B-MODE FROM SPACE WORKSHOP

SECOND MEETING AT THE UNIVERSITY OF CALIFORNIA, BERKELEY

4 Dec 2017

Foregrounds cleaning for LiteBIRD with ***xForecast-multipatch*** and ***SMICA***

complementary slides from the San Diego workshop:

https://www.dropbox.com/s/2hpof74eje9dkjg/foregrounds_workshop.pdf?dl=0

Josquin Errard

Maude Le Jeune

Radek Stompor

Conclusions / to-do items after Montreal meeting (Jan 2017)

- we show **consistency** between xForecast and SMICA on constant spectral indices and PySM simulations
- **spatial variability of dust is important to characterize, and high frequency channels are crucial**

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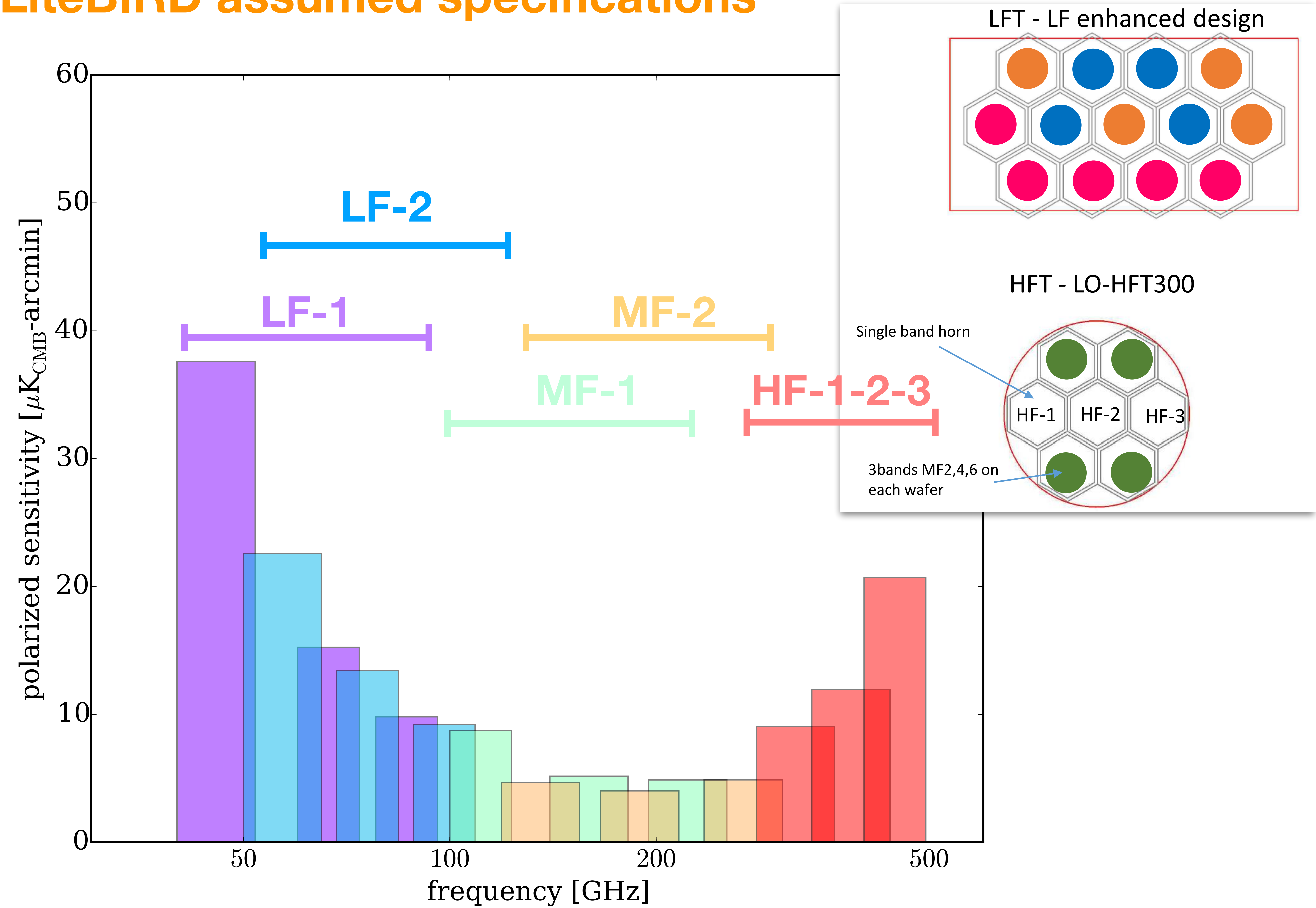
+ focal plane sensitivity has been updated

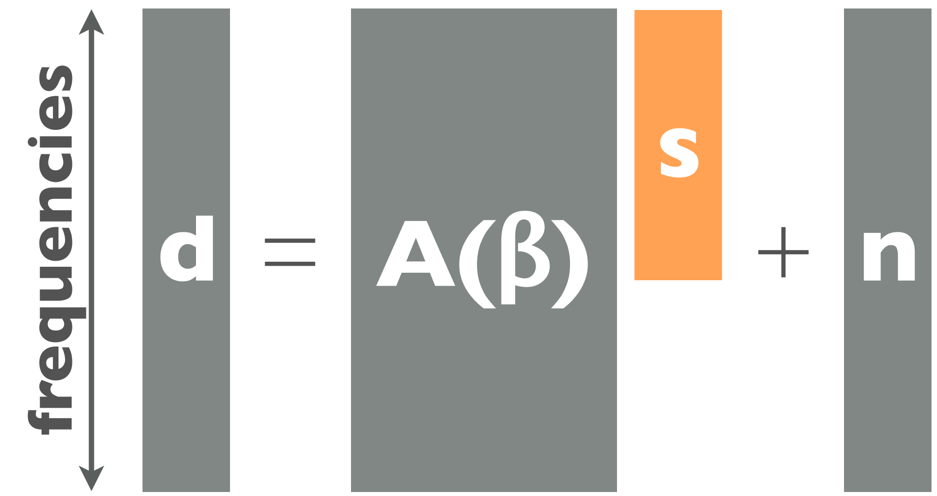
LiteBIRD assumed specifications



Method — xForecast

$$d_i(p) = A_{ij}\, s_j(p) + n_i(p)$$

data modeling
for each sky pixel:



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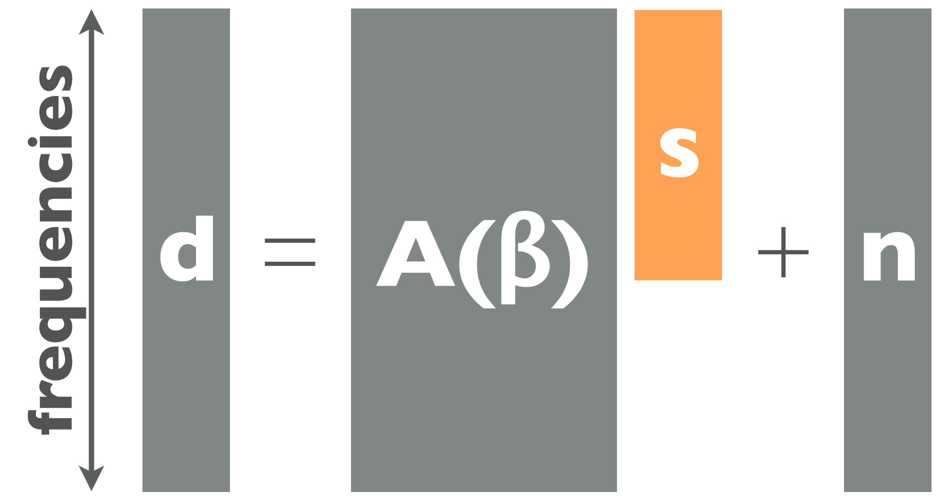

1. estimation of the mixing matrix A

e.g. **Stompor et al. (2009)**

$$A^{\rm raw}_{\rm sync}(\nu, \nu_{\rm ref}) \equiv \left(\frac{\nu}{\nu_{\rm ref}}\right)^{\beta_s}$$

$$A^{\rm raw}_{\rm dust}(\nu, \nu_{\rm ref}) \equiv \left(\frac{\nu}{\nu_{\rm ref}}\right)^{\beta_d+1} \frac{e^{\frac{h\nu_{\rm ref}}{k\,T_d}}-1}{e^{\frac{h\nu}{kT_d}}-1}$$

$$\mathbf{A} \equiv \mathbf{A}(\beta = \beta_d, \beta_s, ...) \longrightarrow \max\left(\mathcal{L}(\beta)\right)$$

not perfect recovery of input spectral parameters ➤ foregrounds residuals

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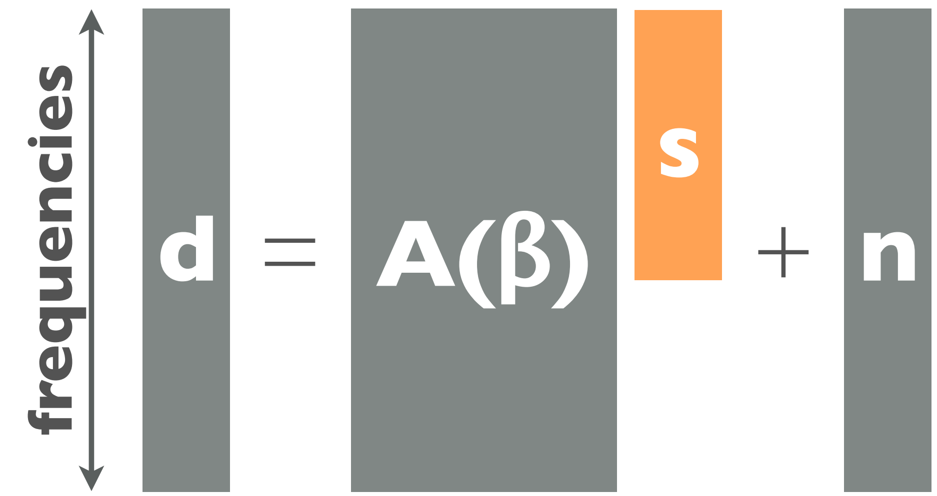

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$$\mathbf{A} \equiv \mathbf{A}(\beta = \beta_d, \beta_s, \ldots) \longrightarrow \max\left(\mathcal{L}(\beta)\right)$$

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2. solve for s [rather general to any comp sep method]

$$\mathbf{s} = \left(\mathbf{A}^T\mathbf{N}^{-1}\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{N}^{-1}\mathbf{d}$$

linear combination of various frequency maps ➤ boosted noise

xForecast results on PySM — a1d1f1s1 simulation (nside=16 / 3.5deg spatial variations for spectral indices)

[r_{sim}=0]

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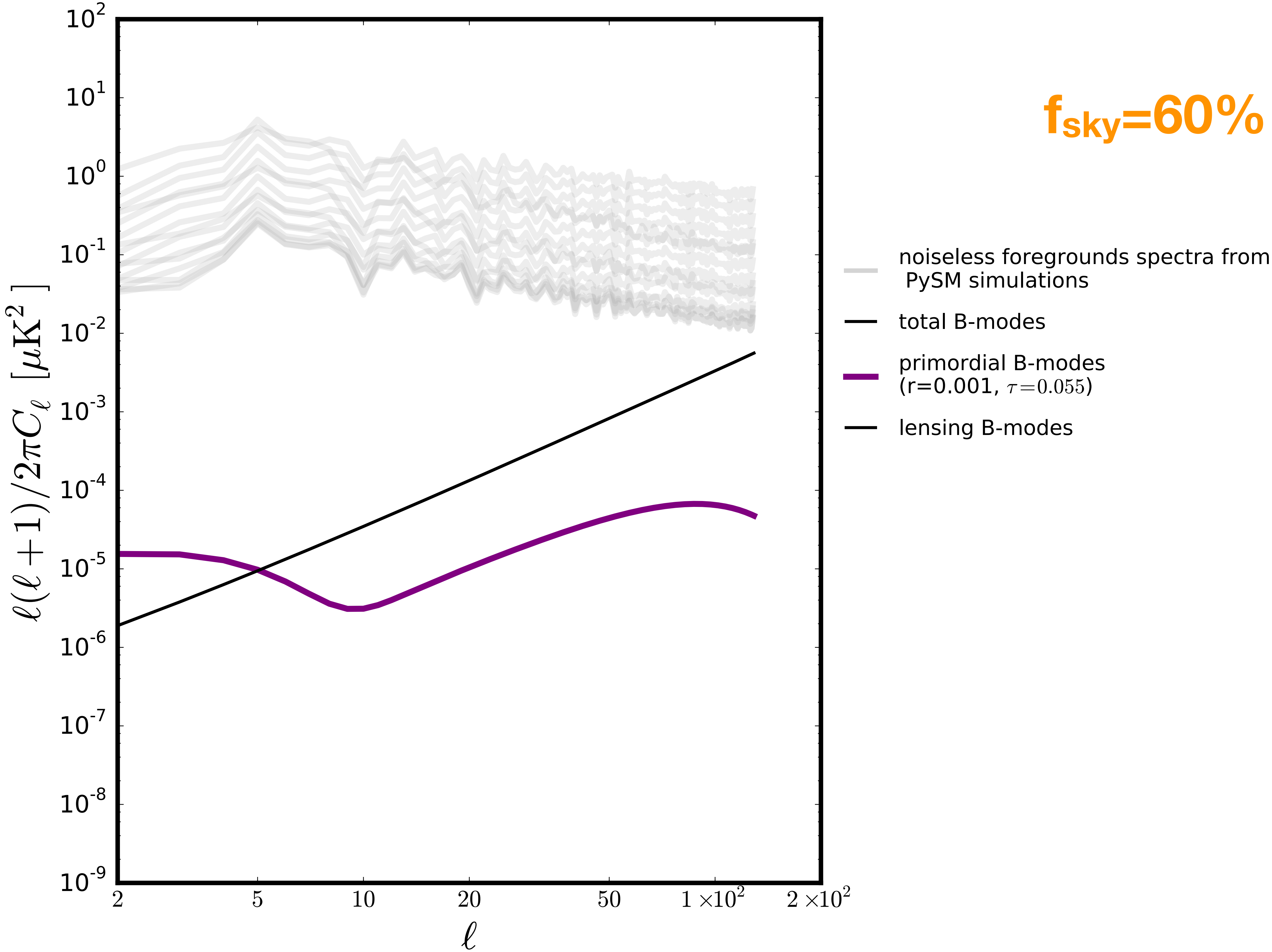

f_{sky}=60%

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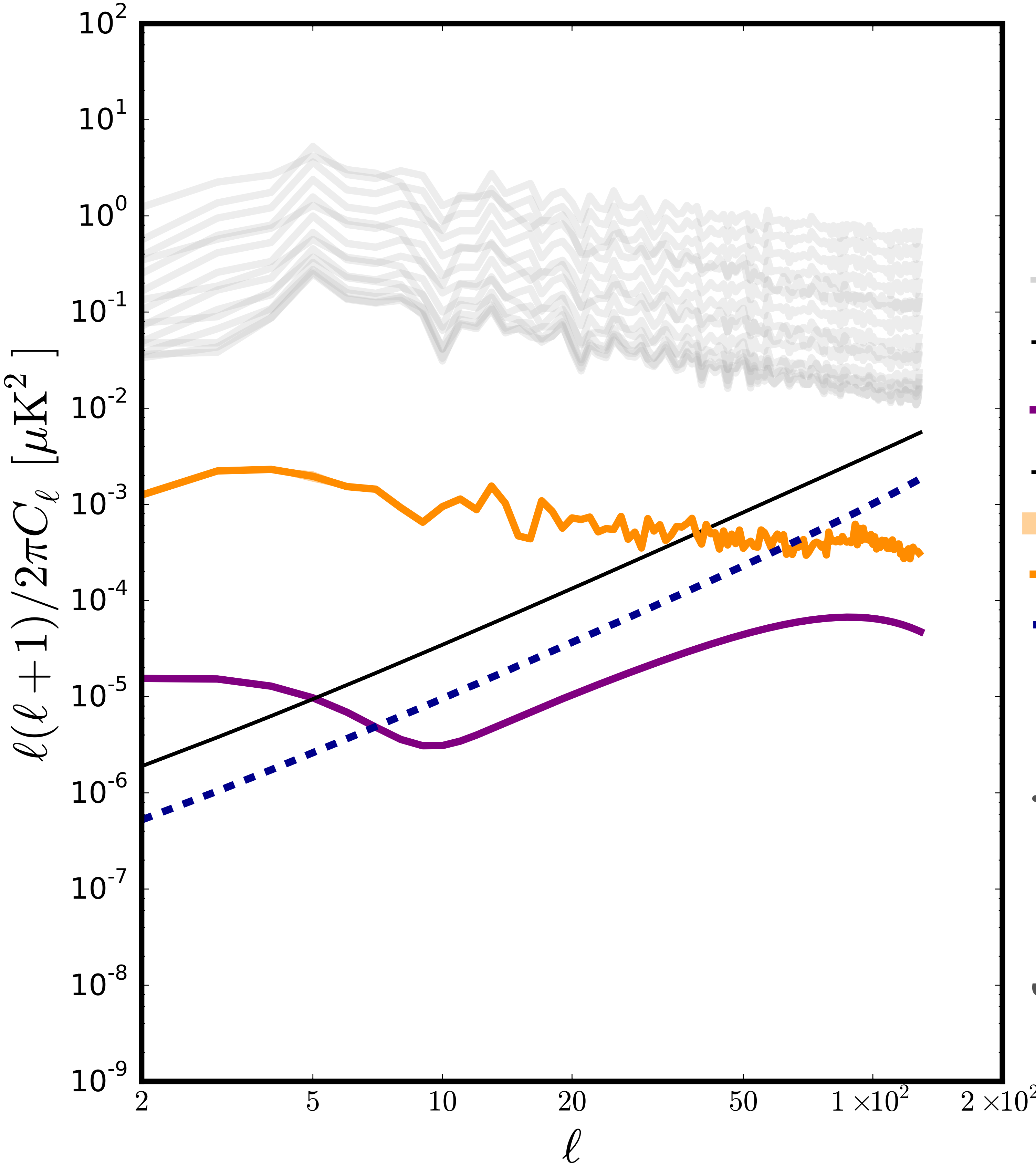

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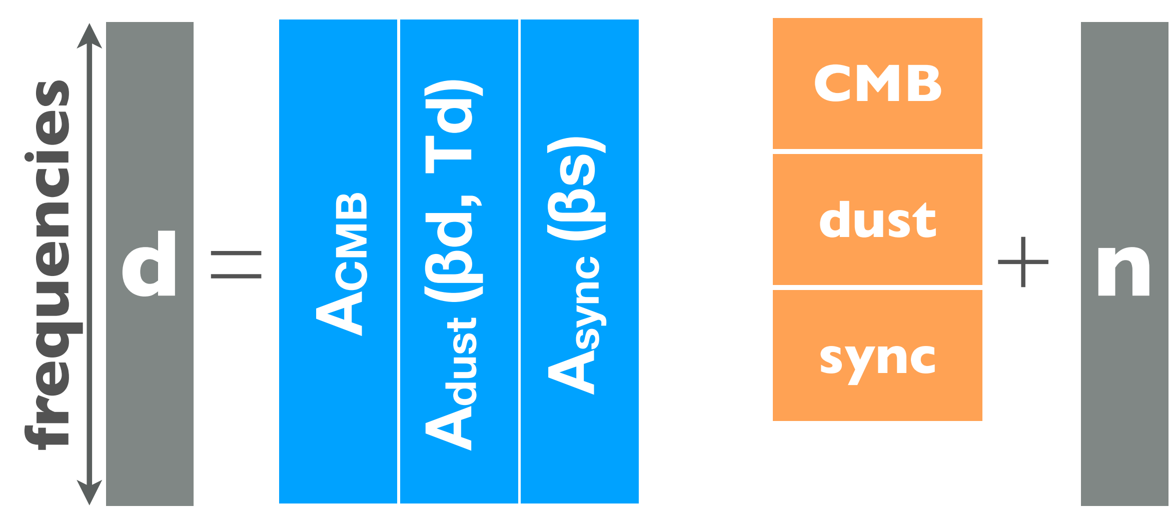

