Foreground removal for B-mode detection with Clustering methods

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From Planck to the future of CMB

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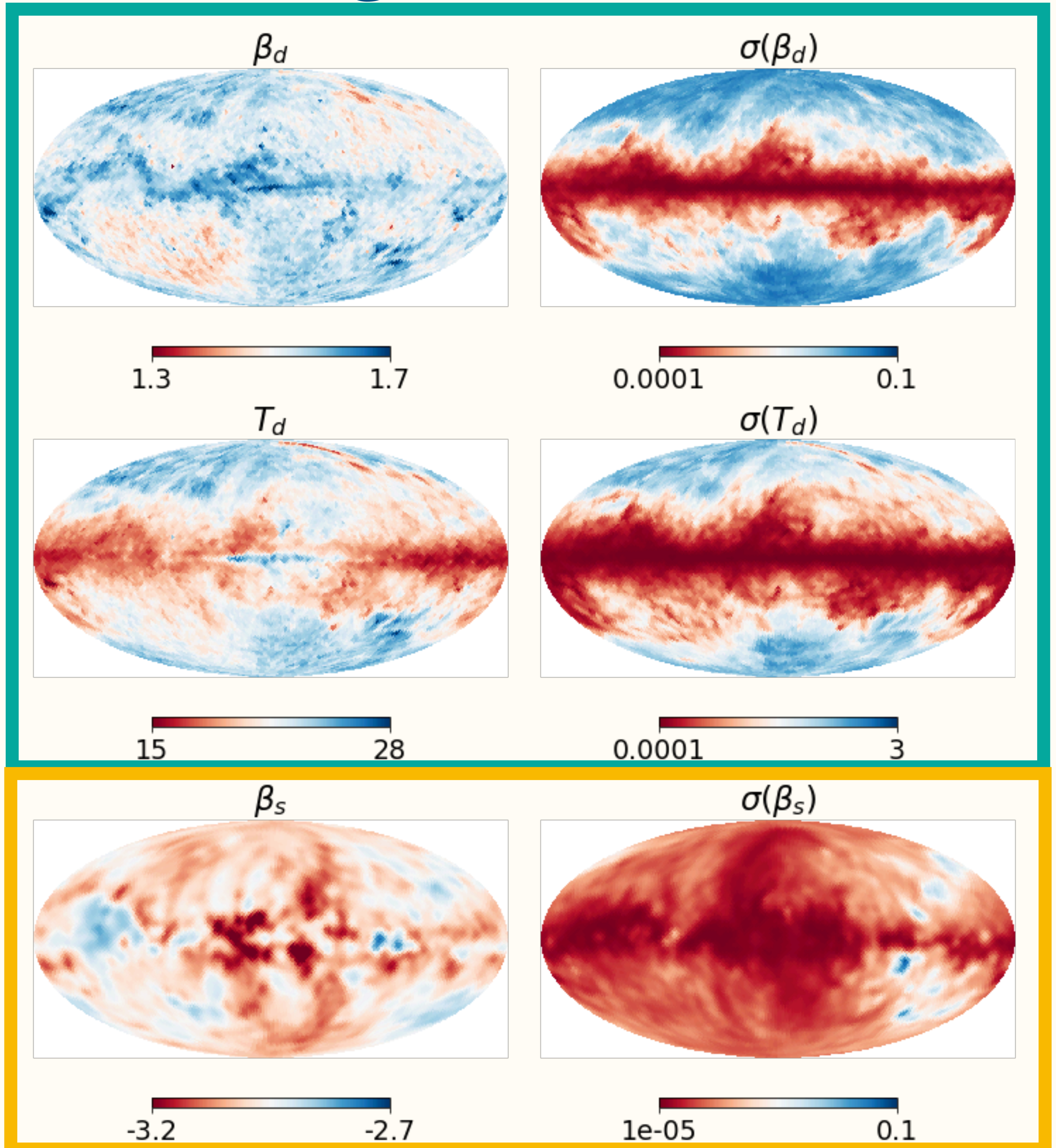
Spatial variability of Galactic foregrounds

G. Puglisi et al. 2022

- Spatial variability is hard to be tackled in both blind and non -blind comp sep approaches (-> See A. Carones Poster)
- However, in general Galactic emission could vary along the l.o.s and in different l.o.s



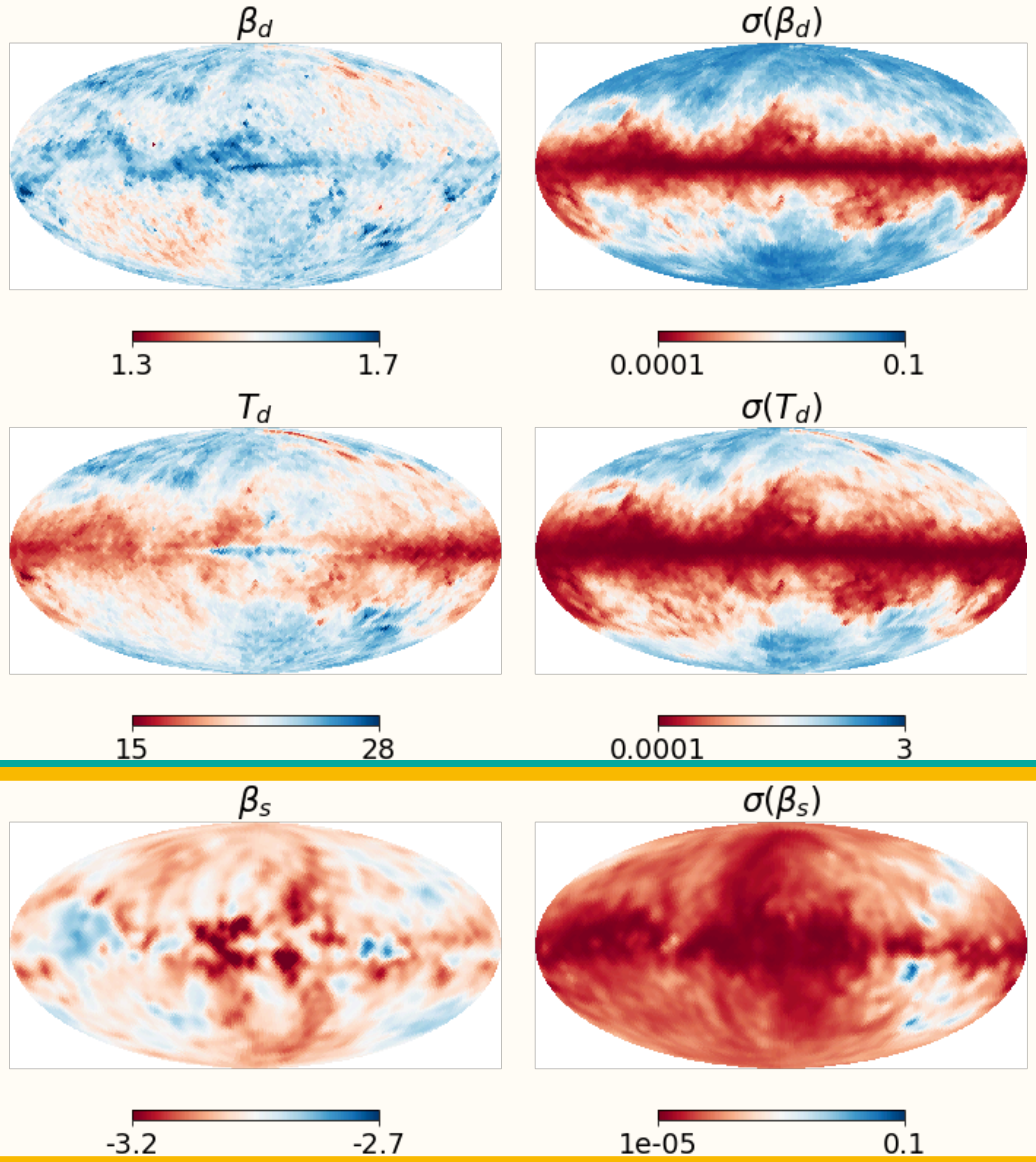
Spatial variability of Galactic foregrounds

$$I_\nu^{dust}(\hat{n}) \propto \nu^{\beta_d(\hat{n})} B_\nu(T_d(\hat{n}))$$

- PySM `d1` (Thorne et al. 2017)
- Spectral Parameters β_d, T_d
- Templates derived from Commander Planck Collaboration 2015.X

$$I_\nu^{synch}(\hat{n}) \propto \nu^{\beta_s(\hat{n})}$$

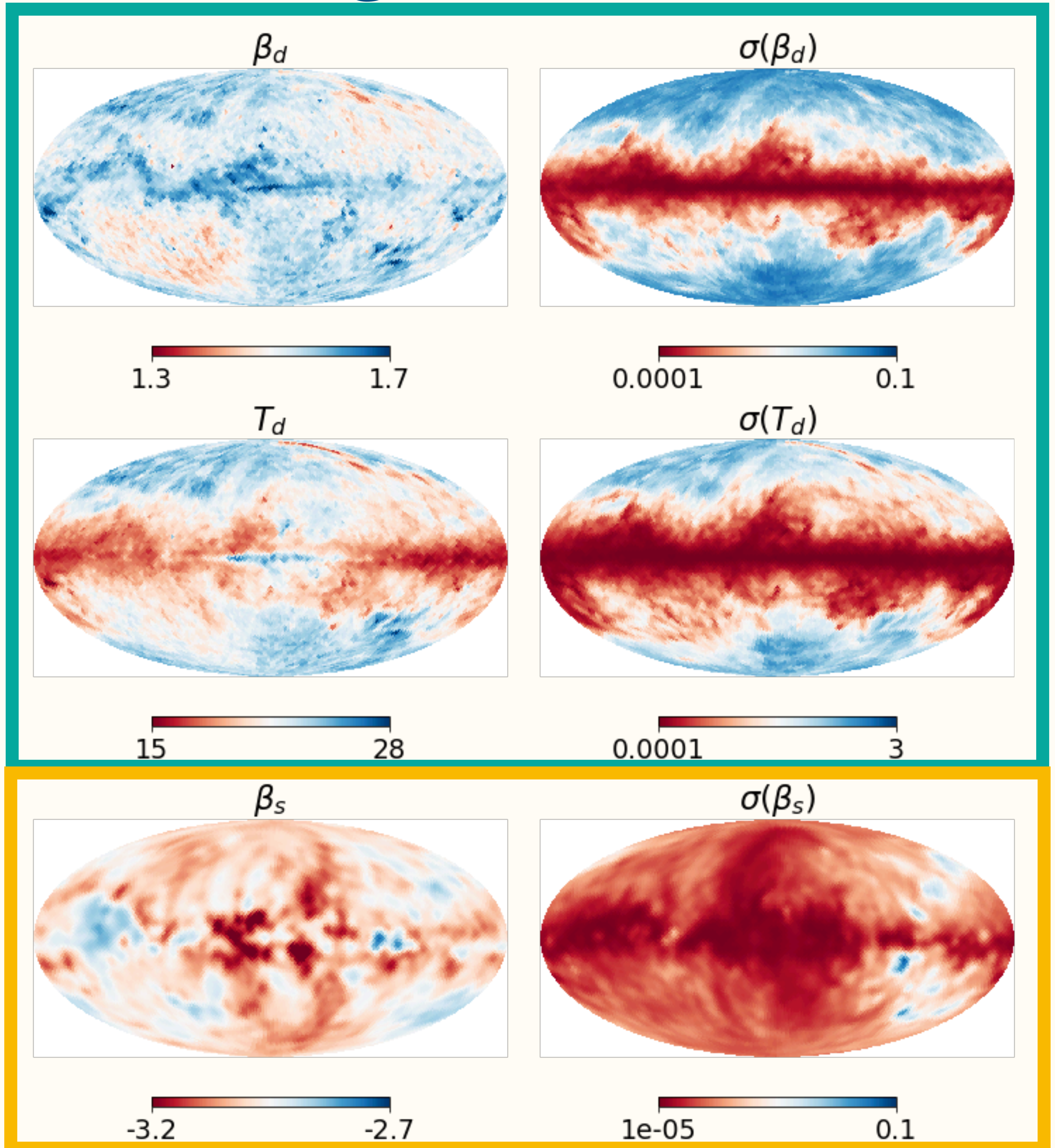
- PySM `s1`
- Spectral Parameter :β_s
- Template from WMAP 2011&Miville Deschenes 2008 template



