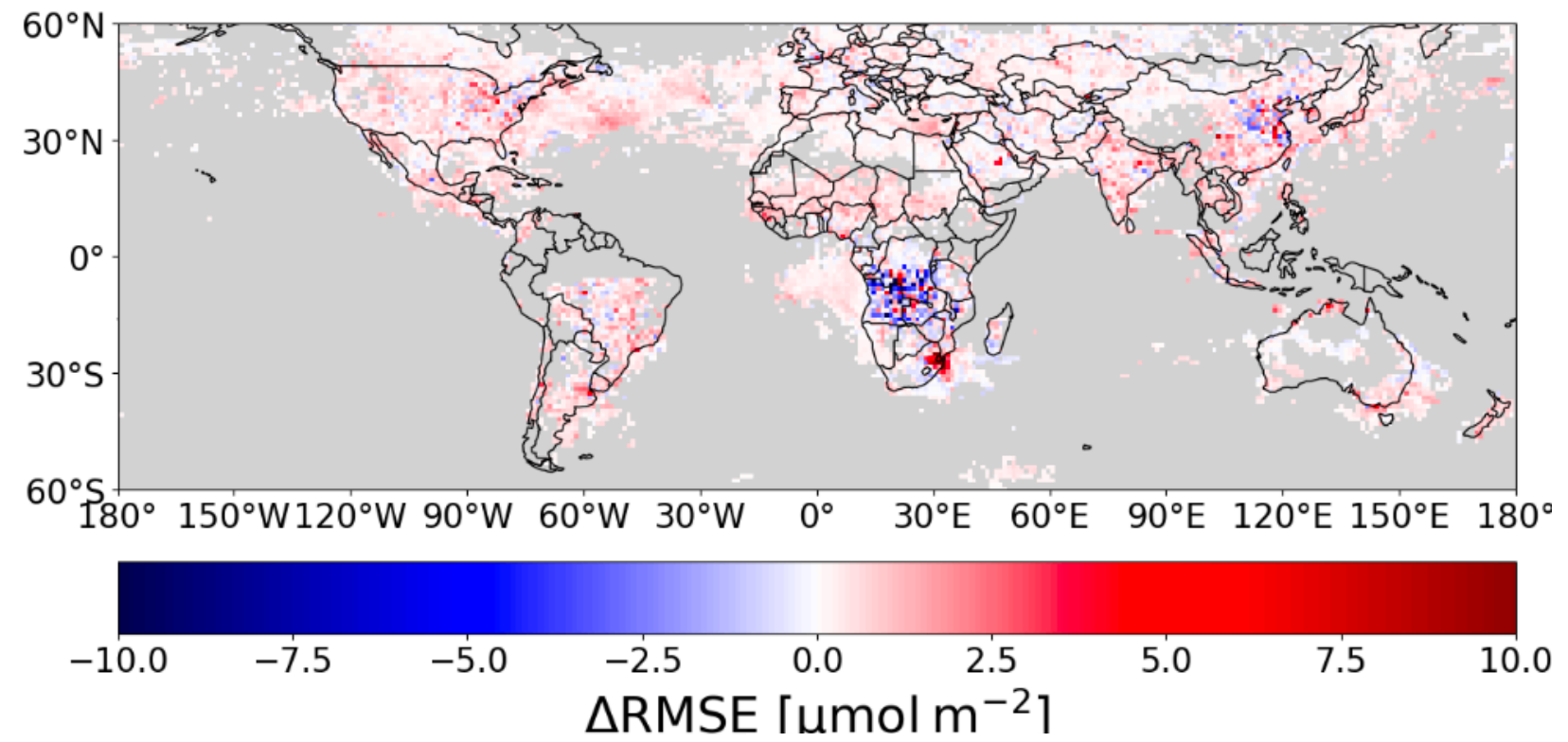
Thinning
much
worse

(c) difference uncorrelated - superobservations



Un-
correlated
worse

(d) difference fully correlated - superobservations



Fully
correlated
worse

$$RMSE_{x,y} = \sqrt{\frac{1}{t} \sum_1^t (O_{t,x,y} - F_{t,x,y})^2}$$

Application: global-scale data assimilation

Chaser-4/LETKF; MOMO-Chem; TCR-3

Instruments: TROPOMI, OMI, GOME-2, SCIAMACHY

Period: 2003-2023

Species: NO₂, SO₂, HCHO, CO

Filtering: Cloud-free and cloud-covered

ECMWF-CAMS forecasts

Experiments comparing NO₂ superobservations with in-house superobbing approach (ongoing work)

