Foreground Cleaning on Filtered Data in Simons Observatory

Challenges at the CMB Frontier

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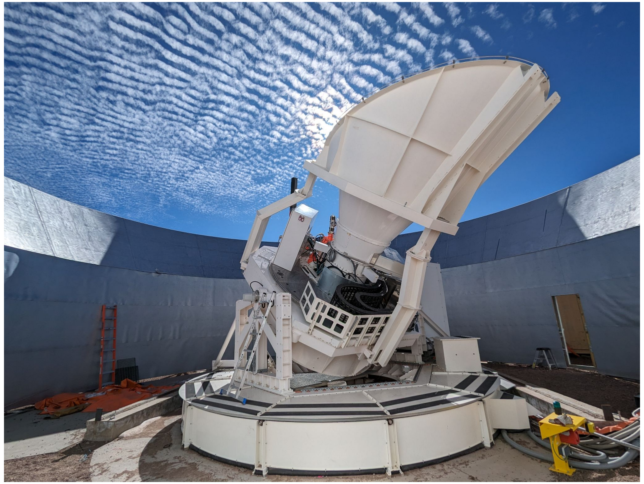
Looking For Primordial B-modes with Simons Observatory

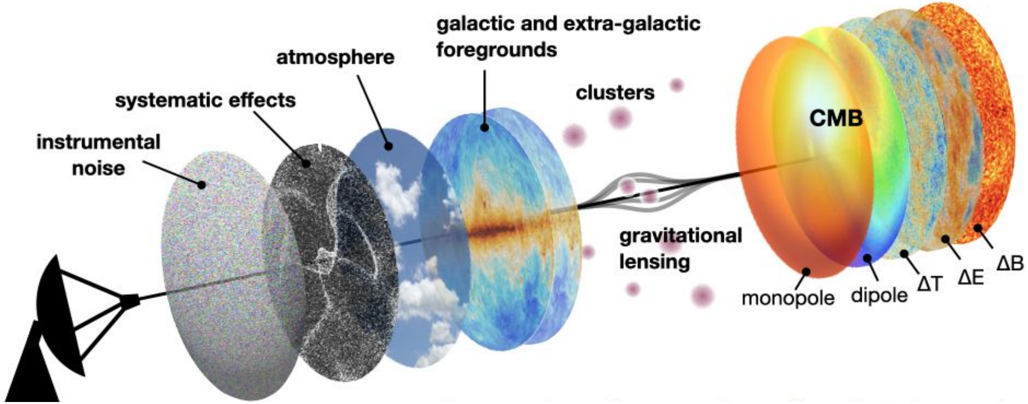
The SO **Small Aperture Telescopes** (SAT) are after large scales primordial B-modes **(see Yoshinori Sueno's talk)**

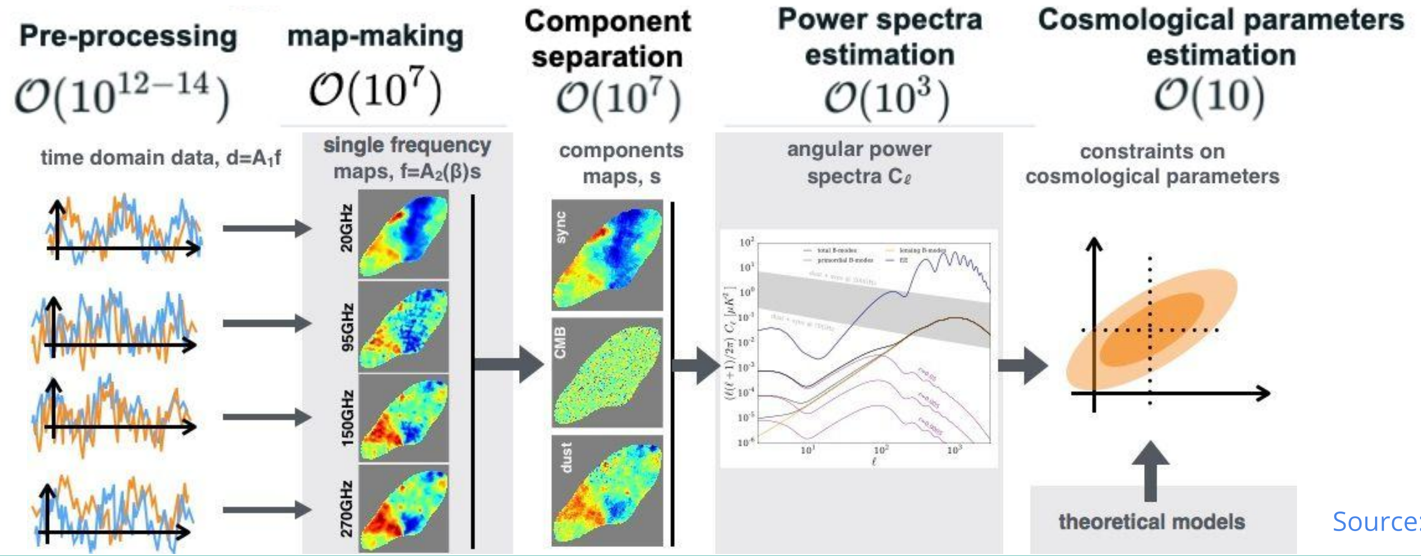
Three main pipelines are being developed **(see Alessandro Carones' talk)**:

- Cl-based **(parametric)**: Existing code: BBPower, Ongoing: SOOPERCOOL
- Map-based **(parametric)**: Existing code: FGBuster/XForecast, Ongoing: MEGATOP
- NILC **(non-parametric)**: BROOM.

