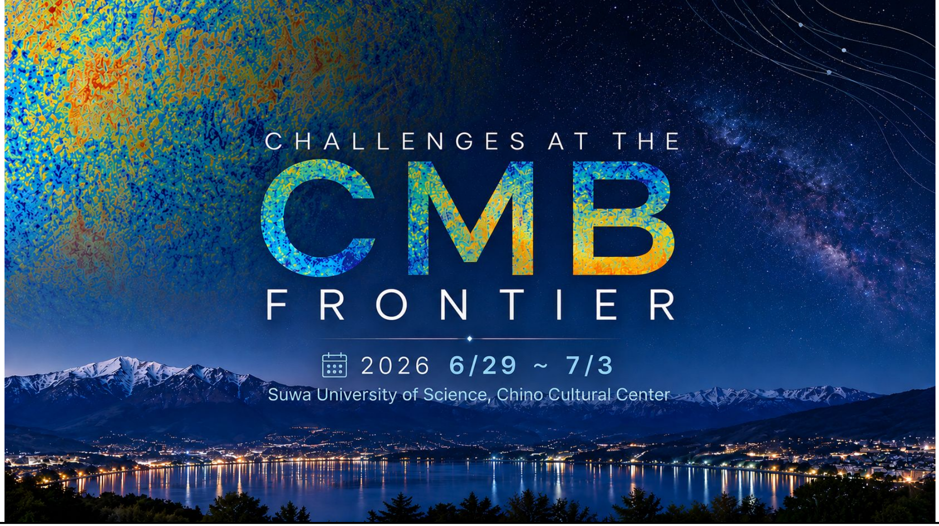


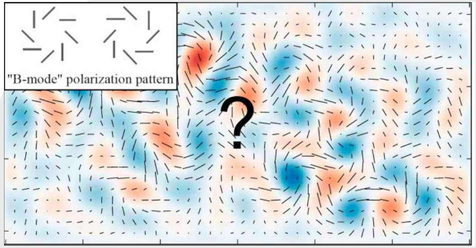
Component separation
for CMB experiments

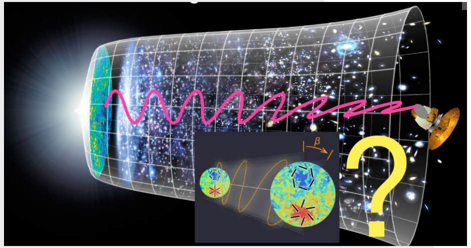
Alessandro Carones

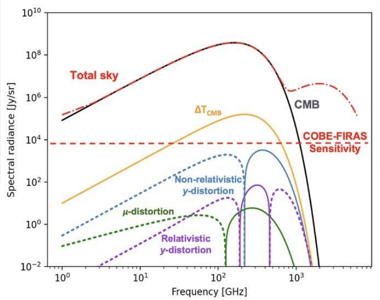
SISSA

INFN
Istituto Nazionale di Fisica Nucleare

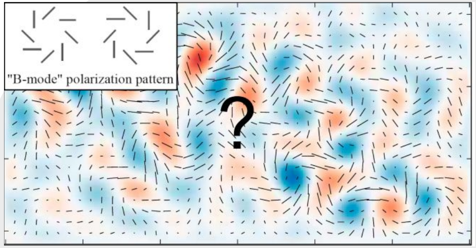
New CMB signals

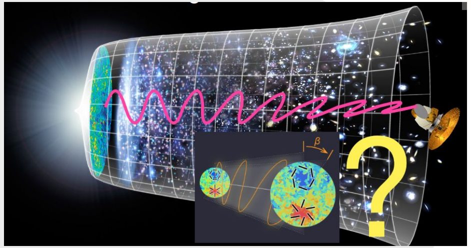


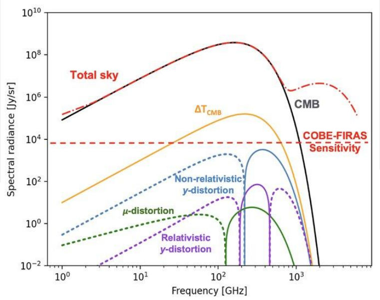


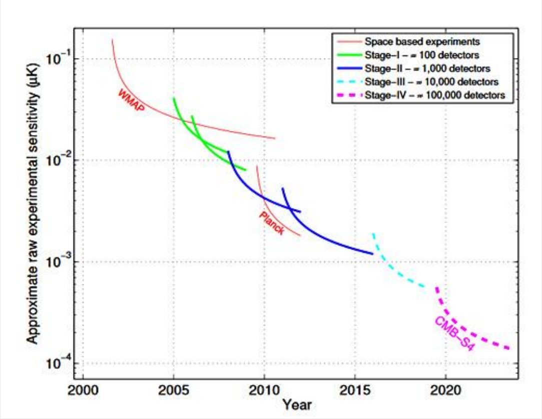


New CMB signals



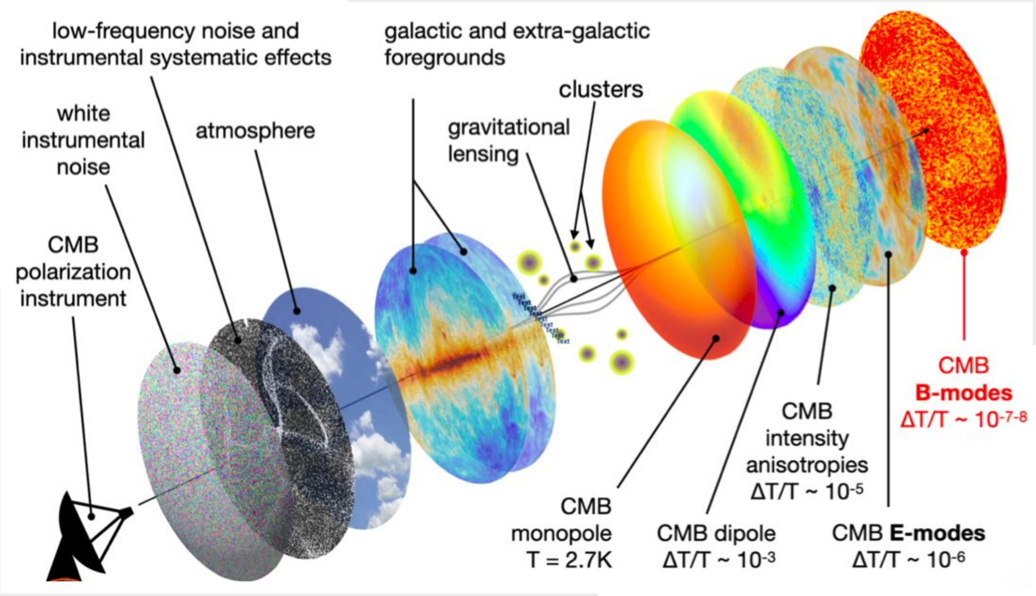






Better sensitivities

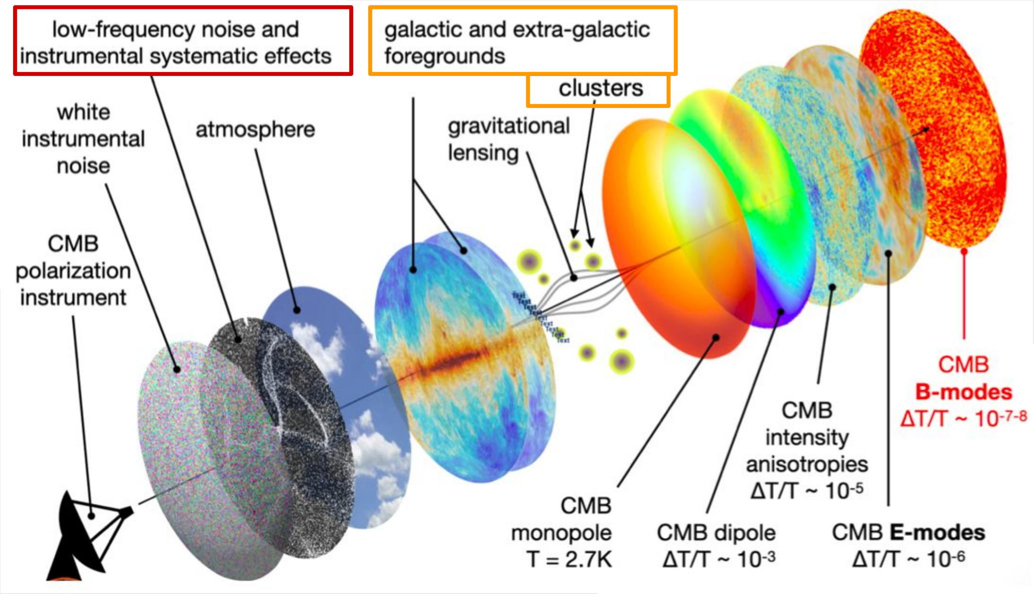
New CMB signals



Credit: J. Errard

Better sensitivities

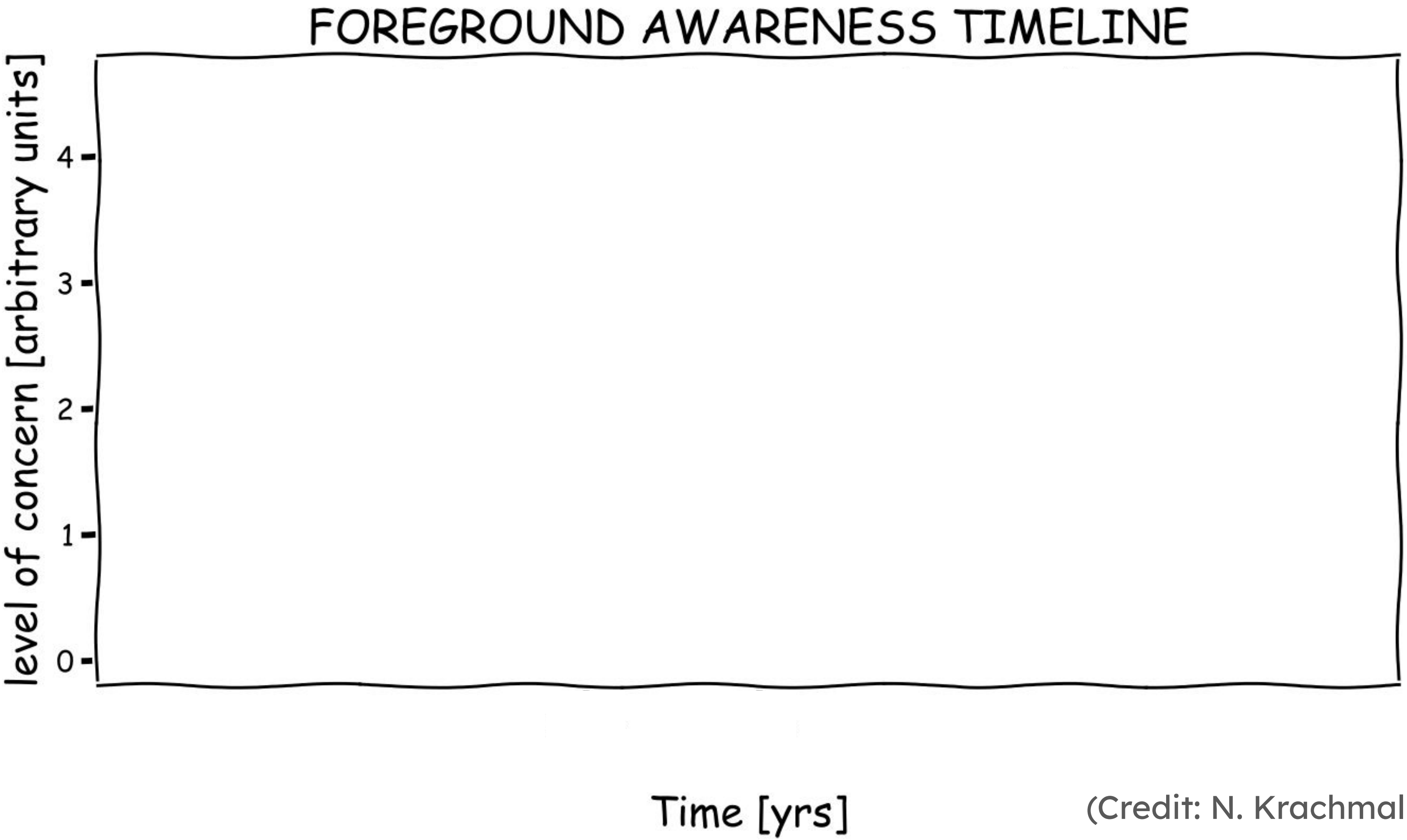
New CMB signals



Credit: J. Errard

Better sensitivities

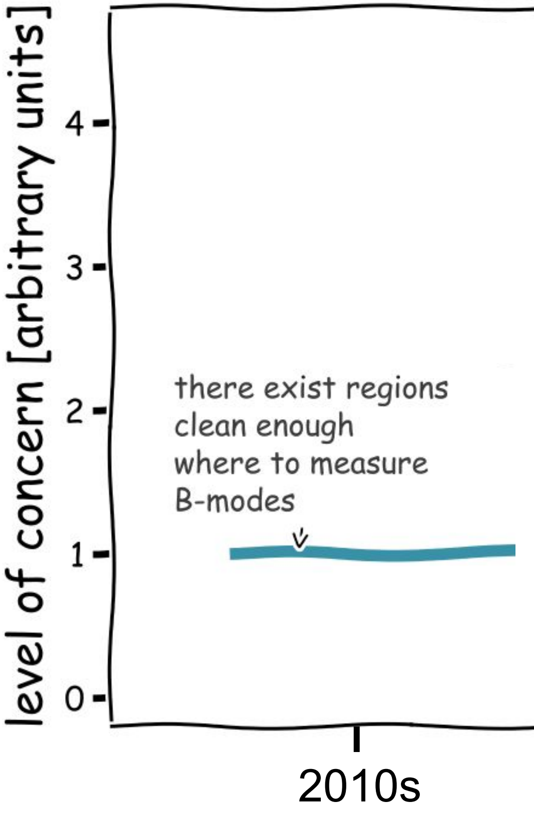
($\propto$ component-separation development)

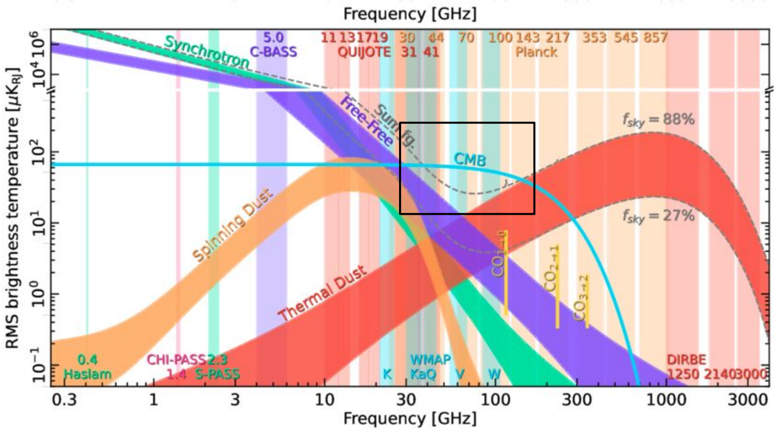


(Credit: N. Krachmalnicoff)