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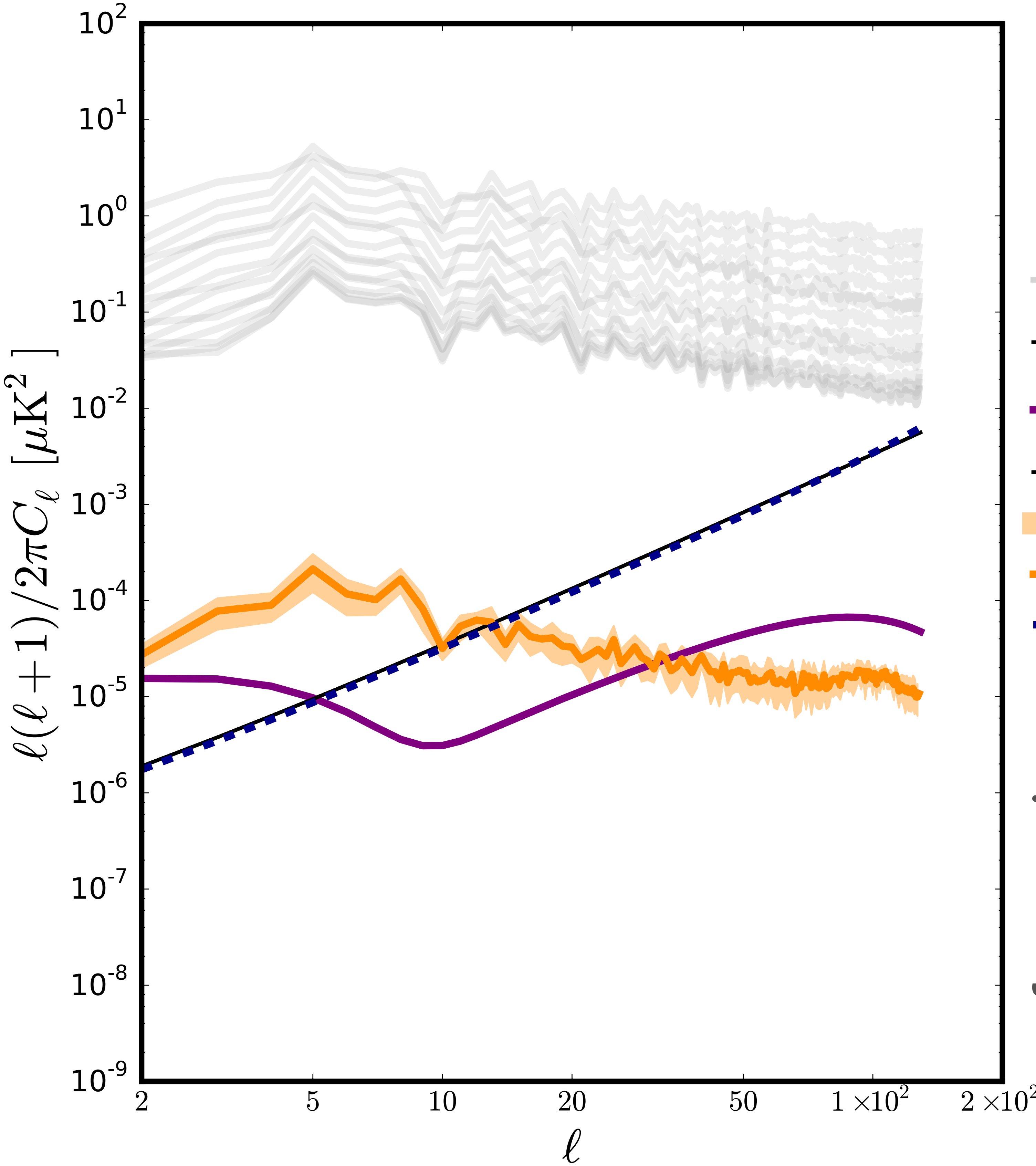

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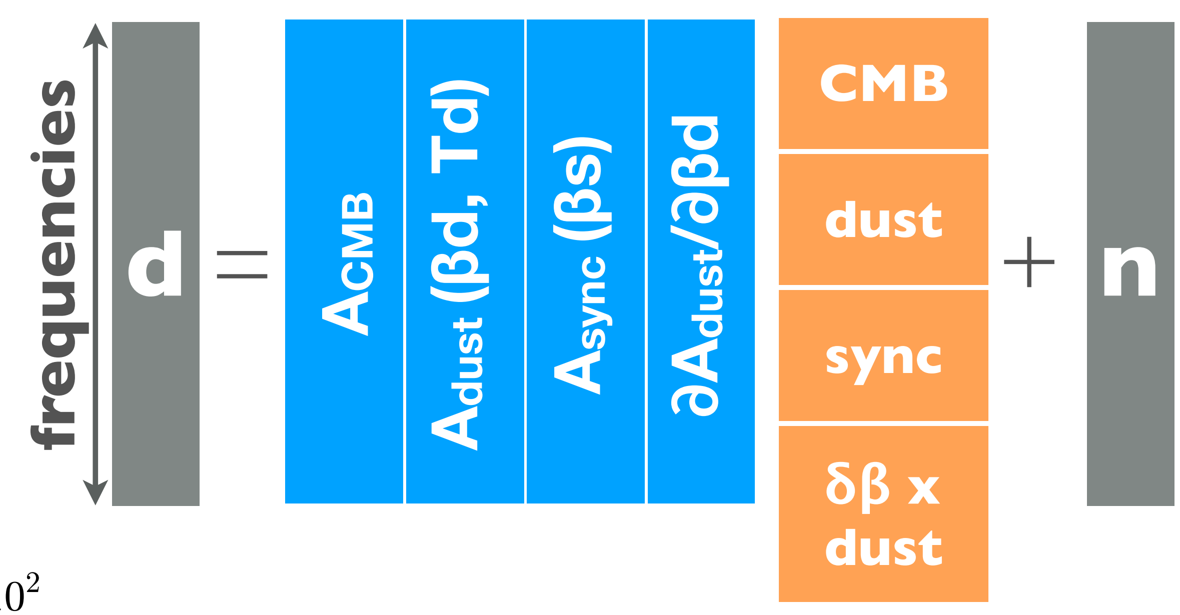

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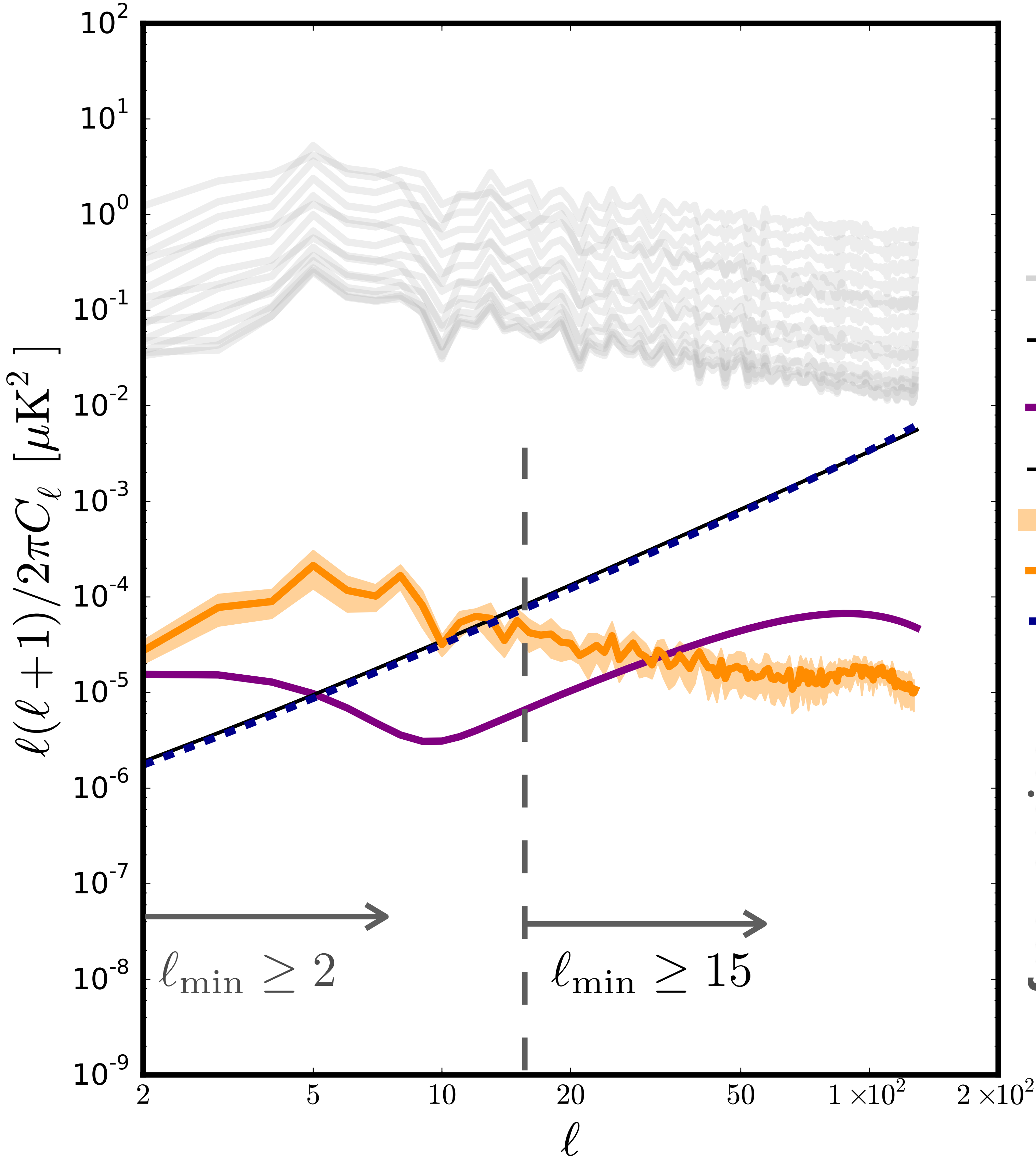

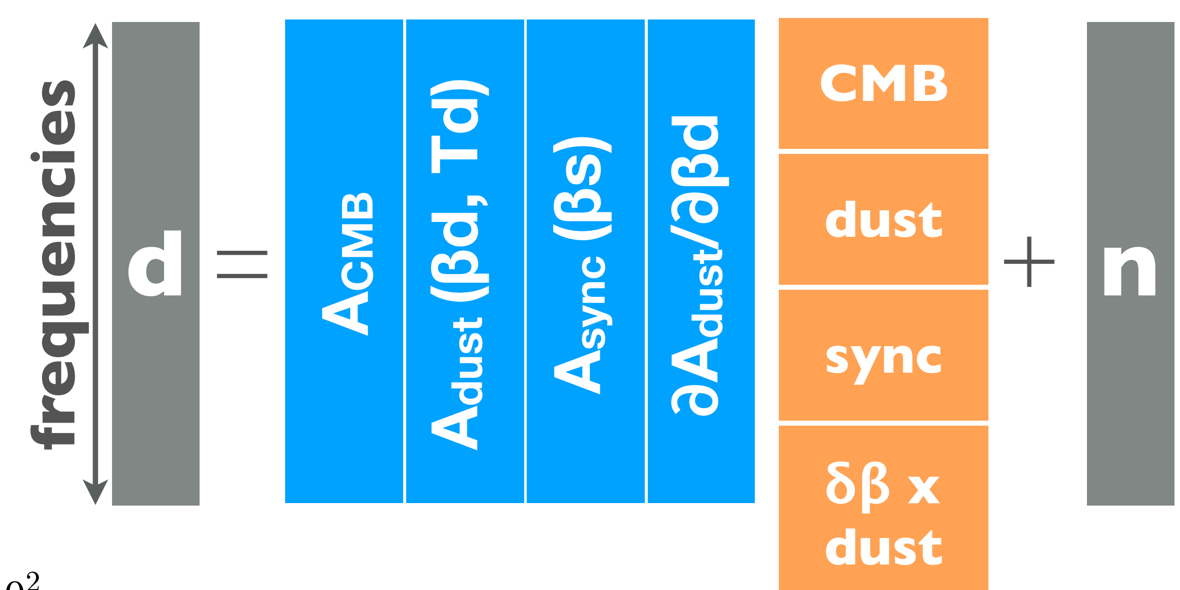

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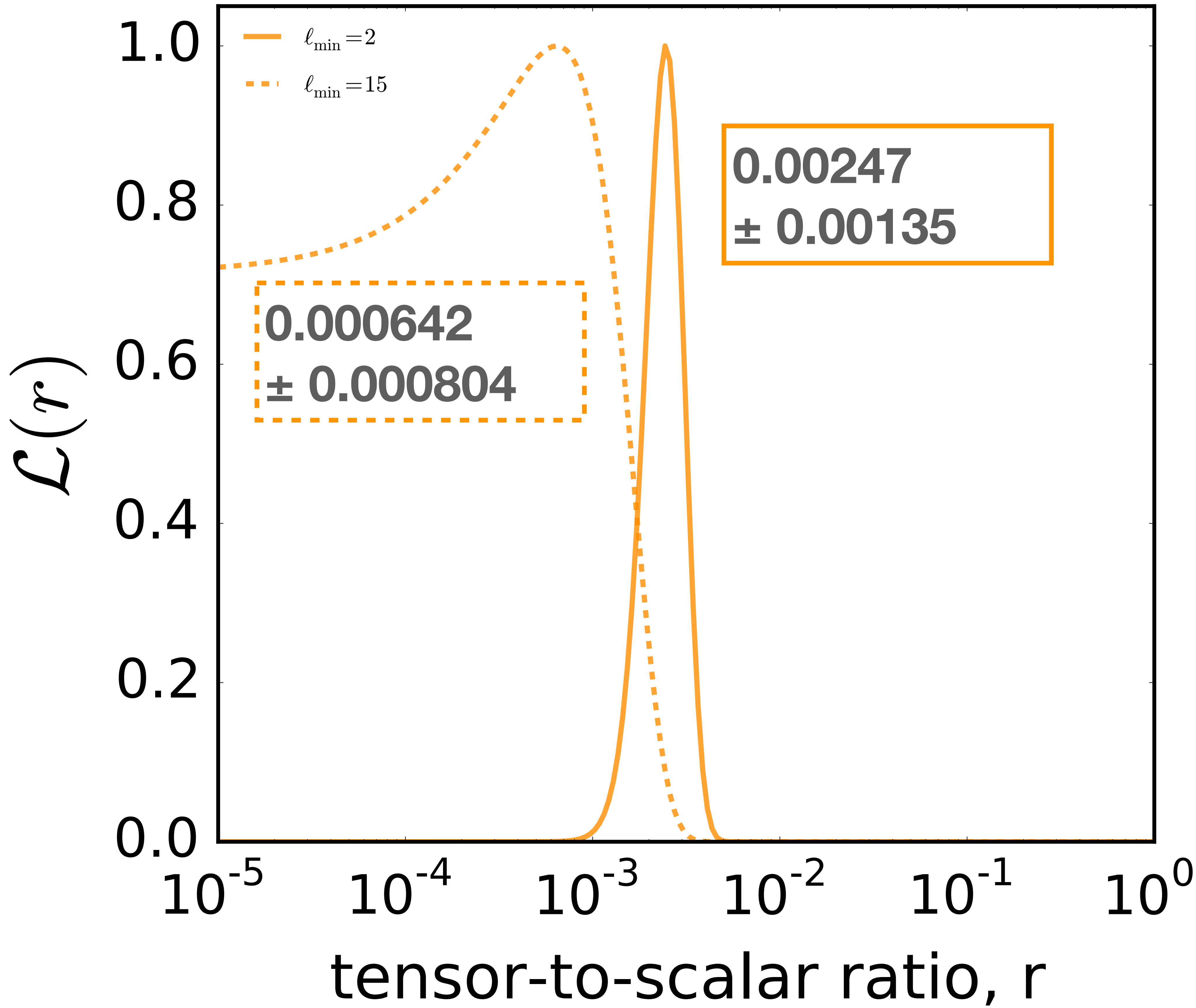

Method — SMICA

Cardoso et al, A&A, 2007

sky simulations + noise

second order statistics $\hat{R}_q^{BB} = \sum_m \left[a_{lm}^B\right] \left[a_{lm}^B\right]^T$

minimization of $\|\hat{\mathbf{R}} - \mathbf{R}\|$

modeling of the data covariance:

$$R_q = AP_qA^T + N_q$$

e.g. $R_q^{BB} = aa^{cmb^T}(r.c_q^{prim} + c_q^{lensed}) + A^{FG^T} P_q^{FG} A^{FG^T} + diag(\sigma_n^2)$

fit for r, and σ(r) estimated with Fisher

weights

$$W = A^T N^{-1} \left[A^T N^{-1} A\right]^{-1}$$

SMICA results on PySM — a1d1f1s1 simulation (nside=16 / 3.5deg spatial variations for spectral indices)

$$\mathbf{s} = \underbrace{\left(\mathbf{A}^T\mathbf{N}^{-1}\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{N}^{-1}}_{\mathbf{W}}\mathbf{d}$$

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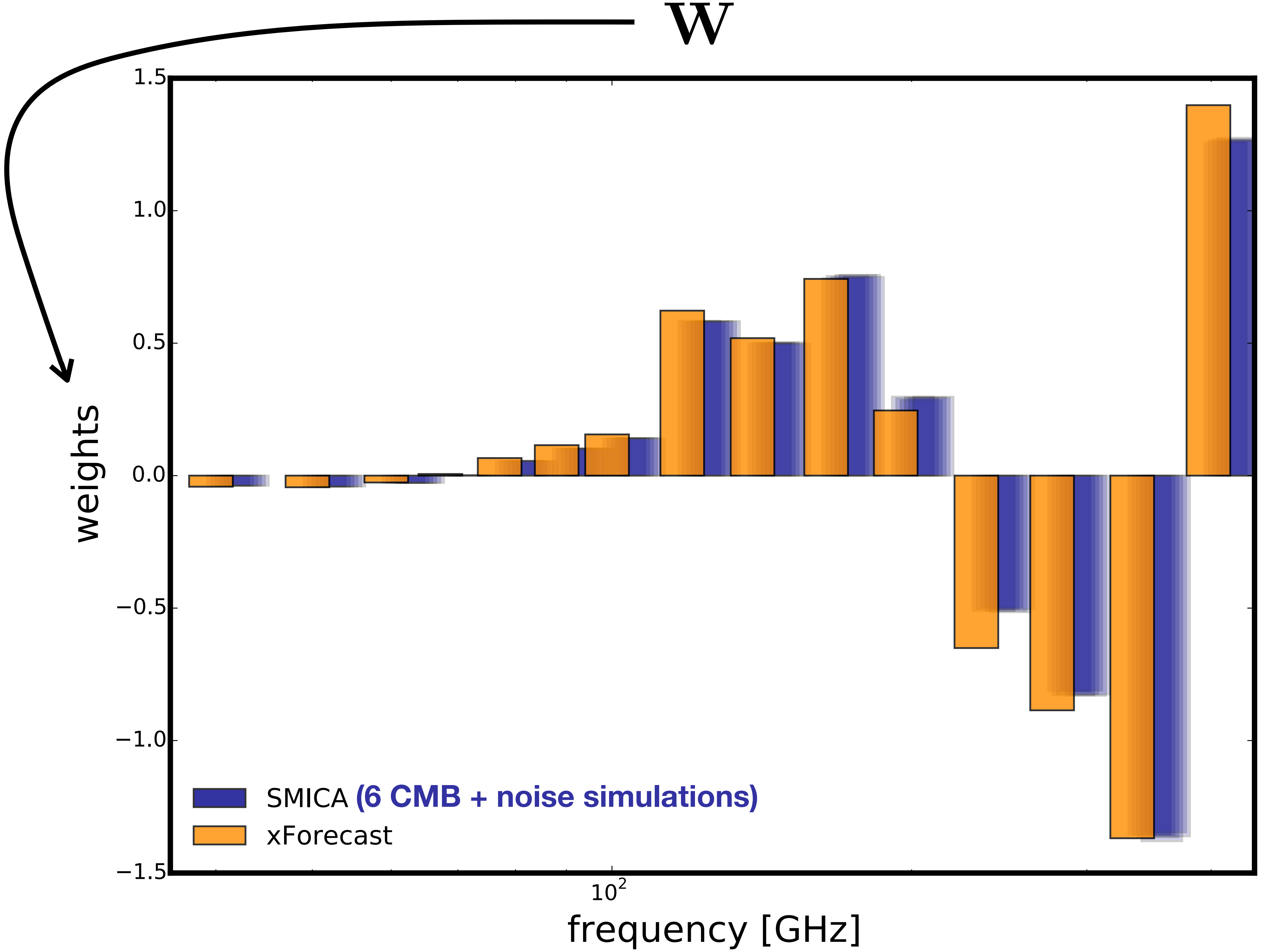