CAMEO project

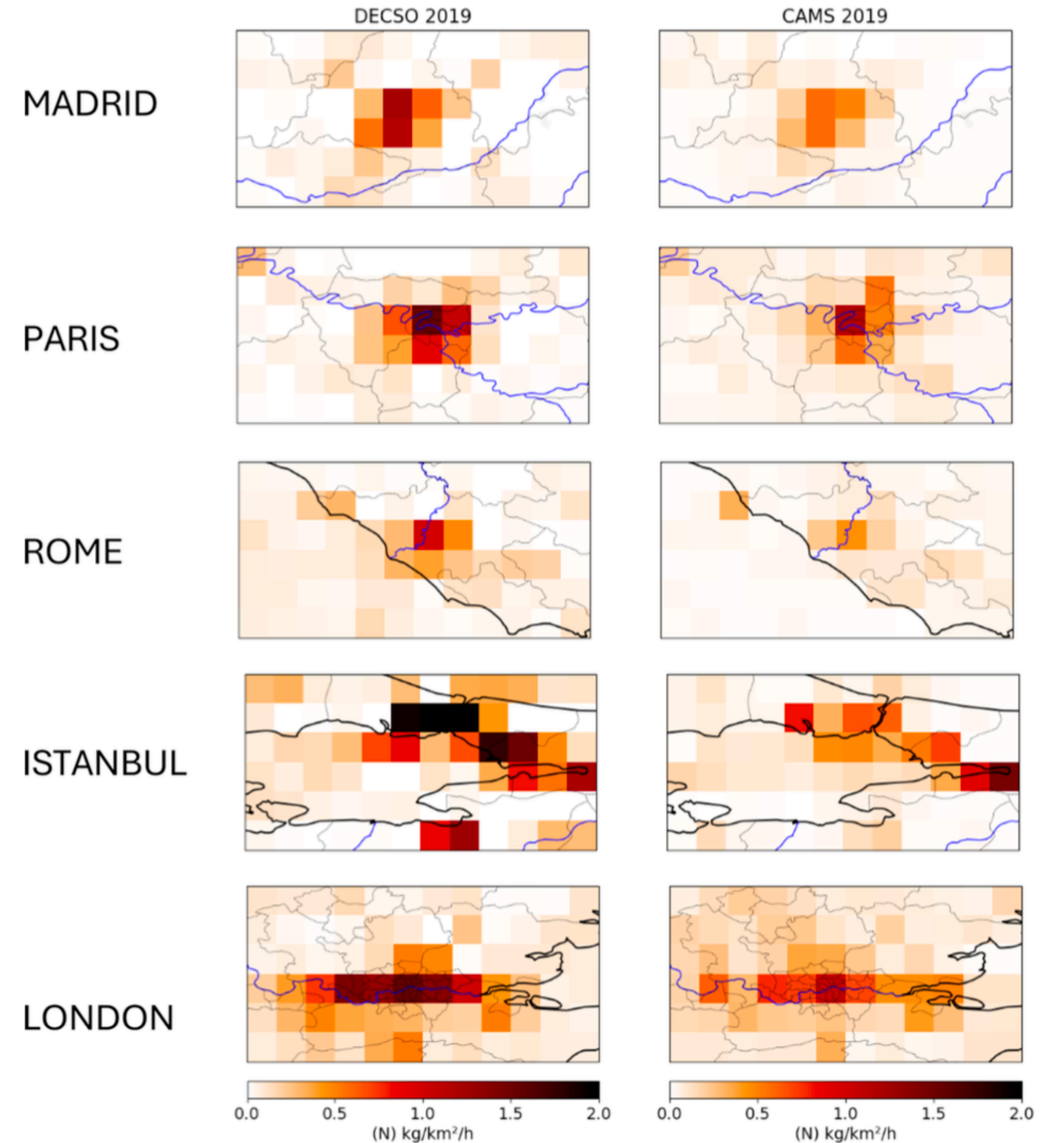
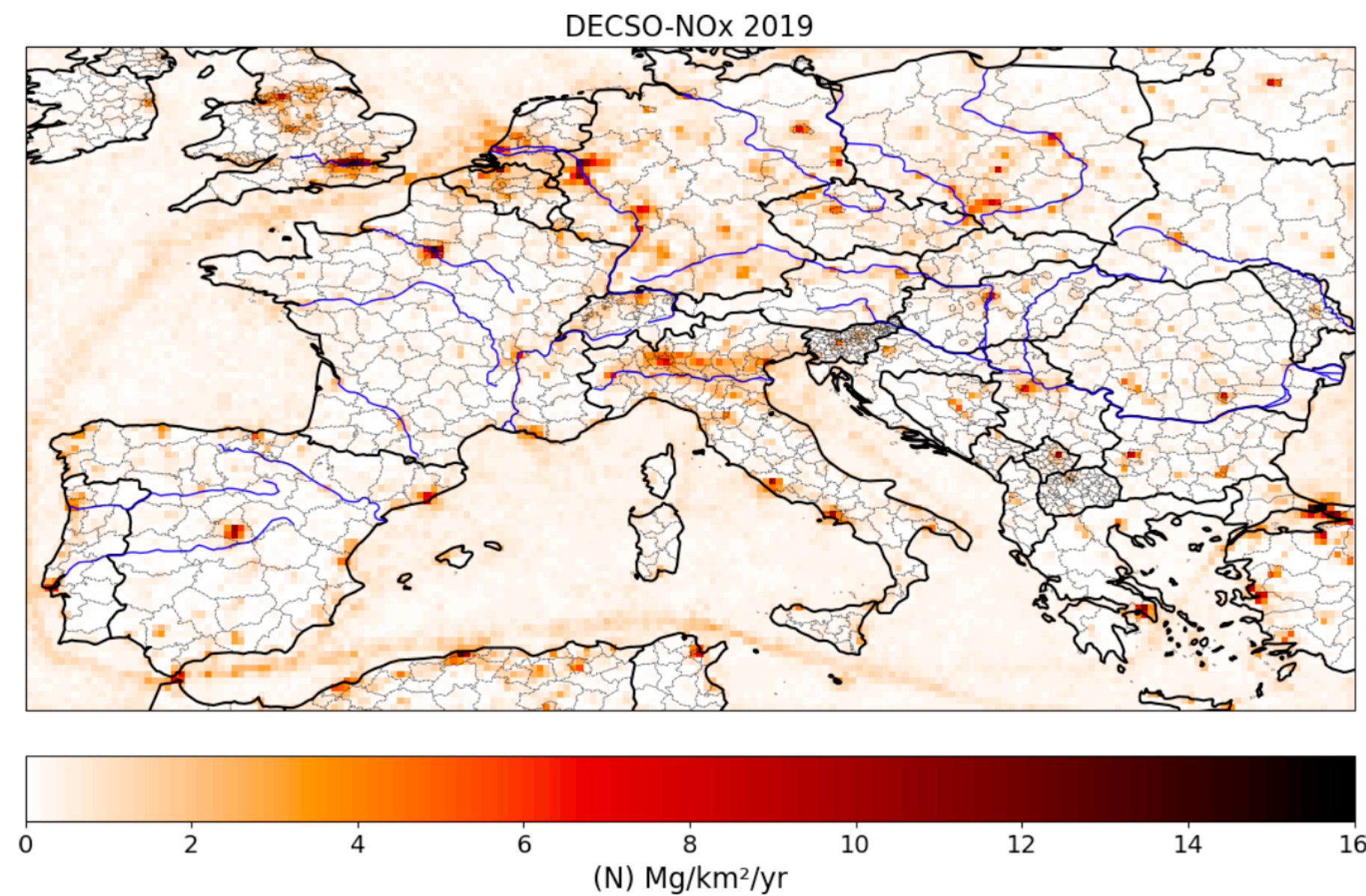
L3 gridded fields

Climate records using multiple instruments, OMI-TROPOMI
ESA CCI+

Application: NO_x emissions with DECSO-CHIMERE (Europe)

Also for regional applications the superobbing can be beneficial, up to resolutions of 0.2 (0.1) degree

DECSO NO_x emissie, 2019



Ronald van der A, et al., ACP 2024

Thanks for your attention!

Paper:

Pieter Rijdsdijk et al.,

Egusphere preprint 2024

<https://doi.org/10.5194/egusphere-2024-632>

Superobbing code:

Available (Python)

Contact:

henk.eskes@knmi.nl