Spatial variability of Galactic foregrounds

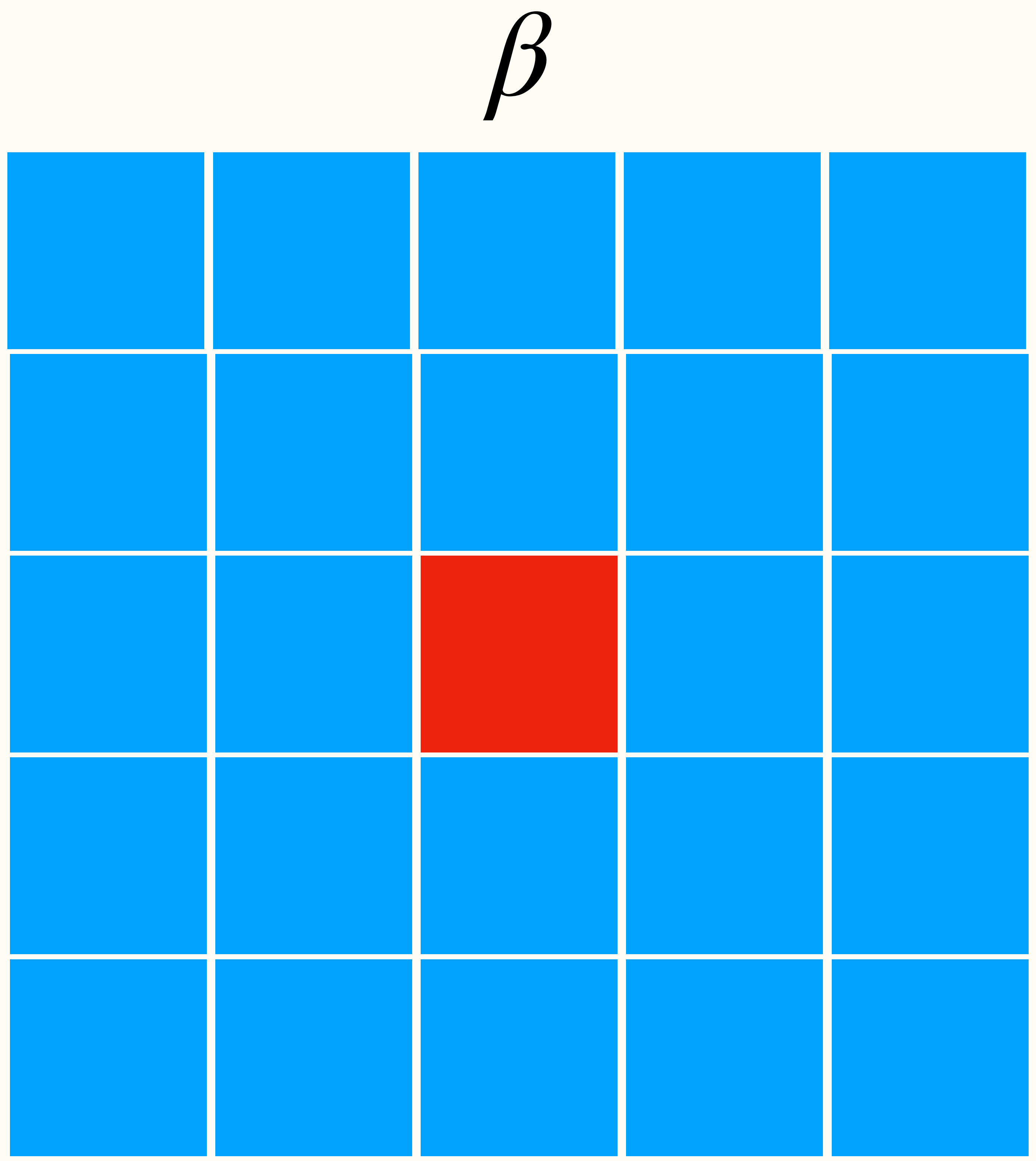
- Clustering methodologies (Grumit et al. 2019, Khatri 2018) employed to divide the sky into multiple domains

GOAL: to identify an *optimal partition* of Galactic emission to reduce B-mode residuals



Spectral clustering pixel-pixel affinity

For a given pixel in a β map, the Affinity accounts for :



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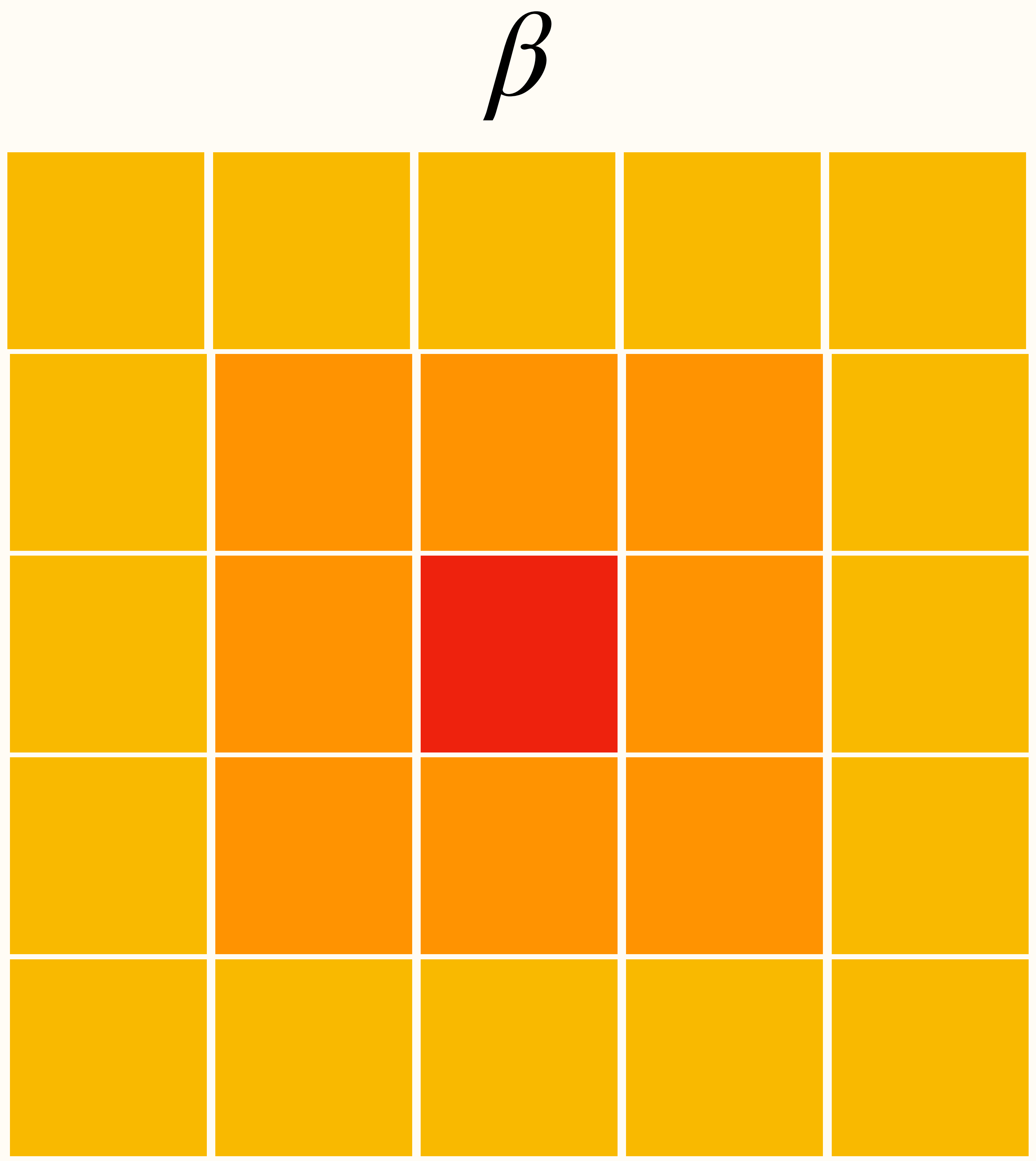

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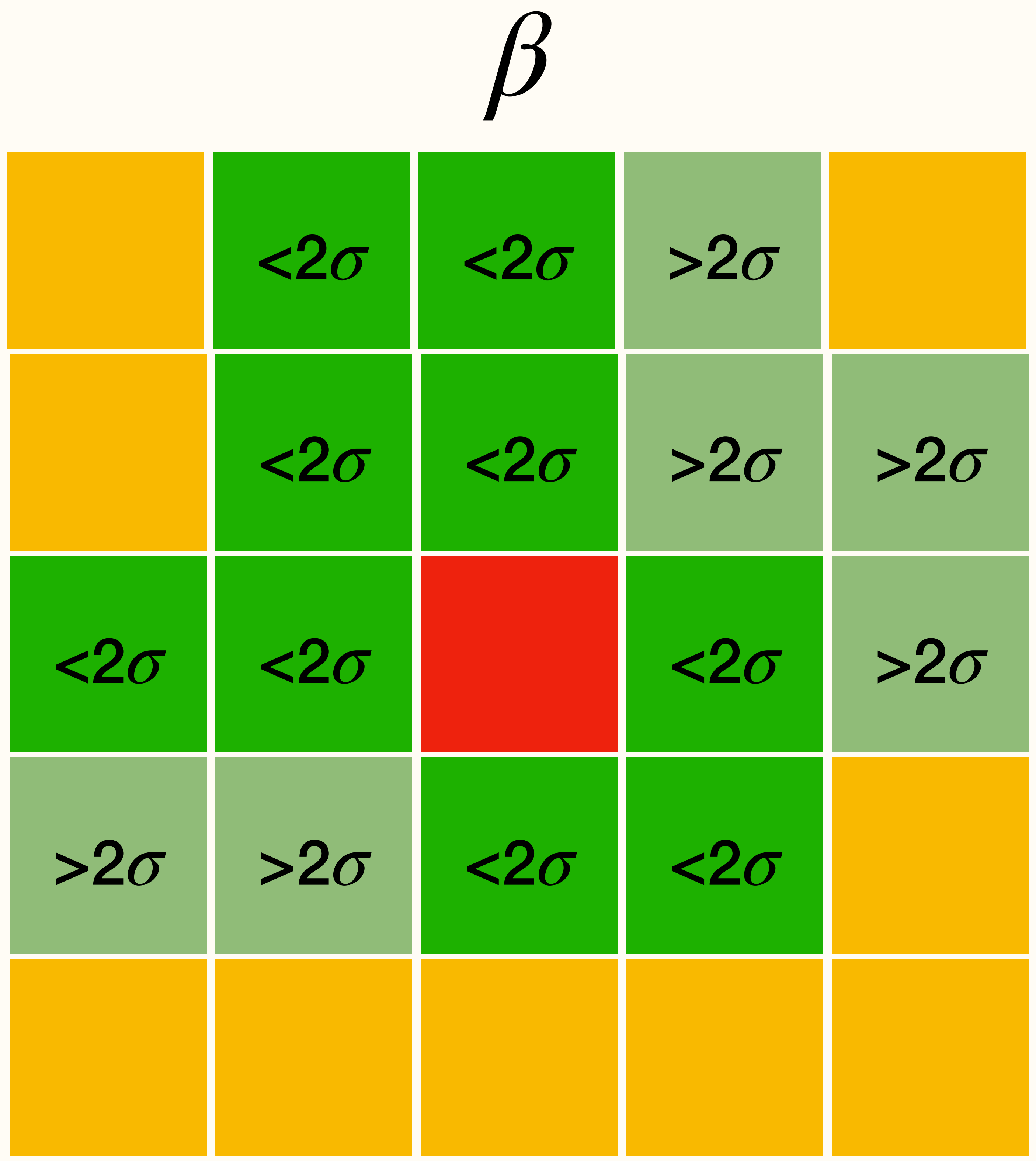
- *statistical affinity* : we group pixels whose spectral param. Values are compatible to 2σ C.L.



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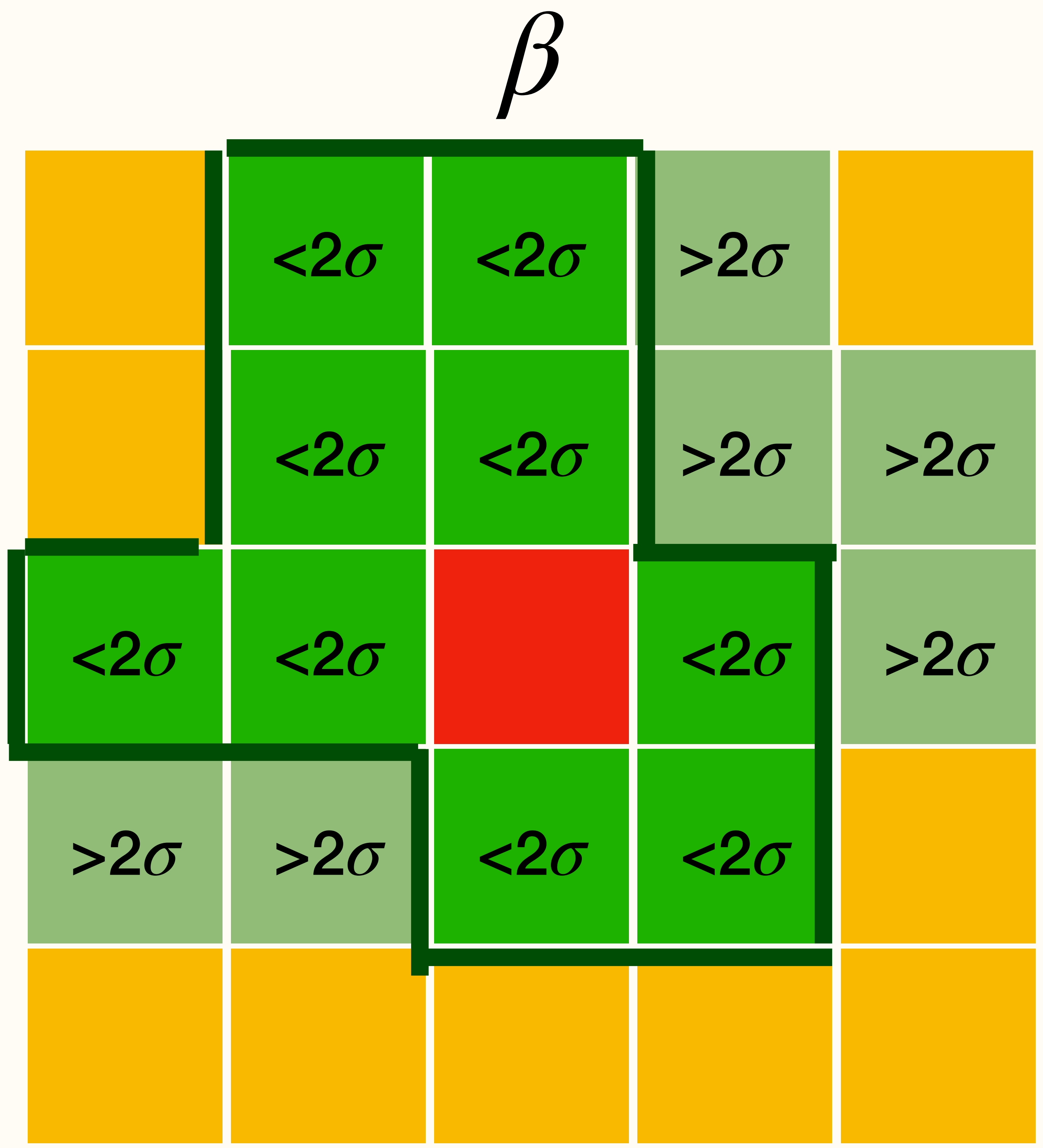
- Employ the clustering routine from sklearn.Clustering package