SMICA results on PySM — a1d1f1s1 simulation (nside=16 / 3.5deg spatial variations for spectral indices)

	$\ell_{\min} \geq 2$	$\ell_{\min} \geq 15$
xForecast	0.00247 ± 0.00135 (Hessian: ± 0.000507)	0.000642 ± 0.000804 (Hessian: ± 0.000792)
SMICA (Hessian error bars)	0.00222 ± 0.000673	0.000565 ± 0.000728

since Montreal:

- simplification of the foregrounds (spatial variation on nside=16): σ(r)=0.001 → σ(r)=0.0009
- new instrumental configuration: σ(r)=0.0009 → σ(r)=0.0007

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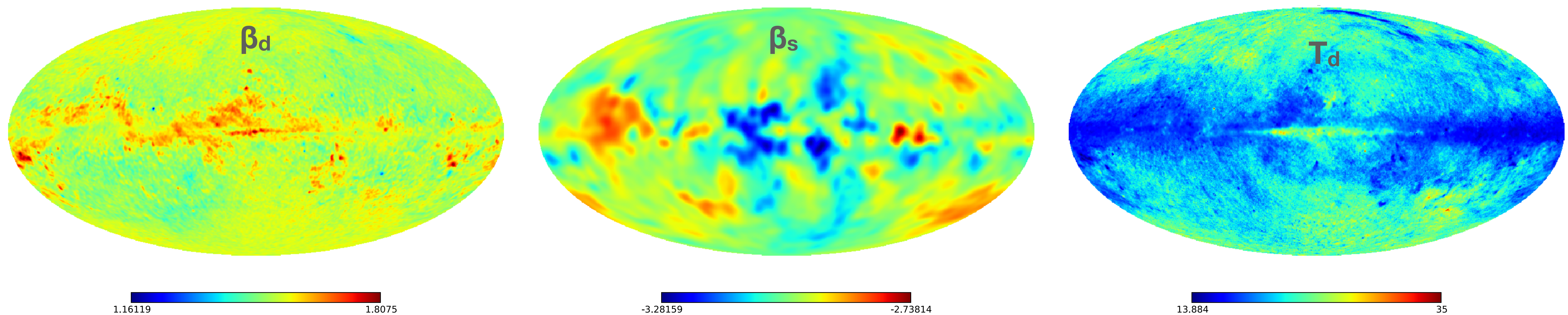
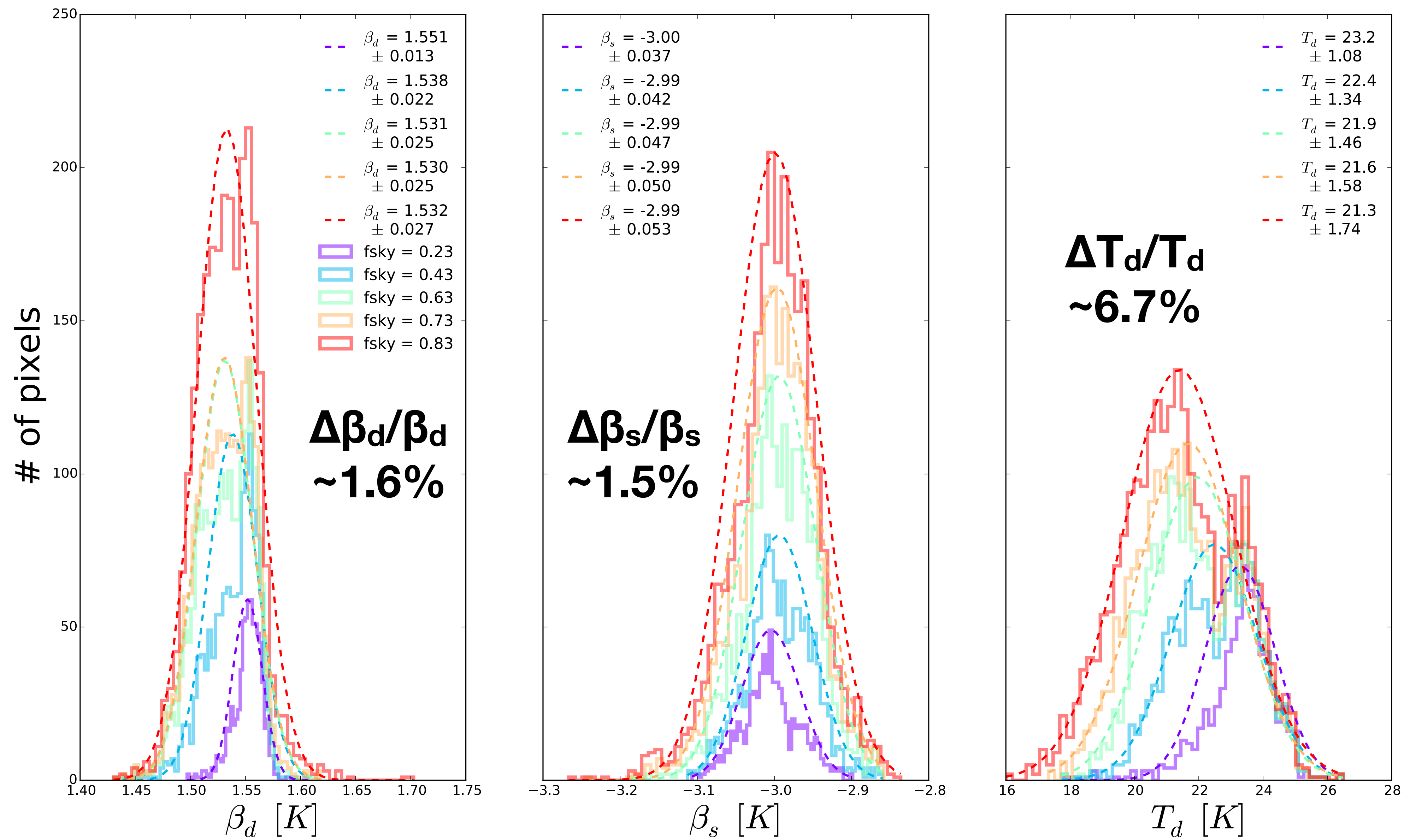
bias ~ O(0.002) on r on the largest angular scales:

it is crucial to take into account the spatial variations of spectral indices in the analysis

spatial variations of the spectral indices in the PySM templates





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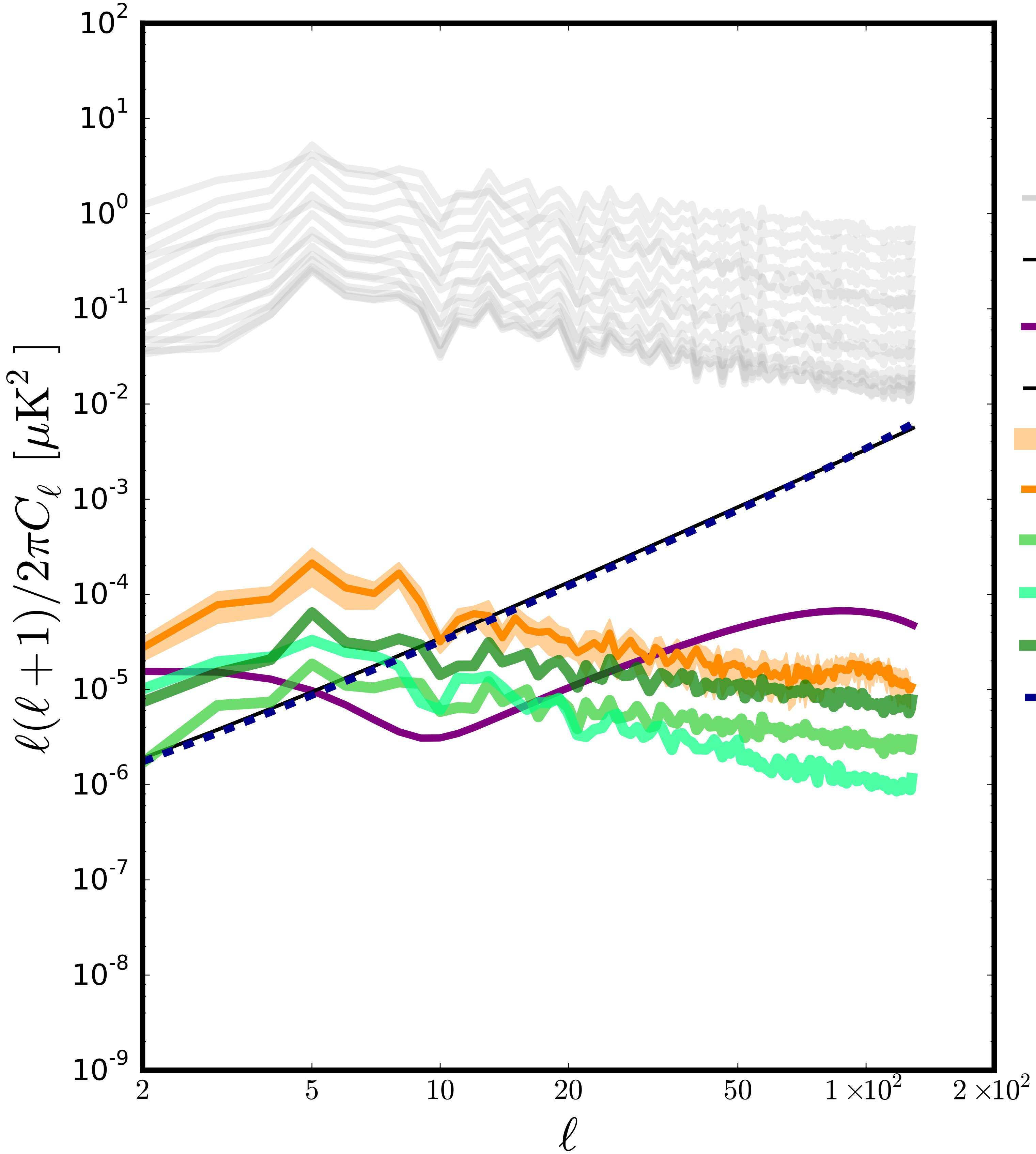

f_{sky}=60%

$$s^{\rm est.} \equiv \mathbf{W} d^{\rm in}$$

$$\Rightarrow \text{residuals} \equiv s^{\rm est.} - s^{\rm in}$$

$$\simeq \delta\beta \left.\frac{\partial \mathbf{W}}{\partial \beta}\right|_{\beta^{\rm true}} d^{\rm in}$$

we should look for a balance between statistical and systematic errors

STATISTICAL error bars on spectral parameters

SYSTEMATIC error bars on spectral parameters

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$$\mathbf{\Sigma} \equiv \begin{bmatrix} \sigma(\beta_d)^2 & \sigma(\beta_d)\sigma(\beta_s) & \sigma(\beta_d)\sigma(T_d) \\ \star & \sigma(\beta_s)^2 & \sigma(\beta_s)\sigma(T_d) \\ \star & \star & \sigma(T_d)^2 \end{bmatrix}$$

STATISTICAL error bars on spectral parameters

- better signal-to-noise (instrumental sensitivity, etc.)
- few degrees of freedom
- broad frequency range
- large sky area (more pixels!)

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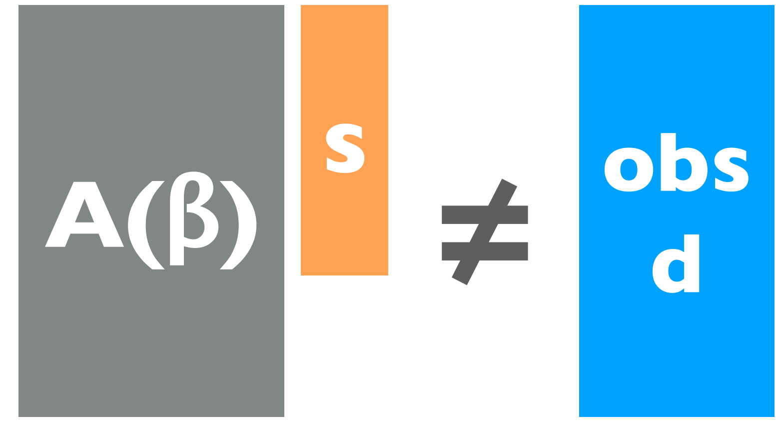
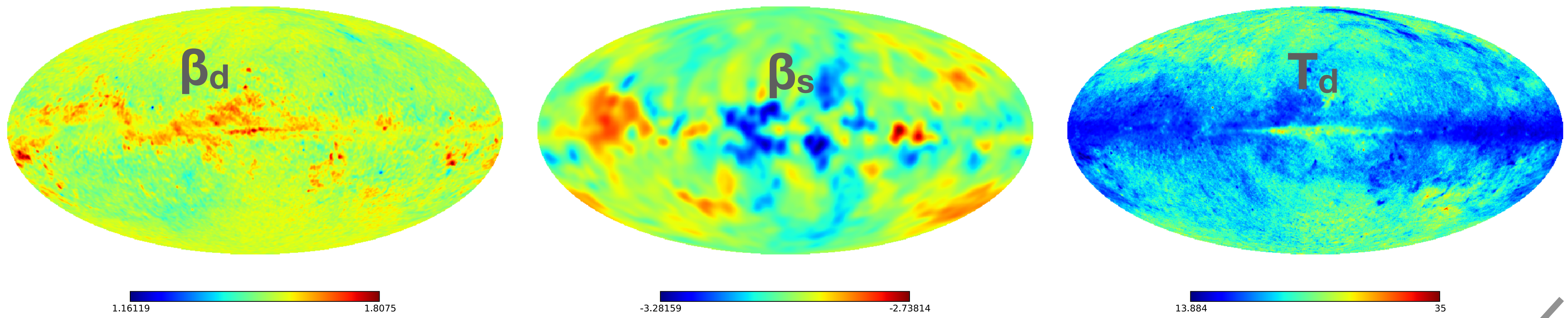


SYSTEMATIC error bars on spectral parameters

- more internal degrees of freedom (free spectral parameters, sky templates, etc.)
- reduced frequency range
- small sky area (less complexity!)

Method — multipatch

simulation



degrading/smoothing β maps down to nside= 2 / 4 / 8 / 16

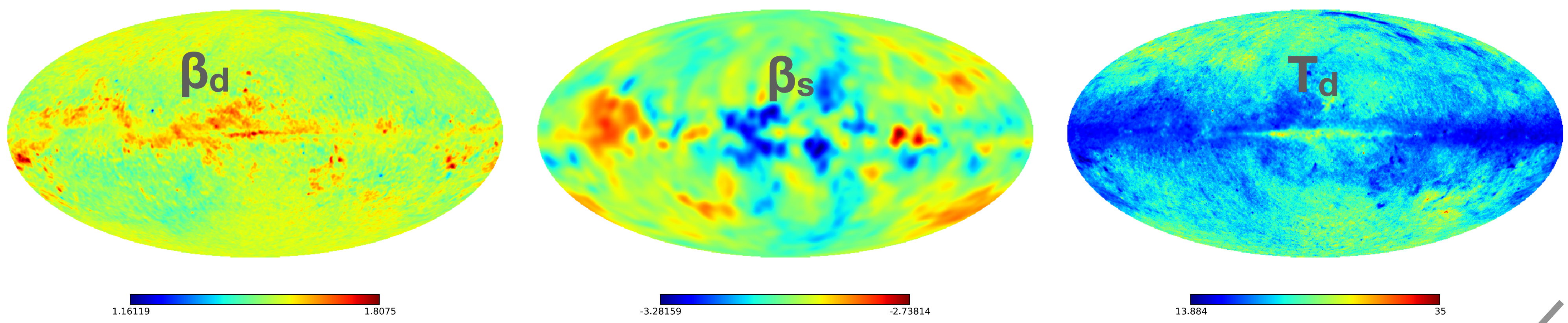
↓

upgrading β maps to nside= 32

↓

simulate frequency maps + CMB + noise

Method — multipatch



simulation

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↓

upgrading β maps to nside= 32

↓

simulate frequency maps + CMB + noise

↓

cleaning

fit for {β} in each nside = 2 / 4 / 8 / 16 pixels, <u>matching</u> the input simulation

↓

estimate foregrounds residuals and noise by combining contribution from each pixels