(∝ component-separation development)

FOREGROUND AWARENESS TIMELINE





Analysis of intensity data

map-based component-separation tools used for:

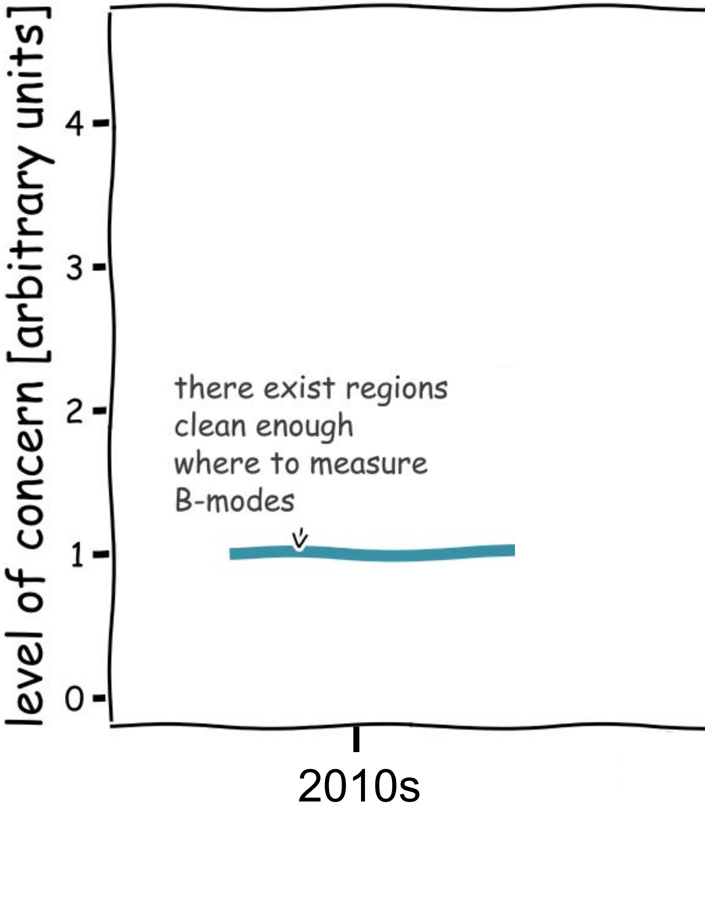
- **statistical analyses** (not main cosmological inference)
- **Galactic and extragalactic science**

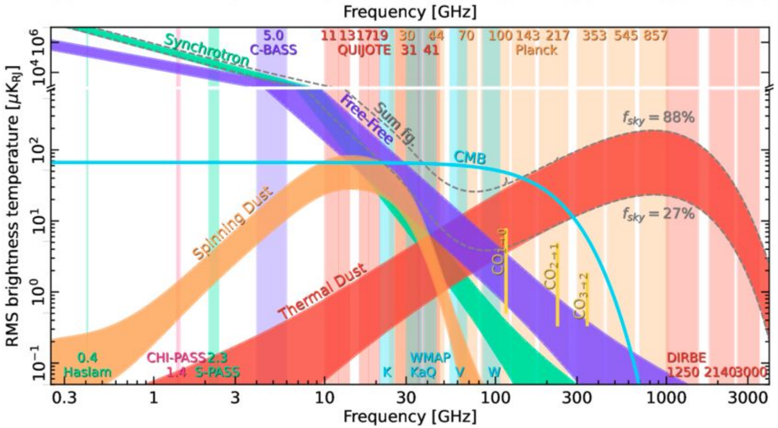
Time [yrs]

(Credit: N. Krachmalnicoff)

(∝ component-separation development)

FOREGROUND AWARENESS TIMELINE



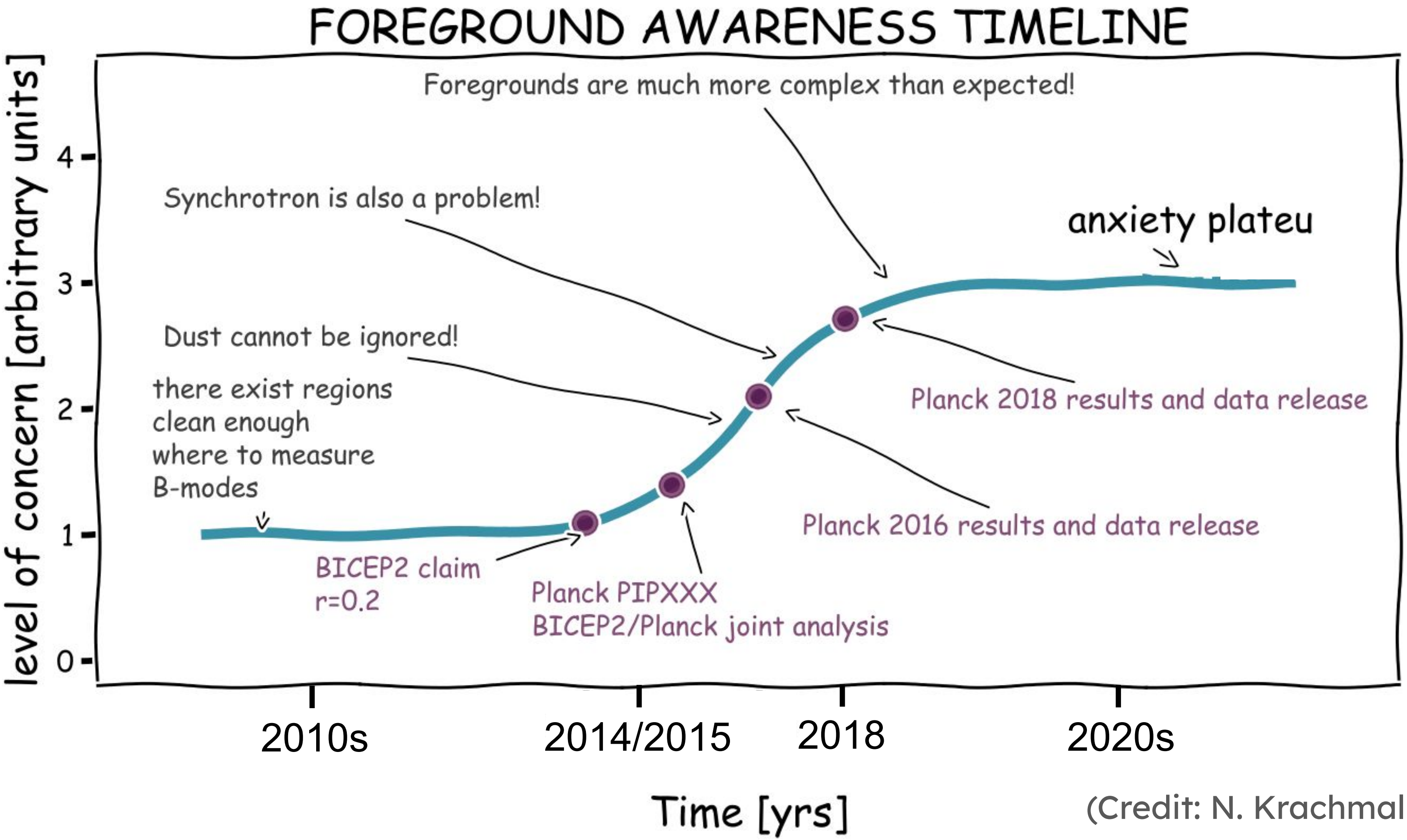


Analysis of intensity data

Most of the approaches we still use today date back to those days.

(Credit: N. Krachmalnicoff)

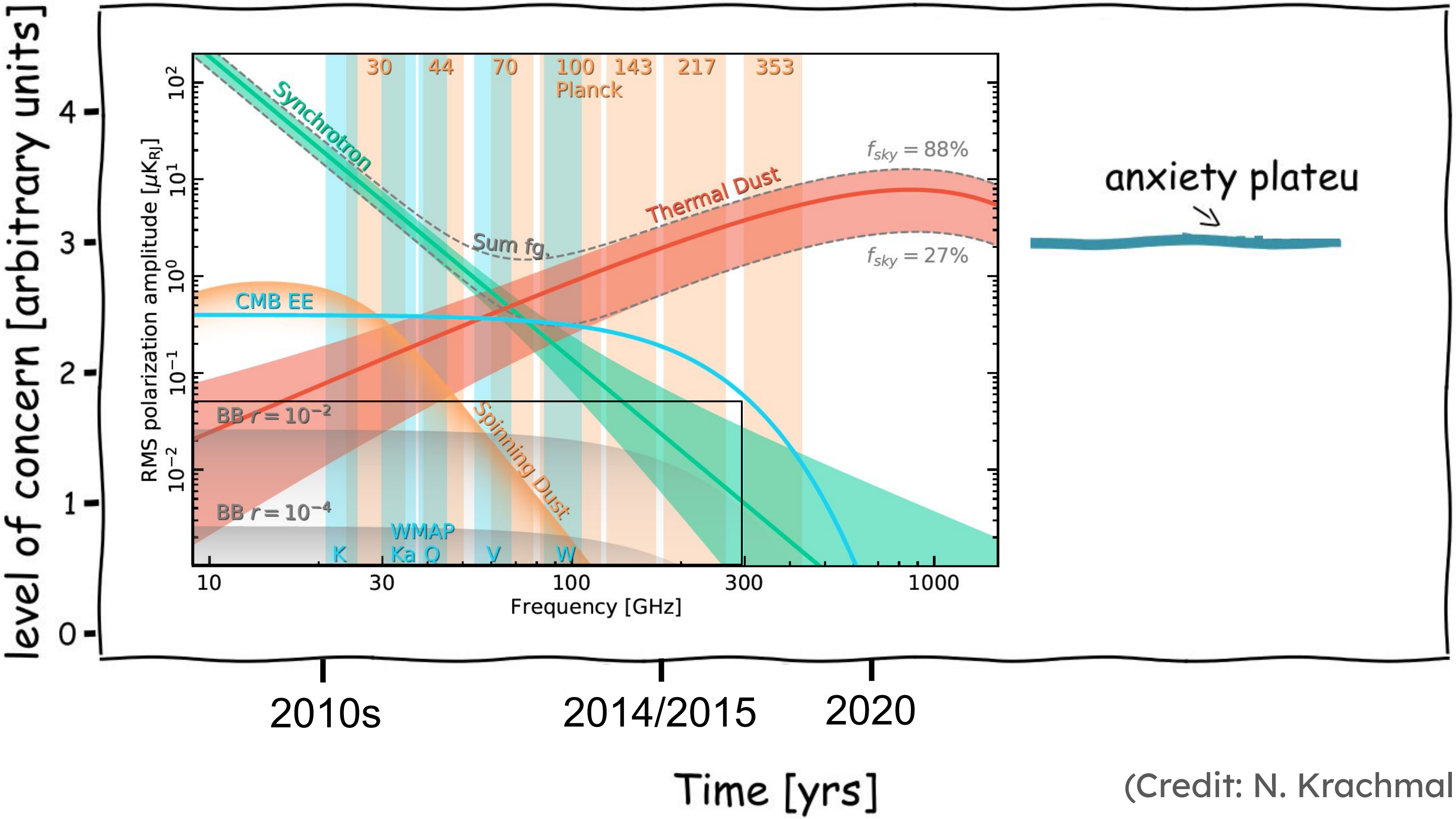
(∝ component-separation development)



(Credit: N. Krachmalnicoff)

($\propto$ component-separation development)

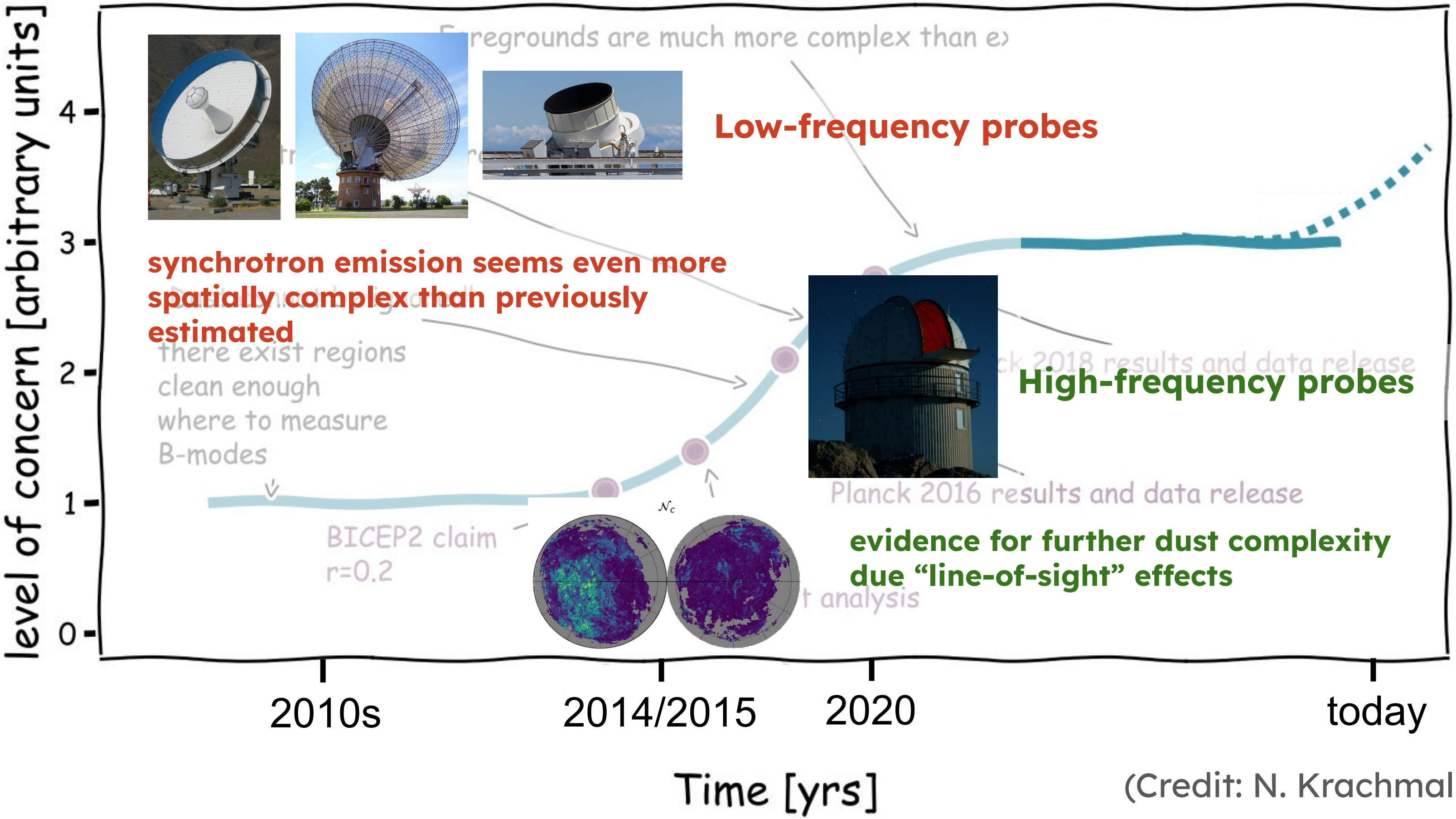
FOREGROUND AWARENESS TIMELINE



(Credit: N. Krachmalnicoff)