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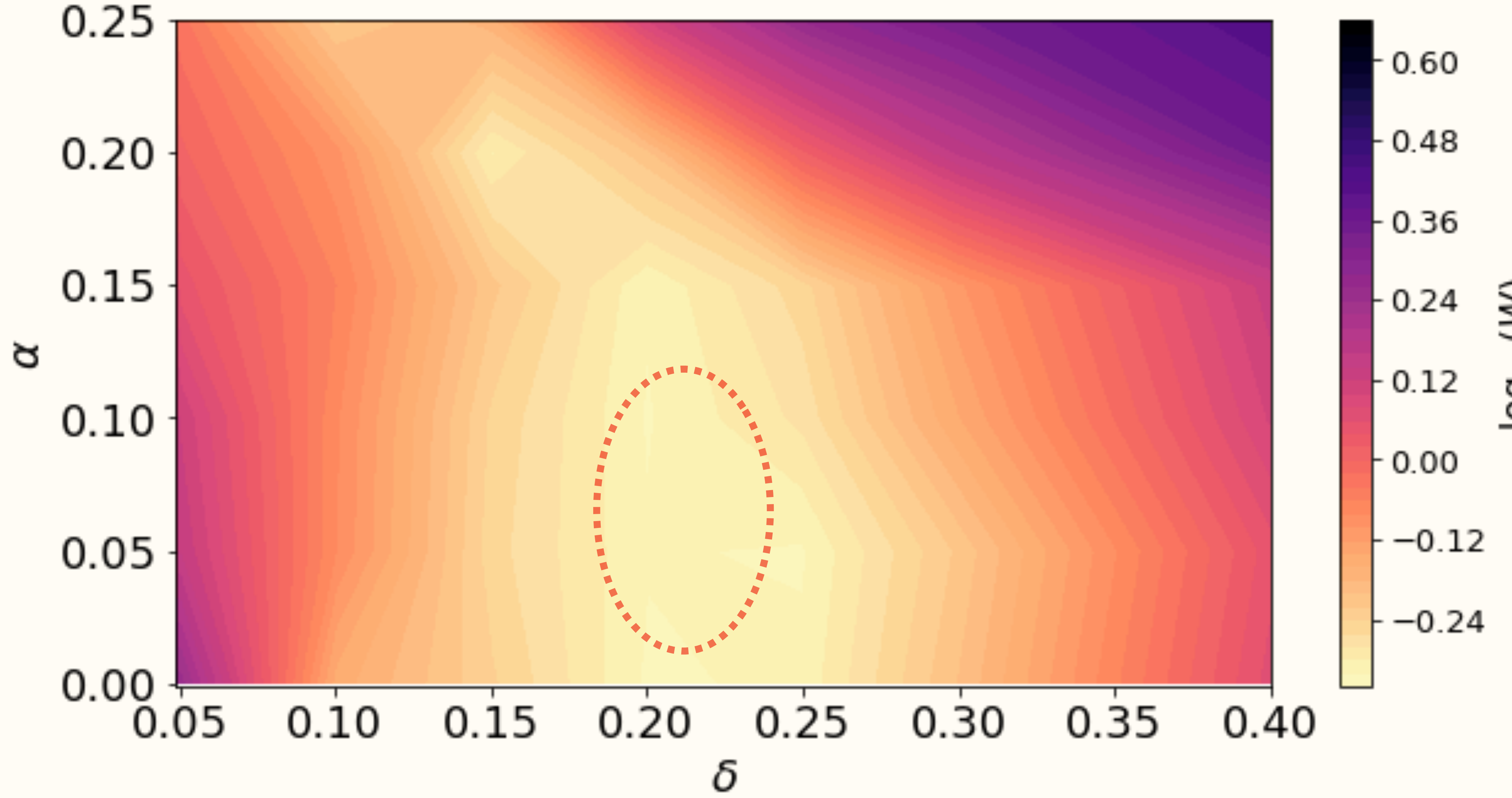
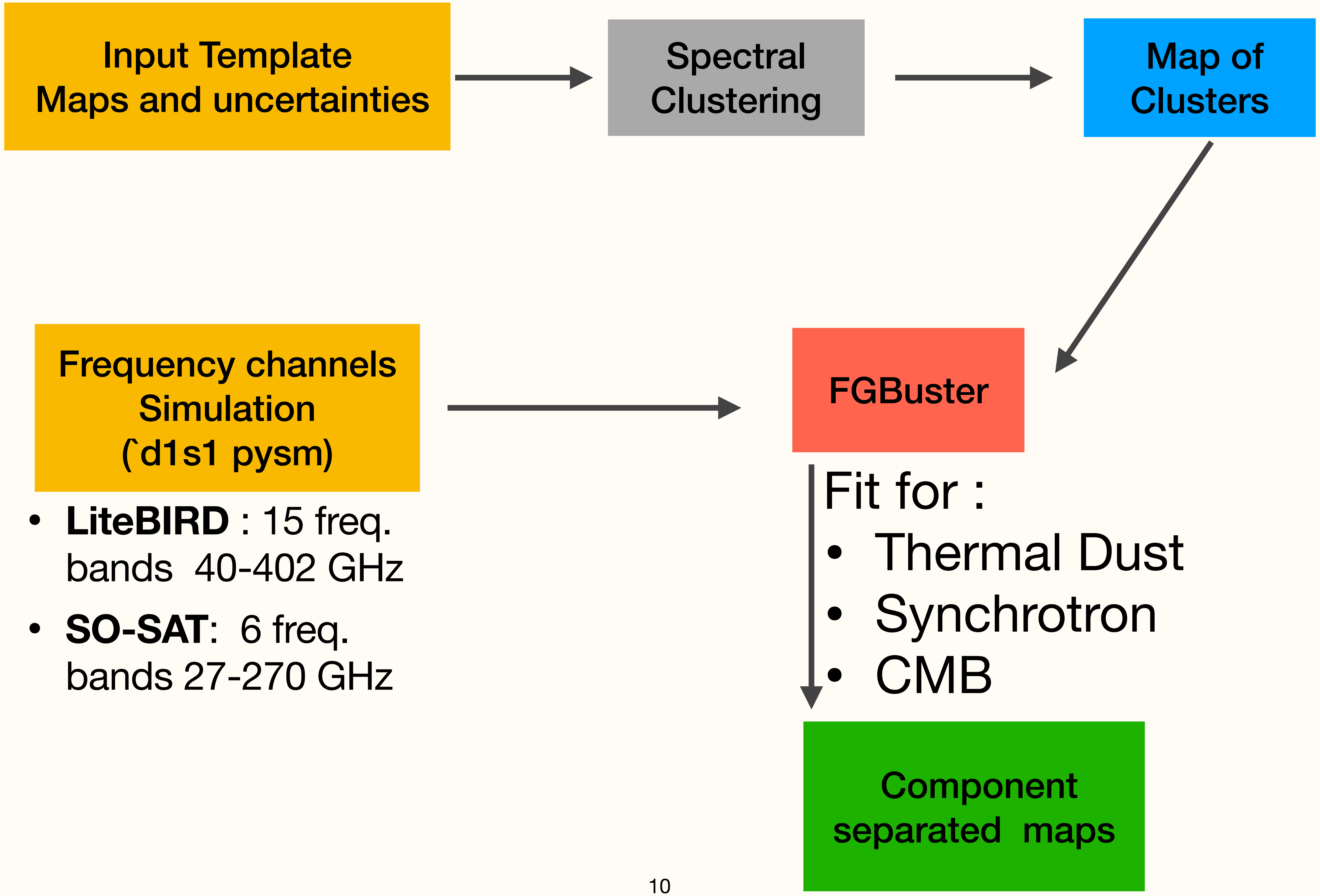
- *geometrical affinity* (nearest neighbors pixels are considered the most similar)
- *statistical affinity* : we group pixels whose spectral param. Values are compatible to 2σ C.L.
- Employ the clustering routine from [sklearn.Clustering]() package
- Optimal configuration at minimum within and between cluster variance



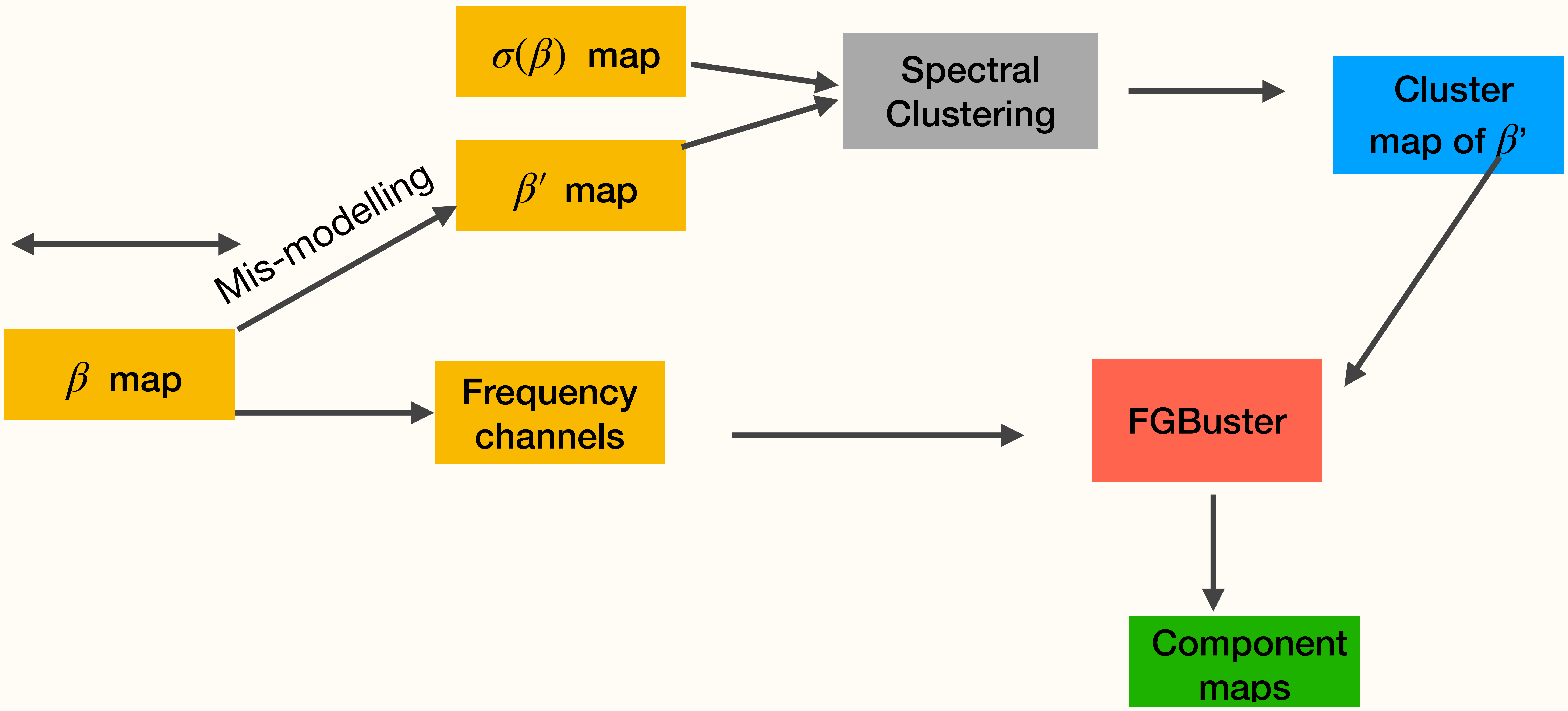
Clustering + Parametric Component Separation



