

# Model-based component separation exploiting sparsity

Mel Irfan  
CosmoStat Lab, CEA

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## Overview

Brief introduction to the CMB component separation

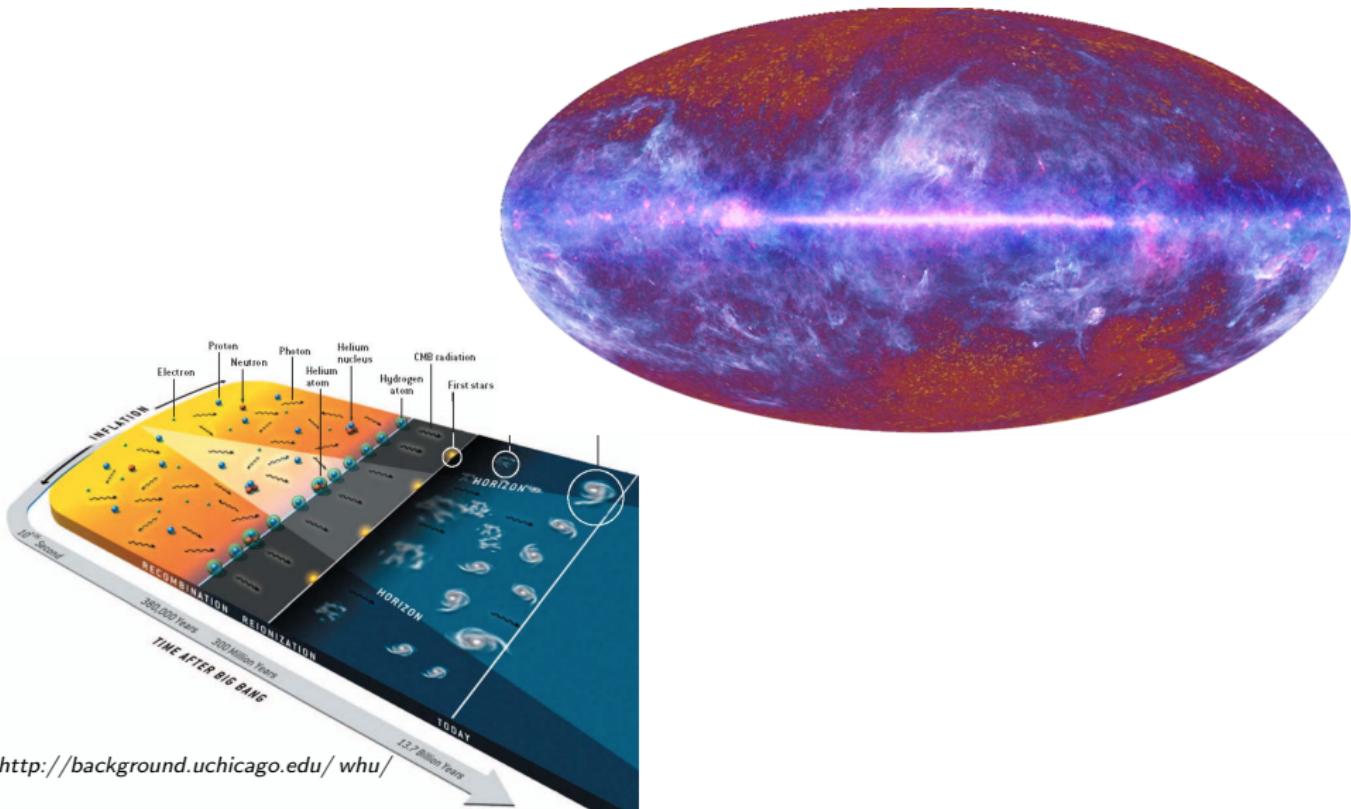
How sparsity can help

The problem at hand: thermal dust and the CIB

The new methodology

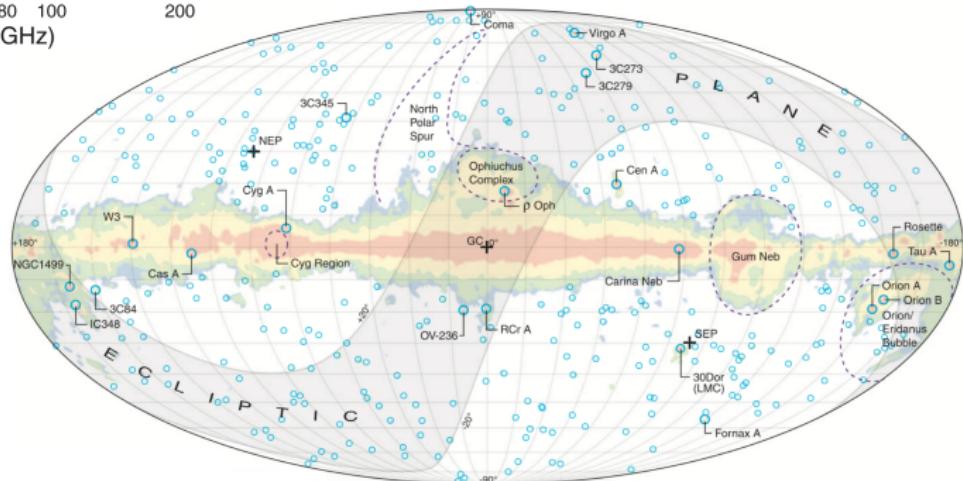
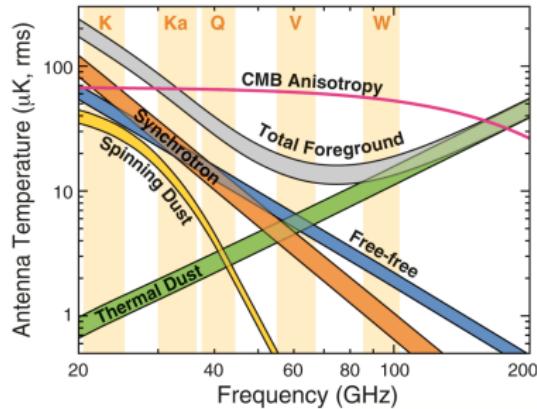
Validation on Planck simulation data

# CMB component separation



<http://background.uchicago.edu/whu/>

# CMB component separation

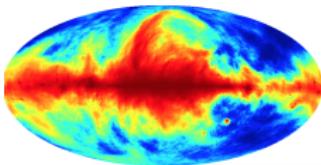