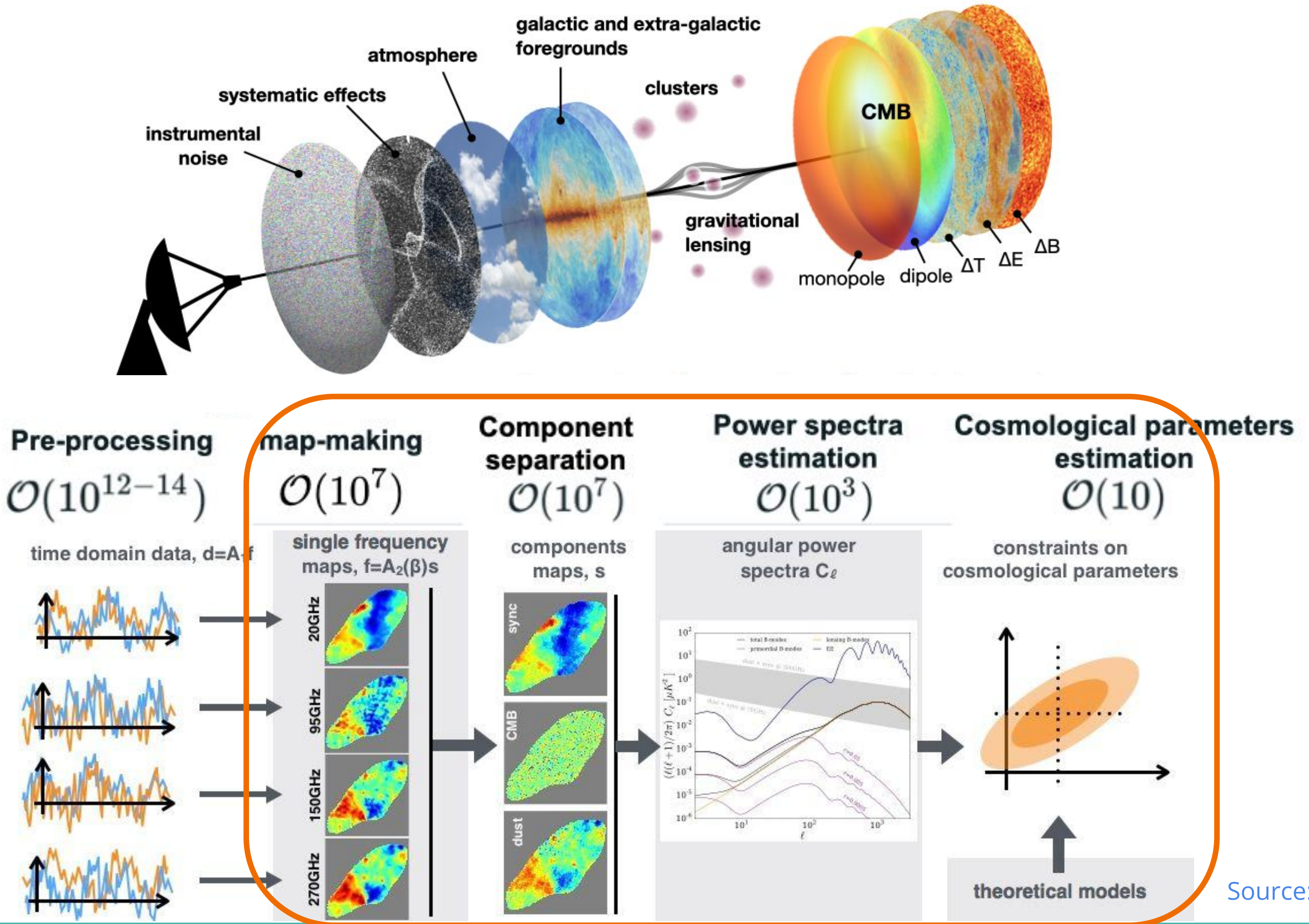
Allows for robustness against different systematic effects







Source: J. Errard



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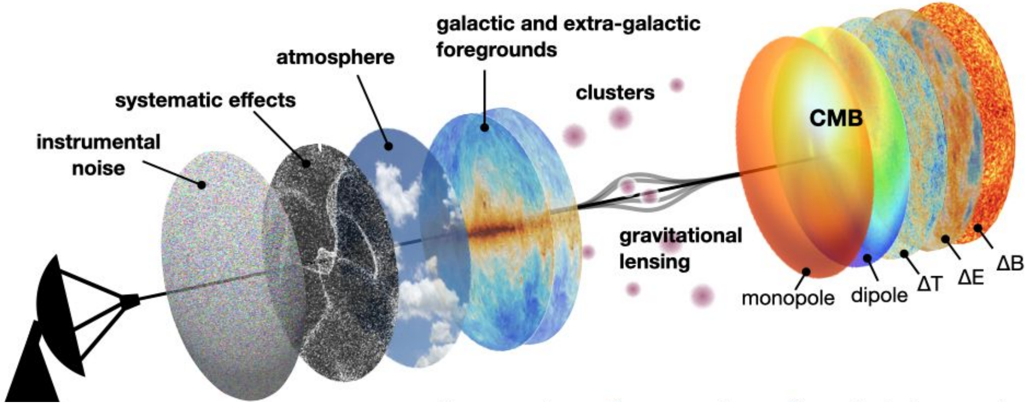
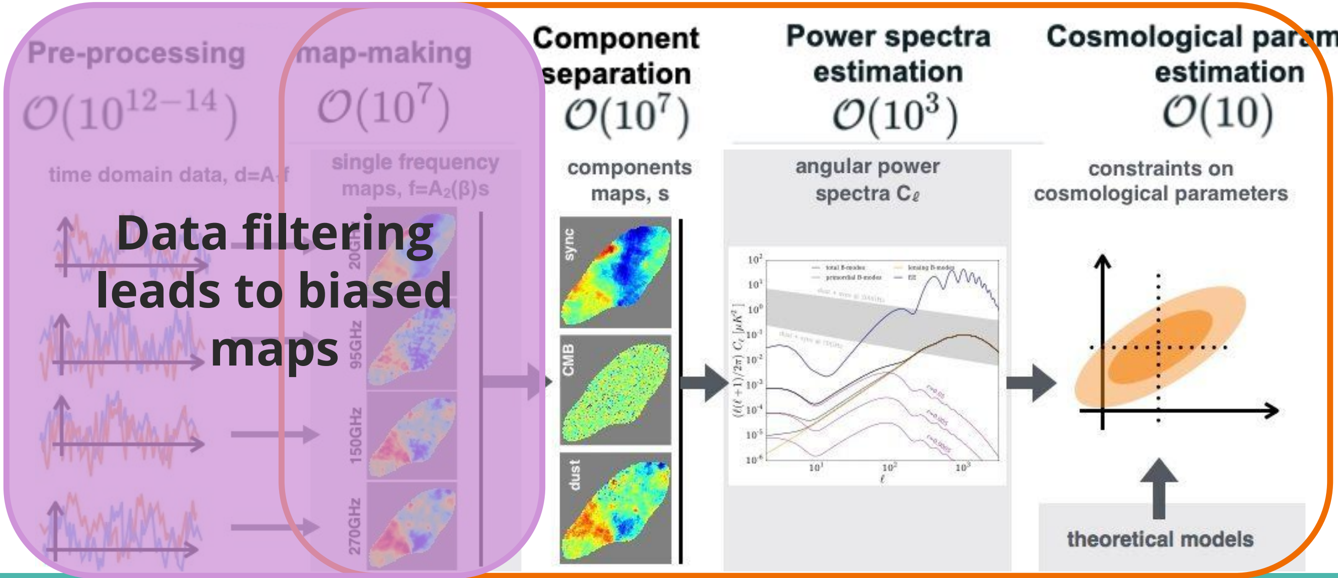