Application #1: Clustering on Spectral Parameters

$$\beta' = \beta + f_{mis}\mathcal{N}(0,\sigma(\beta))$$

With $f_{mis} = 0,\ldots,1$



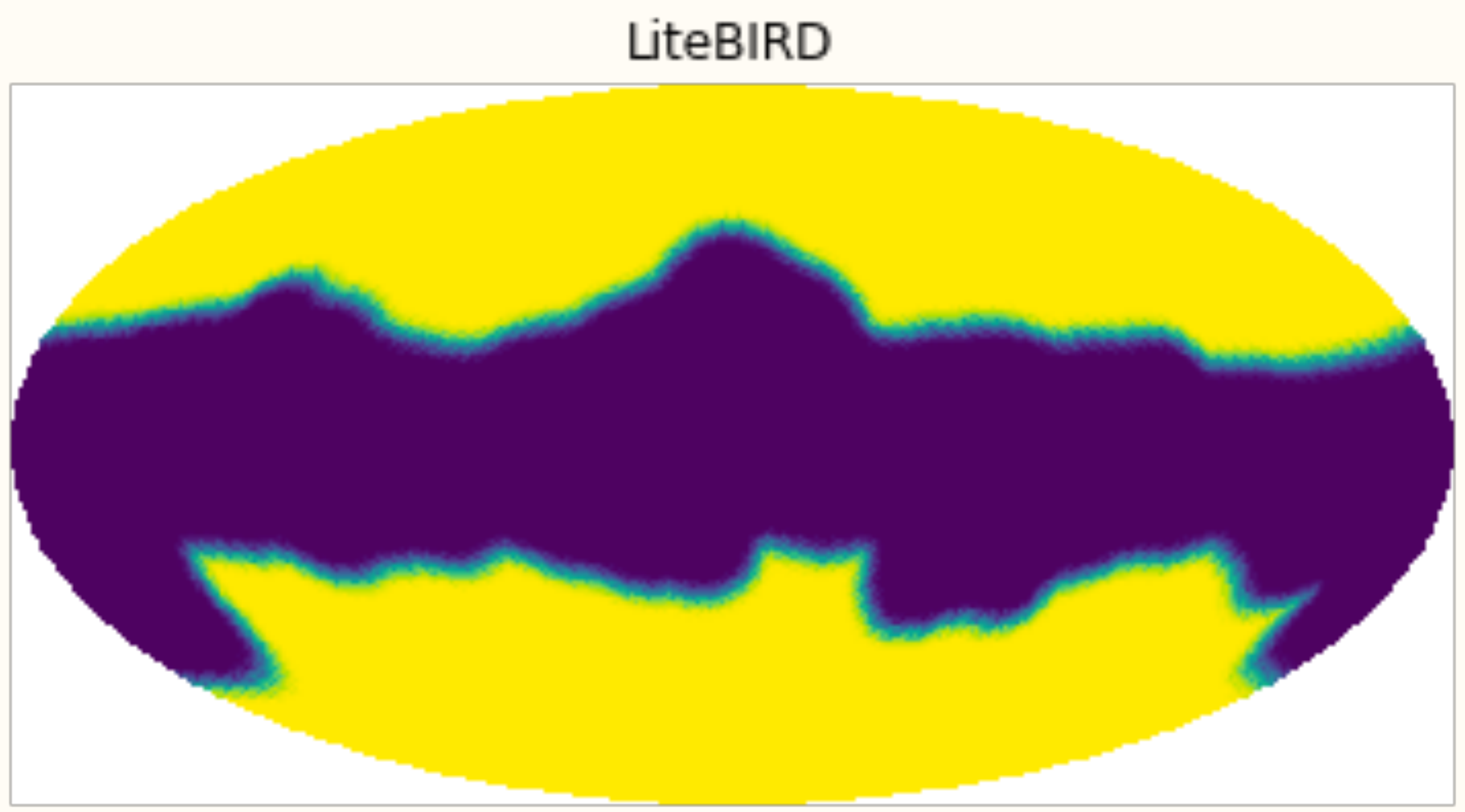
Application #1: Clustering on Spectral Parameters