($\propto$ component-separation development)

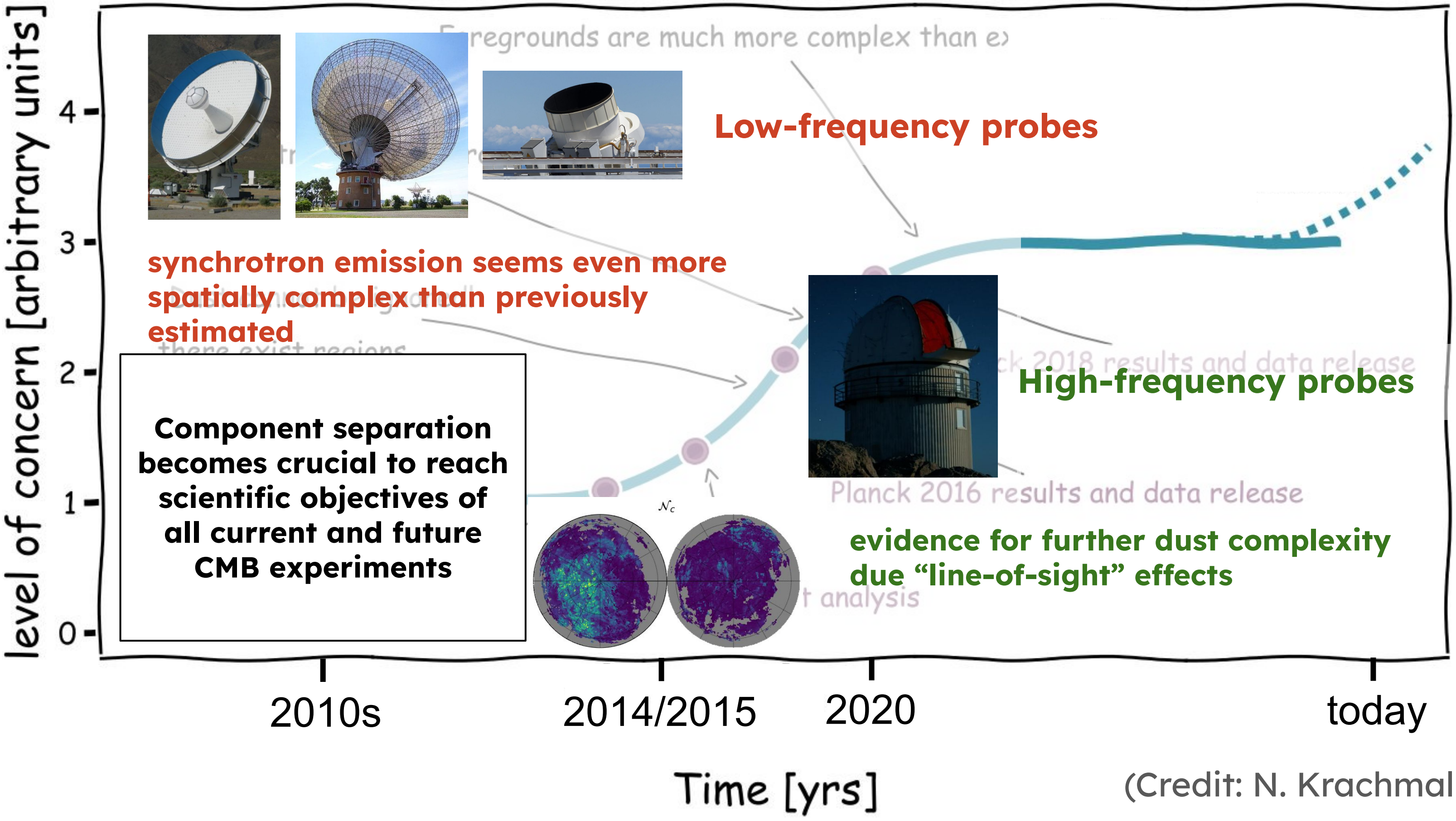
FOREGROUND AWARENESS TIMELINE



(Credit: N. Krachmalnicoff)

$(\propto$ component-separation development$)$

FOREGROUND AWARENESS TIMELINE



(Credit: N. Krachmalnicoff)

Component-separation wishlist

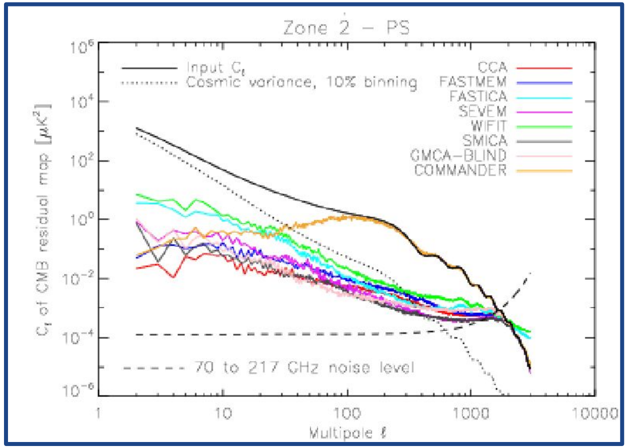
1. Being able to deal with foreground:
   a. projected spatial complexity
   b. spectral complexity

2. Absorb instrumental modelling/mitigate calibration systematics

3. Develop robustness tests - diagnostic of goodness of component separation

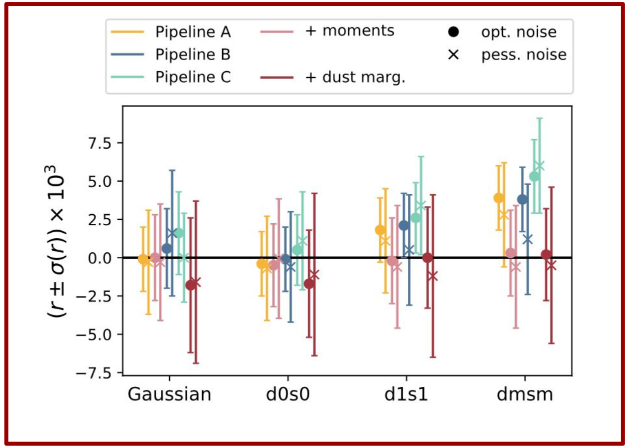
4. Reach the targeted sensitivity for scientific observables

CMB experiments wishlist



Planck

[Leach+ (2008)]



Simons Observatory

[Wolz+ (2023)]

LiteBIRD Science Goals and Forecasts: E Modes from the *LiteBIRD* CMB Polarization Survey

LiteBIRD Science Goals and Forecasts. Foreground Modeling and Component Separation (for CMB B modes)

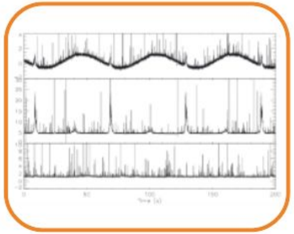
LiteBIRD

[LB Coll. (in prep.)]

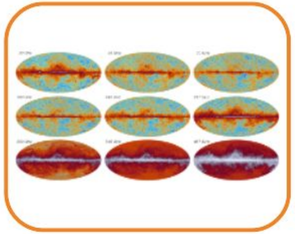
- Applying multiple (different) component separation pipelines
- Having additional strategies to mitigate potential foreground and systematic biases

will allow to validate any potential detection of new observables

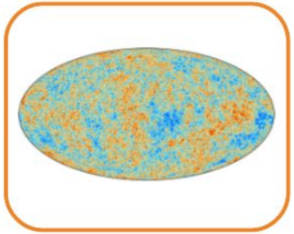
Component-separation basis



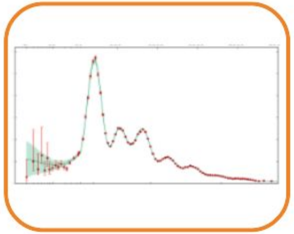
Raw data



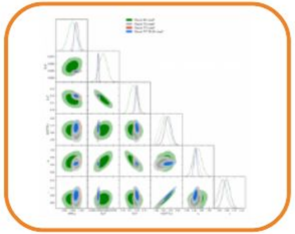
Multifrequency maps



Reconstructed CMB

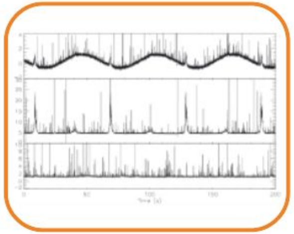


Angular power spectra

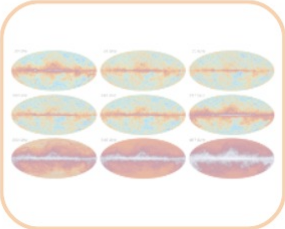


Cosmological parameters

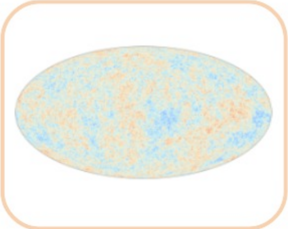
Component-separation from TODs



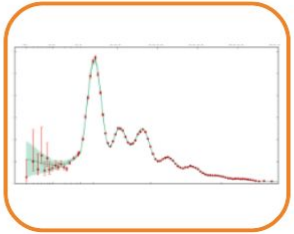
Raw data



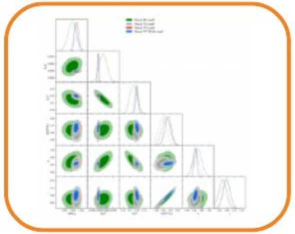
Multifrequency maps



Reconstructed CMB



Angular power spectra



Cosmological parameters

Integration of map-making, component separation and power spectrum estimation in a unified framework

data model

$$d_{j,t} = g_{j,t}\mathsf{P}_{tp,j}\left[\mathsf{B}^{\rm symm}_{pp',j}\sum_c \mathsf{M}_{cj}(\boxed{\beta_{p'}}, \Delta^j_{\rm bp})\boxed{a^c_{p'}} + \mathsf{B}^{\rm asymm}_{pp',j}\left(s^{\rm orb}_{j,t} + s^{\rm fsl}_{j,t}\right)\right] + n^{\rm corr}_{j,t} + n^{\rm w}_{j,t}.$$

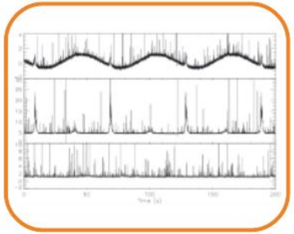
common component-separation parameters

$$\begin{aligned}
\boldsymbol{g} &\leftarrow P(\boldsymbol{g} &&|\,\boldsymbol{d}, && \xi_n, \Delta_{\rm bp}, \boldsymbol{a}, \beta, C_\ell) \\
\boldsymbol{n}_{\rm corr} &\leftarrow P(\boldsymbol{n}_{\rm corr} &&|\,\boldsymbol{d}, \boldsymbol{g}, && \xi_n, \Delta_{\rm bp}, \boldsymbol{a}, \beta, C_\ell) \\
\xi_n &\leftarrow P(\xi_n &&|\,\boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\rm corr}, && \Delta_{\rm bp}, \boldsymbol{a}, \beta, C_\ell) \\
\Delta_{\rm bp} &\leftarrow P(\Delta_{\rm bp} &&|\,\boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\rm corr}, \xi_n, && \boldsymbol{a}, \beta, C_\ell) \\
\beta &\leftarrow P(\beta &&|\,\boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\rm corr}, \xi_n, \Delta_{\rm bp}, && C_\ell) \\
\boldsymbol{a} &\leftarrow P(\boldsymbol{a} &&|\,\boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\rm corr}, \xi_n, \Delta_{\rm bp}, && \beta, C_\ell) \\
C_\ell &\leftarrow P(C_\ell &&|\,\boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\rm corr}, \xi_n, \Delta_{\rm bp}, \boldsymbol{a}, \beta &&),
\end{aligned}$$

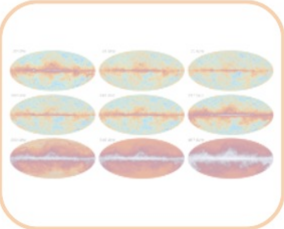
Gibbs sampling

[Galloway+ (2022)]

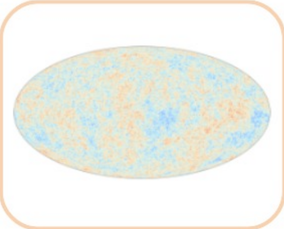
Component-separation from TODs



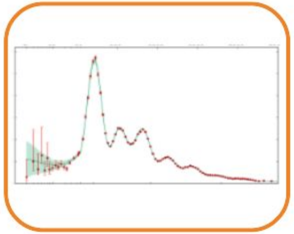
Raw data



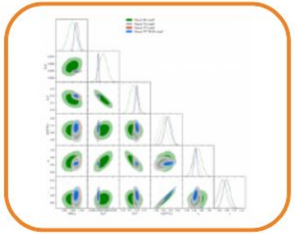
Multifrequency maps



Reconstructed CMB



Angular power spectra



Cosmological parameters

Integration of map-making, component separation and power spectrum estimation in a unified framework

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$$d_{j,t} = g_{j,t}\mathsf{P}_{tp,j}\left[\mathsf{B}^{\mathrm{symm}}_{pp',j}\sum_{c}\mathsf{M}_{cj}(\boxed{\beta_{p'}}, \Delta^{j}_{\mathrm{bp}})\boxed{a^{c}_{p'}} + \mathsf{B}^{\mathrm{asymm}}_{pp',j}\left(s^{\mathrm{orb}}_{j,t} + s^{\mathrm{fsl}}_{j,t}\right)\right] + n^{\mathrm{corr}}_{j,t} + n^{\mathrm{w}}_{j,t}.$$

common component-separation parameters

Extends a philosophy already adopted in latest Planck analyses (SRoll, NPIPE):

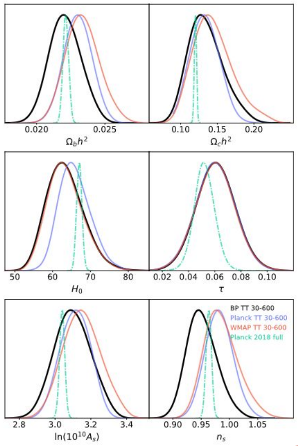
using astrophysical information to help calibrating data and mitigating systematics