Bennett et al. 2013

# CMB component separation

Commander

Pixel space, parametric, priors



*Haslam 1982*

ILC (internal linear combination)

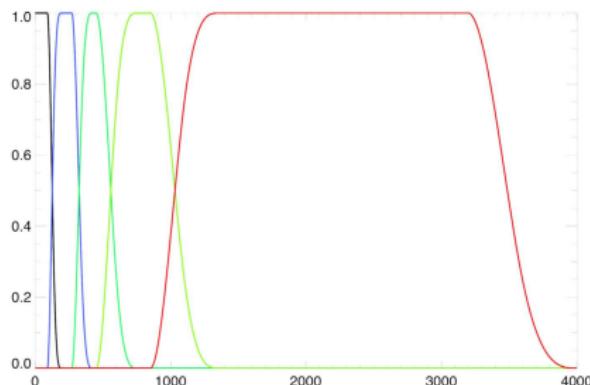
wavelet space, non-parametric, noise information - more to come

Sevem and SMICA

Recovery of just the CMB, no external data sets needed.

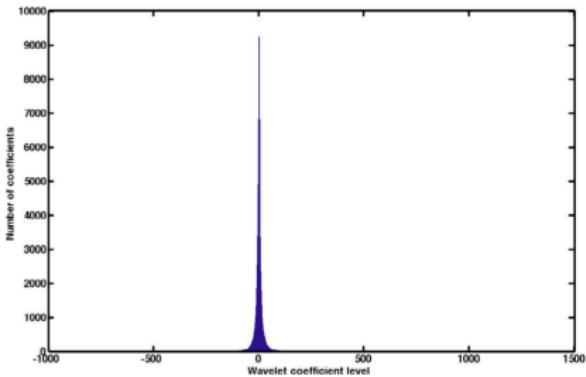
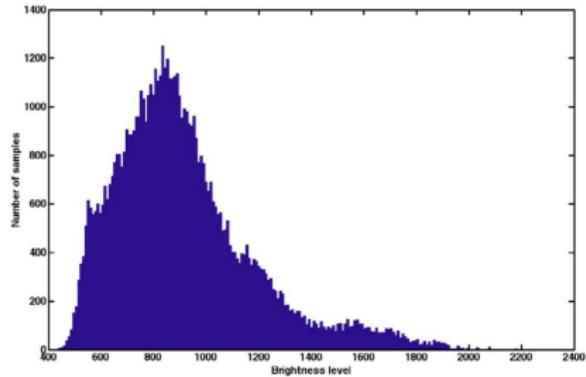
Goals for this work: provide foreground estimates as well as CMB  
full sky, full resolution data  
exploit sparsity in wavelet domain