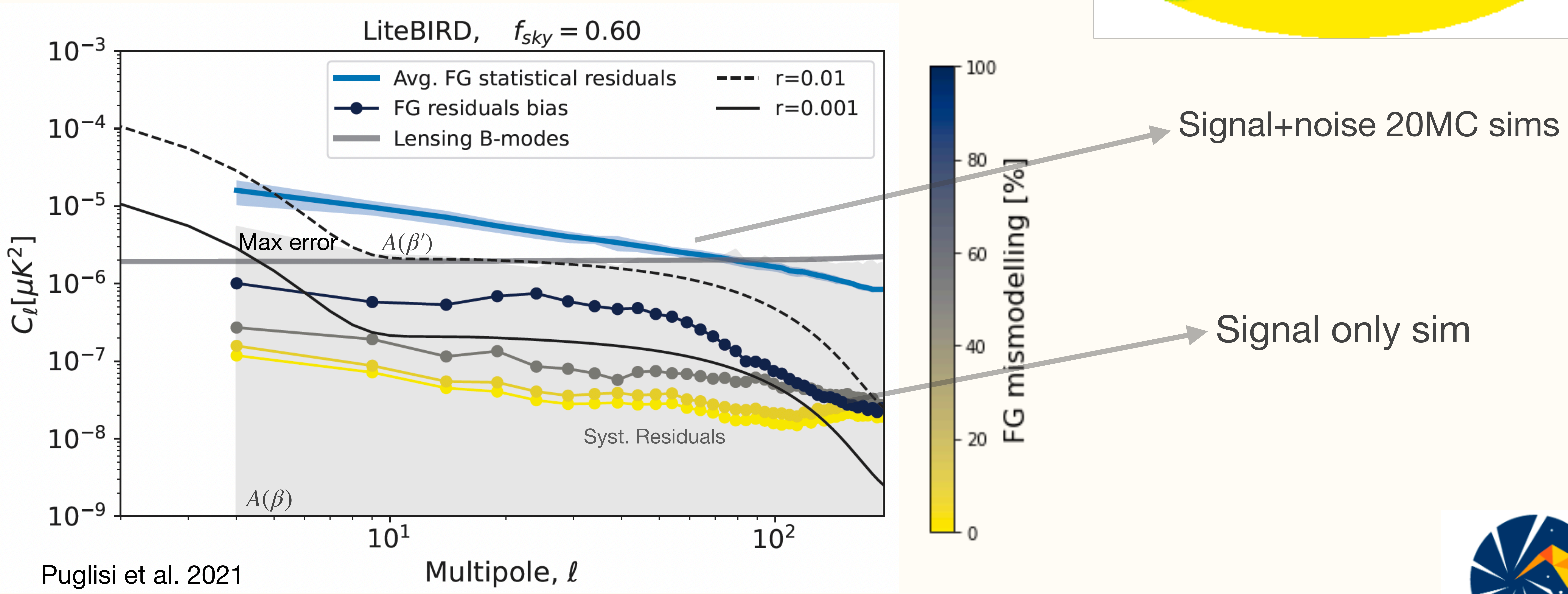
Puglisi et al. 2021

Different colors => different clusters

Cluster shape and size : defined by angular resolution and SNR

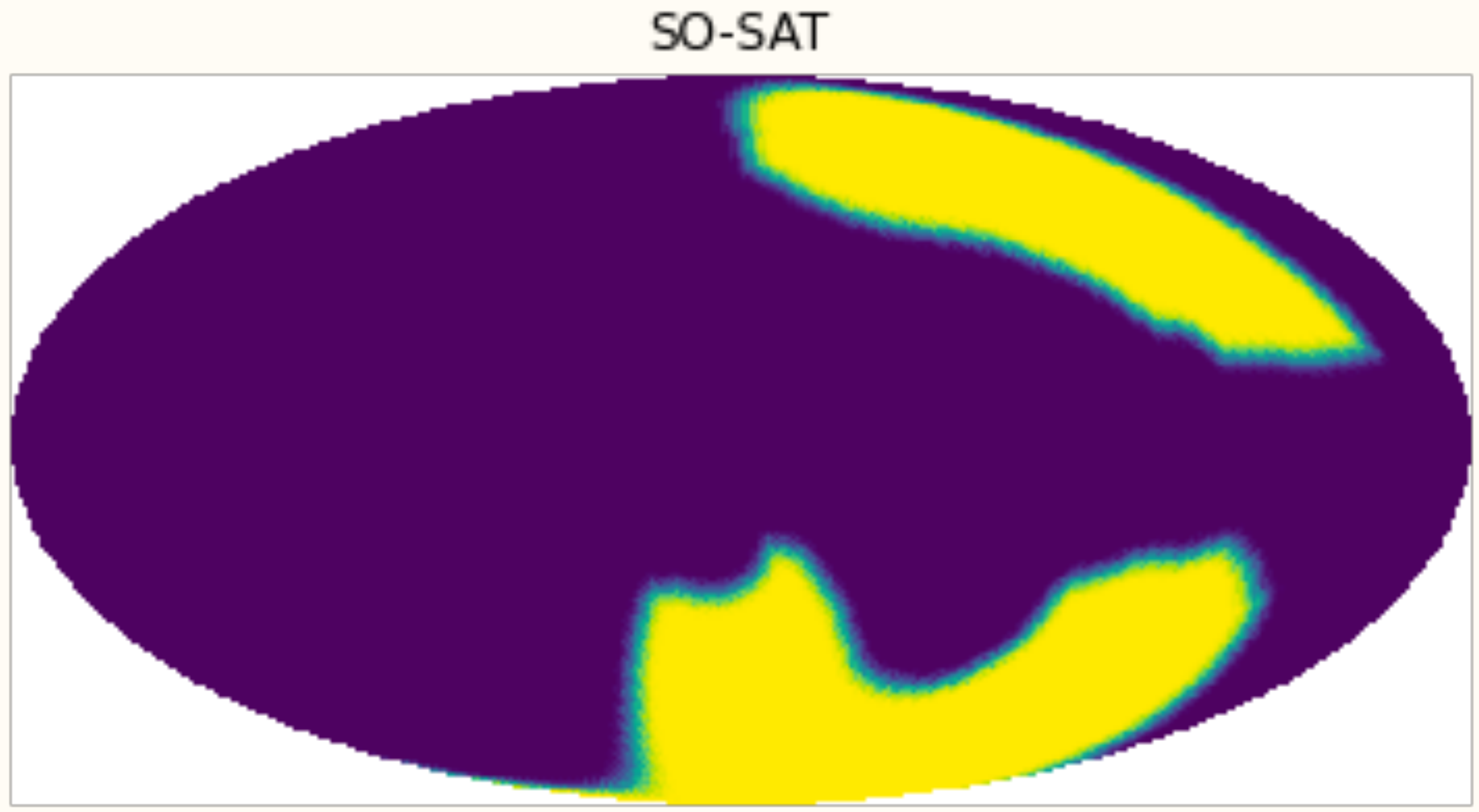
FG residuals- LiteBIRD

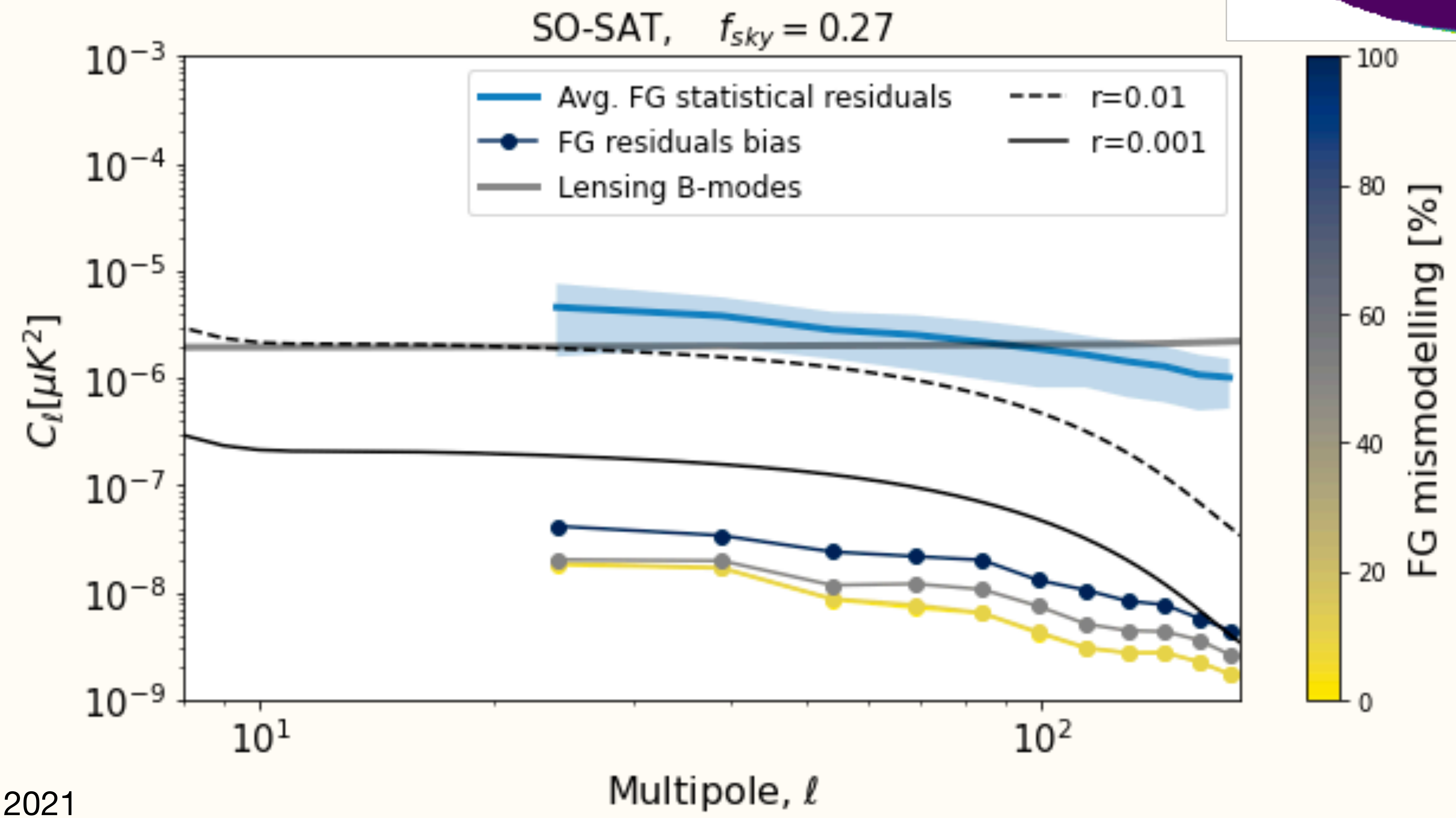




Puglisi et al. 2021

FG residuals - SO SAT

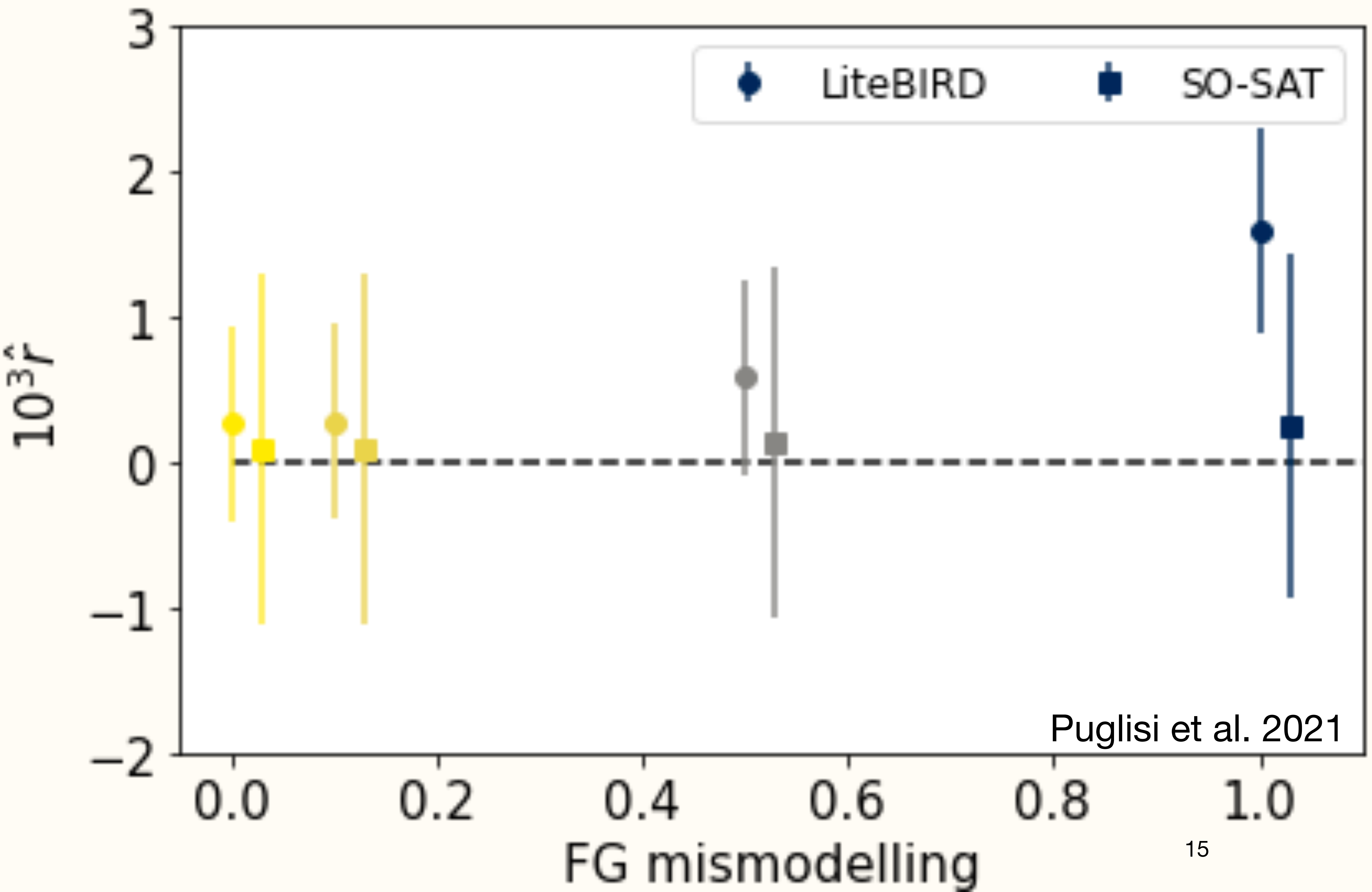




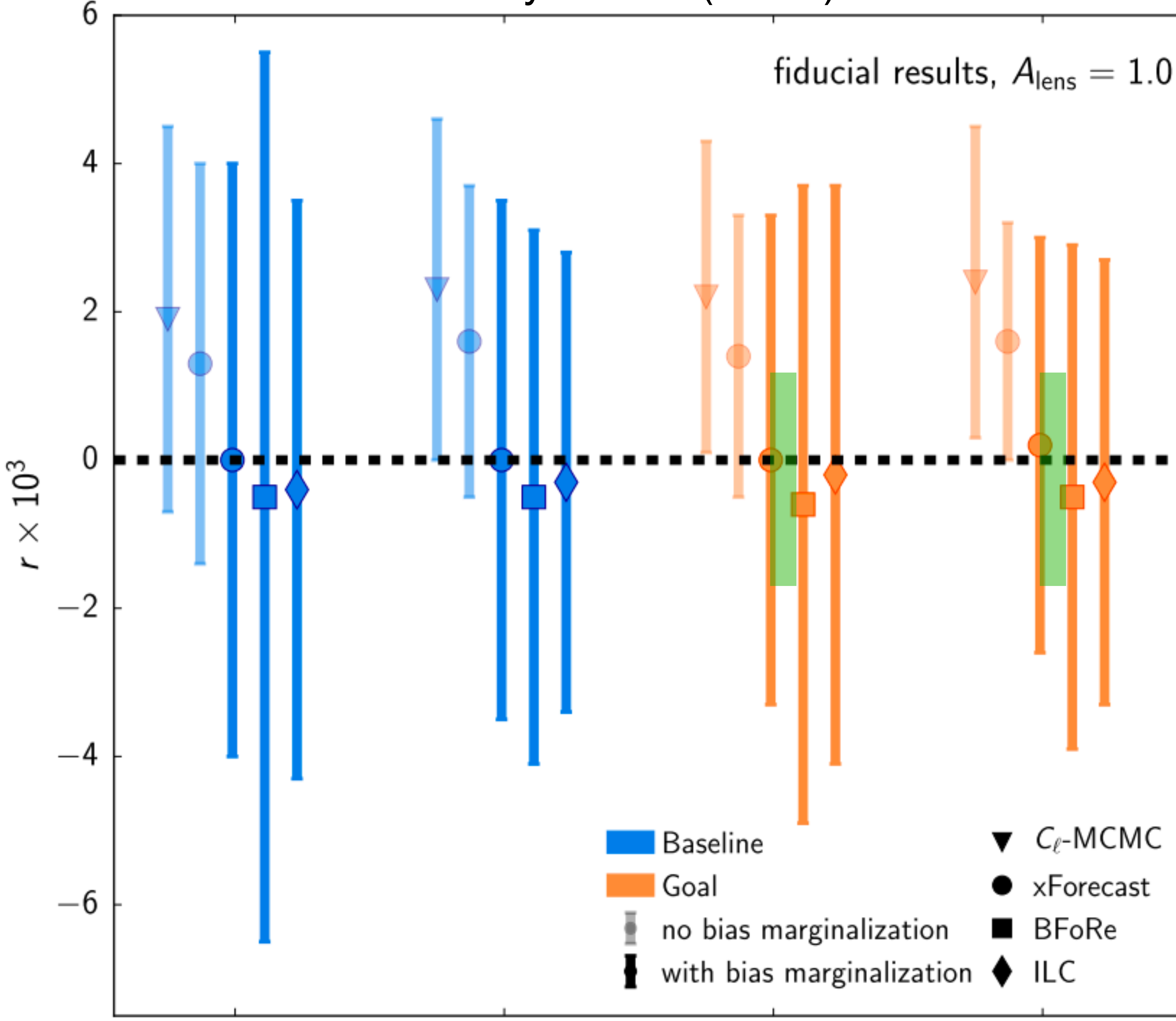
Puglisi et al. 2021

r - estimates

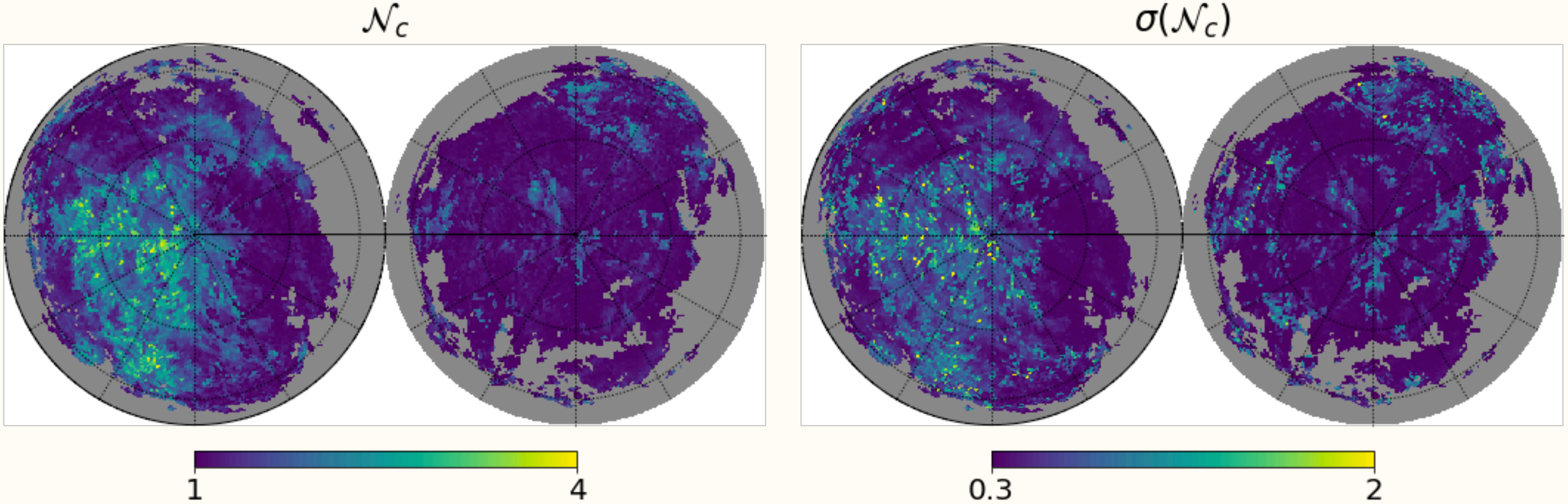
$$\ln \mathcal{L}(r) = \sum_{\ell_b=\ell_{\min}}^{\ell_{\max}} \ln \left(-f_{sky} \Delta\ell \frac{2\ell_b + 1}{2} \left[\frac{\hat{C}_{\ell_b}}{C_{\ell_b}} + \ln C_{\ell_b} \right] \right)$$



Simons Observatory Collab.(2019)