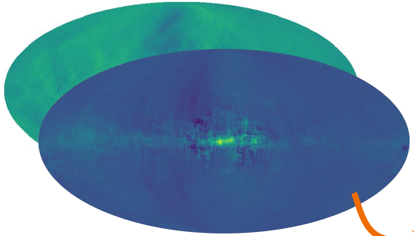
Data filtering leads to biased maps

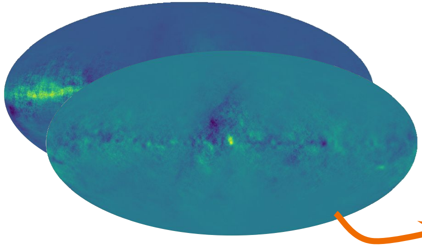
Source: J. Errard

The Standard Data Model

$$\mathbf{d}_p = \mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p$$

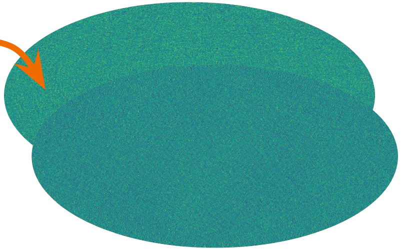
noise





$$\begin{pmatrix} Q_1 \\ U_1 \\ \vdots \\ Q_n \\ U_n \end{pmatrix}$$

$$\begin{pmatrix} Q^{CMB} \\ U^{CMB} \\ Q^d \\ U^d \\ Q^s \\ U^s \end{pmatrix}$$



Input frequency maps

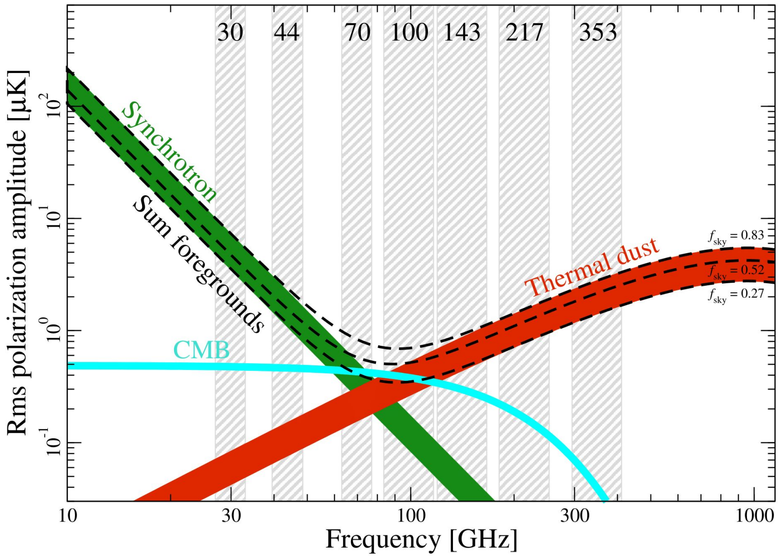
Component maps

The Mixing Matrix

$$\mathbf{d}_p = \mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p$$

$$\mathbf{A}(\{\beta_{\mathrm{fg}}\}) = \begin{pmatrix} 1 & A_1^d & A_1^s \\ \vdots & \vdots & \vdots \\ 1 & A_n^d & A_n^s \end{pmatrix}$$

CMB **Dust** **T_d , β_d** **Synchrotron** **β_s**



Source: Planck Collaboration 2018

Matrix encodes modelled foreground emission laws:

- **modified black-body** for dust
- **power law** for synchrotron

Variation across the sky is possible (Errard et al. 2019)

The Spectral Likelihood

We use the ***spectral likelihood*** (Stompor et al 2008) to estimate those parameters and remove foregrounds contamination:

fgbuster

$$\mathbf{d}_p = \mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p$$

$$-2\ln\mathcal{L}_{\rm spec}(\beta) = \mathrm{cst} - \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{d}\right)^t \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{A}\right)^{-1} \left(\mathbf{A}^t\mathbf{N}^{-1}\mathbf{d}\right)$$

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

Can deal with spatial variation, both in **noise properties** and **foreground parameters**