[Galloway+ (2022)]

Component-separation from TODs

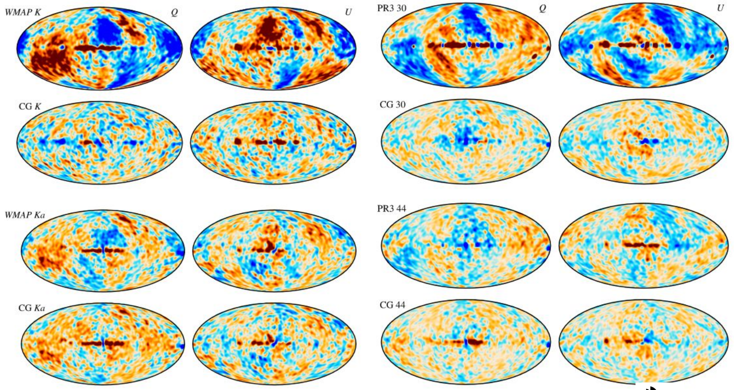
[📖 Paradiso+ (2022)]

End-to-end error propagation
(both in cosmological parameters and foreground modelling)



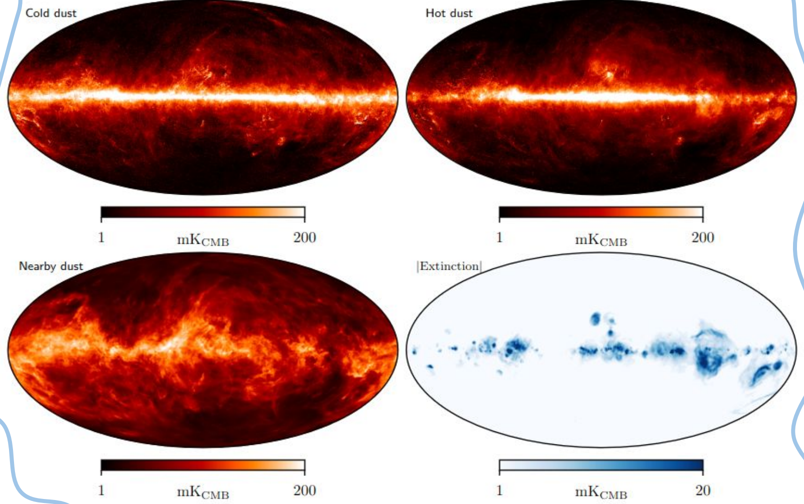
Caveat:
having a *complete* and *robust* model of <u>instrument and sky</u>

Robust **mitigation of systematic effects**
(actual component separation less impacted by instrument systematics)



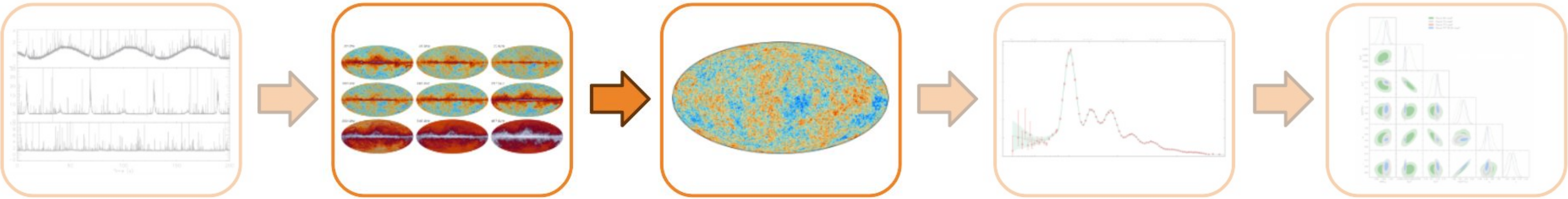
[📖 Watts+ (2022)]

Evidence for
multiple dust populations



[📖 Gjerløw+ (2022)]

Component-separation basis



Raw data → Multifrequency maps → Reconstructed CMB → Angular power spectra → Cosmological parameters

via standard **mapmaking** algorithms

Map-based approaches:

frequency maps

Mixing matrix

sky signals

$$\boxed{m_\nu(\hat{n})} = \mathrm{B} * \left(\sum_c \boxed{\mathrm{A}(\beta_c, \Delta_\nu)} \boxed{s_c(\hat{n})} \right) + n(\hat{n})$$

noise

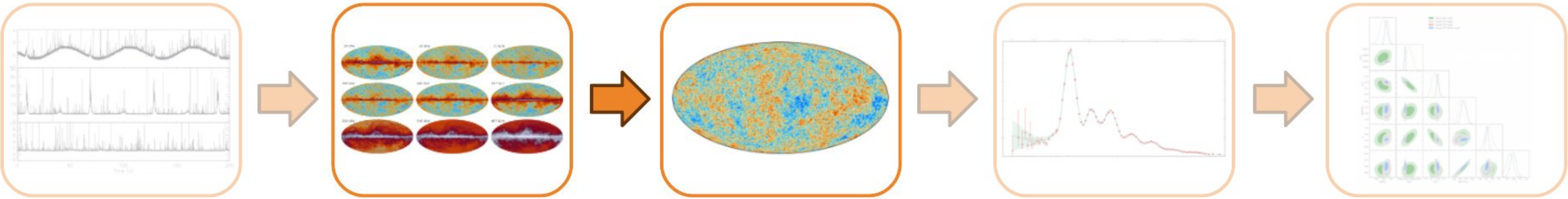
beam convolution

spectral parameters

bandpass

Algorithms differ in
how and how many components they recover

Component-separation basis



Raw data → Multifrequency maps → Reconstructed CMB → Angular power spectra → Cosmological parameters

via standard **mapmaking** algorithms

Map-based approaches:

frequency maps — Mixing matrix — sky signals — noise

$$\boxed{m_\nu(\hat{n})} = \mathrm{B} * \left(\sum_c \boxed{\mathrm{A}(\beta_c, \Delta_\nu)} \boxed{s_c(\hat{n})} \right) + \underbrace{n(\hat{n})}_{\text{noise}}$$

Parametric — create a model $\tilde{m}_\nu(\theta)$ and fit it to data

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_\nu \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

[Eriksen+ (2004), Stompor+ (2009), de la Hoz+ (2020)]

Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_{\nu} \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

$$\theta = \{\beta_c, s_c\}$$

Algorithm	Methodology
Commander (Eriksen+, 2024)	Gibbs sampling
FGBuster (Stompor+, 2009)	Spectral Likelihood
B-seCRET (de la Hoz+, 2020)	MCMC sampling

Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_\nu \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

$$\theta = \{\beta_c, s_c\}$$

extended:
include parameters for instrumental effects

$$\theta = \{\beta_c, s_c\} \cup \{B, \Delta_\nu\}$$

Fit can be affected by
instrument systematics

[Eriksen+ (2004),
Verges+ (2021),
de la Hoz+ (2020),
Jost+ (2023)]

Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_{\nu} \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

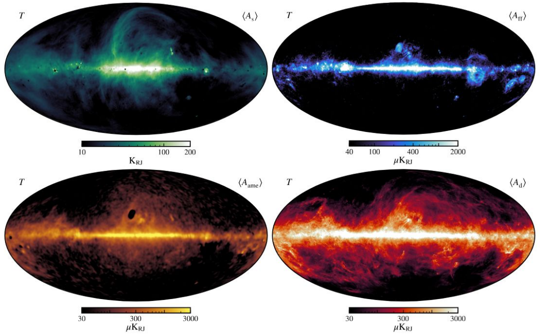
$$\theta = \{\beta_c, s_c\}$$

extended:
include parameters for instrumental effects

$$\theta = \{\beta_c, s_c\} \cup \{B, \Delta_\nu\}$$

Advantages:

- Easily absorb instrument calibration errors
- Provide estimation at the same time of all sky components



Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_{\nu} \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

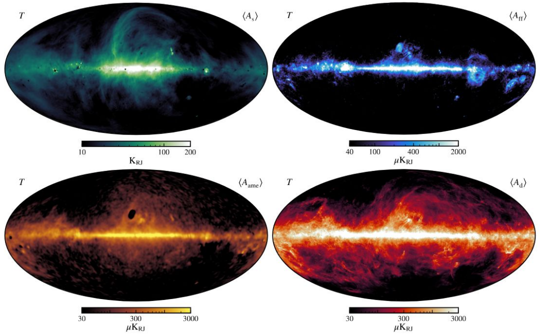
$$\theta = \{\beta_c, s_c\}$$

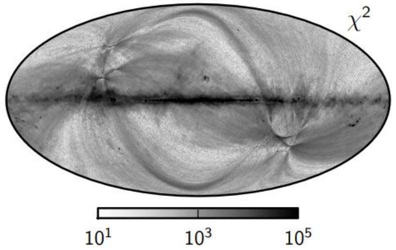
extended:
include parameters for instrumental effects

$$\theta = \{\beta_c, s_c\} \cup \{B, \Delta_\nu\}$$

Advantages:

- Easily absorb instrument calibration errors
- Provide estimation at the same time of all sky components
- Chi-square maps: first robustness test





Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_\nu \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

$$\theta = \{\beta_c, s_c\}$$

Assumptions:

- Emission model for each sky component

Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_\nu \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

$$\theta = \{\beta_c, s_c\}$$

Assumptions:

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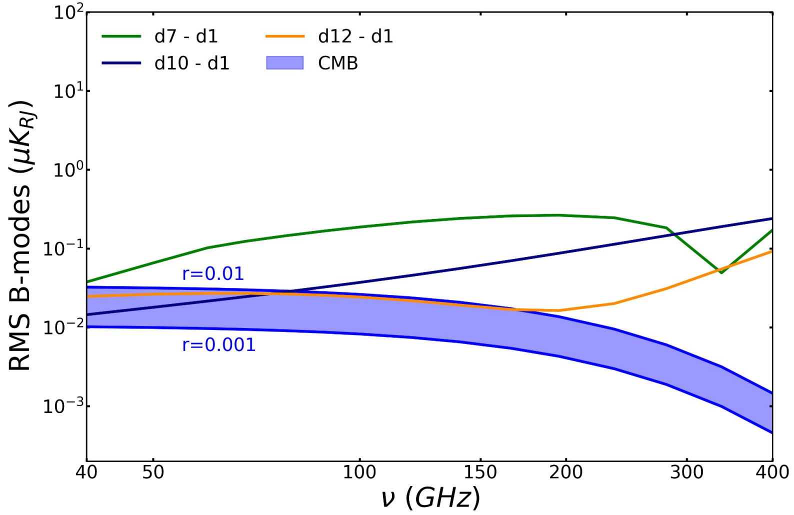


Susceptible to the assumptions underlying the sky model

Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_\nu \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

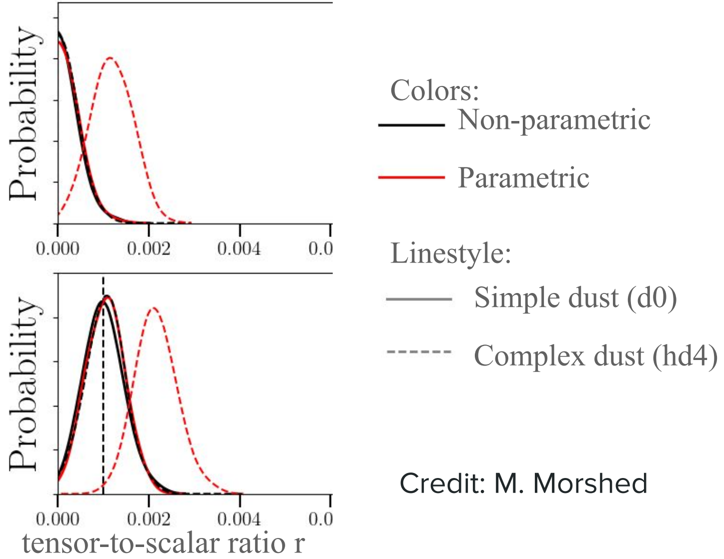
baseline:
just fit sky con nts

$\{ \quad s_c\}$

baseline+: MICMAC
Simplify model assumptions in the mixing matrix

$$\theta = \{A^f_{ik}, s_{\text{CMB}}\}$$

[Leloup+ (2023), Morshed+ (2024)]



Credit: M. Morshed

Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_\nu \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

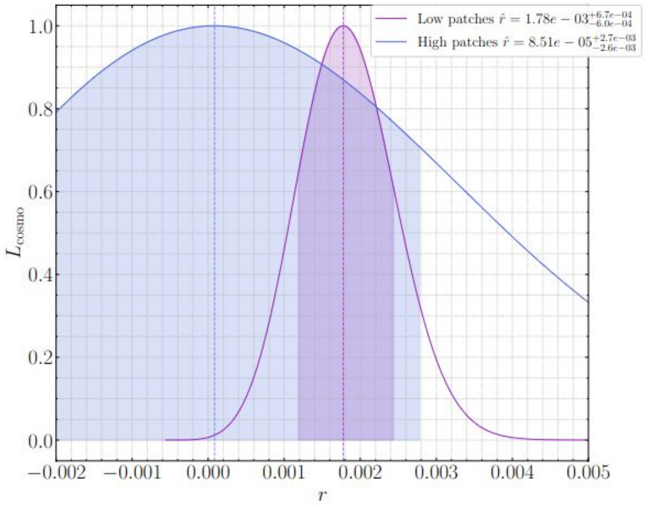
baseline:
just fit sky components

$$\theta = \{\beta_c, s_c\}$$

Limitations:

- Number of fitted spectral parameters coming from trade-off between residual bias and overall sensitivity

[Kabalan+ (2026)]



Parametric approach

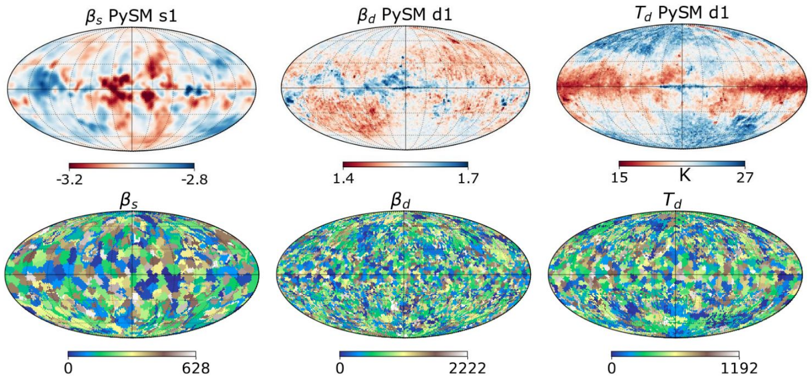
global chi-square minimization

$$\chi^2(\hat{n}) = \sum_{\nu} \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
just fit sky components