# Sparsity and the wavelet domain



*Bobin et al. 2013*

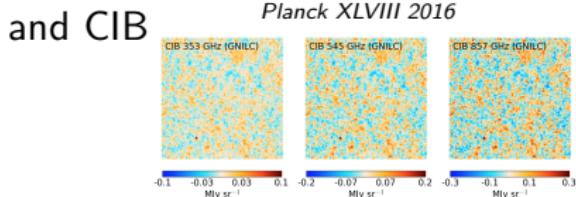
- Sparse: majority of signal is zero
- Spatially correlated source
- Wavelets filter in spherical harmonic domain (x-axis:  $\ell$ )



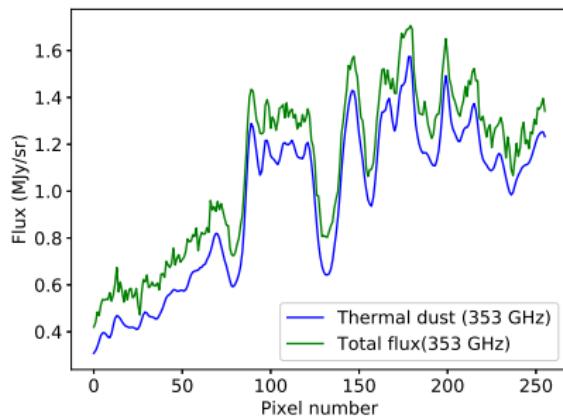
# Thermal dust and the CIB

- Planck HFI: 217, 353, 545, 857 GHz
- Thermal dust

$$x_{\nu_i}^{\text{dust}} = \tau_{353} \times B(T, \nu) \times \left(\frac{\nu}{353 \text{ GHz}}\right)^{\beta}$$

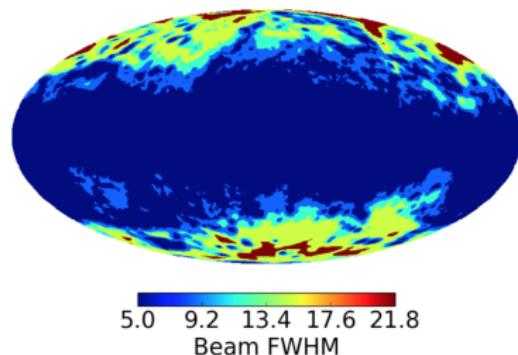


- Both BB, CIB flatter power spectrum
- Smoothing conundrum!



$$\text{total flux} = \text{dust} + \underbrace{\text{CIB} + \text{CMB} + \text{noise}}_{\text{nuisance, Gaussian approx}}$$

- Clever smoothing using nuisance estimates.



At each wavelet scale:

whitening  $\mathbf{R}_{\text{nus}}^{-1/2} \mathbf{R}_{\text{tot}} \mathbf{R}_{\text{nus}}^{-1/2}$

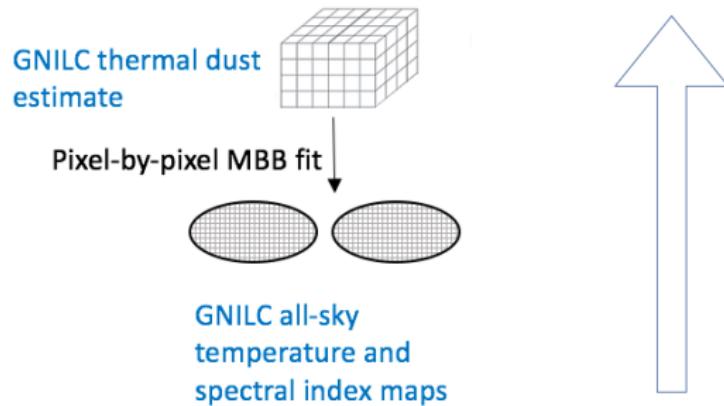
$\mathbf{v} \sim 1 \Rightarrow$  noise dominated  $\rightarrow$  smooth