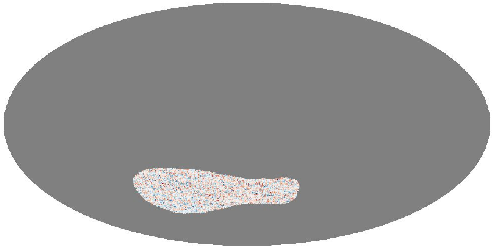
Outputs **CMB** and **Foregrounds maps**, allowing for residual foreground marginalization in the cosmological likelihood

From Component Maps to Cosmology

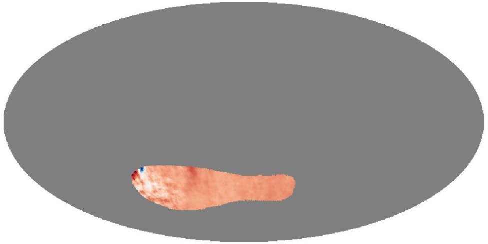
COMPONENT MAPS

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

CMB map



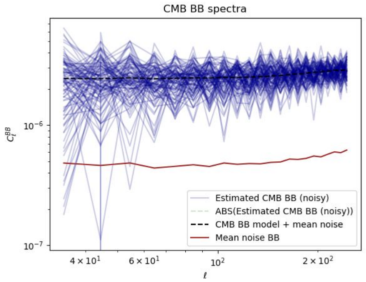
Foreground map



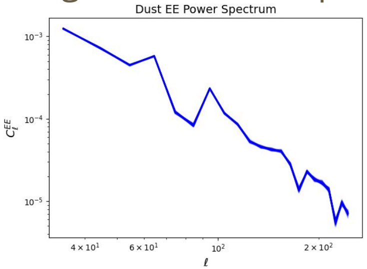
POWER SPECTRA ESTIMATION

Estimated using Namaster pseudo spectra approach

CMB BB Power Spectra



Foreground Power Spectra



COSMOLOGICAL ANALYSIS

➤ The **Cl s** of the observed CMB map are modeled as:

$$\tilde{C}_\ell^{\mathrm{CMB}}(r, A_{\mathrm{lens}}) \equiv C_\ell^{\mathrm{prim}}(r) + C_\ell^{\mathrm{lens}}(A_{\mathrm{lens}}) + \tilde{N}_\ell^{\mathrm{CMB}}$$

➤ Cosmological parameters are inferred via the **likelihood:**

$$-2\,\log\mathscr{L}^{\mathrm{cosmo}} = \sum_\ell (2\ell+1)\, f_{\mathrm{sky}} \left(\frac{\tilde{C}_\ell^{\mathrm{CMB}}}{C_\ell^{\mathrm{CMB}}} + \log\left(C_\ell^{\mathrm{CMB}}\right)\right)$$

➤ The foreground maps allow for **marginalisation** over the residual dust spectra by extending the model:

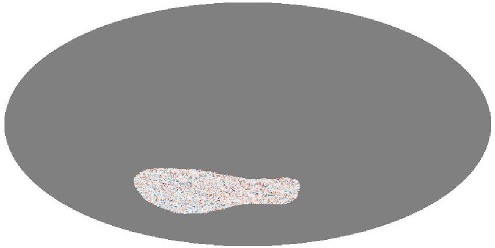
$$\tilde{C}_\ell^{\mathrm{CMB}} = \tilde{C}_\ell^{\mathrm{CMB}}(r, A_{\mathrm{lens}}) + A_{\mathrm{dust}}\tilde{C}_\ell^{\mathrm{dust}}$$

From Component Maps to Cosmology

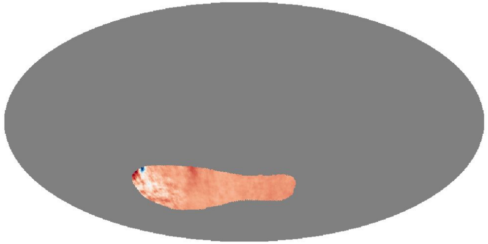
COMPONENT MAPS

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

CMB map



Foreground map



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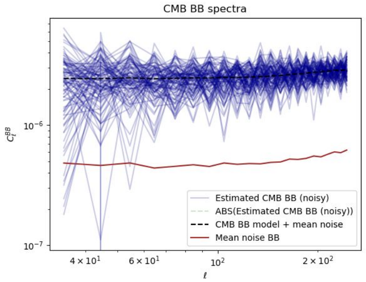
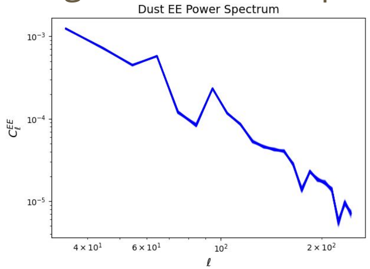
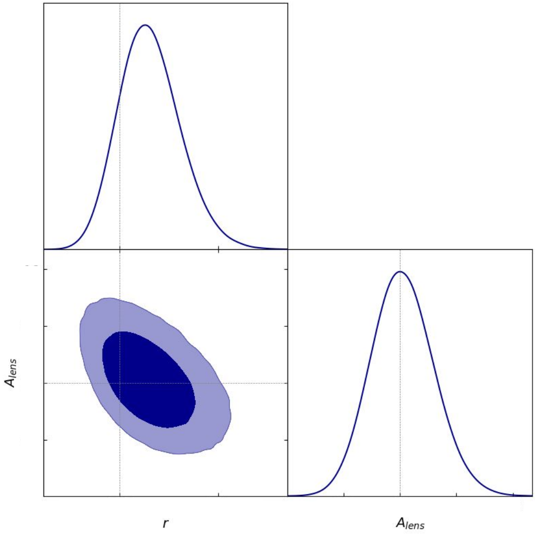


Foreground Power Spectra



COSMOLOGICAL ANALYSIS

Cosmological results for one particular simulation:

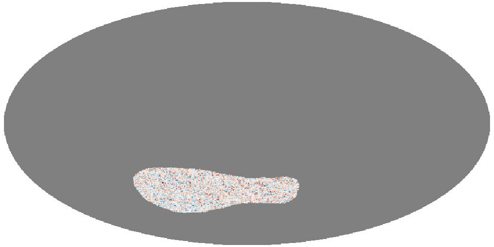


From Component Maps to Cosmology

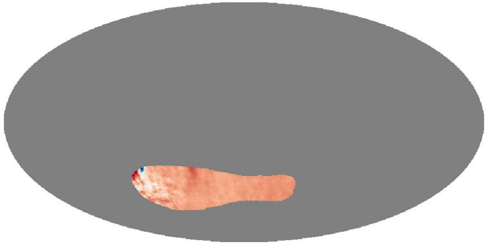
COMPONENT MAPS

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

CMB map



Foreground map



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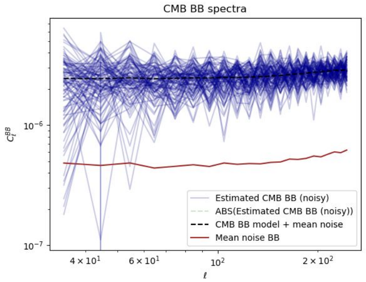

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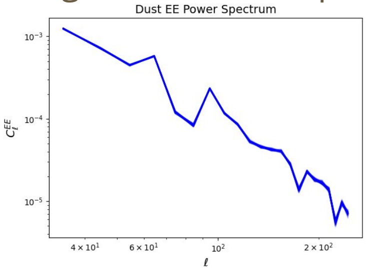
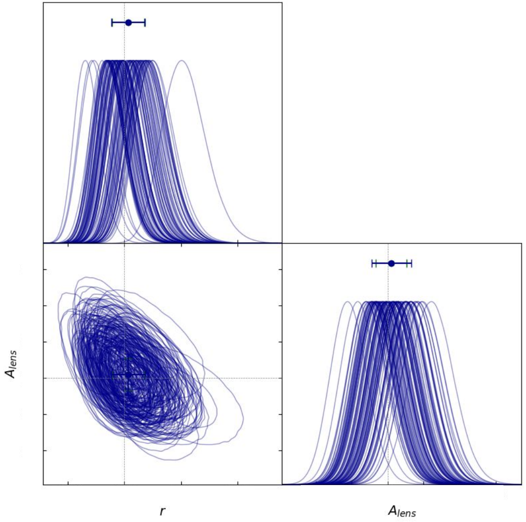


COSMOLOGICAL ANALYSIS

We can run the full pipeline on many simulations efficiently



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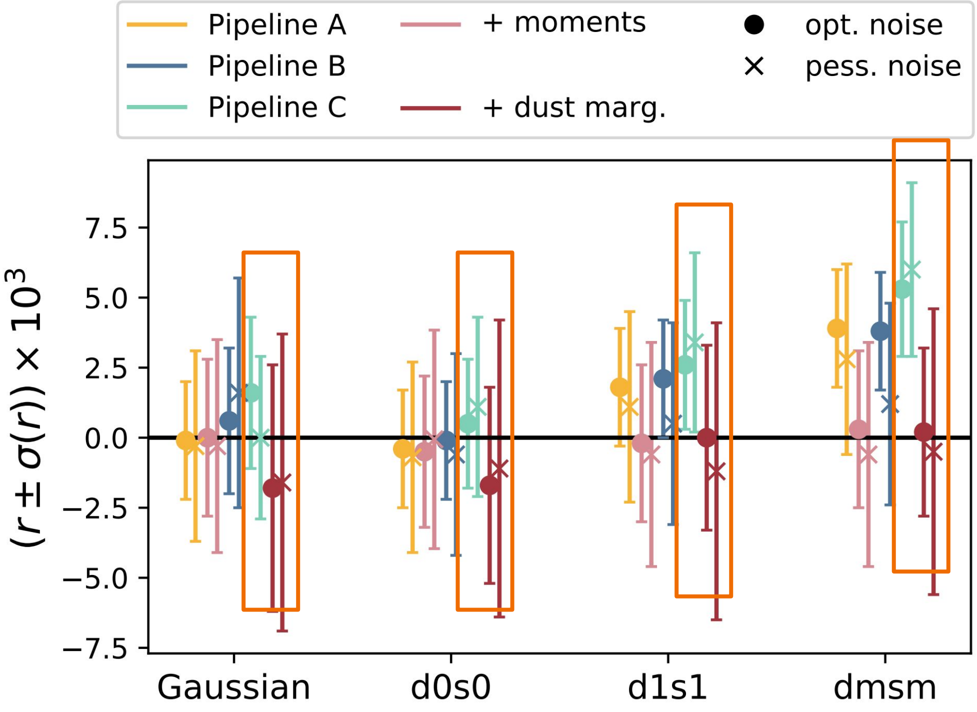
One of the Main Component Separation Pipeline in SO

Map-based method has been tested on Simons Observatory simulations (Wolz et al. 2024):

- comparable to other methods: ILC, Cross-spectra parametric method
- Robust to complex foregrounds thanks to dust marginalization