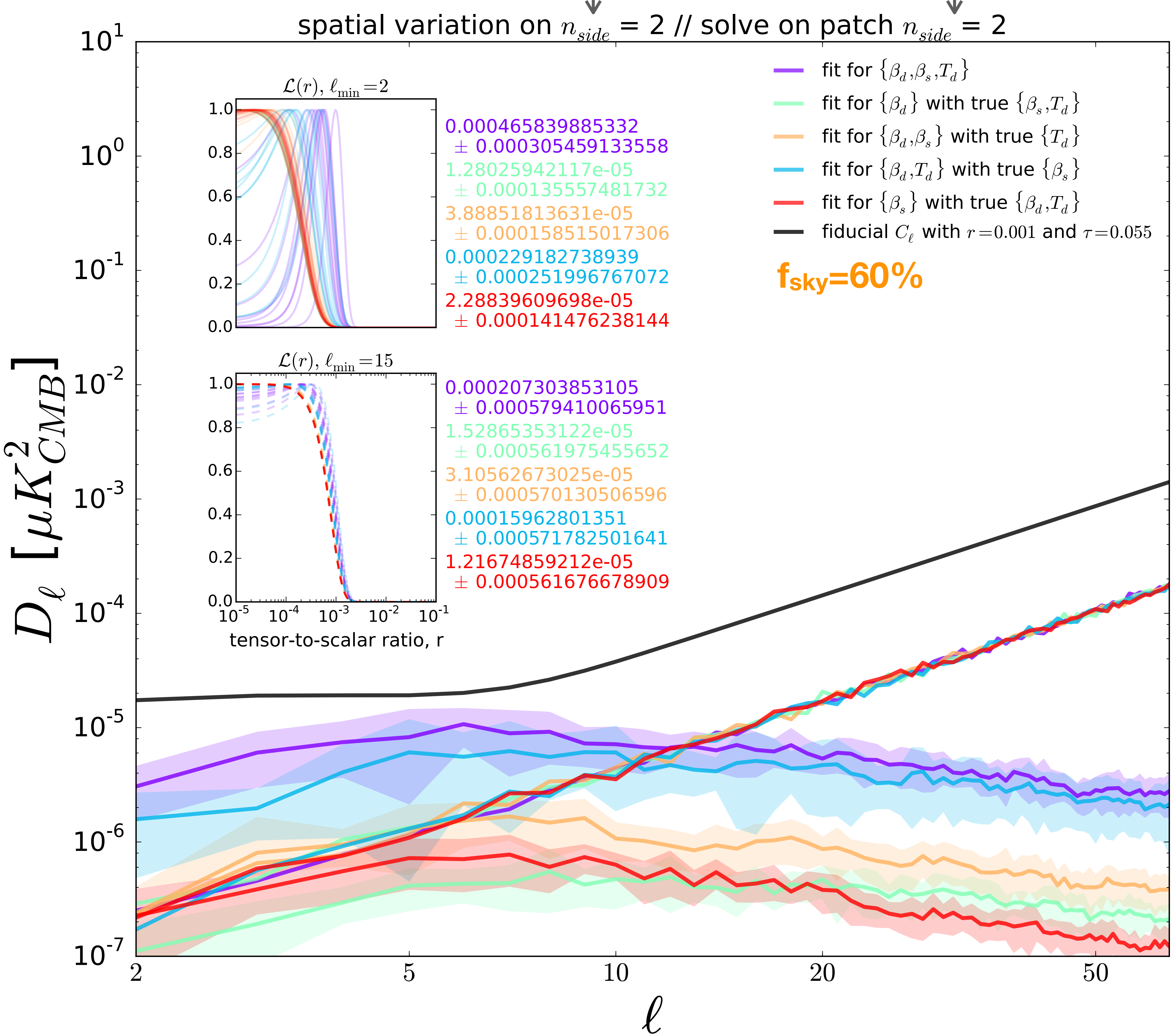
↓

power spectrum estimation and likelihood on r

10 sims

variations of {βd, βs, Td} on this healpix resolution

we perform component separation independently on this healpix resolution



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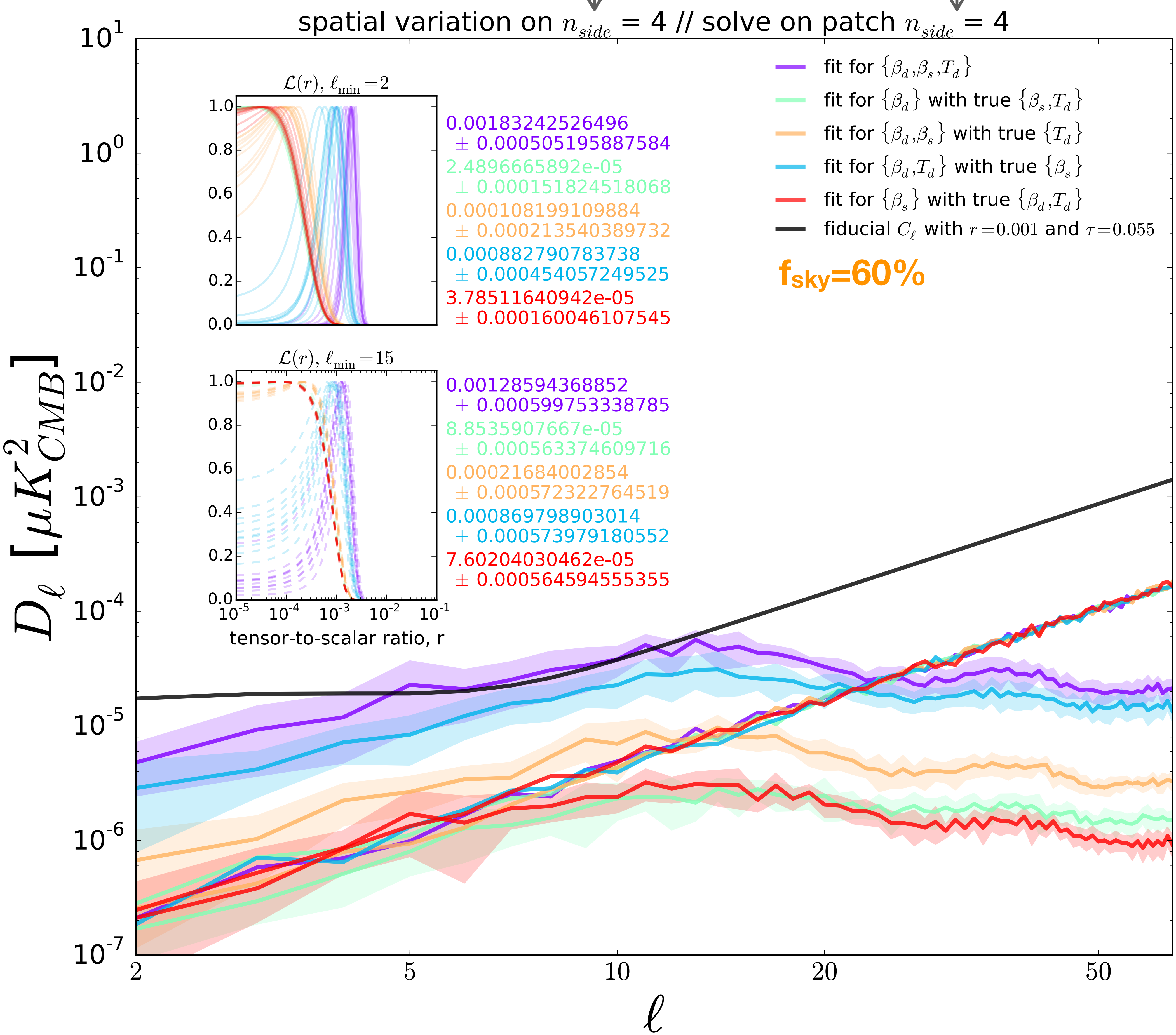

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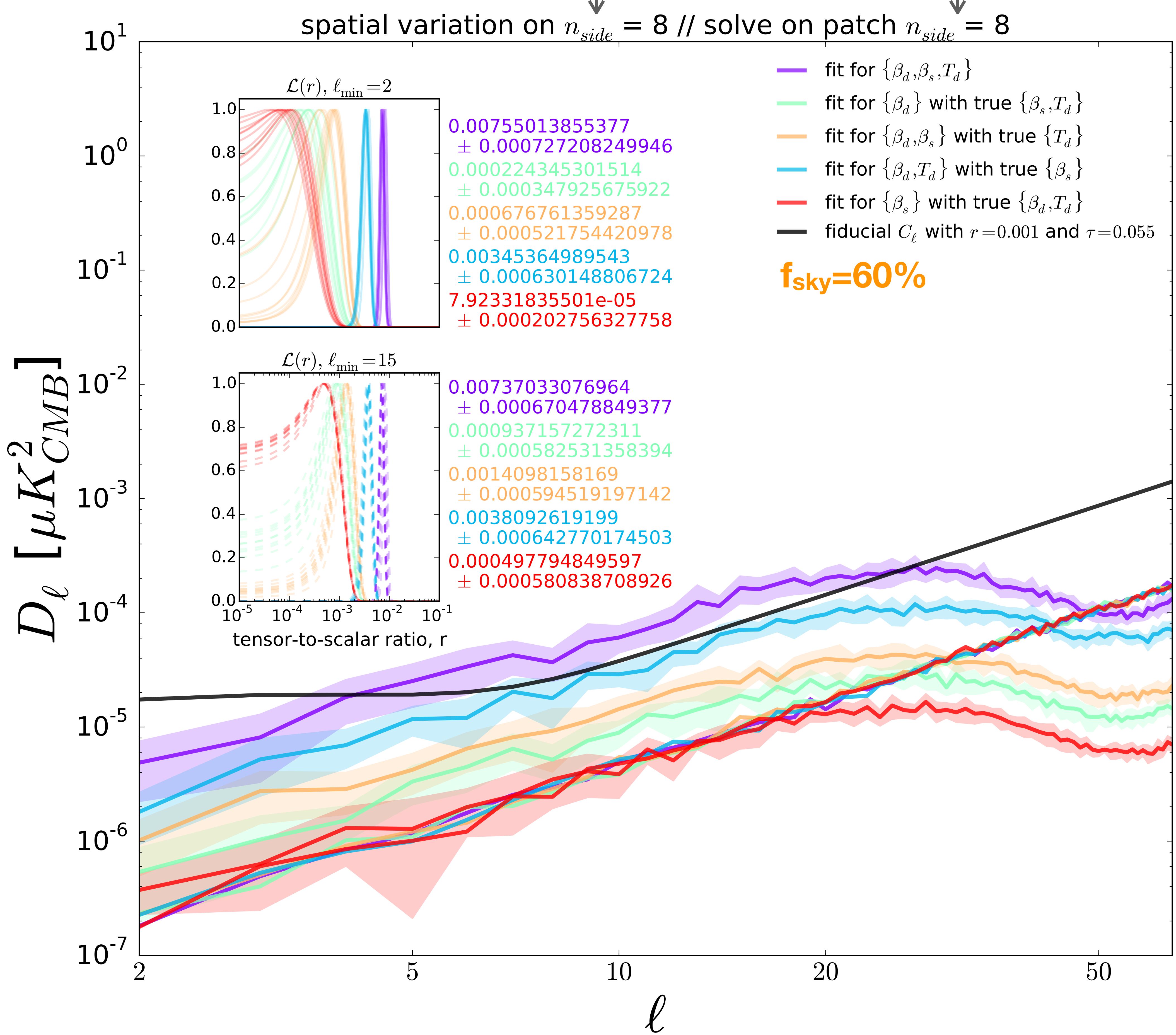

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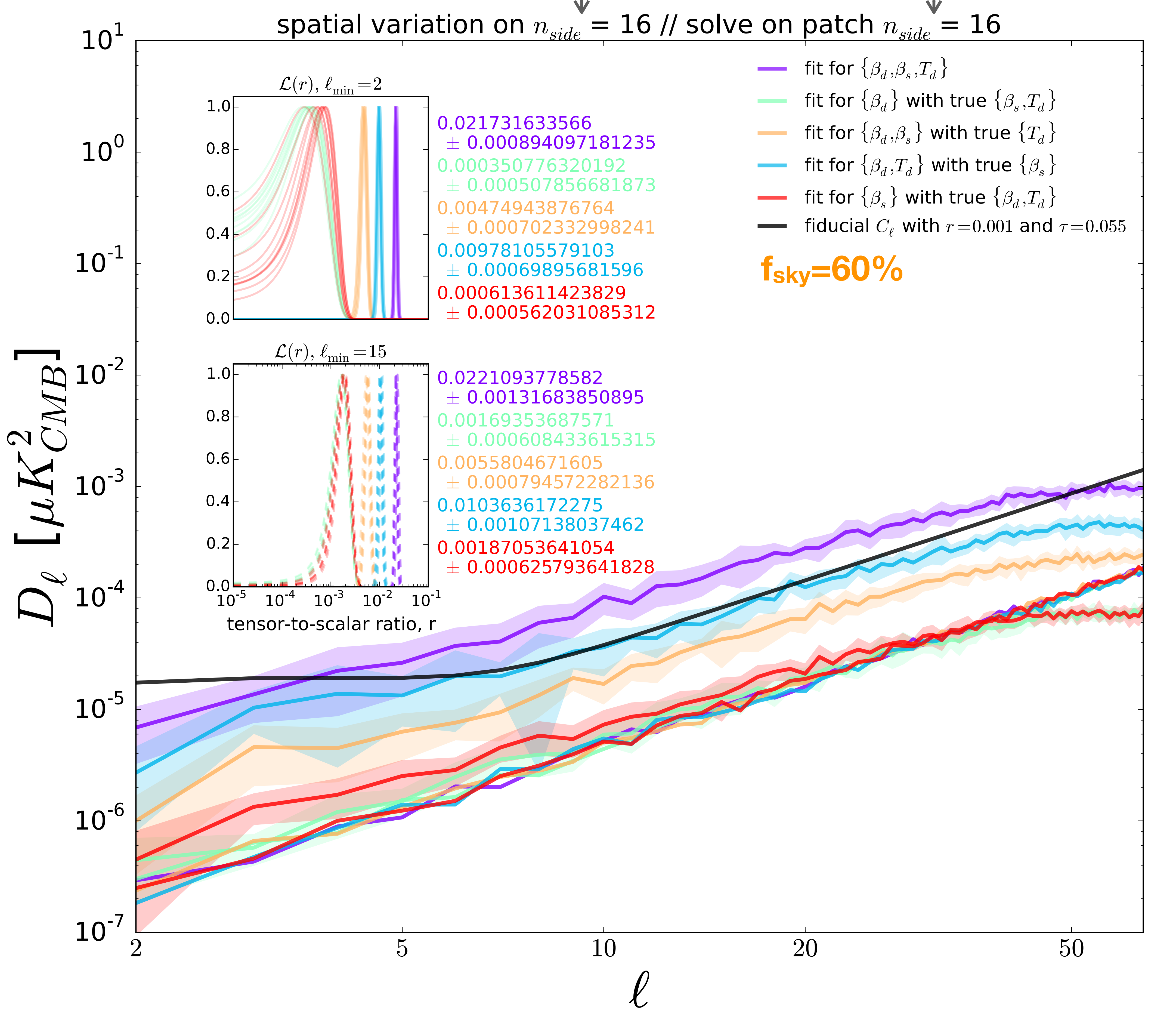

Results — multipatch on nside 2 → 16

■ = $r_{bias} < \sigma(r) < 0.001$

$\ell_{min} \geq 2$	fit for {Bd} true {Bs,Td}	fit for {Bd,Bs} true {Td}	fit for {Bd,Bs,Td}	fit for {Bd,Td} true {Bs}	fit for {Bs} true {Bd,Td}
nside = 2 (sim and cleaning)	1.28e-05 ± 0.000136	3.89e-05 ± 0.000159	**0.000466 ± 0.000305**	0.000229 ± 0.000252	2.29e-05 ± 0.000141
nside = 4 (sim and cleaning)	2.49e-05 ± 0.000152	0.000108 ± 0.000214	**0.00183 ± 0.000505**	0.000883 ± 0.000454	3.79e-05 ± 0.000160
nside = 8 (sim and cleaning)	0.000224 ± 0.000348	0.000677 ± 0.000522	**0.00755 ± 0.000727**	0.00345 ± 0.000630	7.92e-05 ± 0.000203
nside = 16 (sim and cleaning)	0.000351 ± 0.000508	0.00475 ± 0.000702	**0.0217 ± 0.000894**	0.00978 ± 0.000699	0.000614 ± 0.000562

is it possible to reduce the bias on *r* by modeling the foregrounds residuals and marginalizing over them?

variations of {βd, βs, Td} on this healpix resolution

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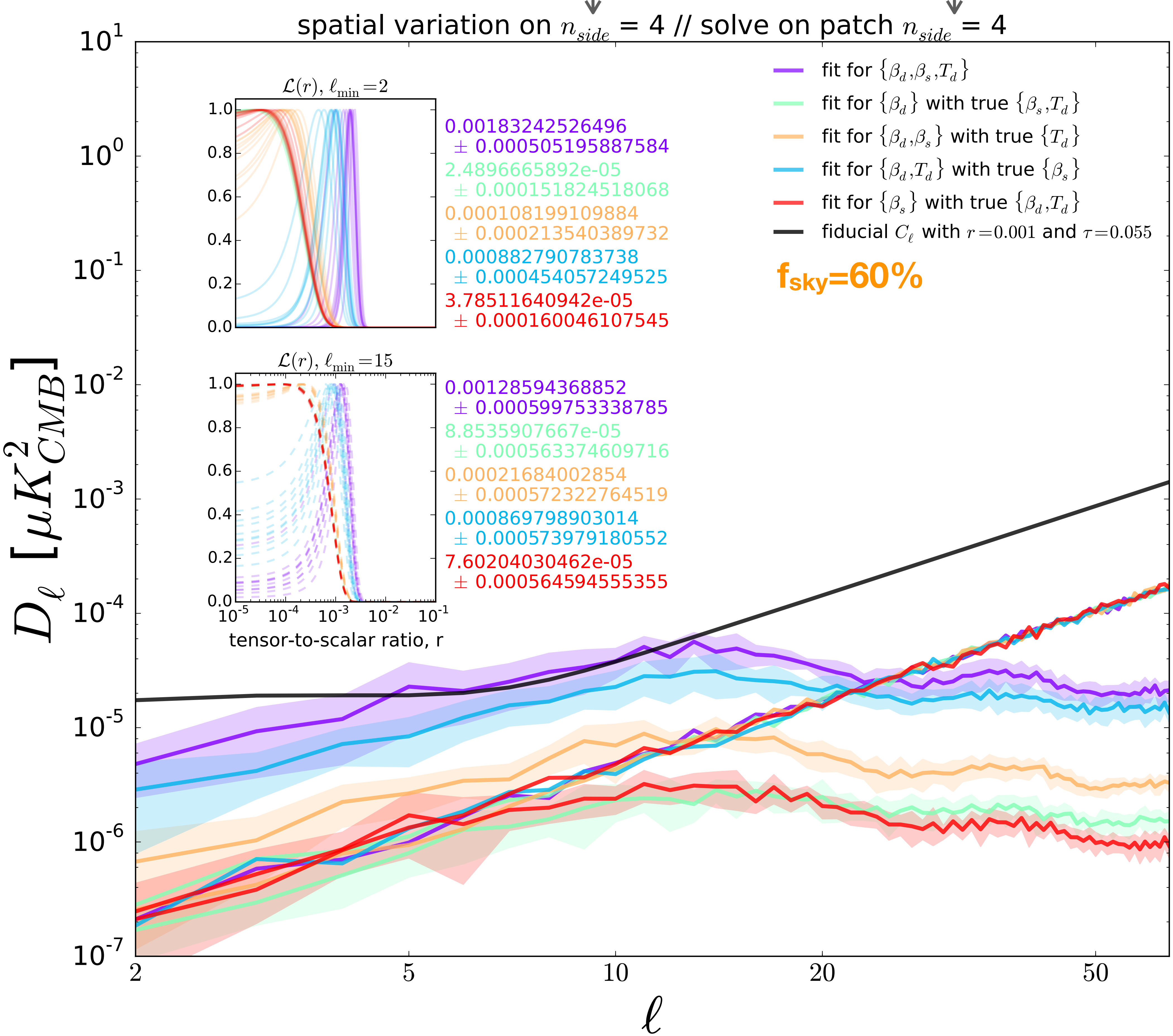