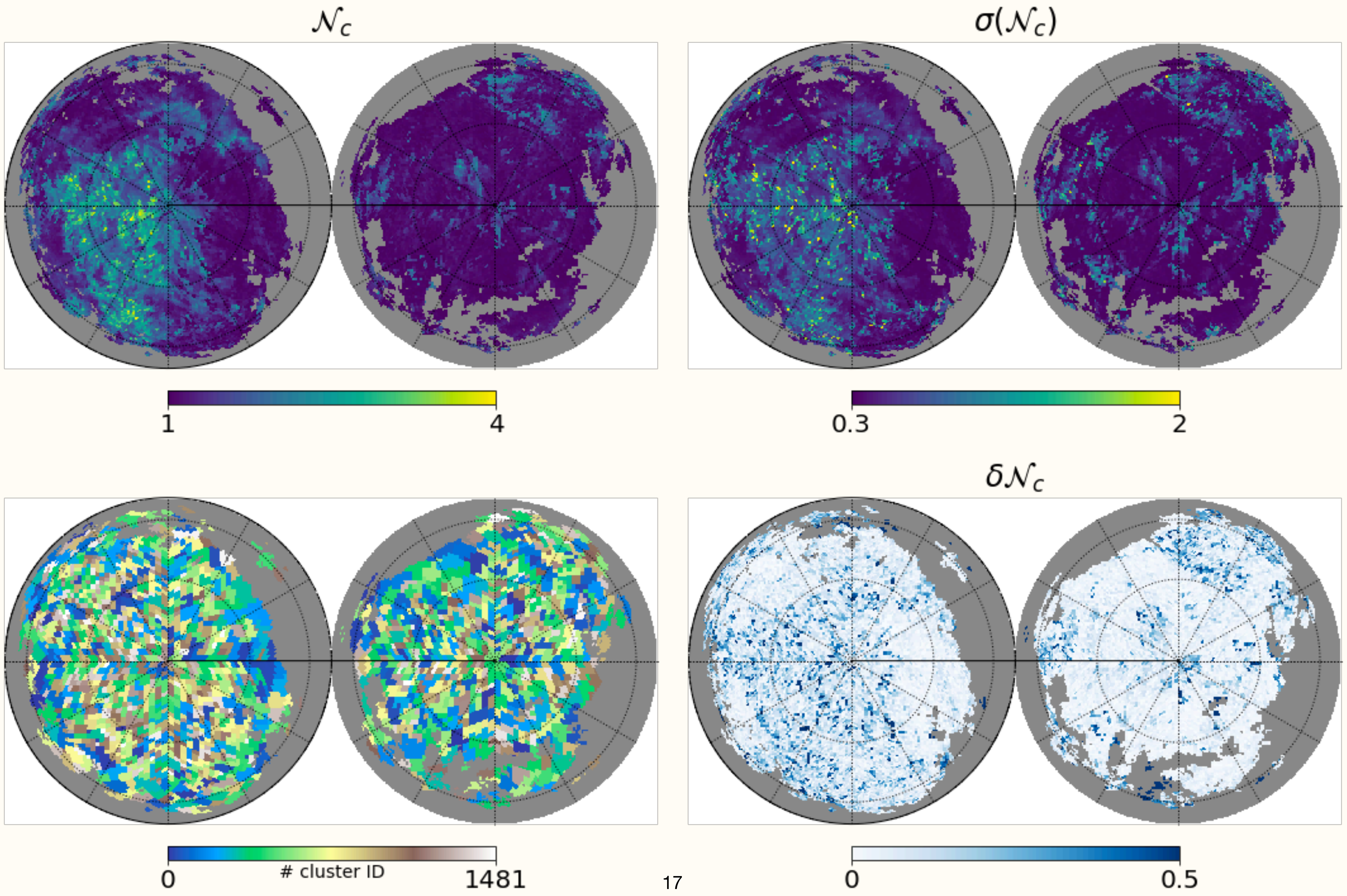


Application#2 : Clusters on number of clouds along l.o.s.



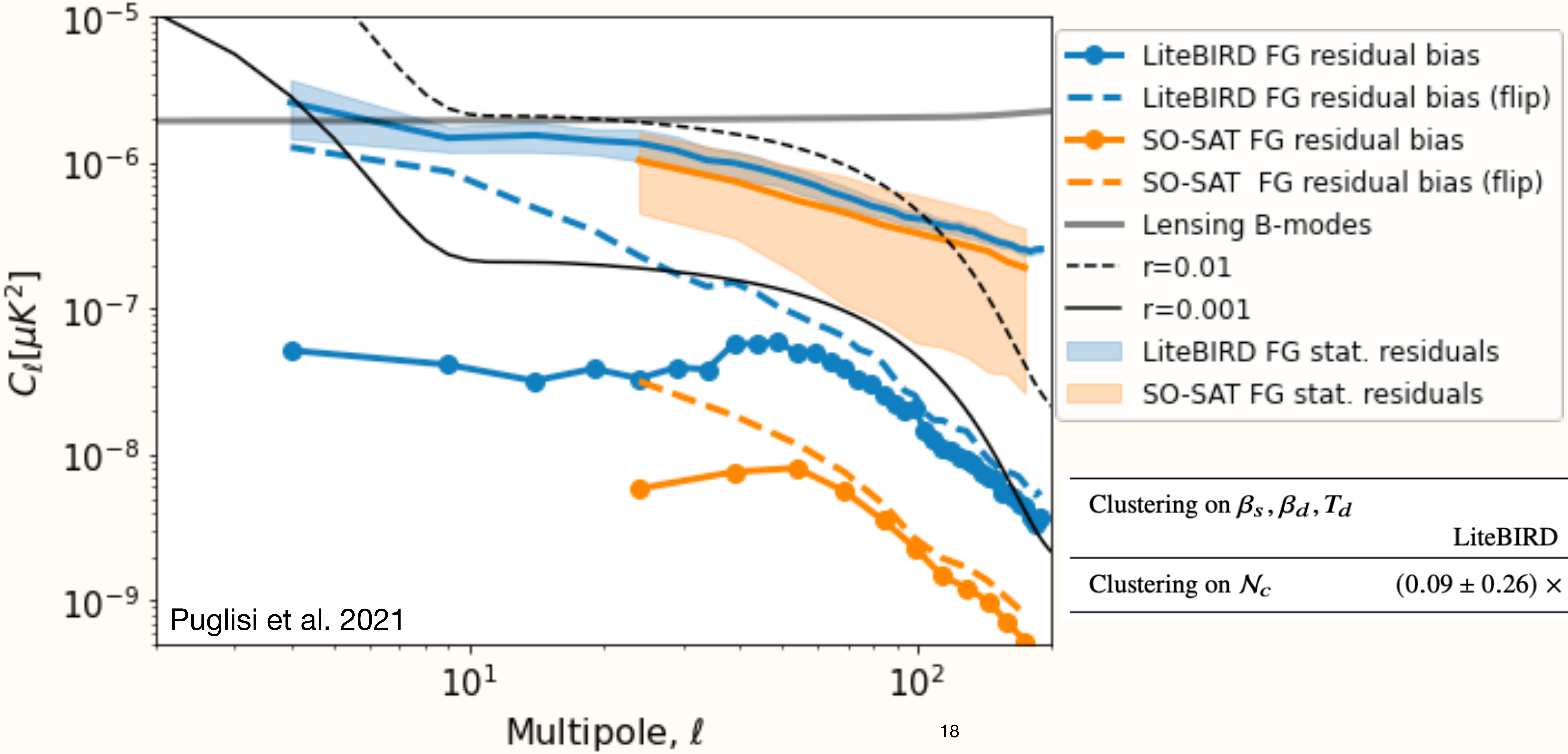
Lenz & Panoupolou 2020

Clusters on number of clouds



Clusters on number of clouds

- no synchrotron
- high freq. channels (>90GHz)



Clustering on β_s, β_d, T_d	LiteBIRD	SO-SAT
Clustering on N_c	$(0.09 \pm 0.26) \times 10^{-3}$	$(0.04 \pm 0.16) \times 10^{-3}$

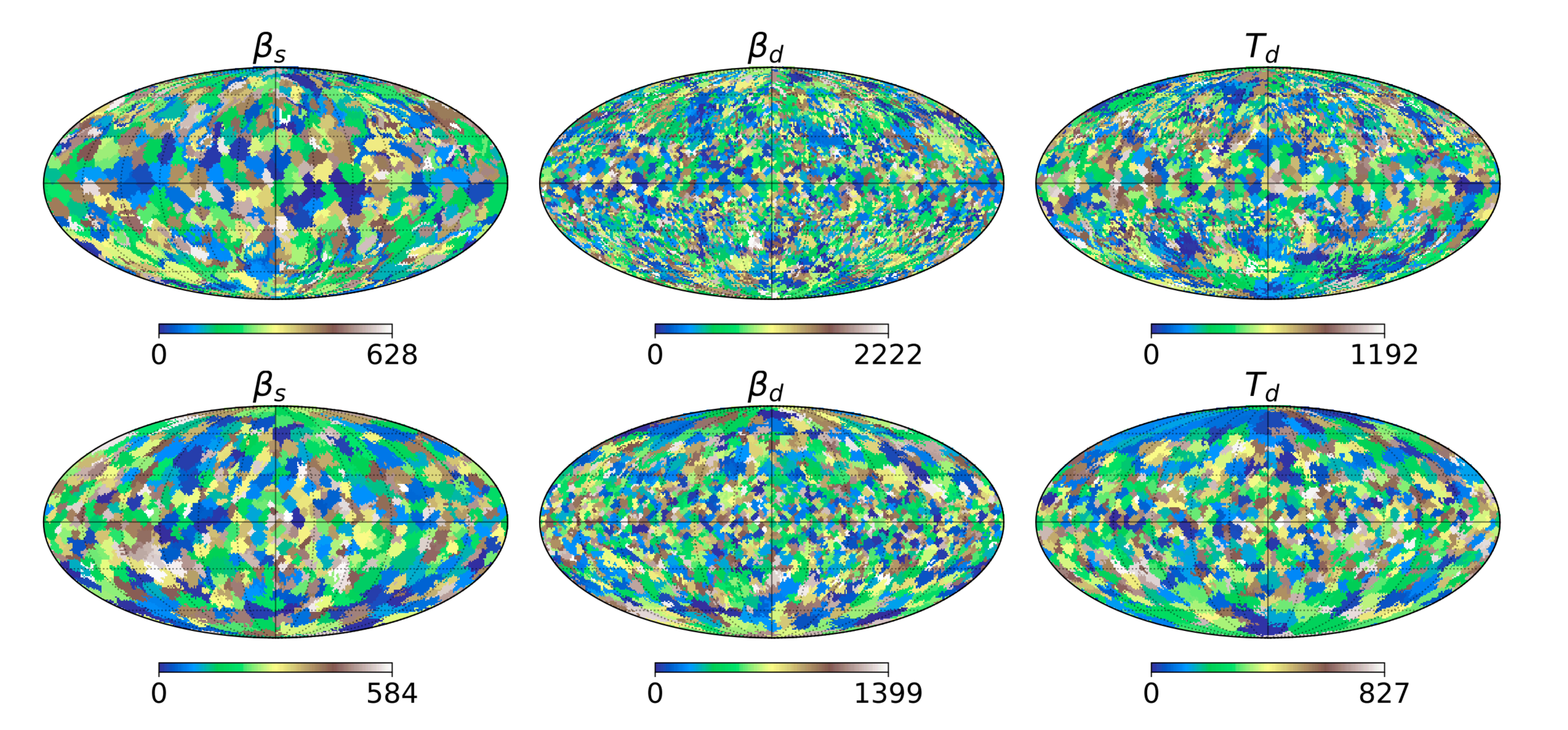
Summary

- We propose a novel methodology for ancillary supporting traditional comp sep techniques
- We tested the component separation with clusters derived by assuming several mis-modelling levels of the spectral parameter
- We exploit the information from the Nc map (Lenz&Panopoulou 2020) as a a tracer for thermal dust and derived clusters from Nc.
- Estimates on *r* are within the level of requirements of SO and Litebird
- **FGcluster** and cluster maps have been made publicly available online at https://github.com/giuspugl/fgcluster
- Application to Needlet-ILC   on going at UniTorvergata (see A. Carones Poster)

GRAZIE!!