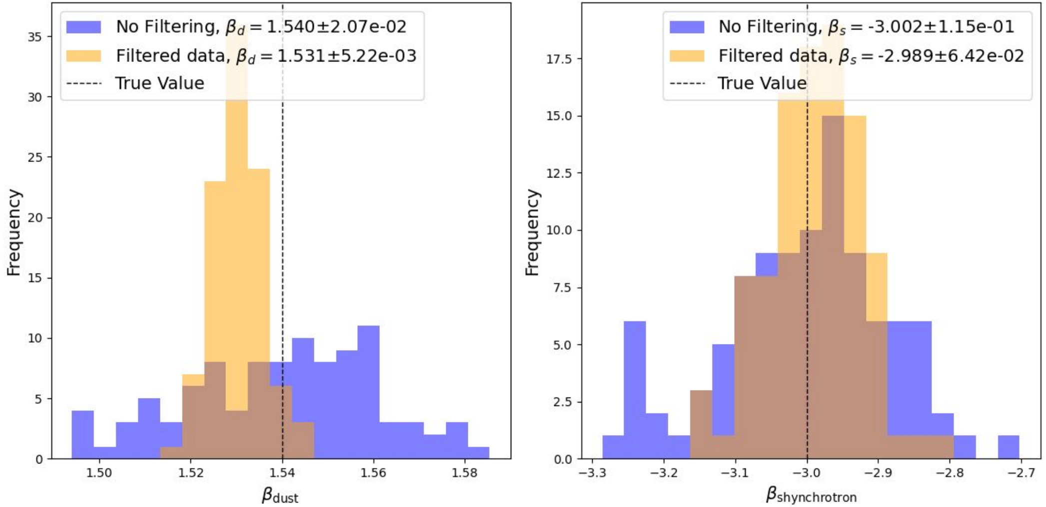


Source: Wolz et al 2024

Map-Based Parametric Component Separation On Filtered Data

Simulations with CMB + low complexity foregrounds (d0s0) for SO SAT survey using filtering operator (credit: SO simulations team).

The filtering is frequency dependent.



Ignoring the filtering in foreground cleaning and subsequent steps

⇒ Correction of filtering is necessary at the component separation level.

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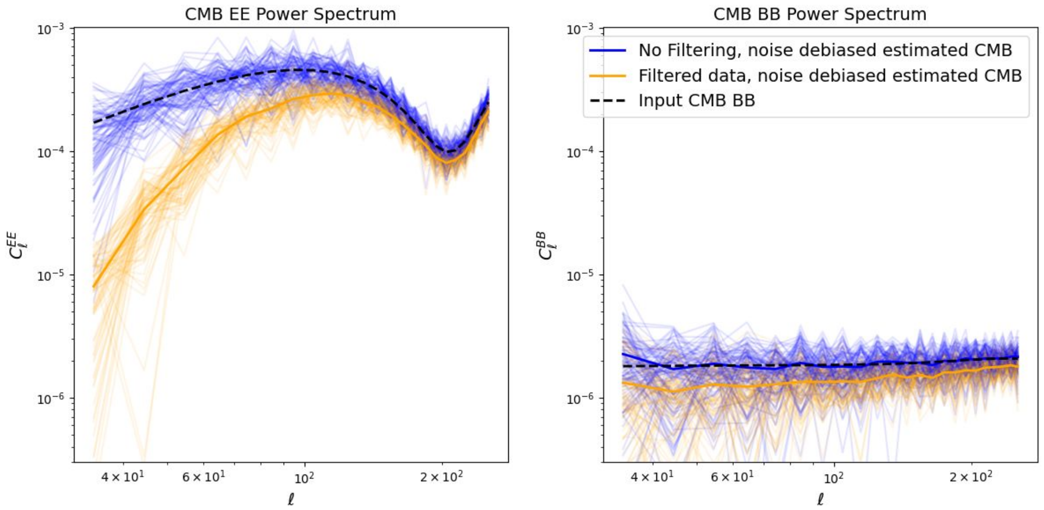

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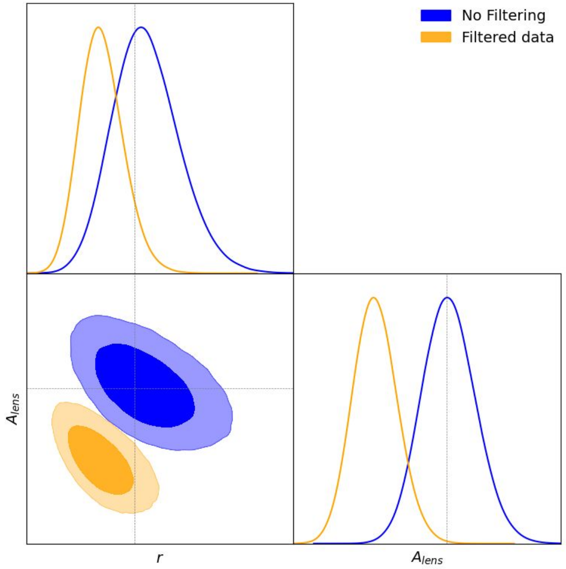

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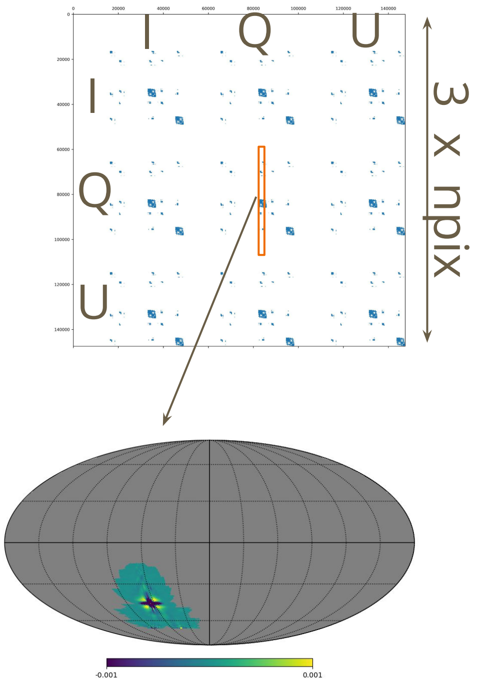
Accounting for Filtering in Component Separation

Data filtering expressed as linear operator on map space: the **Observation matrix** (Keck Array, BICEP2 Collaborations 2016)

$$\mathbf{m}_p^{\mathrm{out}} = \mathbf{O}_{pp'}\mathbf{m}_{p'}^{\mathrm{in}}$$



Constructed using instrument model and data preprocessing scheme.