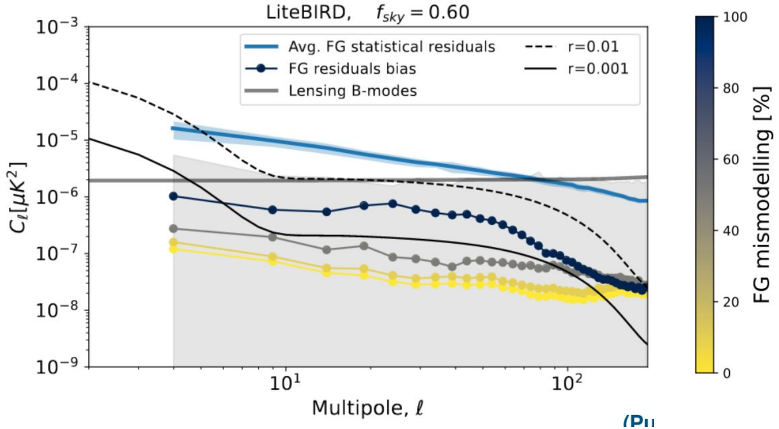
$$\theta = \{\beta_c, s_c\}$$

[Puglisi+ (2022)]



Limitations:

- Number of fitted spectral parameters coming from trade-off between residual bias and overall sensitivity



Parametric approach

global chi-square minimization

$$\chi^2(\hat{n}) = \sum_{\nu} \left(\frac{m_\nu(\hat{n}) - \tilde{m}_\nu(\hat{n})}{\sigma_\nu(\hat{n})} \right)^2$$

baseline:
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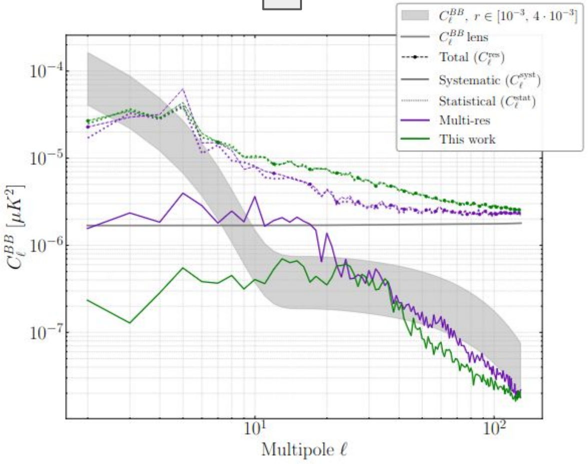

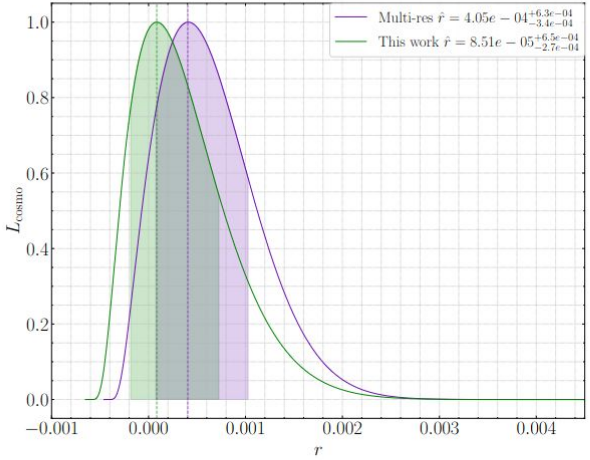

[Kabalan+ (2026)]

Parametric approach

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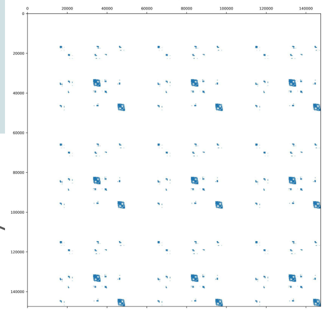
baseline:
just fit sky components

$$\theta = \{\beta_c, s_c\}$$

baseline++:
Including TOD filtering (ground-based experiments) into the data model

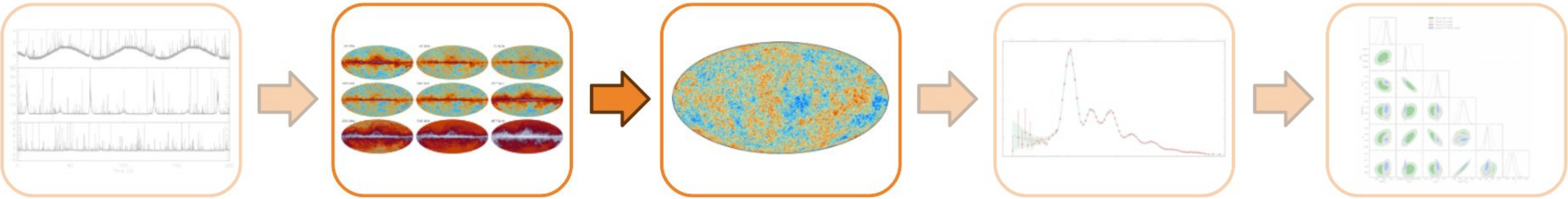
$$\mathbf{d} = \mathcal{O}\mathbf{A}\mathbf{s} + \mathbf{n}$$

[See Baptiste's talk]



Observation matrix $\mathcal{O}$ accounts for all (linear) effects of TODs filtering at the map level

Component-separation basis



Raw data → **Multifrequency maps** → **Reconstructed CMB** → Angular power spectra → Cosmological parameters

via standard **mapmaking** algorithms

Map-based approaches:

$$\underbrace{\boxed{m_\nu(\hat{n})}}_{\text{frequency maps}} = \mathrm{B} * \left(\sum_c \underbrace{\boxed{\mathrm{A}(\beta_c, \Delta_\nu)}}_{\text{Mixing matrix}} \underbrace{\boxed{s_c(\hat{n})}}_{\text{sky signals}} \right) + \underbrace{n(\hat{n})}_{\text{noise}}$$

Blind (ILC) combine your data and minime variance of contaminants: $\hat{s}_{\mathrm{ILC}}(\hat{n}) = \sum_\nu w_\nu(\hat{n}) m_\nu(\hat{n})$

global variance minimization

$$\mathrm{Var}(\hat{s}_{\mathrm{ILC}}) = \mathrm{Var}(s_{\mathrm{CMB}}) + w_\nu (F+N)_{\nu\nu'} w_{\nu'}$$

Blind (ILC) approach

global variance minimization

$$\mathrm{Var}(\hat{s}_{\mathrm{ILC}}) = \mathrm{Var}(s_{\mathrm{CMB}}) + w_\nu (F+N)_{\nu\nu'} w_{\nu'}$$

baseline:
applying the formalism in different sub-bases: pixel, harmonic, wavelets

for CMB reconstruction:

$$\sum_\nu w_\nu A_\nu^{\mathrm{CMB}} = 1$$

$$\min_w \mathrm{Var}\left[\sum_\nu w_\nu d_\nu\right]$$

$$\mathbf{w} = \left[\mathbf{A}_{\mathrm{CMB}}^T \mathbf{C}^{-1} \mathbf{A}_{\mathrm{CMB}}\right]^{-1} \mathbf{A}_{\mathrm{CMB}}^T \mathbf{C}^{-1}$$

data covariance

Assumptions:

- Components are statistically independent
- The SED of the component to be reconstructed must be known

Advantages:

- Simple implementation
- No affected by sky mismodelling

Blind (ILC) approach

global variance minimization

$$\mathrm{Var}(\hat{s}_{\mathrm{ILC}}) = \mathrm{Var}(s_{\mathrm{CMB}}) + w_\nu (F+N)_{\nu\nu'} w_{\nu'}$$

[📖 Remazeilles+ (2011), Planck Collab. (2016)]

Generalized ILC:
Use statistical and spatial information to blindly deproject components with known statistical and SED properties (CMB, noise, CIB) and reconstruct components with unknown SEDs

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[Remazeilles+ (2011), Planck Collab. (2

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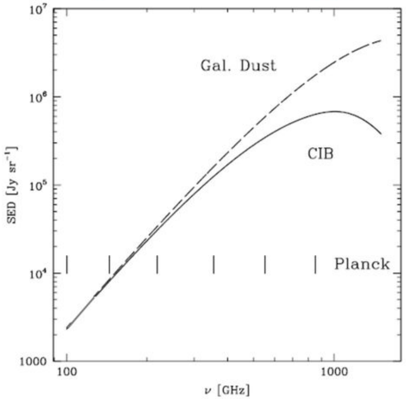
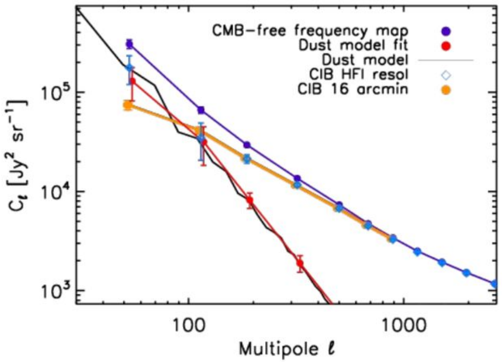
Thermal dust and CIB have similar spectral signatures (modified blackbody)



Thermal dust and CIB have different angular power spectrum



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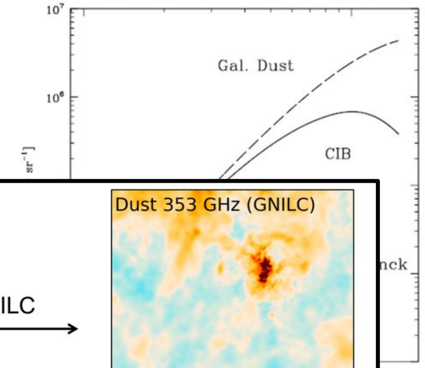

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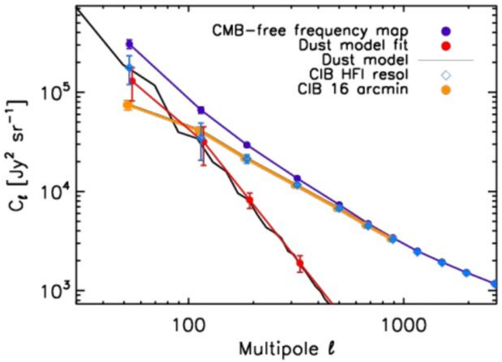

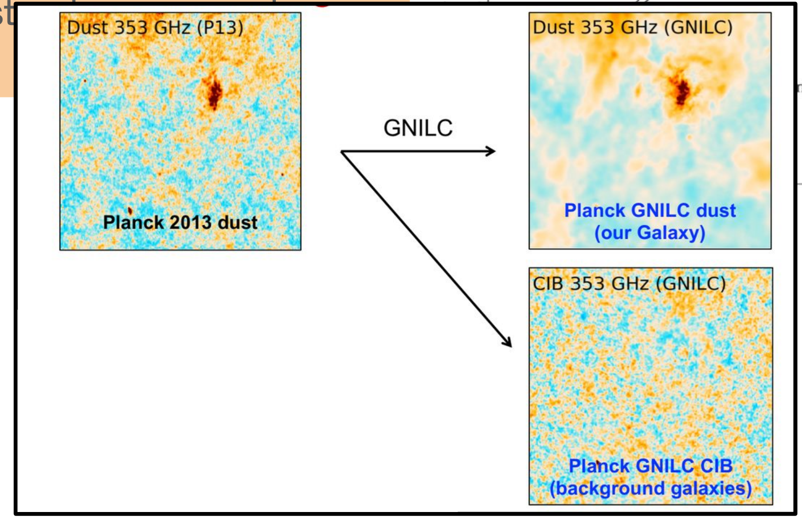

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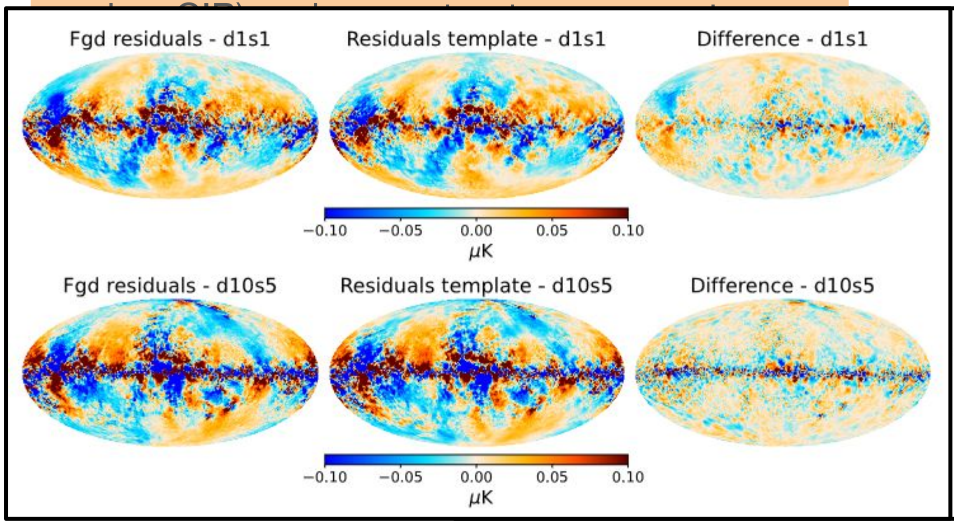

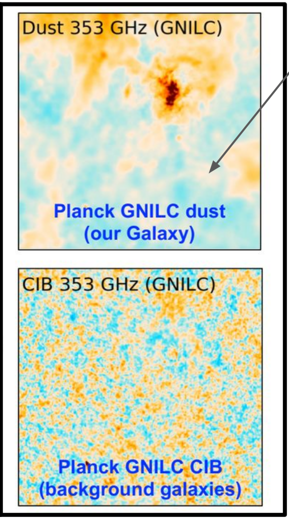

CMB and noise
are also deprojected

GILC denoising can be used to predict spatial distribution of foreground residuals after component separation

[Carones (2025)]

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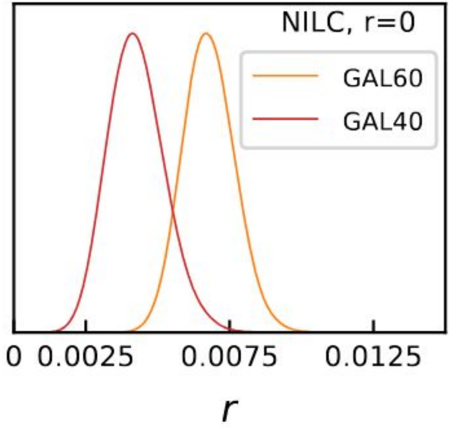
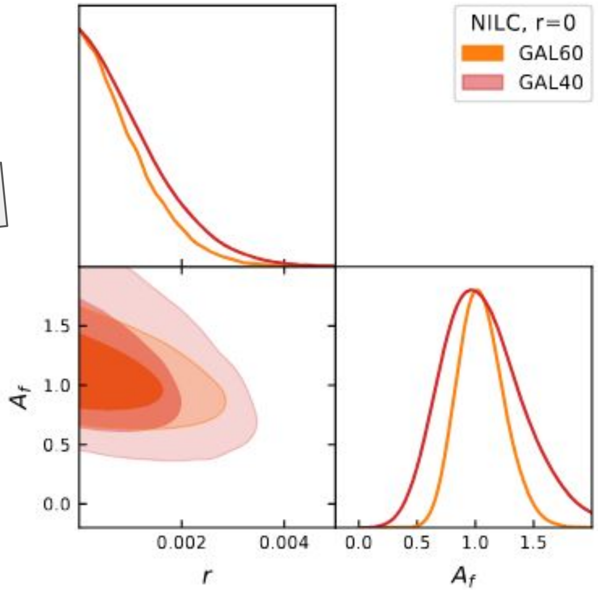