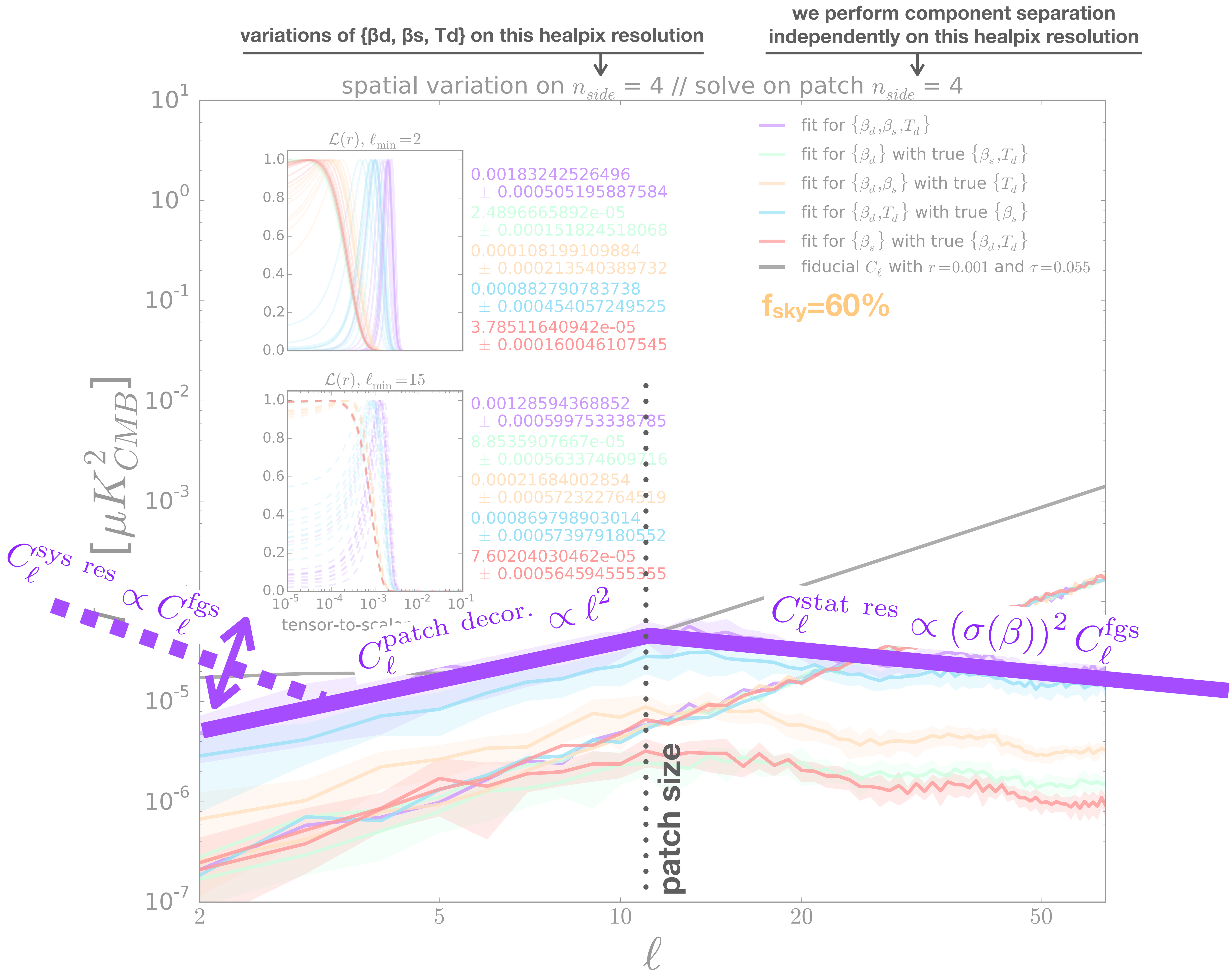

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fit for $\{\beta_d, \beta_s, T_d\}$
fit for $\{\beta_d\}$ with true $\{\beta_s, T_d\}$
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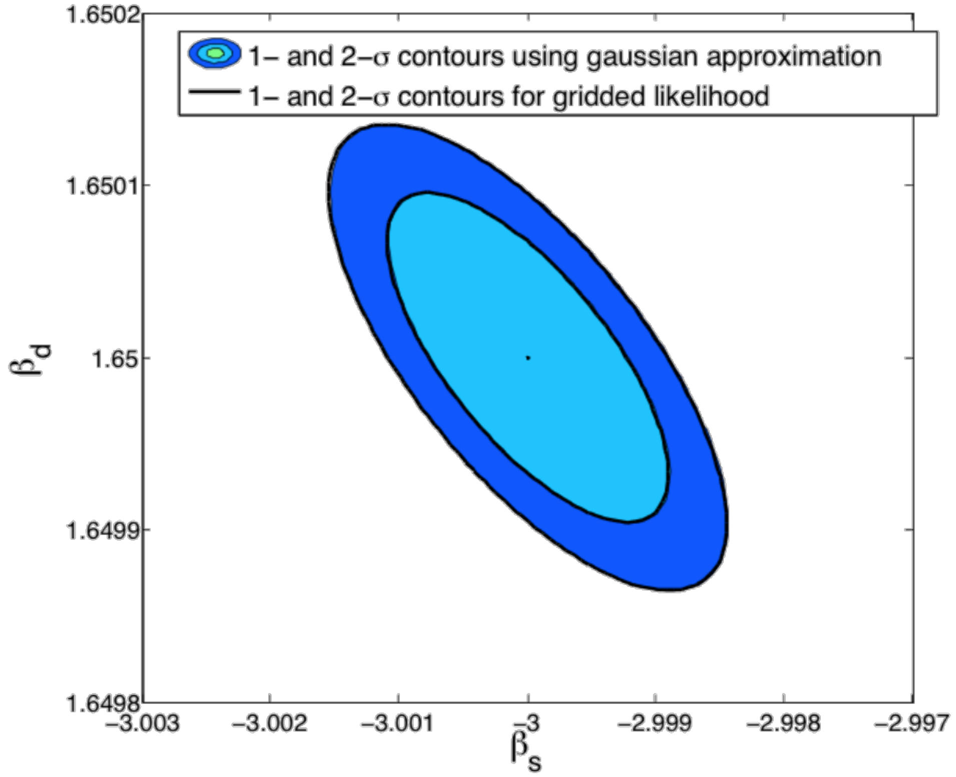
fit for $\{\beta_s\}$ with true $\{\beta_d, T_d\}$
fiducial C_ℓ with $r=0.001$ and $\tau=0.055$
f_{sky}=60%
$\mathcal{L}(r)$, $\ell_{min}=2$
0.00183242526496 ± 0.000505195887584
2.4896665892e-05 ± 0.000151824518068
0.000108199109884 ± 0.000213540389732
0.000882790783738 ± 0.000454057249525
3.78511640942e-05 ± 0.000160046107545
$\mathcal{L}(r)$, $\ell_{min}=15$
0.00128594368852 ± 0.000599753338785
8.8535907667e-05 ± 0.000563374609716
0.00021684002854 ± 0.000572322764519
0.000869798903014 ± 0.000573979180552
7.60204030462e-05 ± 0.000564594555355
tensor-to-scalar
$[\mu K^2_{CMB}]$
ℓ
$C_\ell^{sys\ res} \propto C_\ell^{fgs}$
$C_\ell^{patch\ decor.} \propto \ell^2$
$C_\ell^{stat\ res} \propto (\sigma(\beta))^2 C_\ell^{fgs}$
patch size

Yet, we can semi-analytically estimate what are the statistical foregrounds residuals

Statistical error bars on spectral parameters:



$$-2\,\ln \mathcal{L}_{spec}\left(\boldsymbol{\beta}\right) \;=\; \mathrm{CONST} - \left(\boldsymbol{A}^t\,\boldsymbol{N}^{-1}\,\boldsymbol{d}\right)^t \left(\boldsymbol{A}^t\,\boldsymbol{N}^{-1}\,\boldsymbol{A}\right)^{-1} \left(\boldsymbol{A}^t\,\boldsymbol{N}^{-1}\,\boldsymbol{d}\right)$$

Errard, Stivoli and Stompor (PRD, 2011)

$$\boldsymbol{\Sigma}^{-1} \simeq -\left\langle \frac{\partial^2 \mathcal{L}}{\partial\beta\partial\beta'} \right\rangle_{\mathrm{noise}} \Bigg|_{\mathrm{true}\ \beta}$$

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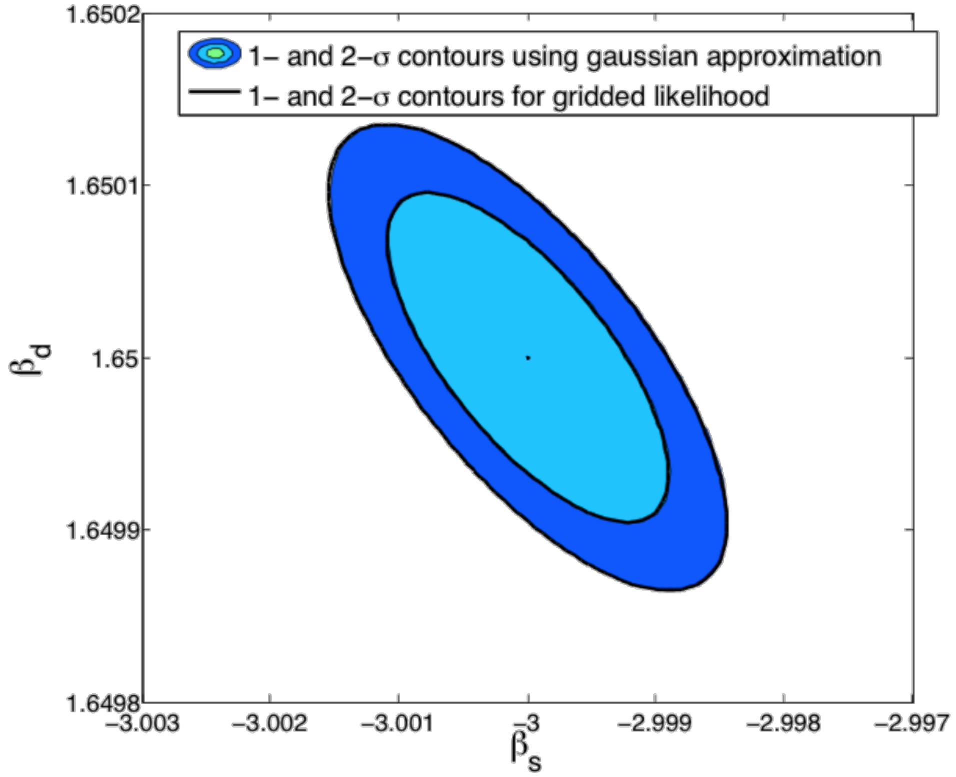

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Synchrotron and dust templates

➔ estimated using the most extreme frequency channels of LiteBIRD (scaling them to 150GHz using the estimated spectral indices in each pixels)

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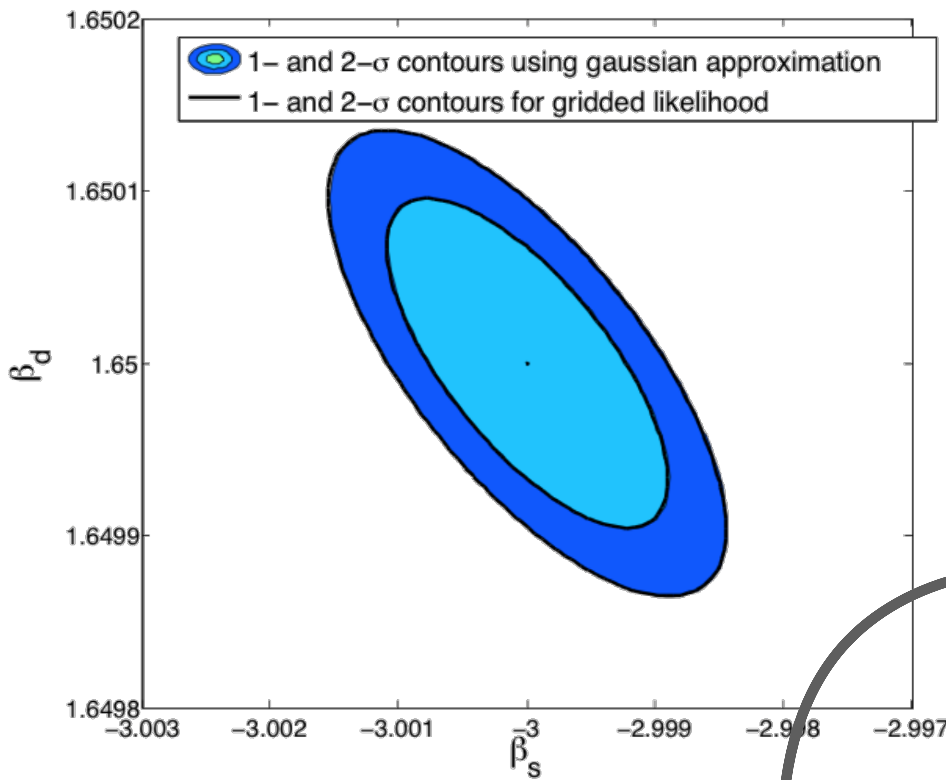

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$$\boldsymbol{\Sigma}^{-1} \simeq -\left\langle \frac{\partial^2\mathcal{L}}{\partial\beta\partial\beta'}\right\rangle_{\text{noise}}\Big|_{\text{true }\beta}$$

Amplitude of statistical foregrounds residuals:

$$C_\ell^{\text{fg res}} \equiv \sum_{k,k'}\sum_{j,j'}\Sigma_{kk'}\,\kappa_{kk'}^{jj'}C_\ell^{jj'}$$

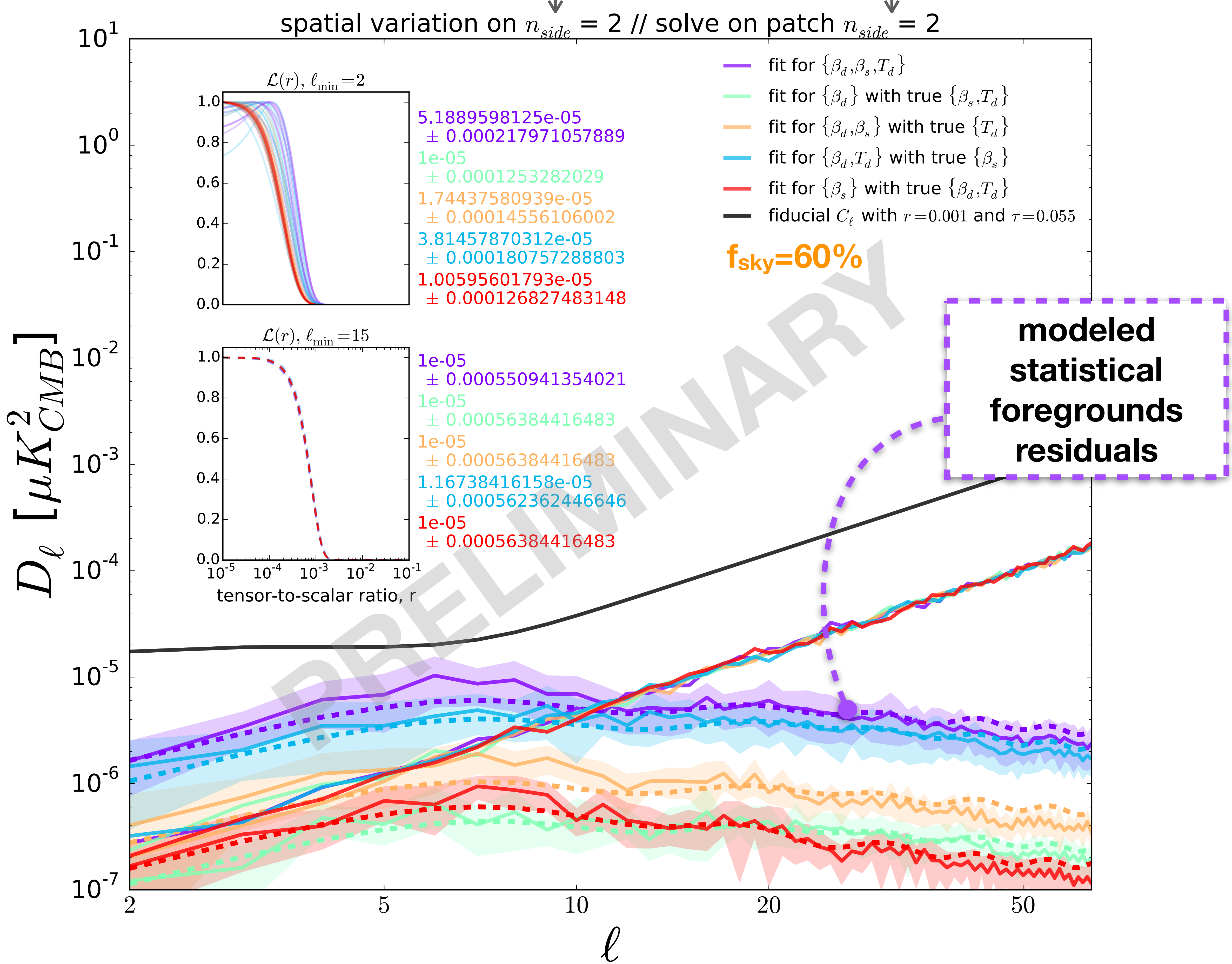
Stivoli, Grain, Leach, Tristram, Baccigalupi, Stompor (MNRAS, 2010)

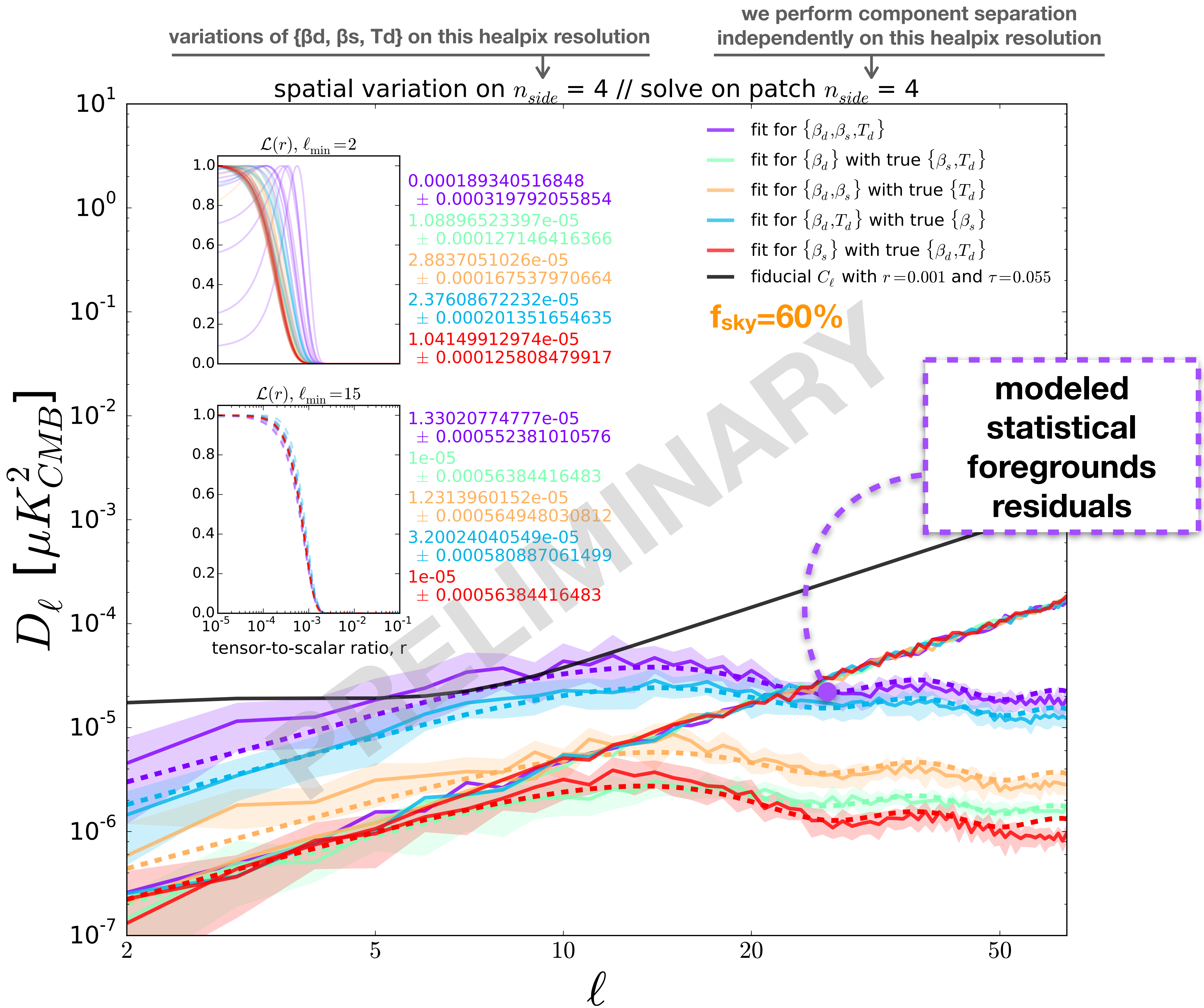
Synchrotron and dust templates

➔ estimated using the most extreme frequency channels of LiteBIRD (scaling them to 150GHz using the estimated spectral indices in each pixels)