$\mathbf{v} \gg 1 \Rightarrow$  signal dominated

$\min ||\mathbf{X} - \mathbf{AS}||^2$  for thermal dust map

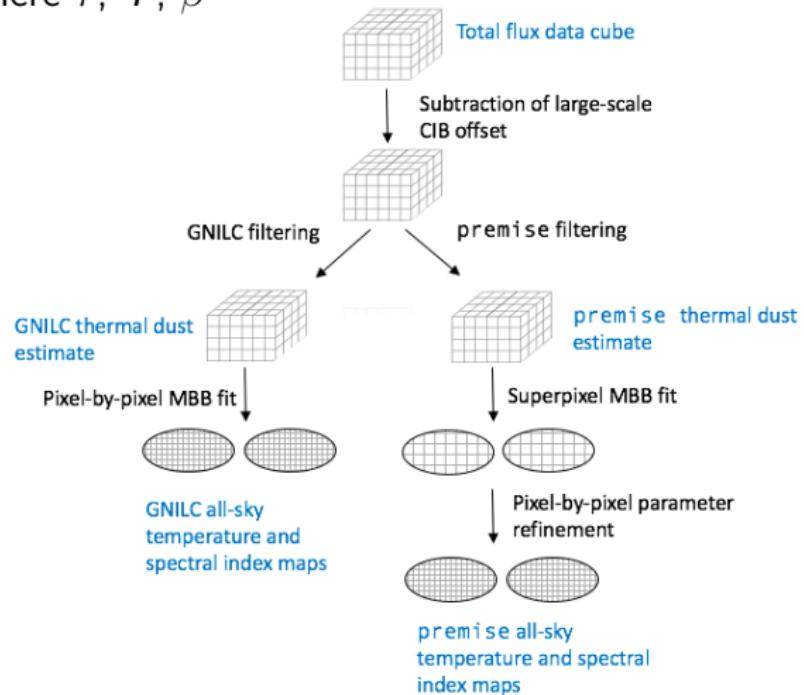
# Objectives

- Don't want to smooth
- To remove sub-dominant CIB
- Don't want to complete a per pixel fit
- Parametric fit - not just dust



# PREMISE

- Parameter Recovery Exploiting Model Informed Sparse Estimates
- Requires model - here  $\tau$ ,  $T$ ,  $\beta$



# Filtering and Super-pixels

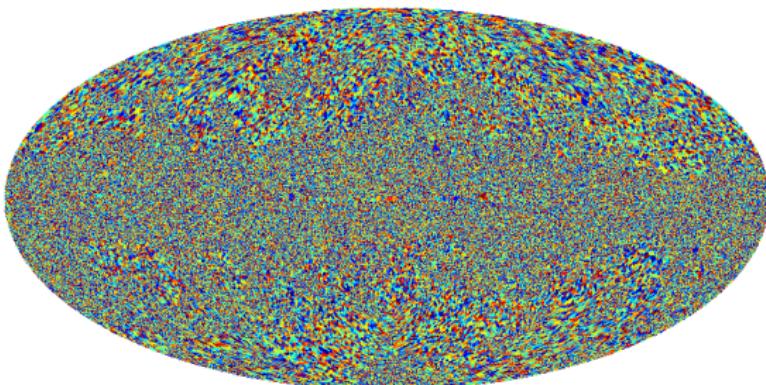
- Use GNILC filtering BUT  
Marcenko-Pastur distribution  
Penalise in favour of sparsity

$$\min ( ||X - A\alpha\Phi||^2 + \lambda ||\alpha||_1^1 )$$

- Accurate and fast parameter estimates from fit -  $\tau$ ,  $T$ ,  $\beta$



$\chi^2_{red}$  in wavelet domain!