Very large matrix, here for reduced resolution (nside=128):

- 600 000 x 600 000 elements
- >11 GB per map / frequency channel

Accounting for Filtering in Component Separation

We update the data model to include the observation matrix:

$$\mathbf{d}_p = \mathbf{O}_{pp'}(\mathbf{A}(\beta)\mathbf{s}_p + \mathbf{n}_p)$$

The spectral likelihood is modified accordingly:

$$-2\ln\mathcal{L}_{\rm spec}(\beta) \sim (\mathbf{A}^t\mathbf{O}^t\mathbf{N}^{-1}\mathbf{d})^t(\mathbf{A}^t\mathbf{O}^t\mathbf{N}^{-1}\mathbf{O}\mathbf{A})^{-1}(\mathbf{A}^t\mathbf{O}^t\mathbf{N}^{-1}\mathbf{d})$$

PROS

- No need for **simulations**
- Better suited for **pixel-based** analysis
- Describes filtering **spatial variability** and **correlations**
- Optimal noise weighting
- No need to filter external data
- No assumption of gaussianity of the foregrounds

CONS

- High **computational cost**
- Observations matrices need to be available
- Non-linear filtering are trickier to implement

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***See Camille Gubeno's talk**

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With a precomputed preconditioner and JAX acceleration using the FURAX framework we are able to estimate foreground parameters! (credit: Magdy Morshed)

We can then estimate CMB and foreground maps using (BICEP/Keck Collaboration 2025 **see Dominic Beck's talk tomorrow!**):

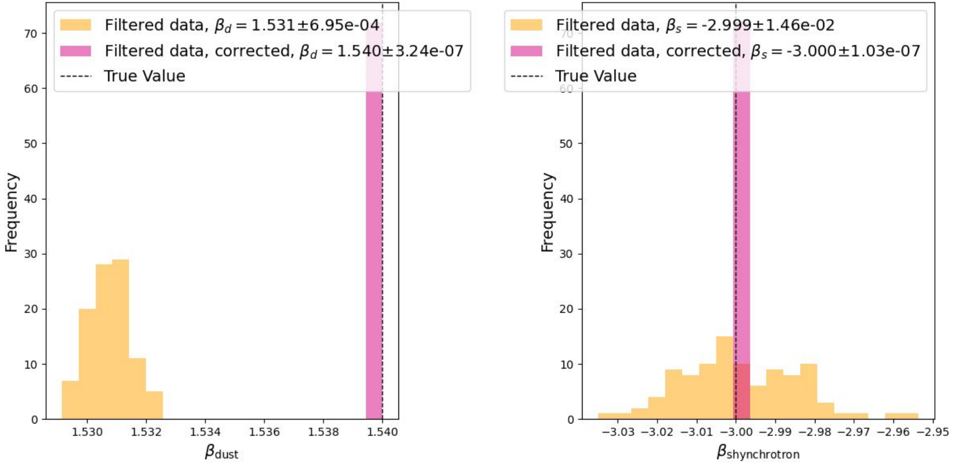
$$\hat{\mathbf{s}} = (\mathbf{A}^t\mathbf{O}^t\mathbf{N}^{-1}\mathbf{O}\mathbf{A})^{-1}\mathbf{A}^t\mathbf{N}^{-1}\mathbf{d}$$

Map-Based Parametric Component Separation On Filtered Data

Running on **noiseless** CMB + low complexity foregrounds for SO SAT survey.

Filtered using observation matrix for SO (credit: SO simulations team), one per frequency channel. Two cases:

- Ignoring the filtering in foreground cleaning and subsequent steps
- Including observation matrices



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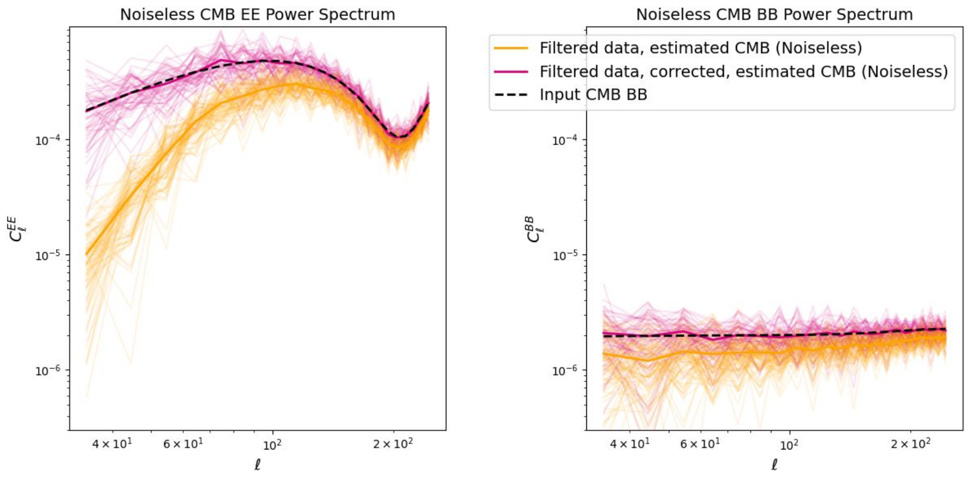

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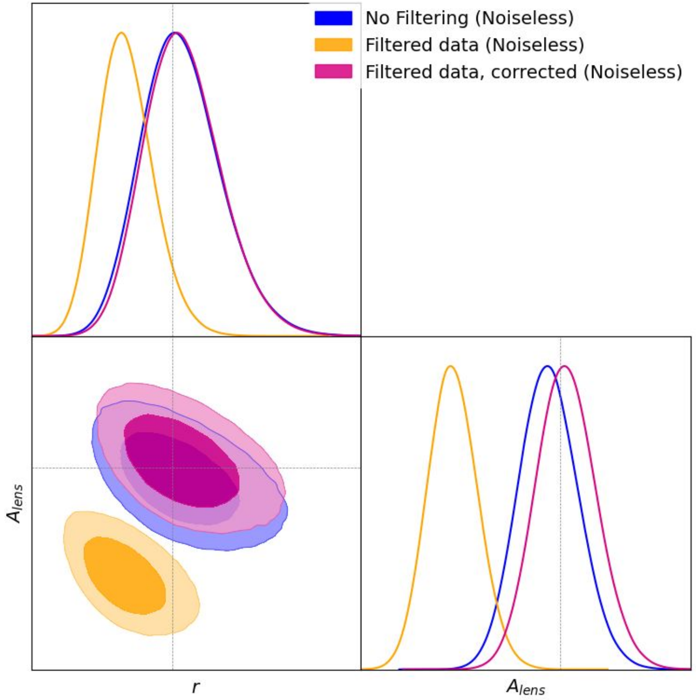

Map-Based Parametric Component Separation On Filtered Data

Preliminary results on **noisy** CMB + low complexity foregrounds for SO SAT survey.