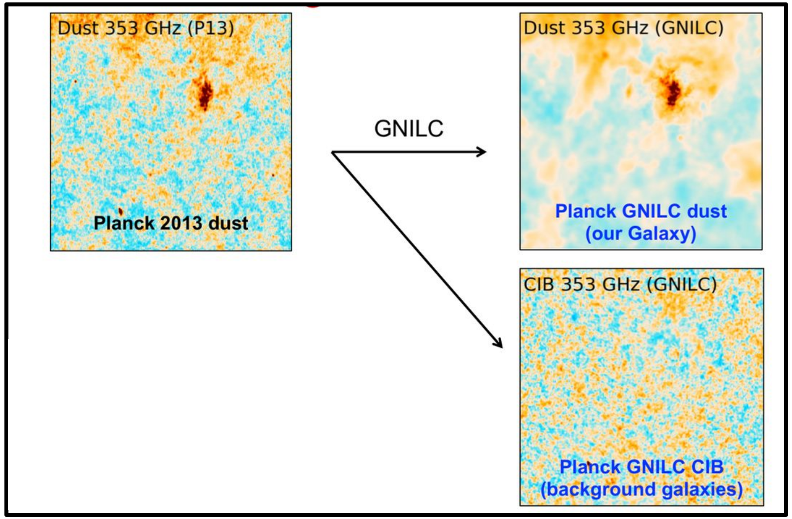


GILC denoising can be used to predict spatial distribution of foreground residuals after component separation

[Carones (2025)]

Statistical deprojection

[📚 Tsouros+ (2026)]



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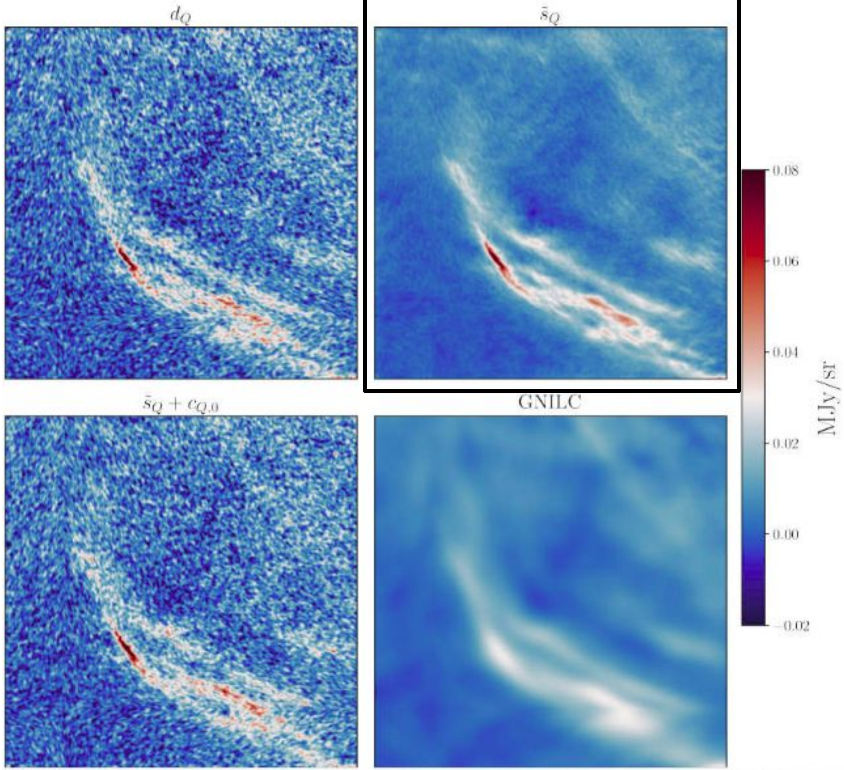

$$S_1(\lambda_1) \equiv \langle |x \star \psi^{\lambda_1}| \rangle$$

$$S_2(\lambda_1) \equiv \langle |x \star \psi^{\lambda_1}|^2 \rangle$$

$$S_3(\lambda_1, \lambda_2) \equiv \frac{\mathrm{Cov}[x \star \psi^{\lambda_2}, |x \star \psi^{\lambda_1}| \star \psi^{\lambda_2}]}{\sqrt{\langle |x \star \psi^{\lambda_1}|^2 \rangle} \sqrt{\langle |x \star \psi^{\lambda_2}|^2 \rangle}}$$

$$S_4(\lambda_1, \lambda_2, \lambda_3) \equiv \frac{\mathrm{Cov}[|x \star \psi^{\lambda_1}| \star \psi^{\lambda_3}, |x \star \psi^{\lambda_2}| \star \psi^{\lambda_3}]}{\sqrt{\langle |x \star \psi^{\lambda_1}|^2 \rangle} \sqrt{\langle |x \star \psi^{\lambda_2}|^2 \rangle}}$$

Enhanced reconstruction of foregrounds signal exploiting higher-order statistical information (no assumption on foreground properties again) by means of WST

Blind (ILC) approach

global variance minimization

$$\mathrm{Var}(\hat{s}_{\mathrm{ILC}}) = \mathrm{Var}(s_{\mathrm{CMB}}) + w_\nu (F+N)_{\nu\nu'} w_{\nu'}$$

baseline:
applying the formalism in different sub-bases: pixel, harmonic, wavelets

for CMB reconstruction:

$$\sum_\nu w_\nu A_\nu^{\mathrm{CMB}} = 1$$

$$\min_w \mathrm{Var}\left[\sum_\nu w_\nu d_\nu\right]$$

$$\mathbf{w} = \left[\mathbf{A}_{\mathrm{CMB}}^T \mathbf{C}^{-1} \mathbf{A}_{\mathrm{CMB}}\right]^{-1} \mathbf{A}_{\mathrm{CMB}}^T \mathbf{C}^{-1}$$

Limitations:

- Complex spatial variations may limit effectiveness of these methods
- Just one component can be reconstructed each time and no control on removal of components
- If impacted by systematics, it is not trivial to implement mitigation strategies at the component-separation level

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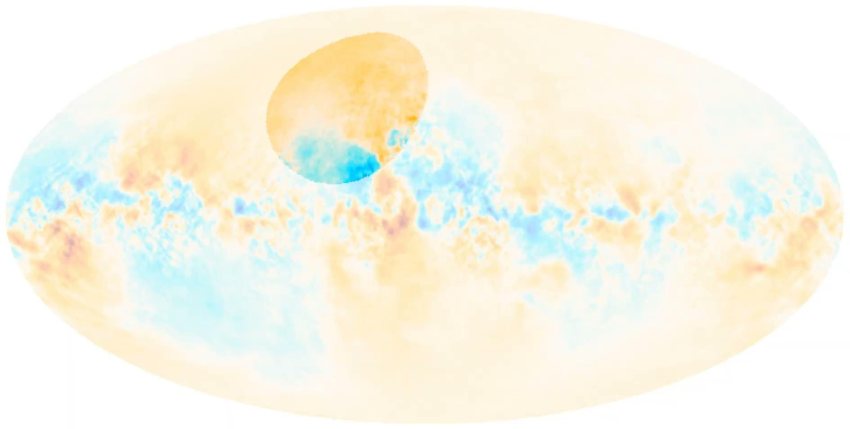

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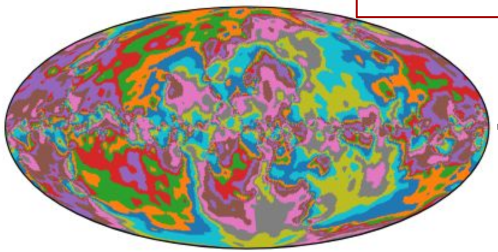
New approach for covariance computation.
It adapts to foreground properties

[📖 Carones+ (2023)]

Blind spectral foreground tracer



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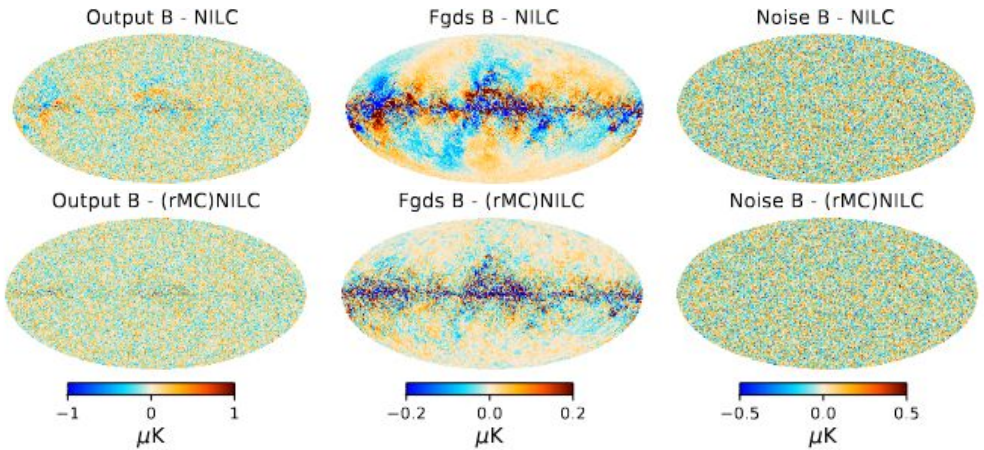
significant reduction of residuals at large scales



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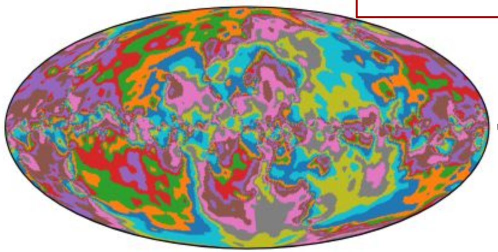

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$$\mathrm{Var}(\hat{s}_{\mathrm{ILC}}) = \mathrm{Var}(s_{\mathrm{CMB}}) + w_\nu (F+N)_{\nu\nu'} w_{\nu'}$$

[Remazeilles+ (2011)]

constrained ILC:
constrain ILC weights to deproject undesired components or keep more than one sky component (all with known SEDs)

$$\mathbf{w}_{\mathrm{cILC}} = e^T \left[A^T C^{-1} A\right]^{-1} A^T C^{-1}$$

deprojection coefficients

SEDs of all components of interest

full deprojection:

$$e = (1\ 0\ 0\ .\ .)$$

full reconstruction:

$$e = (1\ 1\ 1\ .\ .)$$

Limitations:

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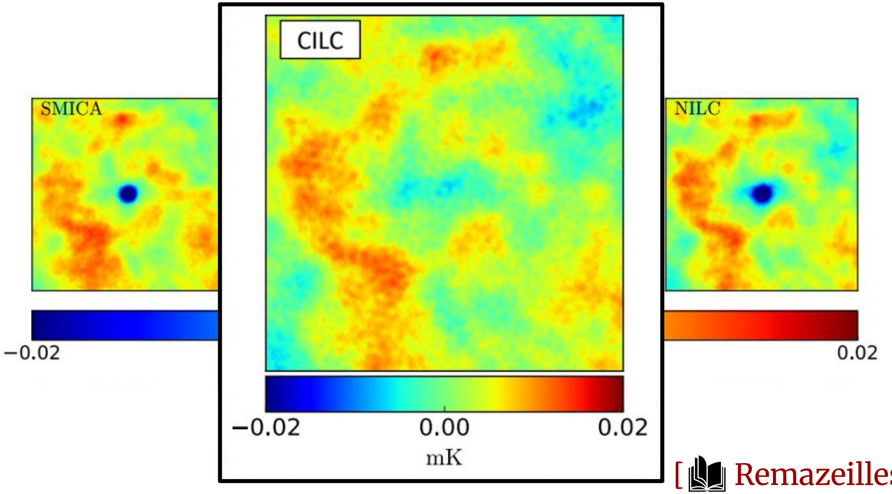
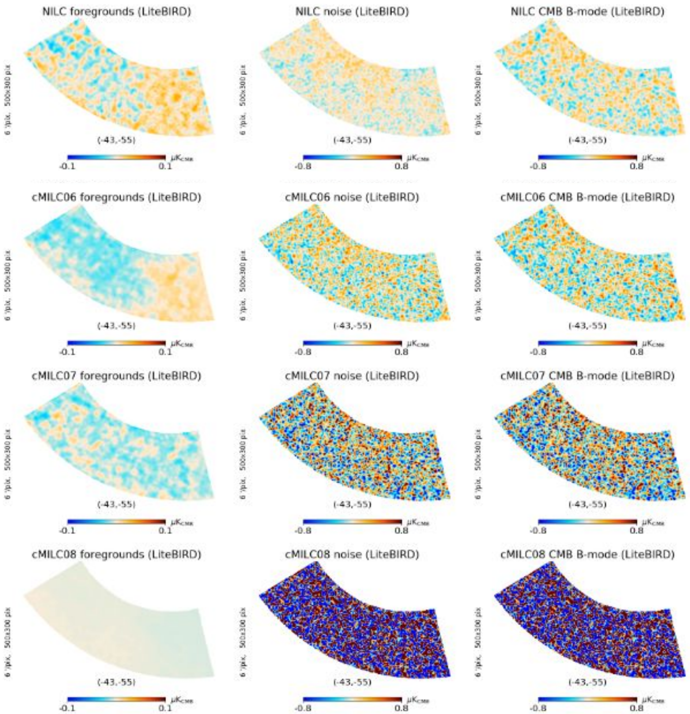
TSZ deprojection



[📖 Remazeilles+ (2011)]

trade-off between
residual bias and variance



[📖 Remazeilles+ (2021)]

deprojection of foreground moments

Blind (ILC) approach

constrained ILC:

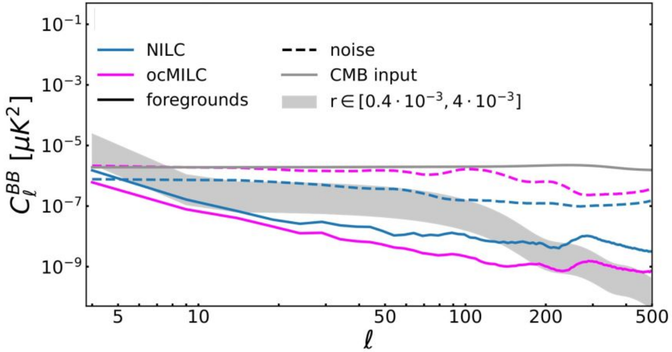
$$\mathbf{w}_{\mathrm{cILC}} = e^T \left[A^T C^{-1} A\right]^{-1} A^T C^{-1}$$

optimizing deprojection

Full optimisation of:

- number of moments to deproject
- set of moments to deproject
- values of dust pivot spectral indices
- deprojection coefficients:

$$\begin{cases} \omega^j \cdot A^{\mathrm{CMB}} = 1 \\ \omega^j \cdot f_1 = \epsilon_1 \\ \omega^j \cdot f_2 = \epsilon_2 \\ . \\ \omega^j \cdot f_{m_{\mathrm{fgds}}} = \epsilon_{m_{\mathrm{fgds}}} \end{cases}$$



[Carones+ (2024)]

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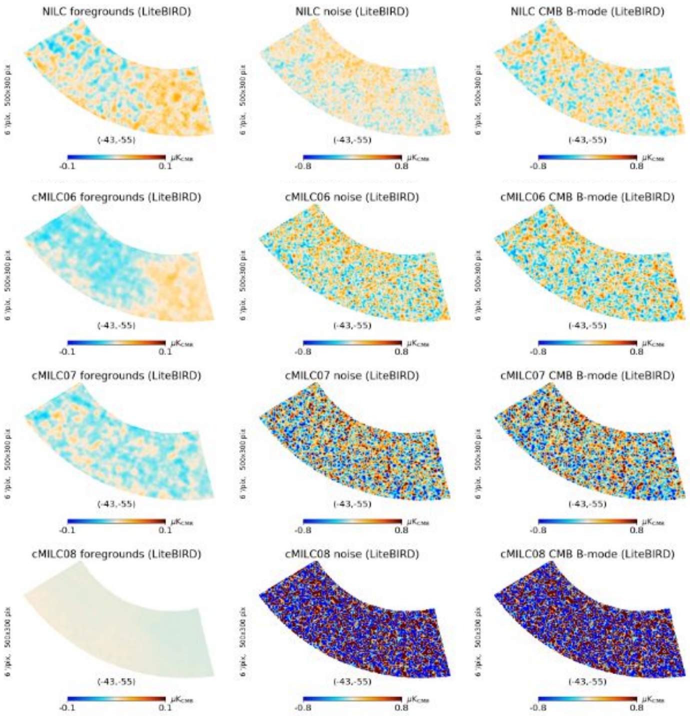

deprojection of
foreground moments

Collection of ILC approaches

https://github.com/alecarones/broom

BROOM: Blind Reconstruction Of Observables in the Microwaves

BROOM is a Python package for blind component separation and Cosmic Microwave Background (CMB) data analysis.

📦 Installation

You can install the base package using:

```
pip install cmbroom
```

Realistic simulations of any CMB experiment

Angular power spectrum computation

[📖 Carones+ (2026)]

Component separation
reconstruction of signals with :

- known SEDs (ILCs)
- unknowns SEDs (GILCs)

CMB Foregrounds.....

- diagnostic
- residuals reconstruction

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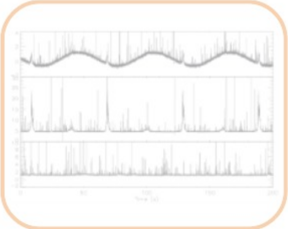
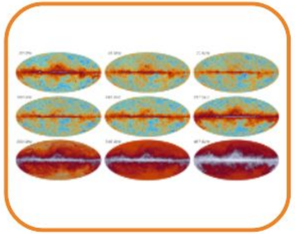
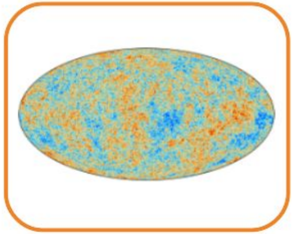
Component-separation basis



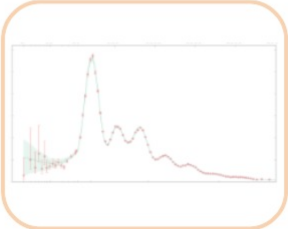
Raw data



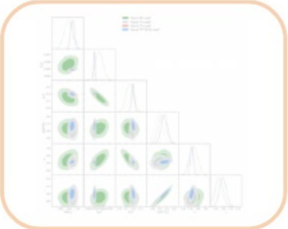
Multifrequency maps



Reconstructed CMB



Angular power spectra



Cosmological parameters

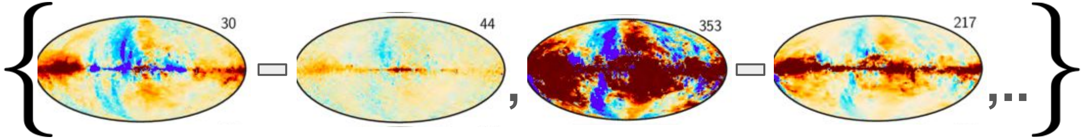
via standard **mapmaking** algorithms

Map-based approaches:

Blind (template-fitting)

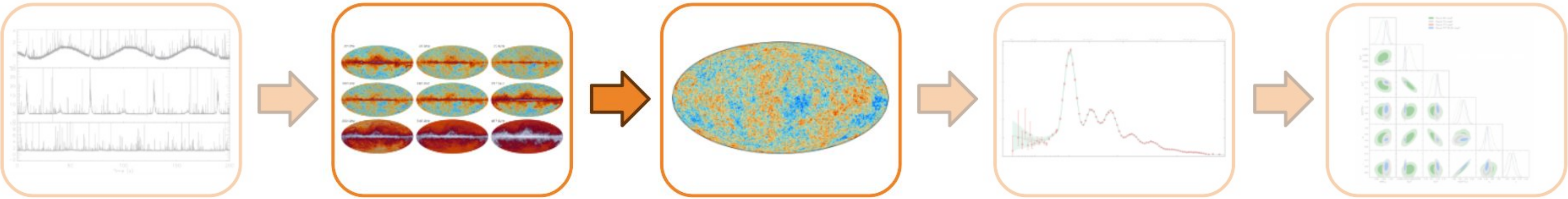
global variance minimization

Foreground templates:



$$\tilde{s}_\nu^{\mathrm{ITF}}(\hat{n}) = m_\nu(\hat{n}) - \sum_i \alpha_\nu^i(\hat{n}) t_i(\hat{n}) \quad \Longleftarrow \quad \underset{\alpha}{\mathrm{argmin}} \left\langle \left(\tilde{s}_\nu^{\mathrm{ITF}}\right)^2 \right\rangle$$

Component-separation basis



Raw data → Multifrequency maps → Reconstructed CMB → Angular power spectra → Cosmological parameters

via standard **mapmaking** algorithms

Map-based approaches:

Blind (template-fitting)

global variance minimization

Advantages:

- Robust against spectral mismodelling
- Provide CMB maps at multiple frequencies!!!!!

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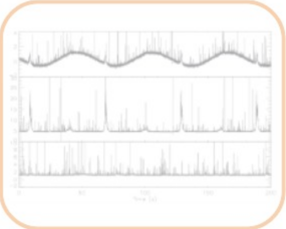
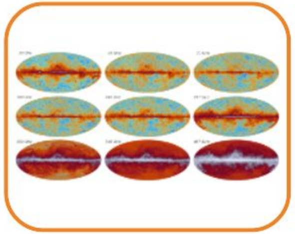
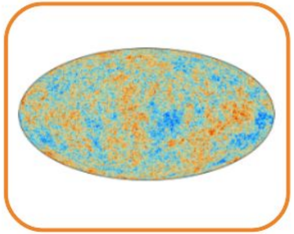
Component-separation basis



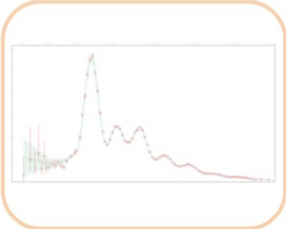
Raw data



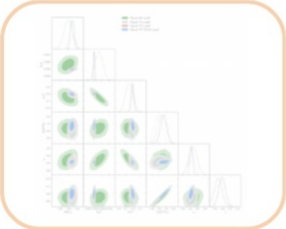
Multifrequency maps



Reconstructed CMB



Angular power spectra



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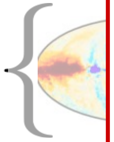

Limitations:

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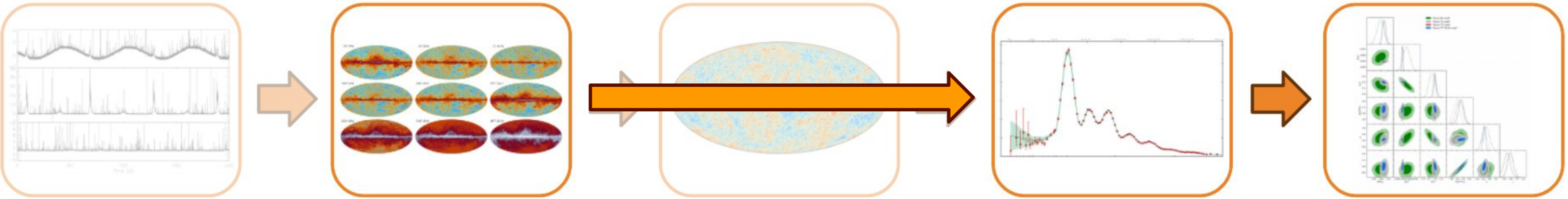
Component-separation basis



Raw data

Multifrequency maps

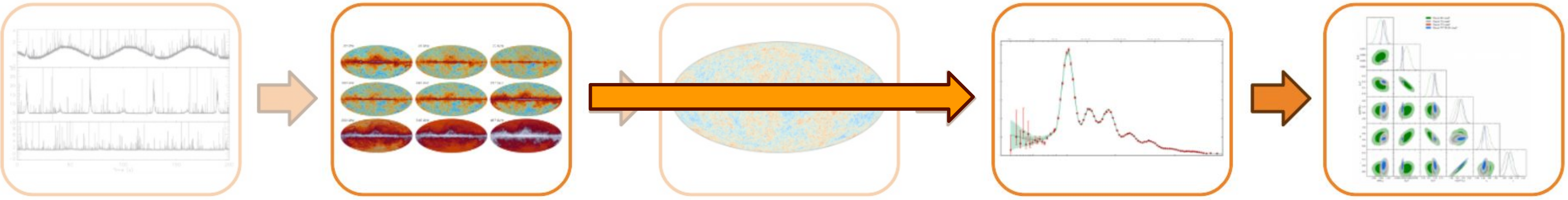
Reconstructed CMB

Angular power spectra

Cosmological parameters

Cℓ-based approaches

Component-separation basis

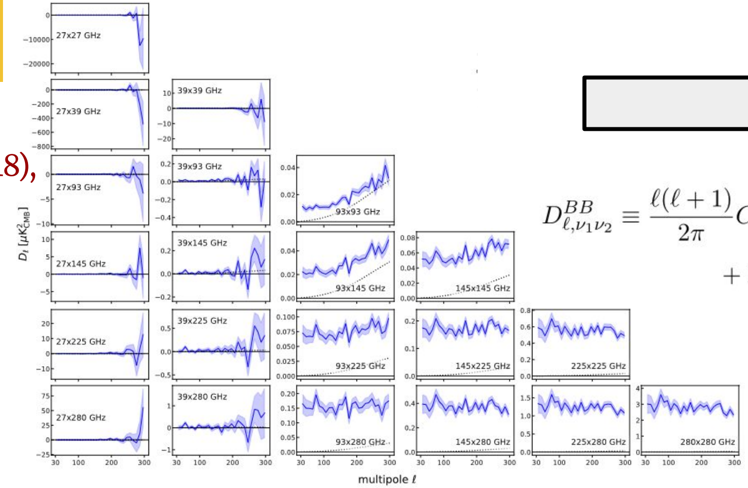


Raw data → Multifrequency maps → Reconstructed CMB → Angular power spectra → Cosmological parameters

Cℓ-based approaches

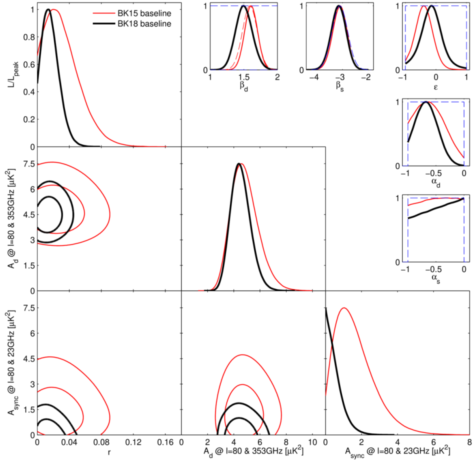
Parametric

[BK Collab. (2016, 2018), Abitbol+ (2021), Azzoni+ (2021), Vacher+ (2022), Vinzl+ (in prep.)]