Backup

Clusters obtained with mismodelled parameters



Parametric Component Separation

We can express multi-freq. maps of a generic CMB experiment as

$$m_\nu(\hat{n}) = A_s f_s^\nu(\hat{n};\beta_s) + A_d f_d^\nu(\hat{n};\beta_d, T_d) + A_{cmb} f_{cmb}^\nu + n_\nu(\hat{n})$$

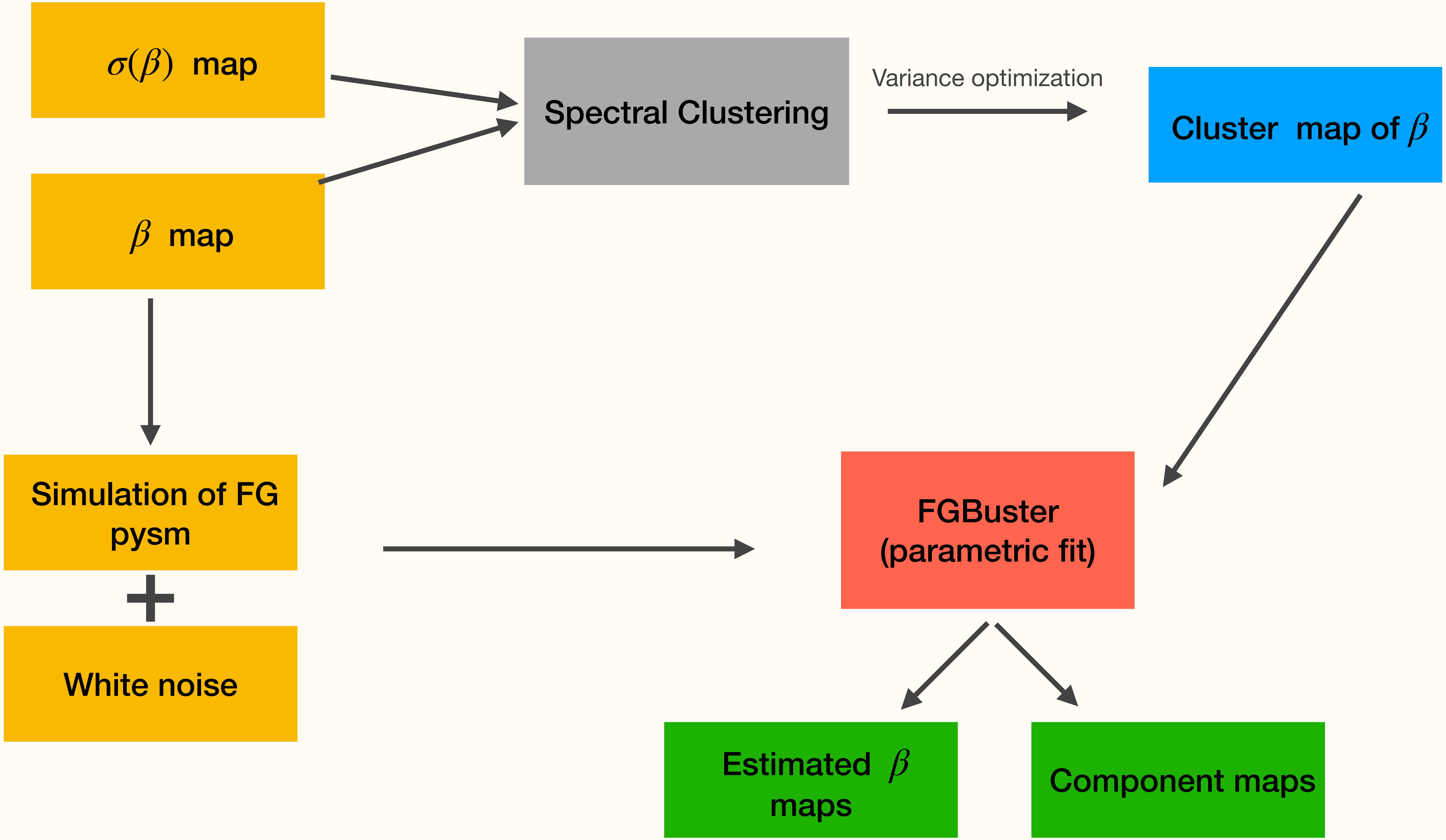
$$\mathrm{m} = \mathrm{A}(\beta)\,\mathrm{s} + \mathrm{n}$$

With some assumptions on the emission model and its spatial variability, i.e. A, it is possible to parametrically get an estimate of the vector $\hat{s}$, via the max likelihood:

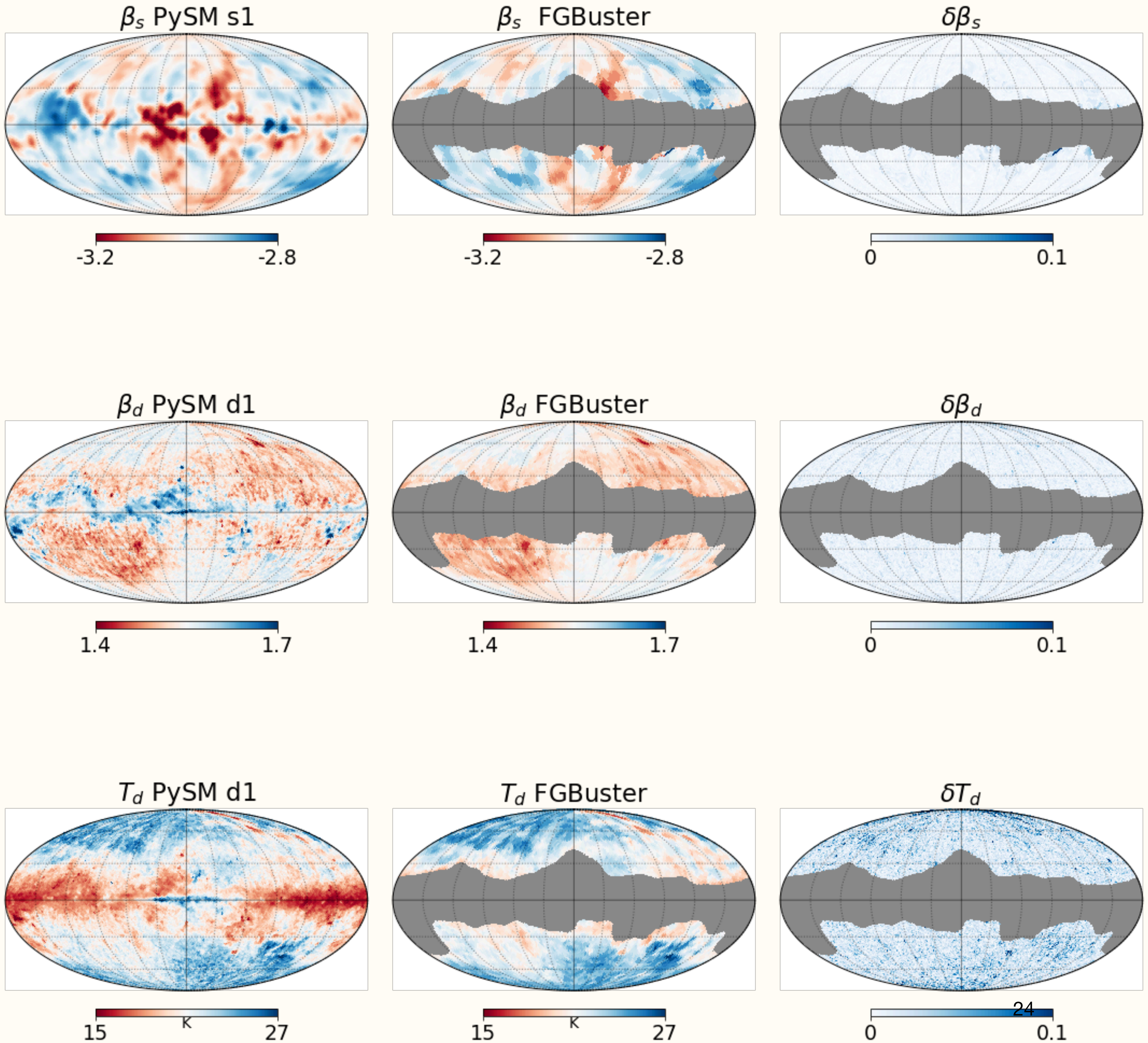
$$\ln \mathscr{L}(s,\beta) \propto (m - As)^t N^{-1}(m - As) + const$$

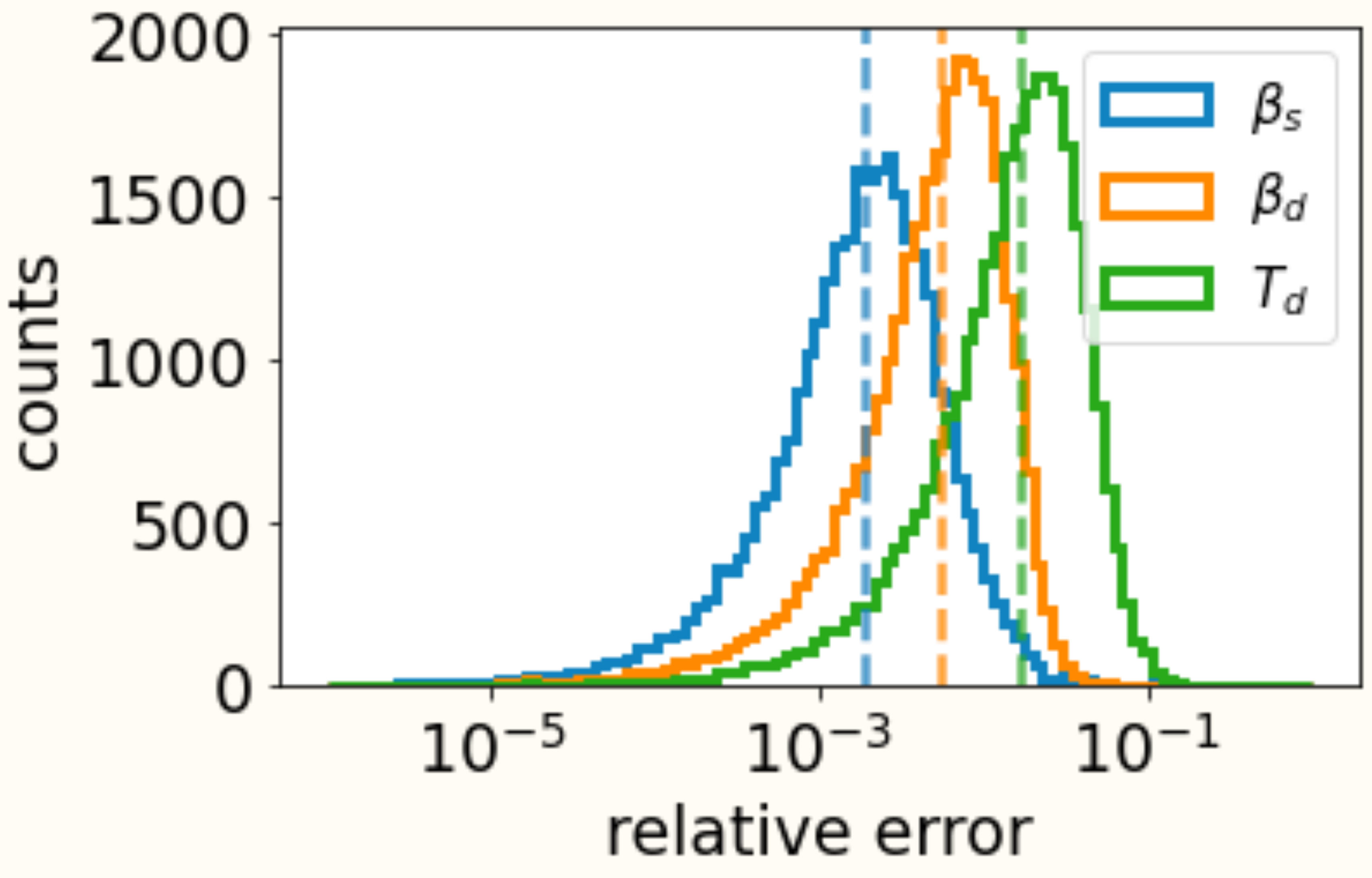
We aim at identifying an *optimal partition* of the sky so that we can perform local estimates of s and β

Clustering + Compsep Pipeline



FGBuster on clusters





/!\ In an ideal case we are tracking very well the spectral parameters !