variations of {βd, βs, Td} on this healpix resolution

we perform component separation independently on this healpix resolution





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± 0.000319792055854
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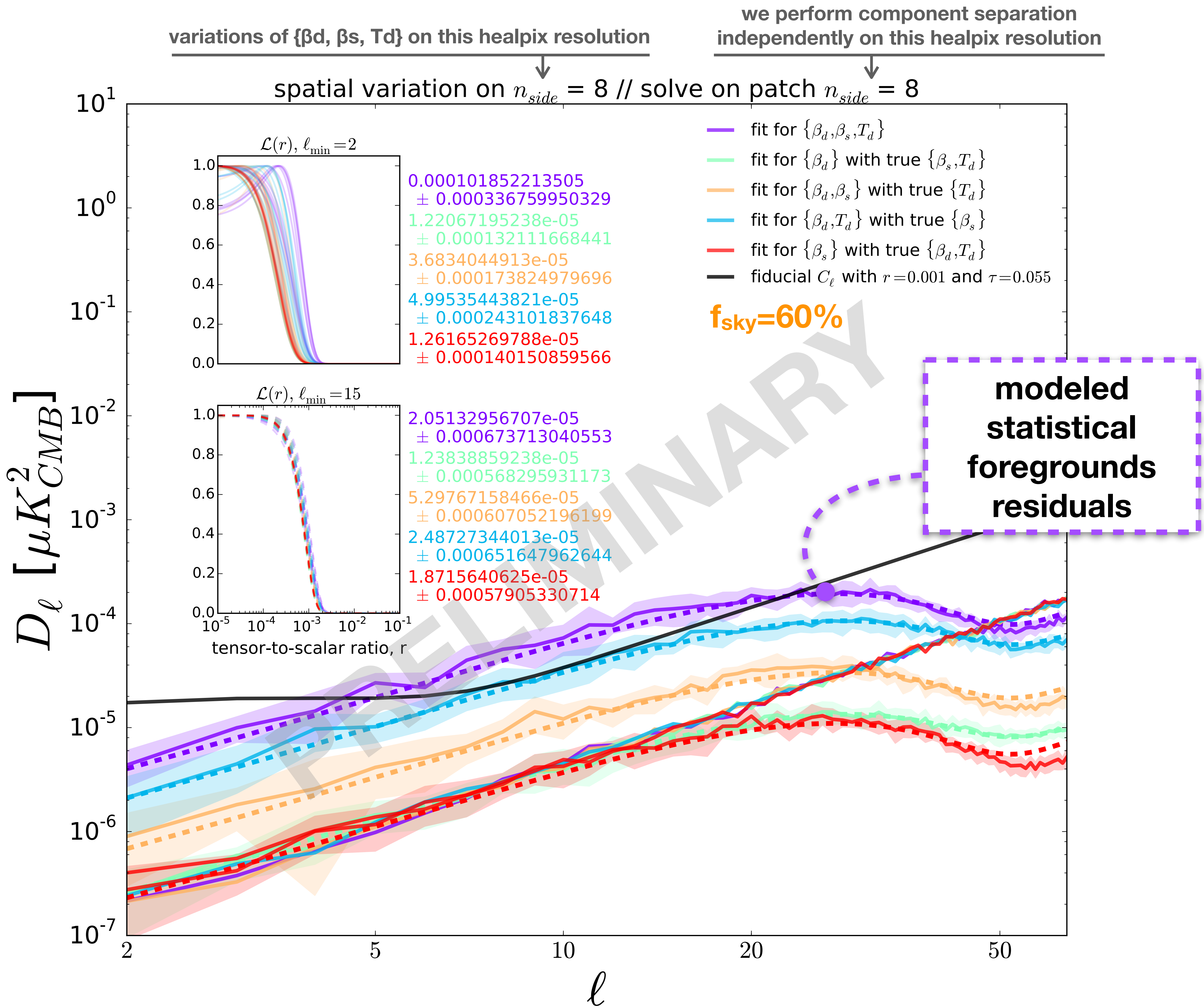
± 0.000127146416366
2.8837051026e-05
± 0.000167537970664
2.37608672232e-05
± 0.000201351654635
1.04149912974e-05
± 0.000125808479917
$\mathcal{L}(r)$, $\ell_{min}=15$
1.33020774777e-05
± 0.000552381010576
1e-05
± 0.00056384416483
1.2313960152e-05
± 0.000564948030812
3.20024040549e-05
± 0.000580887061499
1e-05
± 0.00056384416483
tensor-to-scalar ratio, r
fit for $\{\beta_d, \beta_s, T_d\}$
fit for $\{\beta_d\}$ with true $\{\beta_s, T_d\}$
fit for $\{\beta_d, \beta_s\}$ with true $\{T_d\}$
fit for $\{\beta_d, T_d\}$ with true $\{\beta_s\}$
fit for $\{\beta_s\}$ with true $\{\beta_d, T_d\}$
fiducial C_ℓ with $r=0.001$ and $\tau=0.055$
f_{sky}=60%
modeled statistical foregrounds residuals
PRELIMINARY
$D_\ell\ [\mu K^2_{CMB}]$
ℓ

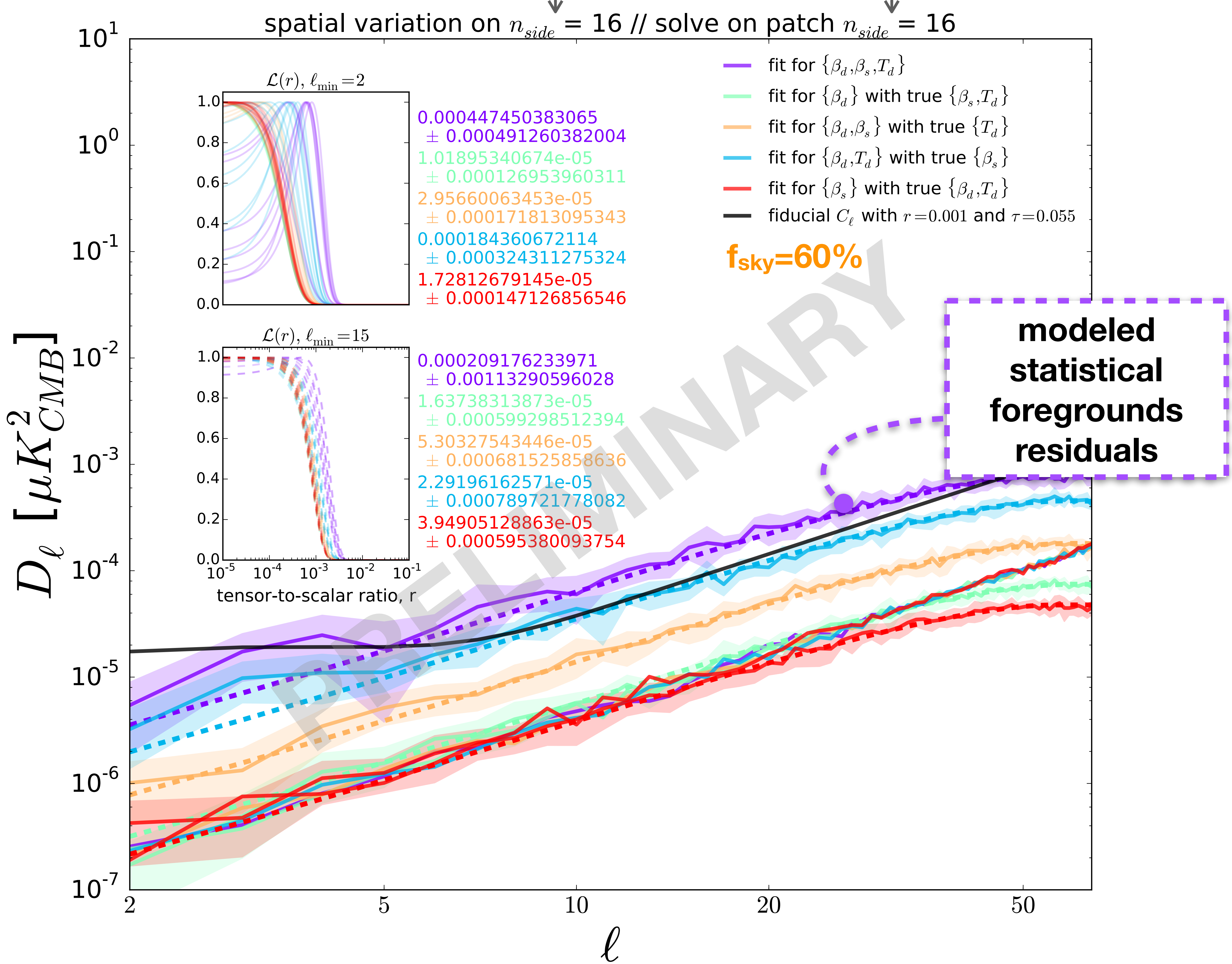


variations of {βd, βs, Td} on this healpix resolution
we perform component separation independently on this healpix resolution
spatial variation on n_{side} = 8 // solve on patch n_{side} = 8
fit for $\{\beta_d, \beta_s, T_d\}$
fit for $\{\beta_d\}$ with true $\{\beta_s, T_d\}$
fit for $\{\beta_d, \beta_s\}$ with true $\{T_d\}$
fit for $\{\beta_d, T_d\}$ with true $\{\beta_s\}$
fit for $\{\beta_s\}$ with true $\{\beta_d, T_d\}$
fiducial C_ℓ with $r=0.001$ and $\tau=0.055$
f_{sky}=60%
$\mathcal{L}(r)$, $\ell_{min}=2$
0.000101852213505 ± 0.000336759950329
1.22067195238e-05 ± 0.000132111668441
3.6834044913e-05 ± 0.000173824979696
4.99535443821e-05 ± 0.000243101837648
1.26165269788e-05 ± 0.000140150859566
$\mathcal{L}(r)$, $\ell_{min}=15$
2.05132956707e-05 ± 0.000673713040553
1.23838859238e-05 ± 0.000568295931173
5.29767158466e-05 ± 0.000607052196199
2.48727344013e-05 ± 0.000651647962644
1.8715640625e-05 ± 0.00057905330714
tensor-to-scalar ratio, r
modeled statistical foregrounds residuals
PRELIMINARY
D_ℓ $[\mu K^2_{CMB}]$
ℓ

J. Errar

variations of {βd, βs, Td} on this healpix resolution

we perform component separation independently on this healpix resolution



Results — multipatch when deprojecting statistical foregrounds residuals

■ = $r_{bias} < \sigma(r) < 0.001$

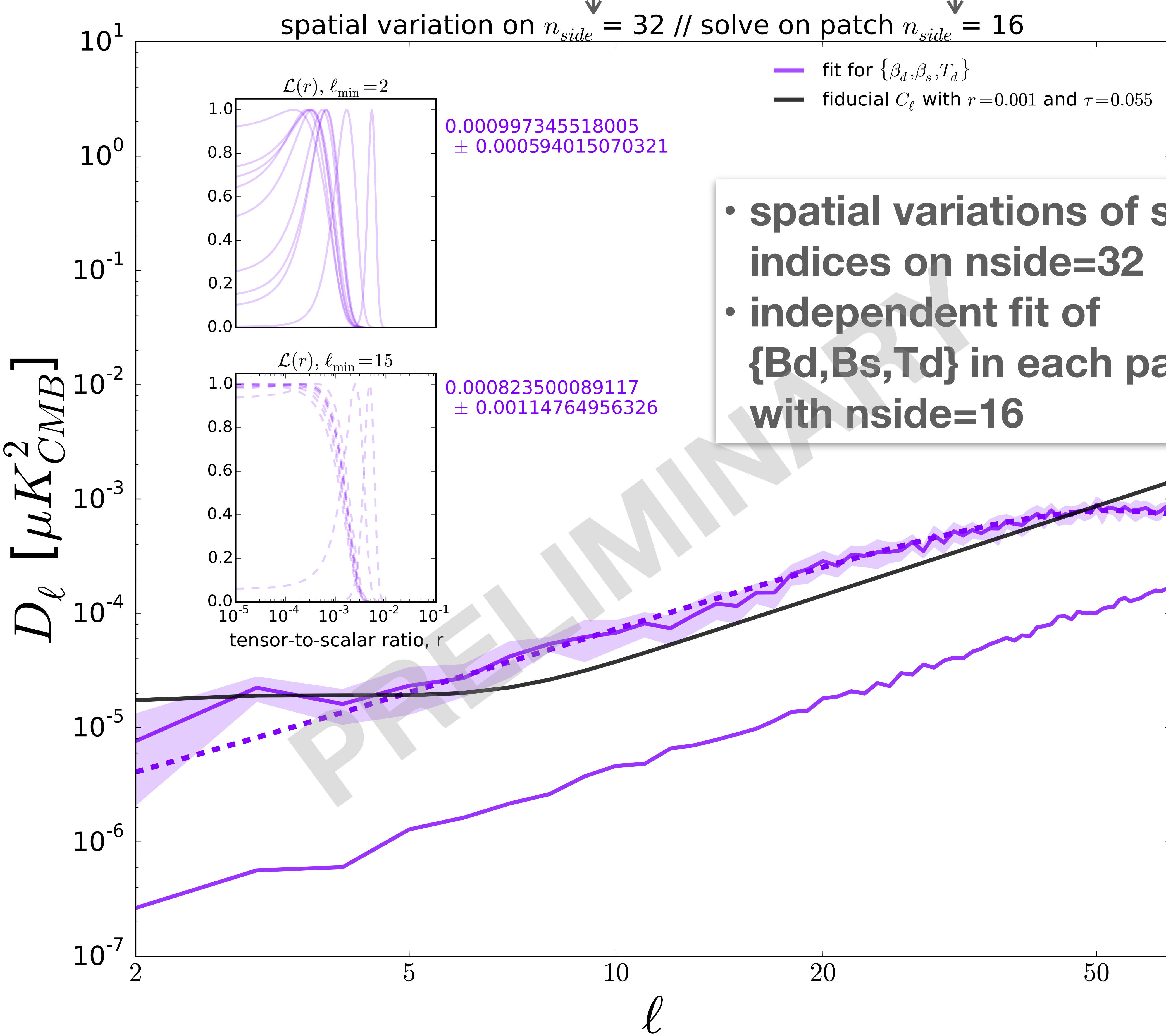
PRELIMINARY

$\ell_{min} \geq 2$	previously ⇩	after adding statistical foregrounds residuals model in the likelihood $\mathscr{L}(r)$
	fit for {Bd,Bs,Td}	fit for {Bd,Bs,Td}
nside = 2 (sim and cleaning)	0.000466 ± 0.000305	**0.0000519 ± 0.000218**
nside = 4 (sim and cleaning)	0.00183 ± 0.000505	**0.000189 ± 0.000320**
nside = 8 (sim and cleaning)	0.00755 ± 0.000727	**0.000102 ± 0.000337**
nside = 16 (sim and cleaning)	0.0217 ± 0.000894	**0.000447 ± 0.000491**

what about more complex skies?

variations of {βd, βs, Td} on this healpix resolution

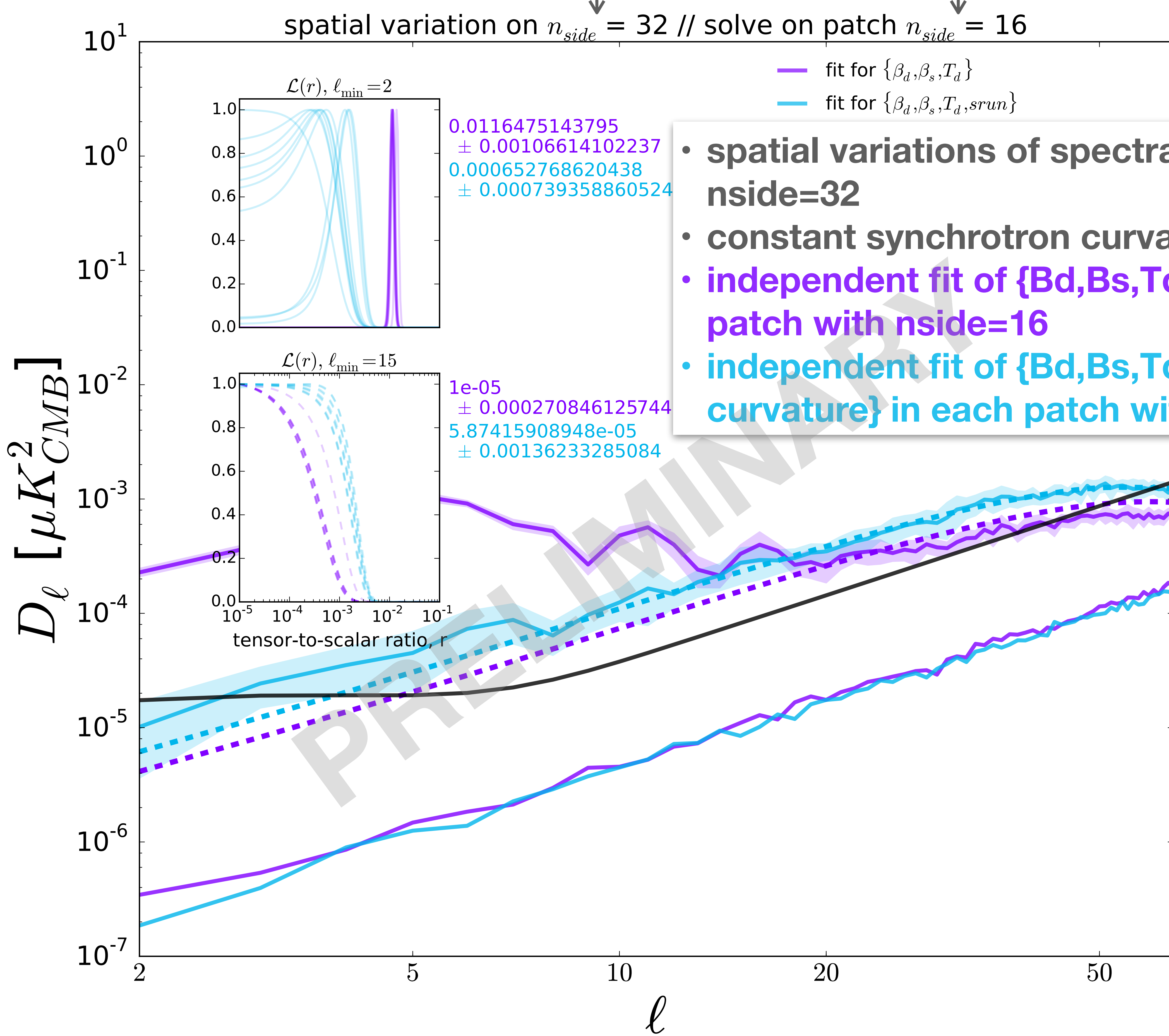
we perform component separation independently on this healpix resolution