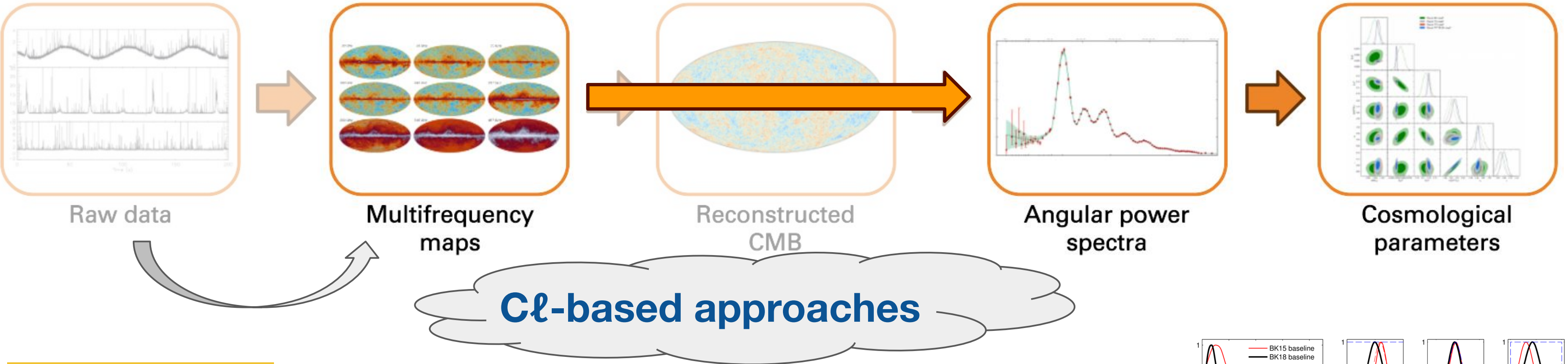


model

$$D^{BB}_{\ell,\nu_1\nu_2} \equiv \frac{\ell(\ell+1)}{2\pi} C^{BB}_{\ell,\nu_1\nu_2} = r \cdot D^{BB}_{\ell,\mathrm{prim}} + D^{BB}_{\ell,\mathrm{lens}} + \ldots$$
$$+ D^{\mathrm{dust}}_{\ell,\nu_1\nu_2} + D^{\mathrm{sync}}_{\ell,\nu_1\nu_2} + D^{\mathrm{dust}\times\mathrm{sync}}_{\ell,\nu_1\nu_2}$$

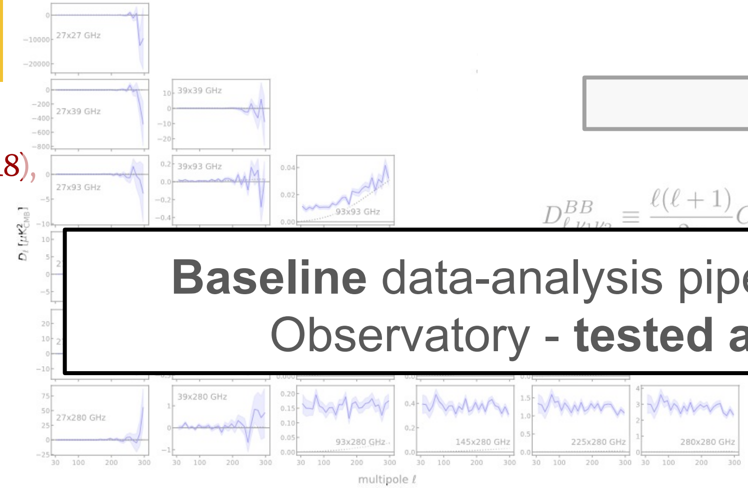


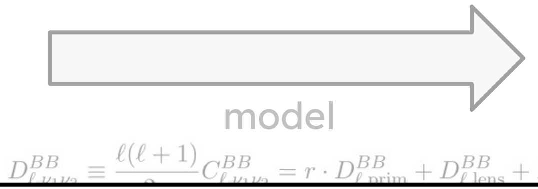
Component-separation basis

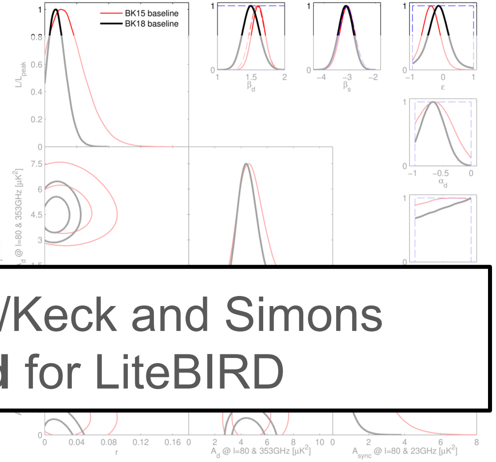


Parametric

[BK Collab. (2016, 2018), Abitbol+ (2021), Azzoni+ (2021), Vacher+ (2022), Vinzl+ (in prep.)]

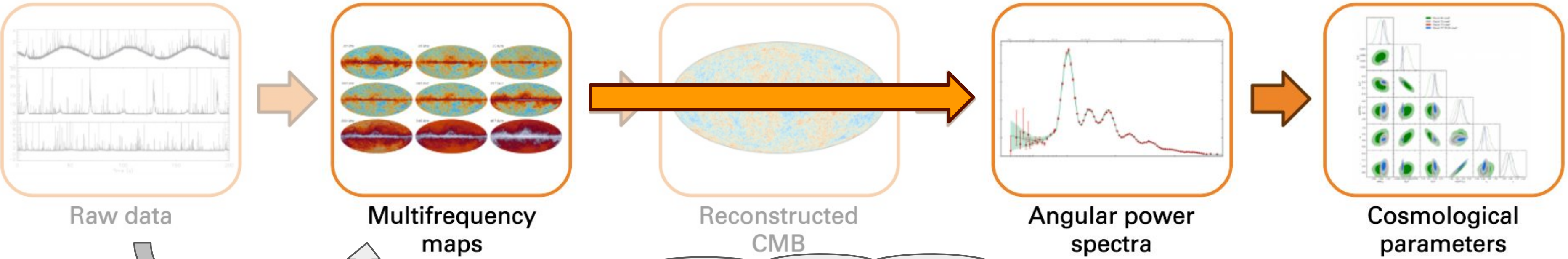






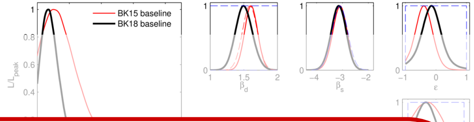
Baseline data-analysis pipeline for BICEP/Keck and Simons Observatory - **tested and augmented** for LiteBIRD

Component-separation basis



Cℓ-based approaches

Parametric



Advantages:

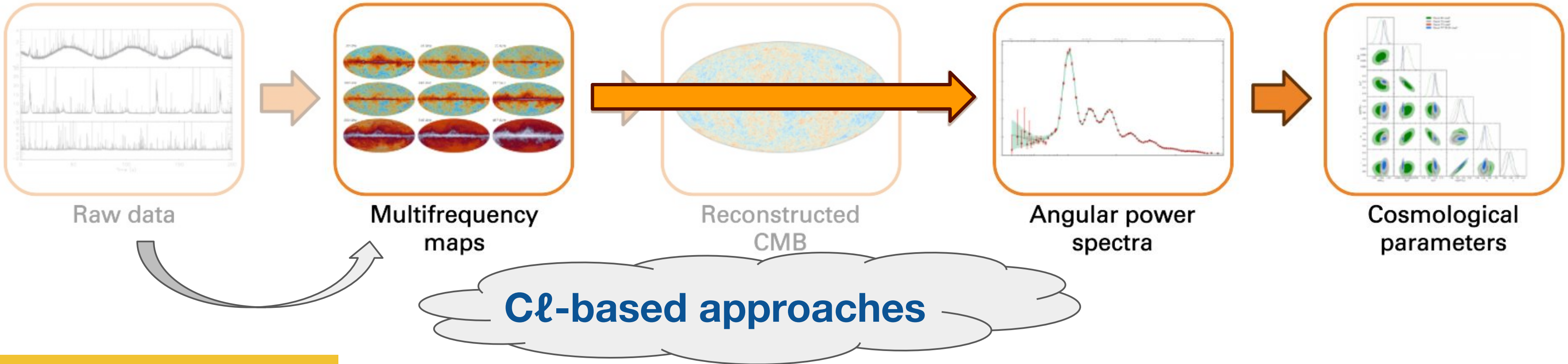
- Simpler implementation than map-based
- Simpler foreground modeling and handling
- Simpler correction for TOD filtering and systematics

- discard spatial (directional) information

Limitations:

- No cleaned CMB maps:
  - no map-based robustness tests
  - no statistical inference

SMICA



Non-parametric

[📖 Delabrouille+ (2003), Cardoso+ (2008), Tran+ (in prep)]

Spectral **M**atching **I**ndependent **C**omponent **A**nalysis (SMICA)

Multi-frequency spectra: [See Viet's talk]

$$\mathbf{R}(\ell) = \mathbf{A}_{\mathrm{CMB}}\mathbf{A}^{\dagger}_{\mathrm{CMB}}\mathrm{C}(\ell) + \mathbf{F}\mathbf{P}_{\mathrm{s}}(\ell)\mathbf{F}^{\dagger} + \mathbf{R}_{\mathrm{n}}(\ell)$$

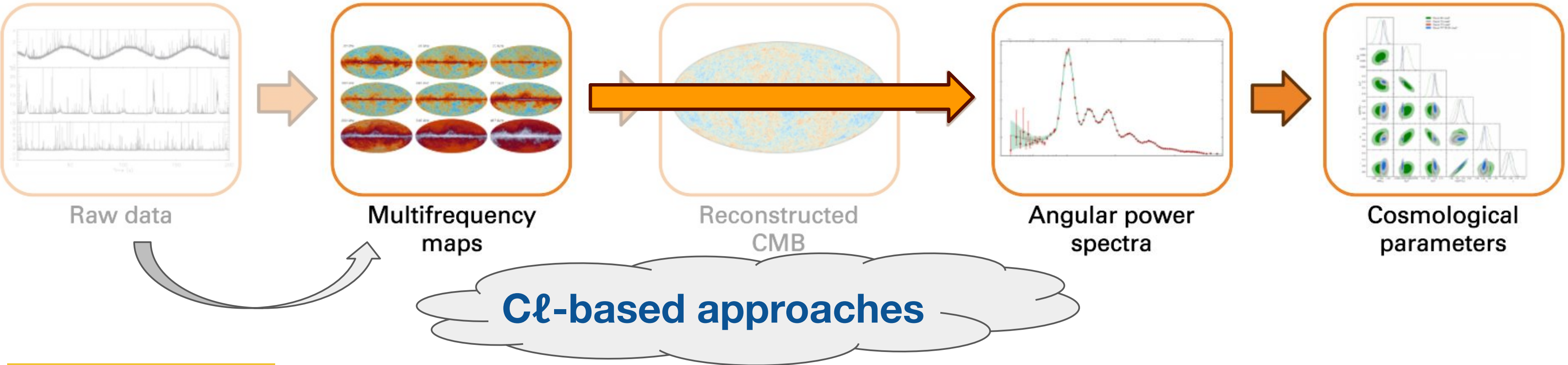
Free parameters

$$\theta = (\mathrm{C}(\ell), \mathbf{F}, \mathbf{P}(\ell), \mathrm{diag}(\mathbf{R}_{\mathrm{n}}(\ell)))$$

found by minimizing:

$$\phi(\theta) = \sum_{\ell} \frac{2\ell+1}{2}\left[\mathrm{Tr}(\hat{R}\mathbf{R}^{-1}(\theta)) - \log\det(\hat{R}\mathbf{R}^{-1}(\theta)) - n\right]$$

SMICA



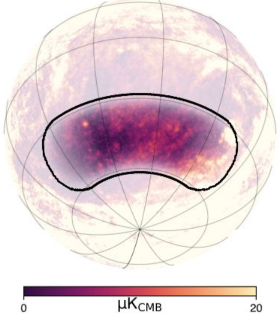
Blind

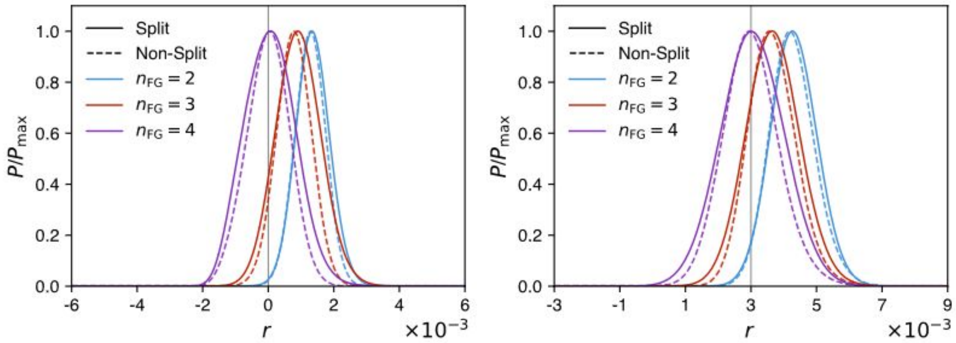
[Steier+ (2025)]

Spectral **M**atching **I**ndependent **C**omponent **A**nalysis (SMICA)

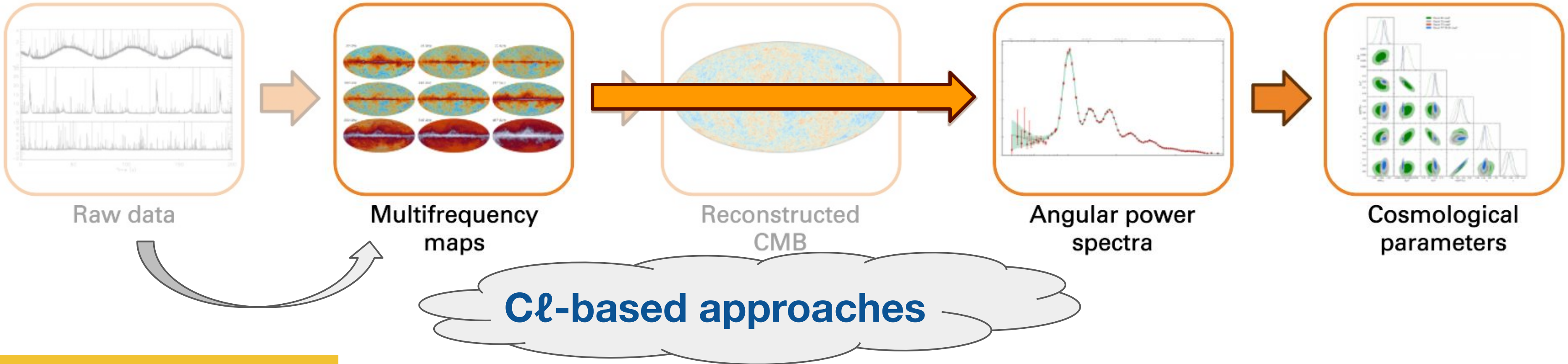
"medium complexity"

CMB-S4-like





SMICA



Non-parametric

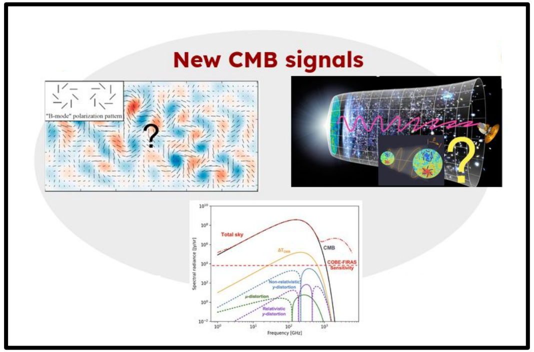
Spectral **M**atching **I**ndependent **C**omponent **A**nalysis (SMICA)

Advantages:

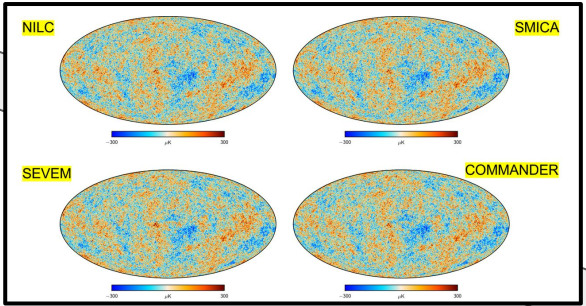
- Robust against sky components mismodelling
- Corrections against TOD filtering and instrumental systematics is easy

- discard spatial (directional) information

Summary



compelling scientific targets ahead of us



Inheriting huge methodological developments from past experiments

1. Being able to deal with foreground:
   a. projected spatial complexity
   b. spectral complexity
2. Absorb instrumental modelling/mitigate calibration systematics
3. Develop robustness tests - diagnostic of goodness of component separation
4. Reach the targeted sensitivity for scientific observables