Flip test w/ Nclouds

We flip the cluster in the Southern cap with the Northern ones, perform comp-sep

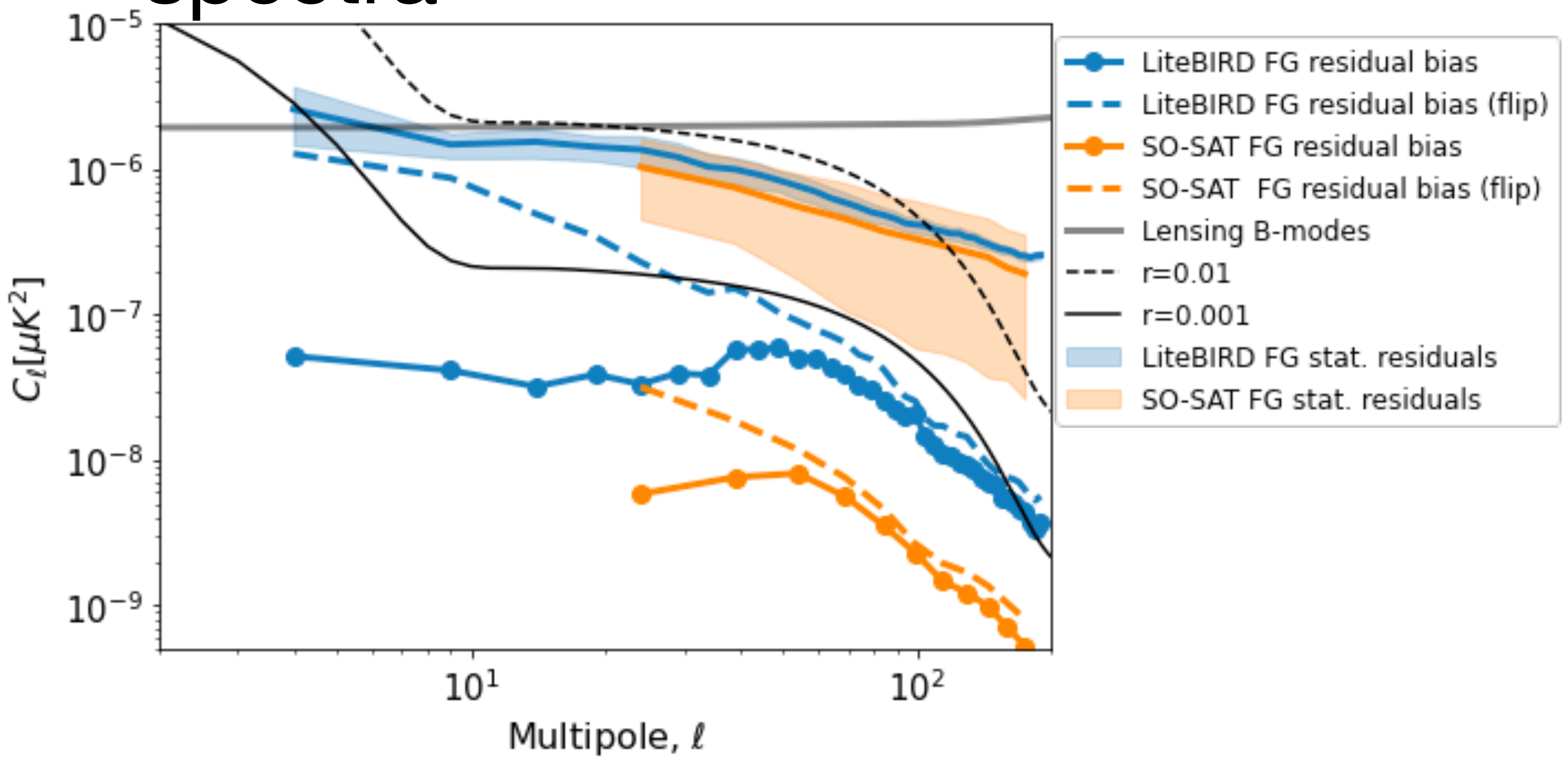
Relative error on Bd and Td estimates

Flip test w/ Nclouds

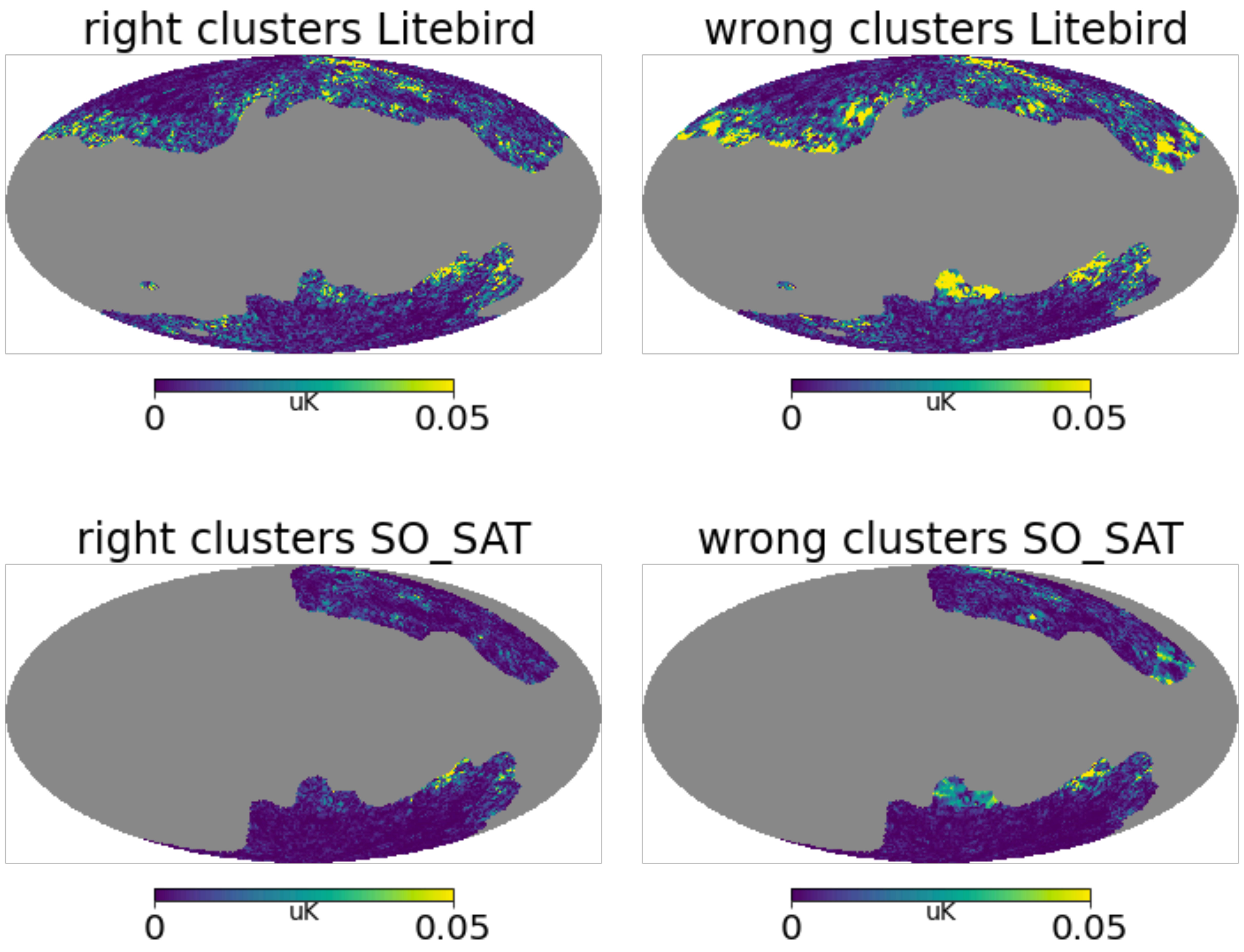
We flip the cluster in the Southern cap with the Northern ones, perform comp-sep

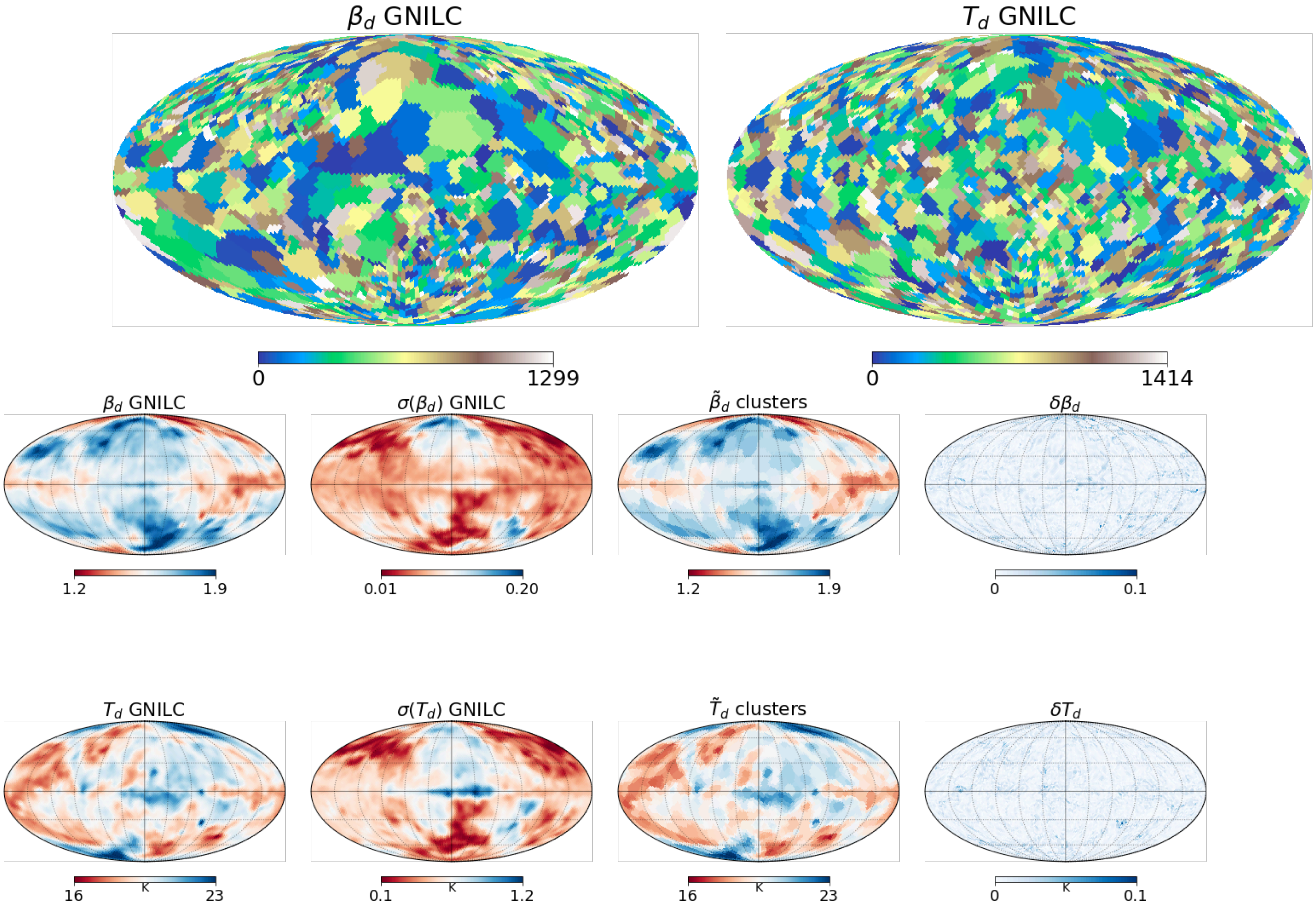
- We notice an increase in both the relative error on Bd and Td and in the CMB- P residuals

- They result residuals in the power spectra

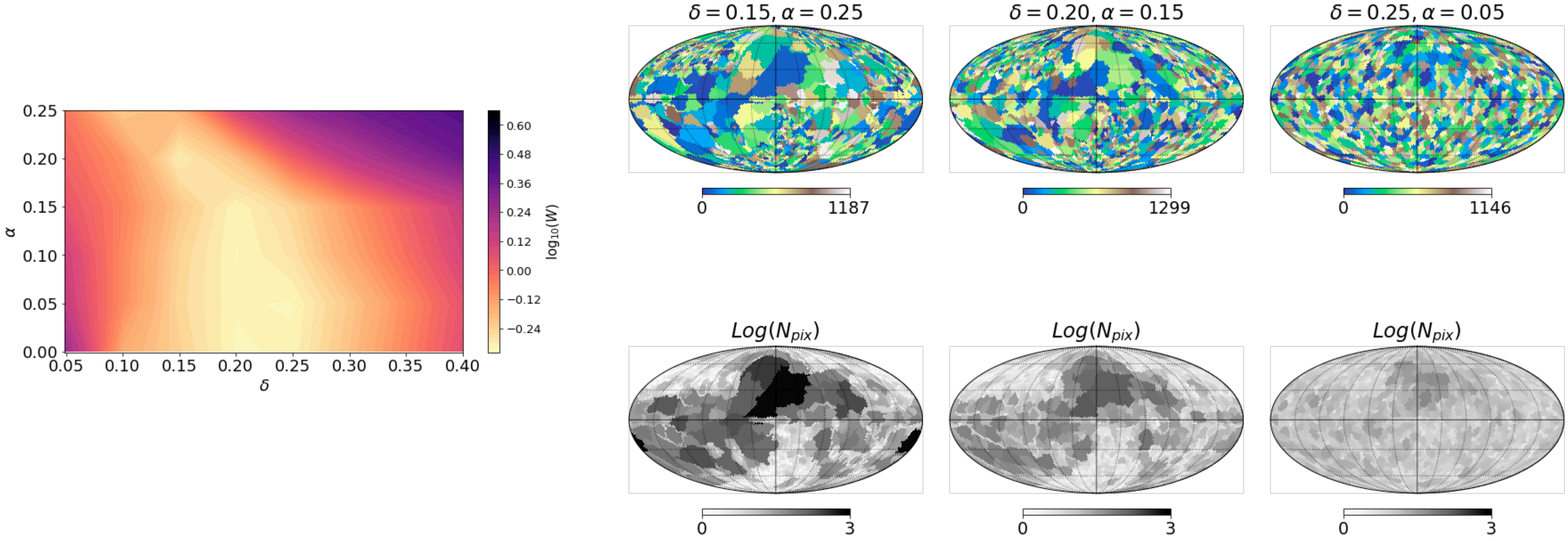


CMB P residuals





β_d GNILC
T_d GNILC
0
1299
0
1414
β_d GNILC
$\sigma(\beta_d)$ GNILC
$\tilde{\beta}_d$ clusters
$\delta\beta_d$
1.2
1.9
0.01
0.20
1.2
1.9
0
0.1
T_d GNILC
$\sigma(T_d)$ GNILC
$\tilde{T}_d$ clusters
δT_d
16
K
23
0.1
K
1.2
16
K
23
0
K
0.1



0.25
0.20
0.15
0.10
0.05
0.00
α
0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
δ
0.60
0.48
0.36
0.24
0.12
0.00
−0.12
−0.24
log10(W)
δ = 0.15, α = 0.25
0 1187
δ = 0.20, α = 0.15
0 1299
δ = 0.25, α = 0.05
0 1146
Log(Npix)
0 3
Log(Npix)
0 3
Log(Npix)
0 3