- **spatial variations of spectral indices on nside=32**
- **independent fit of {Bd,Bs,Td} in each patch with nside=16**

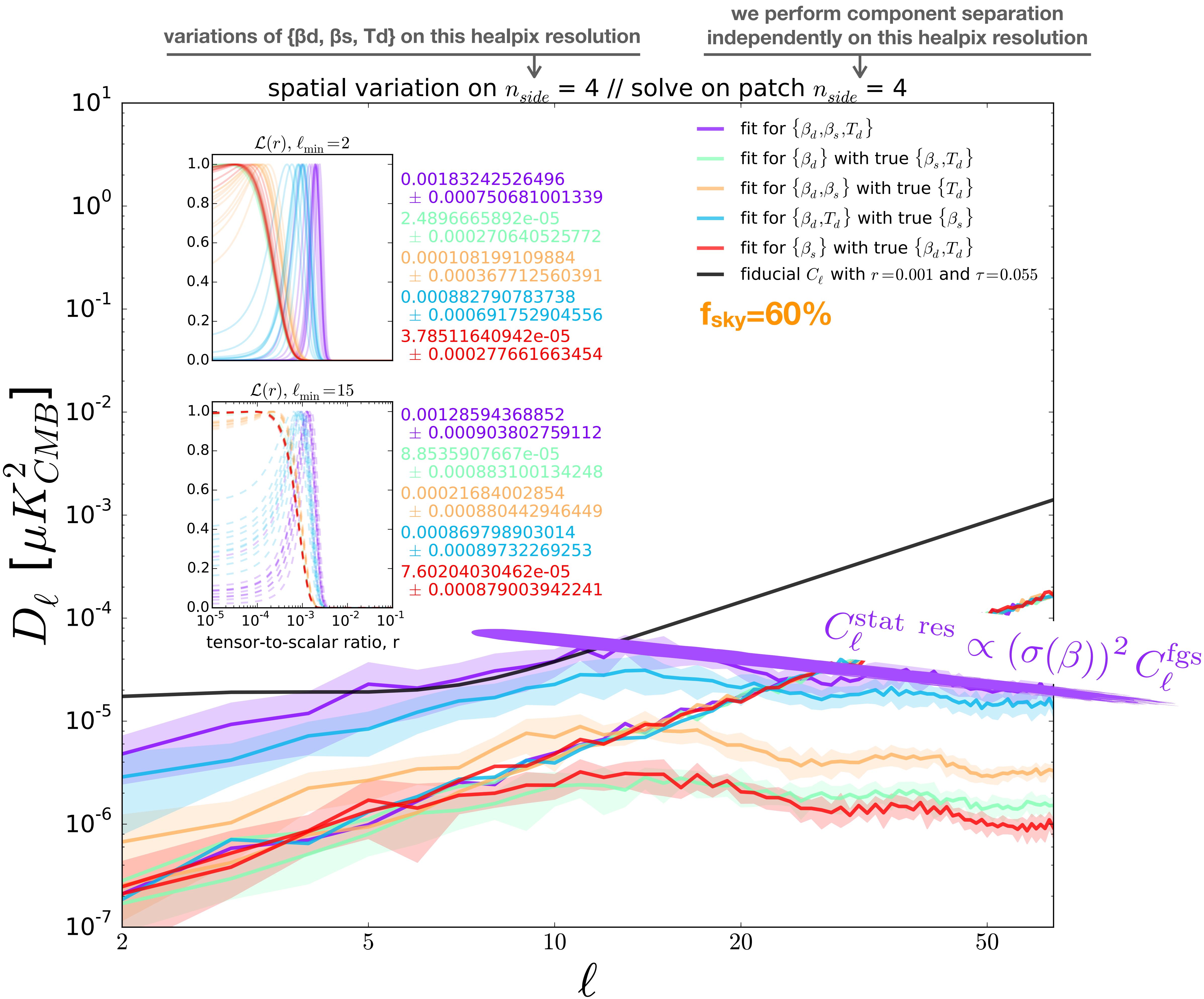
variations of {βd, βs, Td} on this healpix resolution

we perform component separation independently on this healpix resolution



- spatial variations of spectral indices on nside=32
- constant synchrotron curvature in sims
- independent fit of {Bd,Bs,Td} in each patch with nside=16
- independent fit of {Bd,Bs,Td, sync curvature} in each patch with nside=16

is it possible to **optimize** the focal plane to reduce the foregrounds residuals?



variations of {βd, βs, Td} on this healpix resolution
we perform component separation independently on this healpix resolution
spatial variation on n_{side} = 4 // solve on patch n_{side} = 4
fit for $\{\beta_d, \beta_s, T_d\}$
fit for $\{\beta_d\}$ with true $\{\beta_s, T_d\}$
fit for $\{\beta_d, \beta_s\}$ with true $\{T_d\}$
fit for $\{\beta_d, T_d\}$ with true $\{\beta_s\}$
fit for $\{\beta_s\}$ with true $\{\beta_d, T_d\}$
fiducial C_ℓ with $r=0.001$ and $\tau=0.055$
f_{sky}=60%
$\mathcal{L}(r)$, $\ell_{\min}=2$
0.00183242526496 ± 0.000750681001339
2.4896665892e-05 ± 0.000270640525772
0.000108199109884 ± 0.000367712560391
0.000882790783738 ± 0.000691752904556
3.78511640942e-05 ± 0.000277661663454
$\mathcal{L}(r)$, $\ell_{\min}=15$
0.00128594368852 ± 0.000903802759112
8.8535907667e-05 ± 0.000883100134248
0.00021684002854 ± 0.000880442946449
0.000869798903014 ± 0.00089732269253
7.60204030462e-05 ± 0.000879003942241
tensor-to-scalar ratio, r
$C_\ell^{\rm stat\ res} \propto (\sigma(\beta))^2 C_\ell^{\rm fgs}$
$D_\ell\ [\mu K^2_{CMB}]$
ℓ

J. Errard

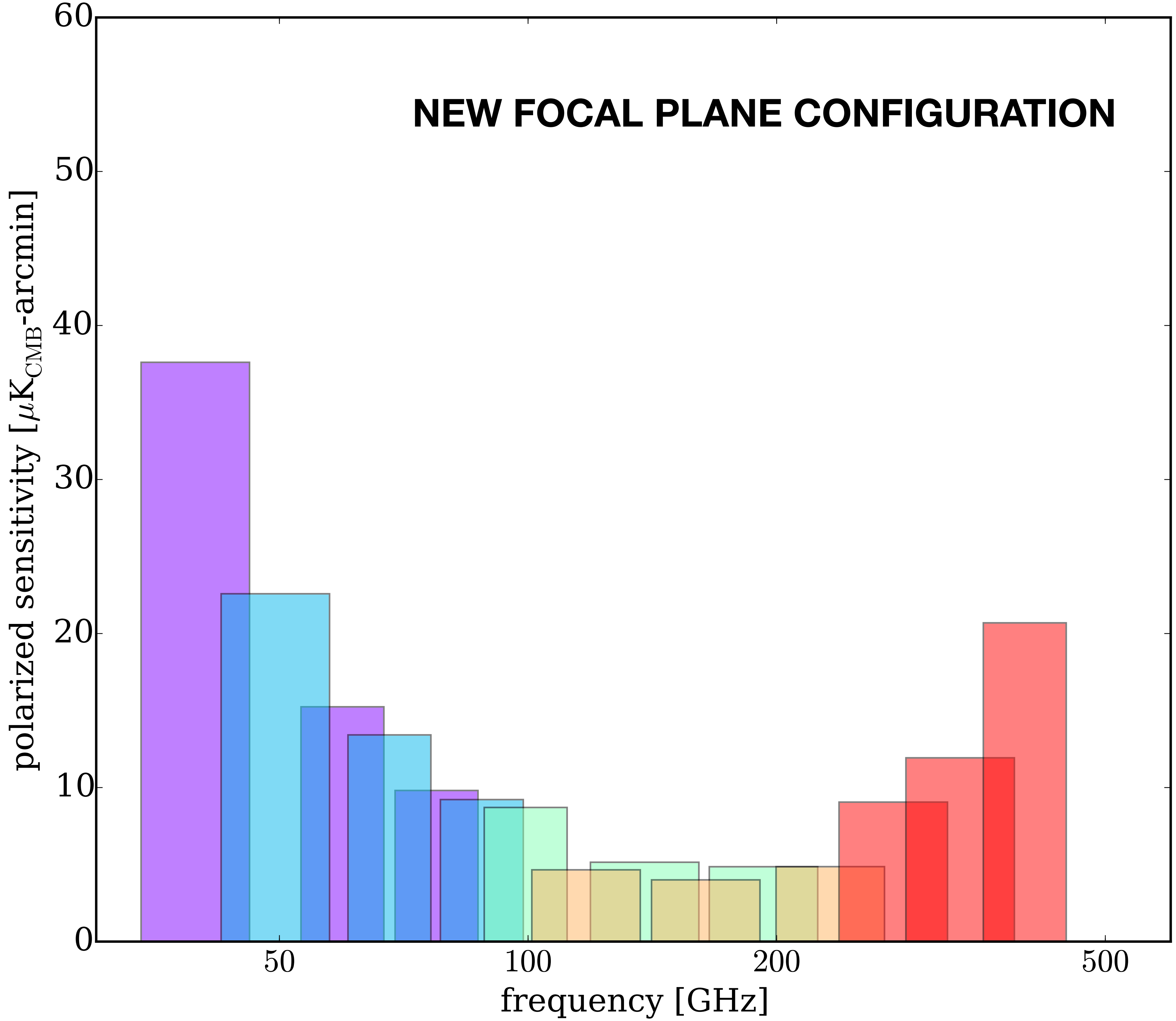
Method — optimization of focal plane

- **minimization of $||\Sigma(\beta)||$ in each patch of the sky, for each simulations**
- **variable is the number of pixels i.e. {LF-1, LF-2, MF-1, MF-2, HF-1, HF-2, HF-3}**
- **we keep the area of the focal plane constant**

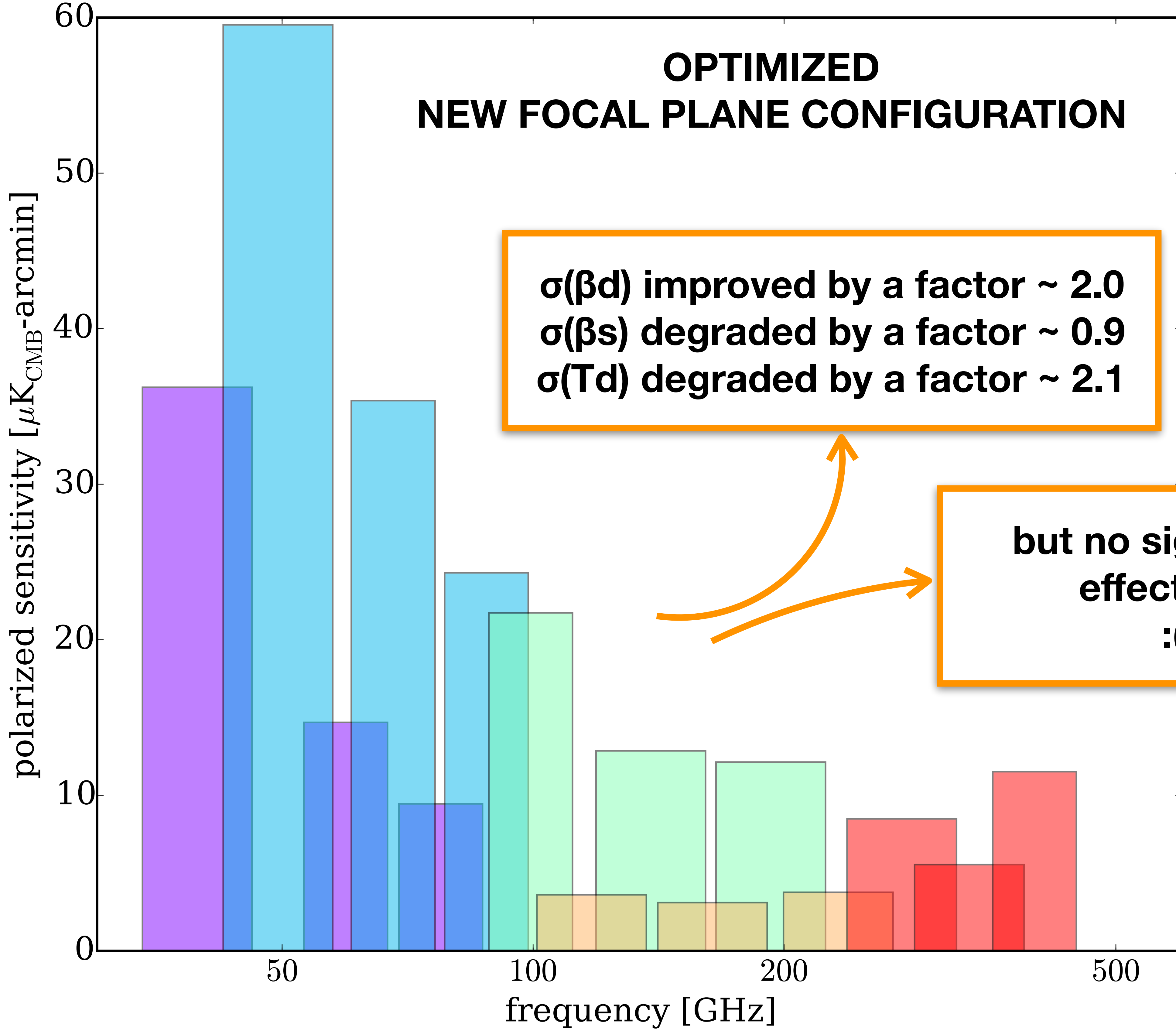
$||\Sigma(\beta)||$ is the norm (I took it as the deteminant) of the error covariance on spectral indices.

$$\Sigma \equiv \begin{bmatrix} \sigma(\beta_d)^2 & \sigma(\beta_d)\sigma(\beta_s) & \sigma(\beta_d)\sigma(T_d) \\ \star & \sigma(\beta_s)^2 & \sigma(\beta_s)\sigma(T_d) \\ \star & \star & \sigma(T_d)^2 \end{bmatrix}$$

We approximate **Σ** using the analytical form of the spectral likelihood curvature (Errard+ 2012) — this is why the optimization is numerically easy.


NEW FOCAL PLANE CONFIGURATION
60
50
40
30
20
10
0
50
100
200
500
polarized sensitivity [μK_{CMB}-arcmin]
frequency [GHz]

OPTIMIZED
NEW FOCAL PLANE CONFIGURATION



σ(βd) improved by a factor ~ 2.0
σ(βs) degraded by a factor ~ 0.9
σ(Td) degraded by a factor ~ 2.1

but no significant effect on r
:(

Conclusion - discussion

- current LiteBIRD focal plane design can reach **bias on r < σ(r) < 0.001** — considering input sky simulations with spatial variations of spectral indices over nside=16 scales:
    - SMICA and xForecast agree on a **r ~ 0.0006 ± 0.0007** when considering scales $\ell \geq 15$
    - Multipatch approach, combined with a deprojection of the statistical residuals, leads to **r ~ 0.0004 ± 0.0005** ($\ell \geq 2$)
- complicating the sky (spatial variations on nside=32 with synchrotron curvature) leads to **r = 0.0007 ± 0.0007** ($\ell \geq 2$). **NB:** synchrotron curvature leads to a strong bias if not fitted for in the modeling.

Conclusion - discussion

- current LiteBIRD focal plane design can reach **bias on r < σ(r) < 0.001** — considering input sky simulations with spatial variations of spectral indices over nside=16 scales:
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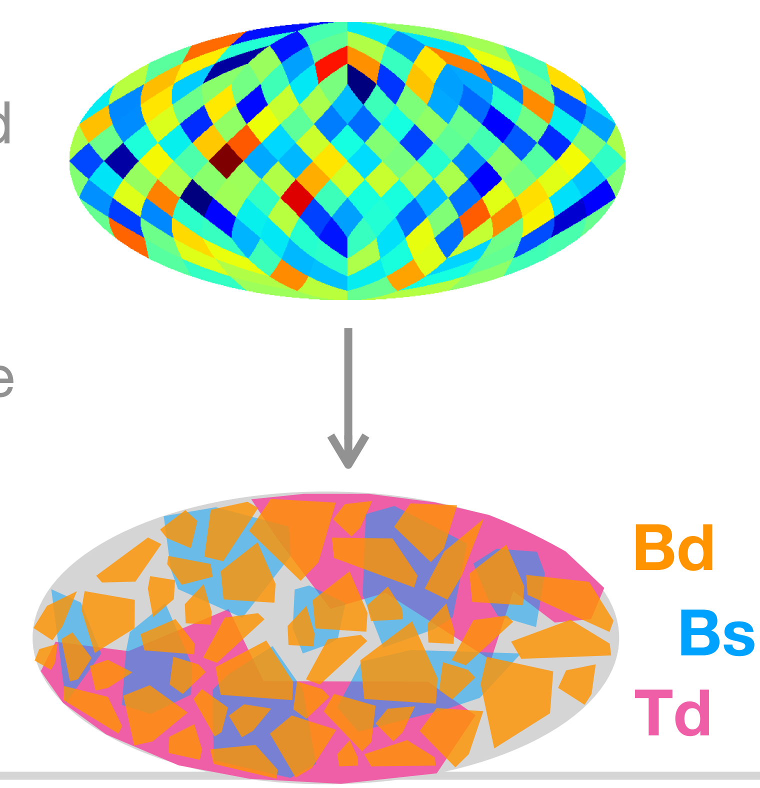
Next steps:

- unique and integrated framework including the estimation of {β} and the marginalization of $\mathscr{L}(r)$ over statistical foregrounds residuals
- iterative patch finder — find optimal regions for each spectral index which would both optimize the statistical errors while minimizing the systematic bias. They would likely follow the morphology of the galactic foregrounds.
- build a consistent and common framework for SMICA and parametric pixel-based methods