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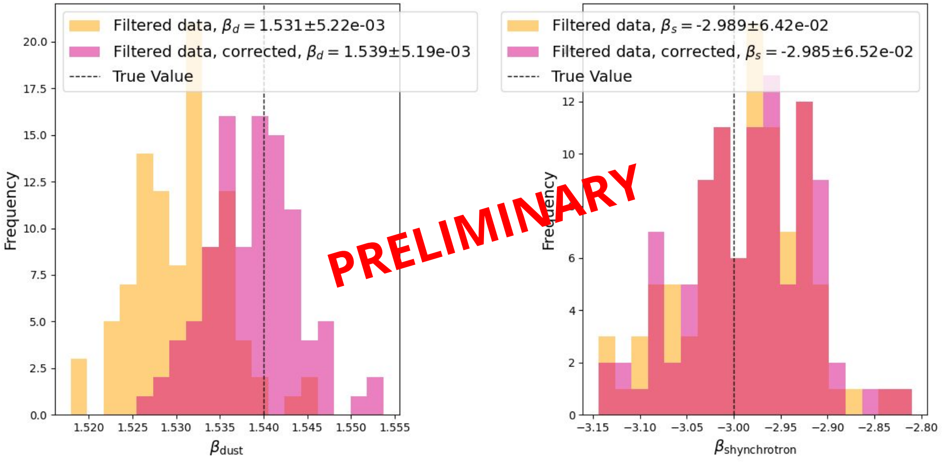
The noise is also filtered with the observation matrix.



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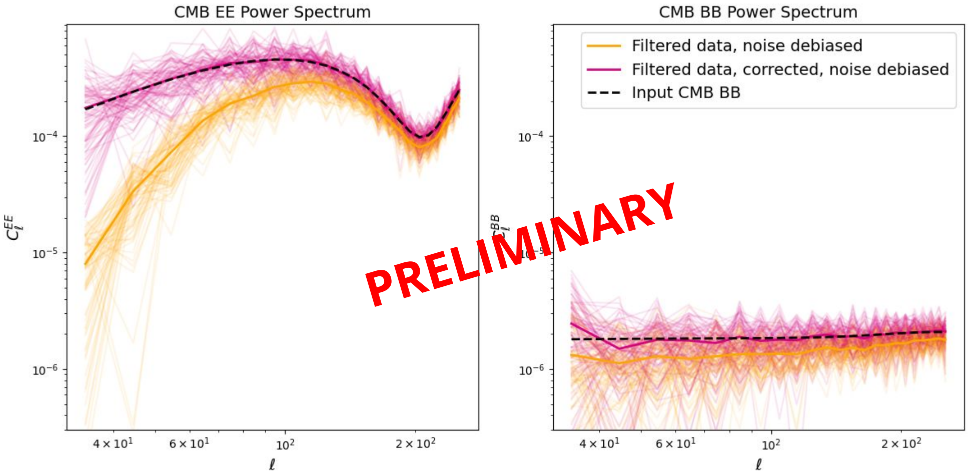

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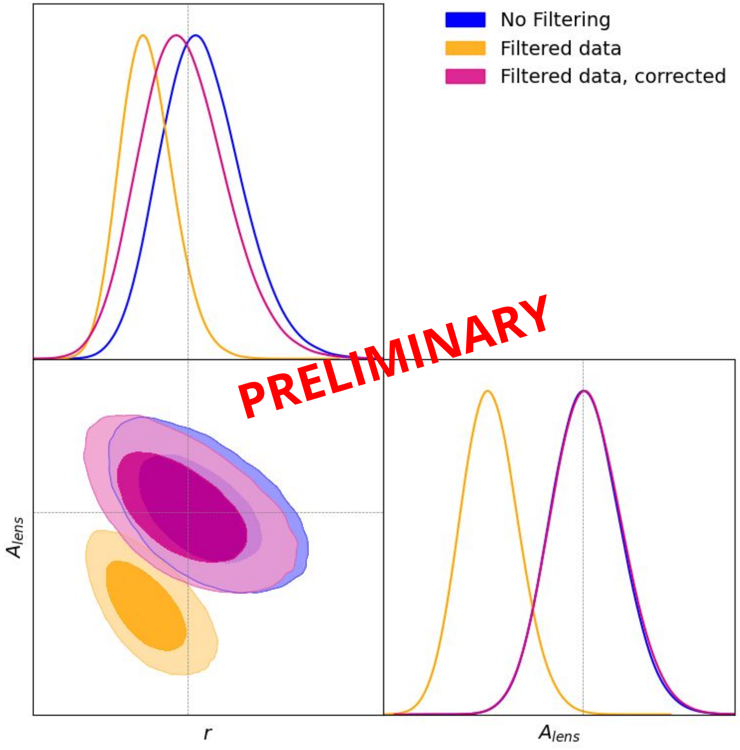

Conclusion

MEGATOP is the **map-based** component separation for the SO SAT analysis

It is a versatile tool and provides cross-check for current and future CMB experiments.

Including the effect of filtering is necessary.

We are able to correct for it at the map level using observation matrices

Current/future prospects:

- application on external (**see Camille Gubeno's talk for preliminary study on NPIPE simulations**)
- internal SO data (work in progress)
- include beam operator in pixel based framework
- complex noise correlation
- polarization angles
- multi patch
- ...

THANK YOU!