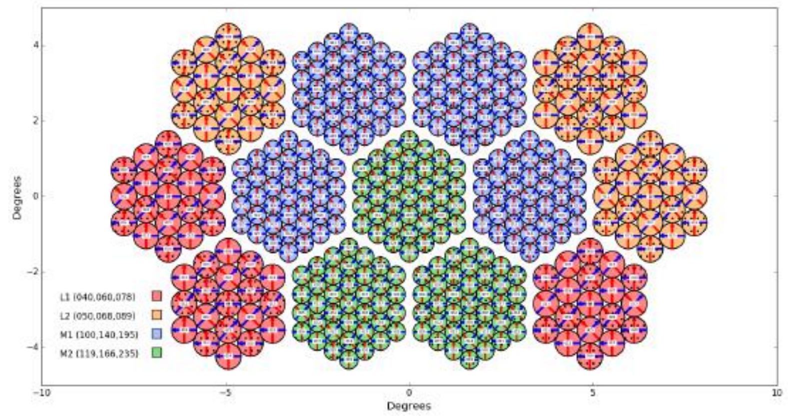


BACKUP

LiteBIRD assumed specifications

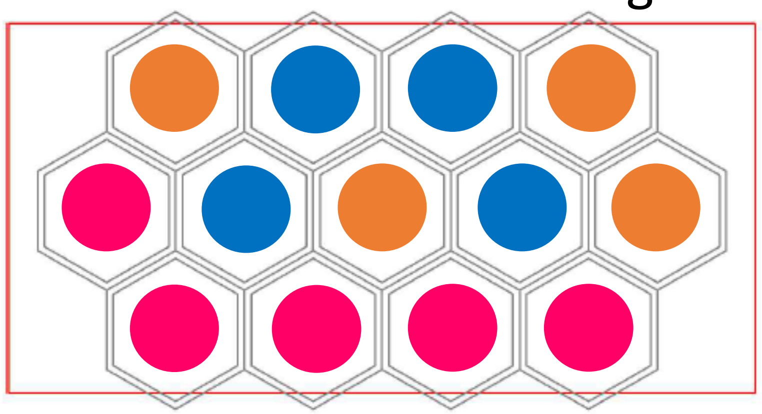
Proposal for Focal Plane Design

LFT - baseline design



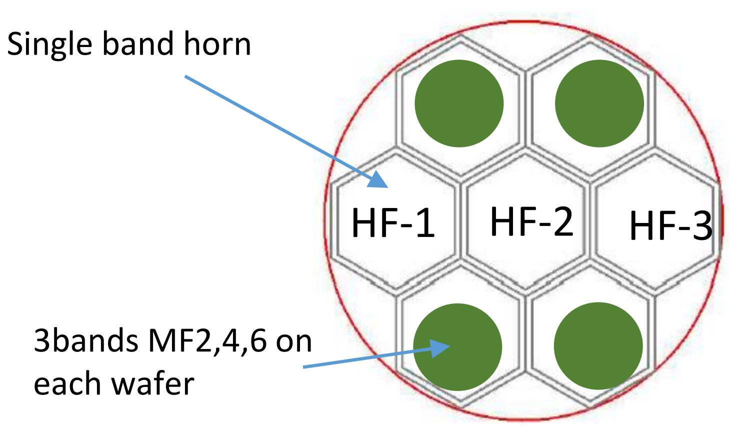
Band	Center Freq [GHz]	Frac BW	Pixel Diameter [mm]	Num Pix	Num Det
LF-1	40	0.30	18	57	114
LF-2	50	0.30	18	57	114
LF-3	60	0.23	18	57	114
LF-4	68	0.23	18	57	114
LF-5	78	0.23	18	57	114
LF-6	89	0.23	18	57	114
MF-1	100	0.23	12	148	296
MF-2	119	0.30	12	111	222
MF-3	140	0.30	12	148	296
MF-4	166	0.30	12	111	222
MF-5	195	0.30	12	148	296
MF-6	235	0.30	12	111	222

LFT - LF enhanced design



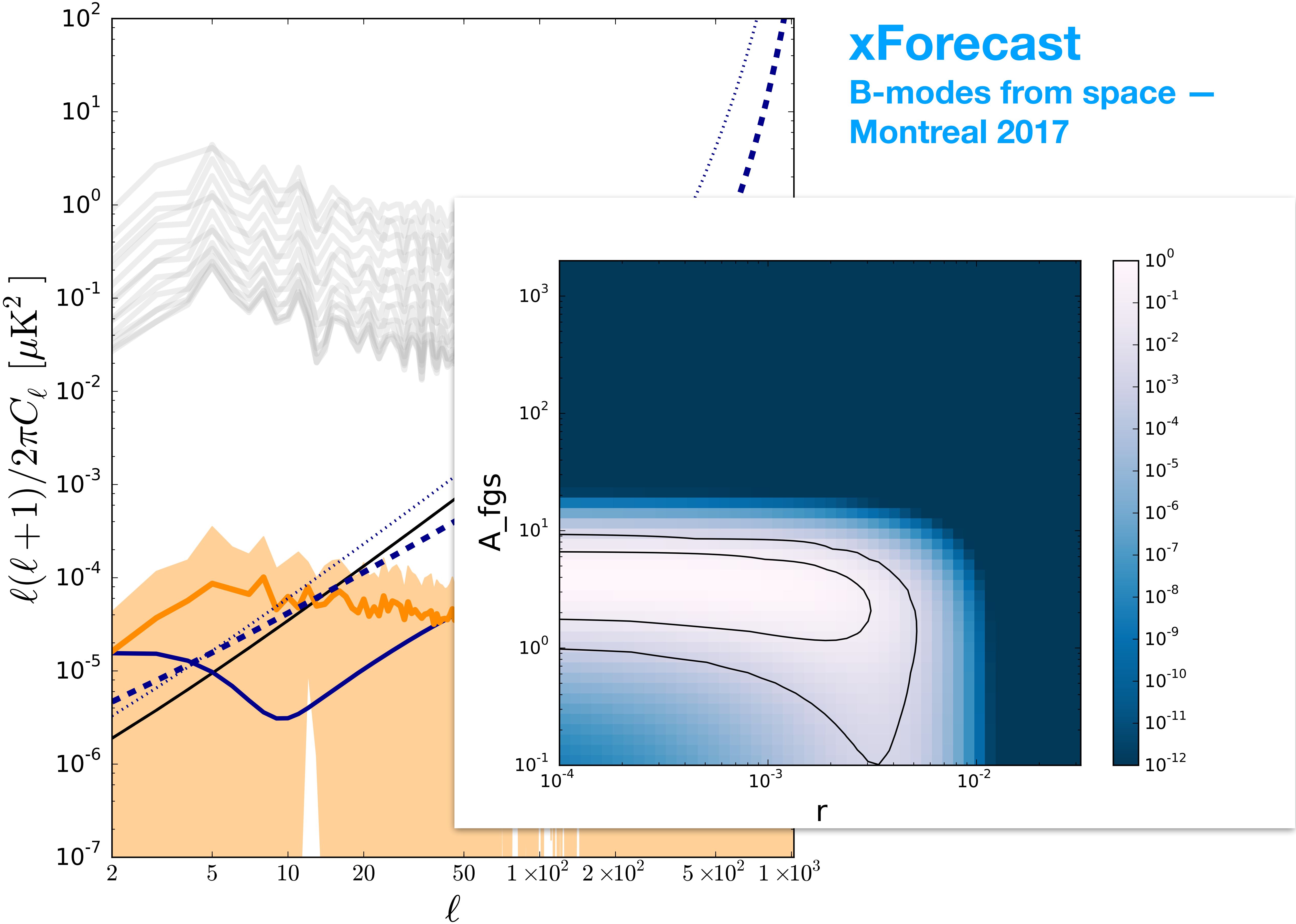
Band	Center Freq [GHz]	Frac BW	Pixel Diameter [mm]	Num Pix	Num Det	
LF-1	40	0.30	18	~~57~~ 95	~~114~~	190
LF-2	50	0.30	18	~~57~~ 76	~~114~~	152
LF-3	60	0.23	18	~~57~~ 95	~~114~~	190
LF-4	68	0.23	18	~~57~~ 76	~~114~~	152
LF-5	78	0.23	18	~~57~~ 95	~~114~~	190
LF-6	89	0.23	18	~~57~~ 76	~~114~~	152
MF-1	100	0.23	12	148	296	
~~MF-2~~	~~119~~	~~0.30~~	~~12~~	~~111~~	~~222~~	
MF-3	140	0.30	12	148	296	
~~MF-4~~	~~166~~	~~0.30~~	~~12~~	~~111~~	~~222~~	
MF-5	195	0.30	12	148	296	
~~MF-6~~	~~235~~	~~0.30~~	~~12~~	~~111~~	~~222~~	

HFT - LO-HFT300



Band	Center Freq [GHz]	Freq BW	Pixel diameter [mm]	Num Pix	Num Det
MF-2	119	0.3	7.7	364	728
MF-4	166	0.3	7.7	364	728
MF-6	235	0.3	7.7	364	728
HF-1	280	0.3	3.9	271	542
HF-2	337	0.3	3.4	331	662
HF-3	402	0.23	2.7	469	938

6



xForecast

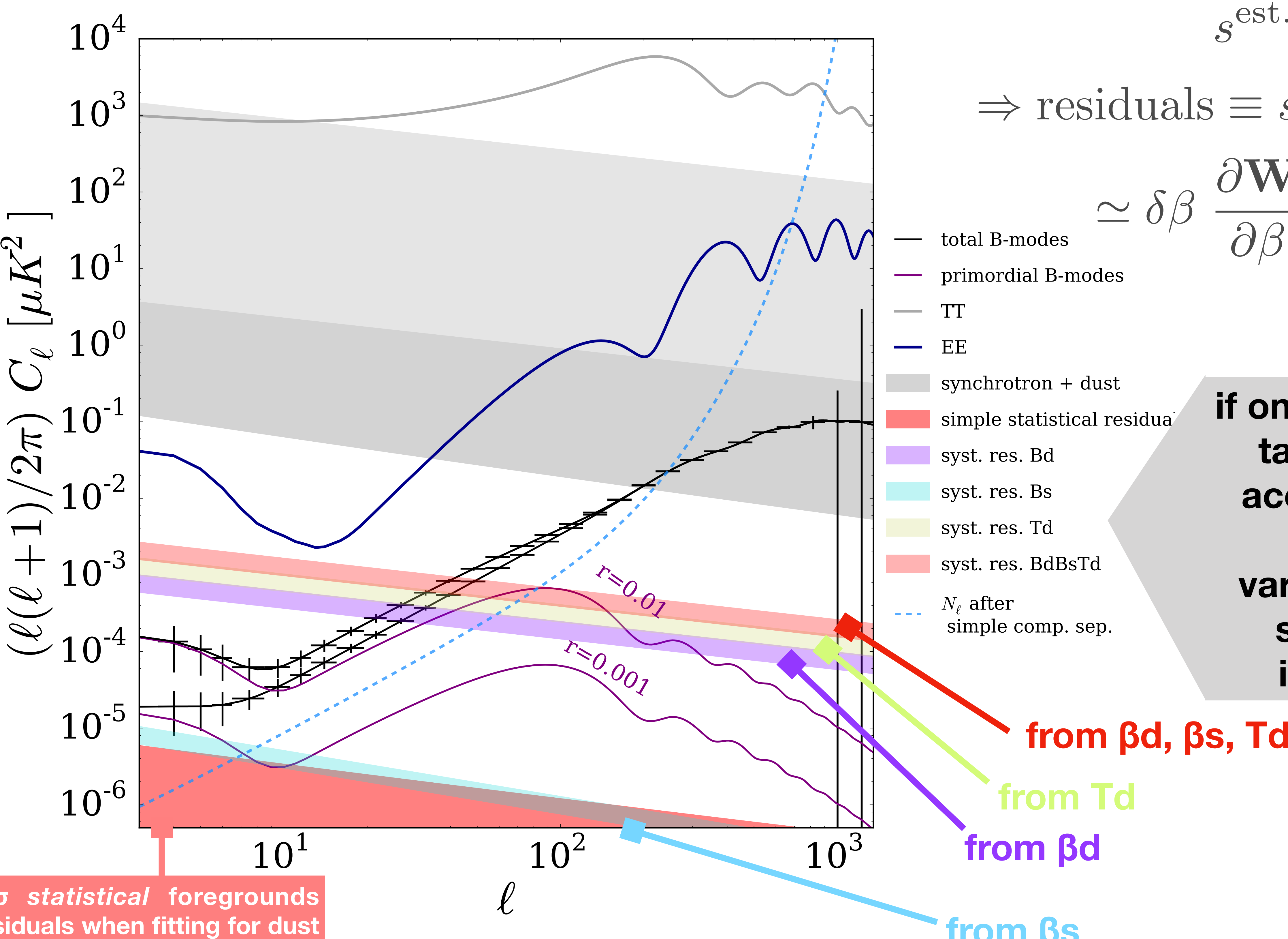
B-modes from space — Montreal 2017

Foregrounds residuals due spatial variability of spectral indices, in the case of LiteBIRD

$$s^{\rm est.} \equiv \mathbf{W} d^{\rm in}$$

$$\Rightarrow \text{residuals} \equiv s^{\rm est.} - s^{\rm in}$$

$$\simeq \delta\beta \left.\frac{\partial \mathbf{W}}{\partial \beta}\right|_{\beta^{\rm true}} d^{\rm in}$$



if one does not taken into account the spatial variations of spectral indices!

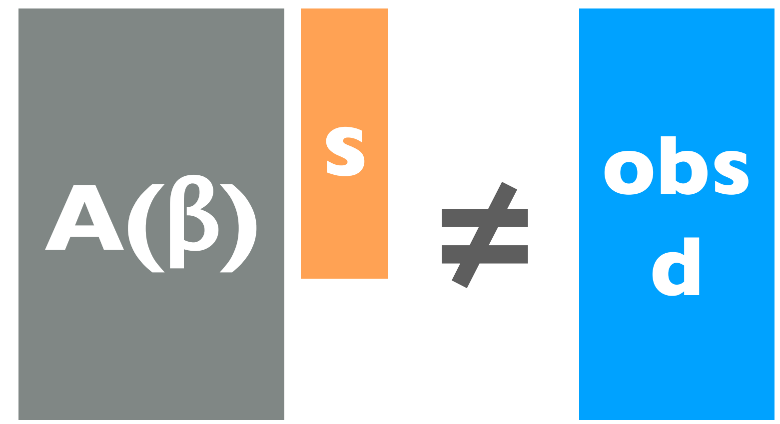
1-σ *statistical* foregrounds residuals when fitting for dust and synchrotron spectral indices, $\{\beta_d,\beta_s\}$, in *each* pixel of a healpix sky with nside=4

Balance between statistical and systematic errors

$$\Sigma \equiv \begin{bmatrix} \sigma(\beta_d)^2 & \sigma(\beta_d)\sigma(\beta_s) & \sigma(\beta_d)\sigma(T_d) \\ \star & \sigma(\beta_s)^2 & \sigma(\beta_s)\sigma(T_d) \\ \star & \star & \sigma(T_d)^2 \end{bmatrix}$$

STATISTICAL error bars on spectral parameters

- better signal-to-noise (instrumental sensitivity, more sky pixels to count on for a given spectral index, etc.)
- broad frequency range
- large sky area (more pixels!)



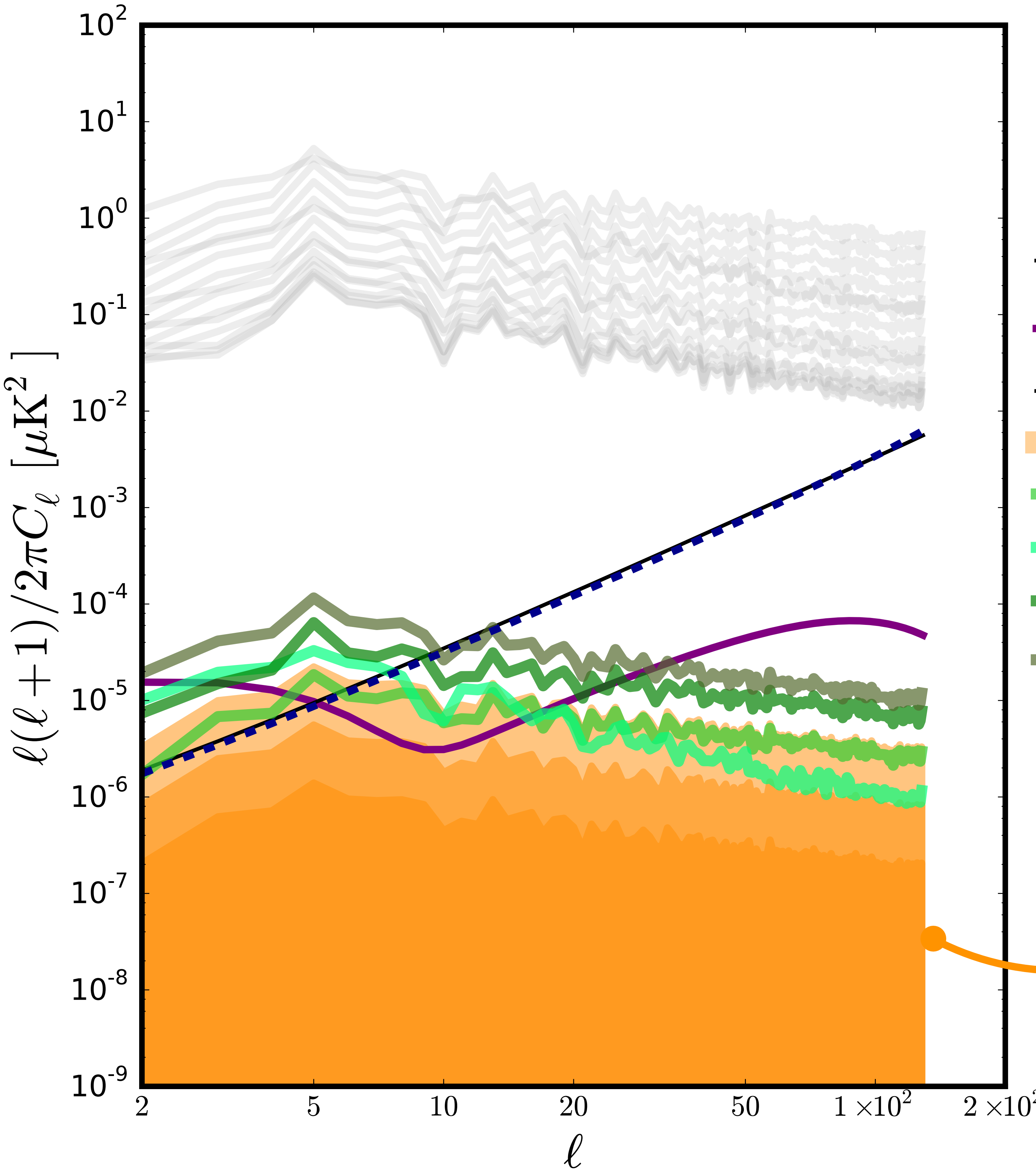
SYSTEMATIC error bars on spectral parameters

- more internal degrees of freedom (free spectral parameters, sky templates, etc.)
- reduced frequency range
- small sky area (less complexity!)

$$s^{\mathrm{est.}} \equiv \mathbf{W} d^{\mathrm{in}}$$

$$\Rightarrow \text{residuals} \equiv s^{\mathrm{est.}} - s^{\mathrm{in}}$$

$$\simeq \delta\beta \left.\frac{\partial \mathbf{W}}{\partial \beta}\right|_{\beta^{\mathrm{true}}} d^{\mathrm{in}}$$



1-σ *statistical* foregrounds residuals when fitting for dust and synchrotron spectral indices, $\{\beta_d,\beta_s,T_d\}$, in *each* pixel of a healpix sky with nside=16

$\ell_{min} \geq 15$

Green = $\sigma(r) < 0.001$ and $r_{bias} < \sigma(r)$

	fit for {Bd} true {Bs,Td}	fit for {Bd,Bs} true {Td}	fit for {Bd,Bs,Td}	fit for {Bd,Td} true {Bs}	fit for {Bs} true {Bd,Td}
nside = 2 (sim and cleaning)	**1.53e-05 ± 0.000562**	**3.11e-05 ± 0.000570**	**0.000207 ± 0.000579**	**0.000160 ± 0.000572**	**1.22e-05 ± 0.000562**
nside = 4 (sim and cleaning)	**8.85e-05 ± 0.000563**	**0.000217 ± 0.000572**	**0.00129 ± 0.000600**	**0.000870 ± 0.000574**	**7.60e-05 ± 0.000565**
nside = 8 (sim and cleaning)	**0.000937 ± 0.000583**	**0.000141 ± 0.000595**	**0.00737 ± 0.000670**	**0.00381 ± 0.000643**	**0.000498 ± 0.000581**
nside = 16 (sim and cleaning)	**0.00169 ± 0.000608**	**0.00558 ± 0.000795**	**0.0221 ± 0.00132**	**0.0104 ± 0.00107**	**0.00187 ± 0.000626**

Excerpt of our conclusions in Montreal 2017

- we show **consistency** between xForecast and SMICA on constant spectral indices and PySM simulations
- **spatial variability of dust is important to characterize, and high frequency channels are crucial**