## Refinement

- Low resolution informed initial guesses (64 times faster than pix-by-pix)
- $T$  and  $\beta$  refinement - normalisation factor subject to degeneracies

$$x_{\nu_i}^{\text{dust}} = \tau_{353} \times B(T, \nu) \times \left( \frac{\nu}{353 \text{ GHz}} \right)^{\beta}$$

- Gradient descent at each pixel (until convergance)

$$\beta_n / T_n = \beta_0 / T_0 + \rho \times \Delta (\text{w.r.t } \beta \text{ and } T)$$

- Threshold all-sky  $\beta$  and  $T$  estimates in wavelet domain
- Template for normalisation

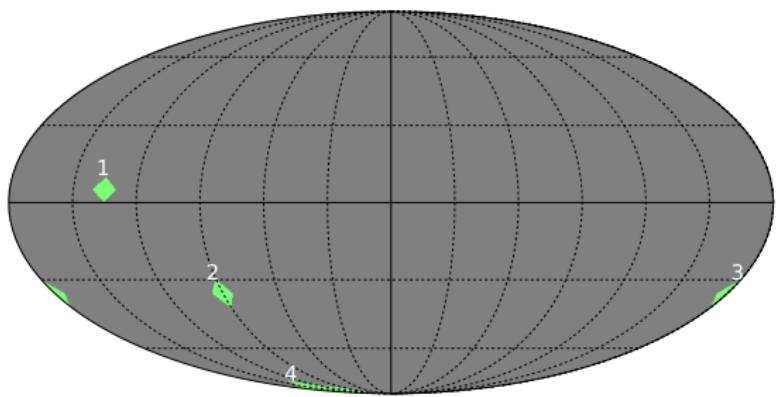
$$\tau_{353} = \frac{X_{857}}{B(T, 857 \text{ GHz}) \times \left( \frac{\nu}{353 \text{ GHz}} \right)^{\beta}}$$

# Validation

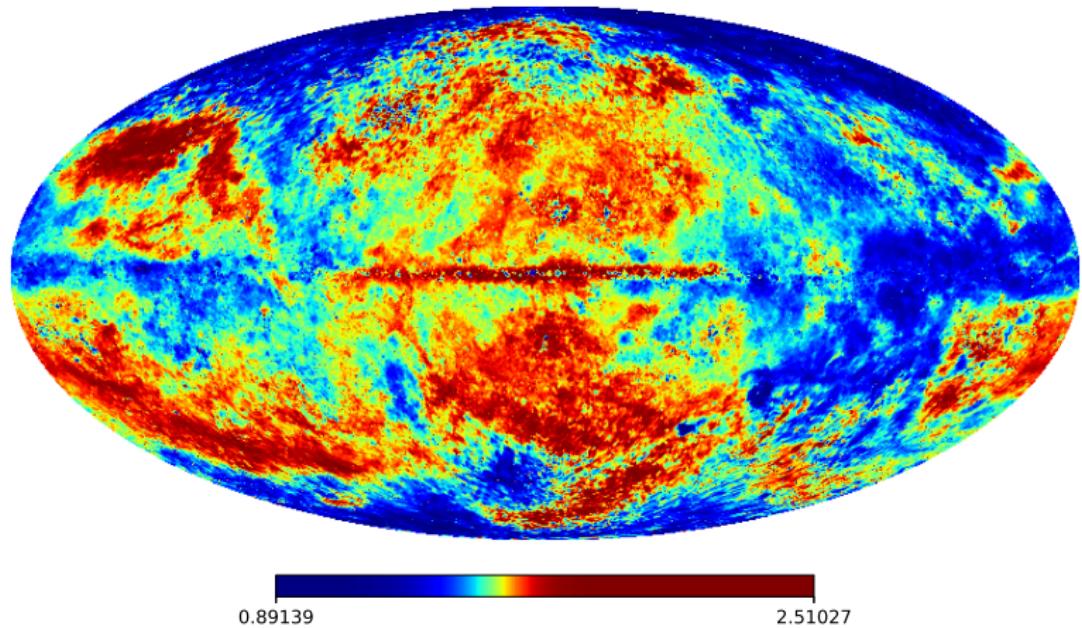
- Simulated data - known parameters

$$x_{\nu_i}^{\text{dust}} = x_{353 \text{ GHz}}^{\text{ffp8}} \times \frac{B(T, \nu)}{B(T, 353 \text{ GHz})} \times \left( \frac{\nu}{353 \text{ GHz}} \right)^\beta$$

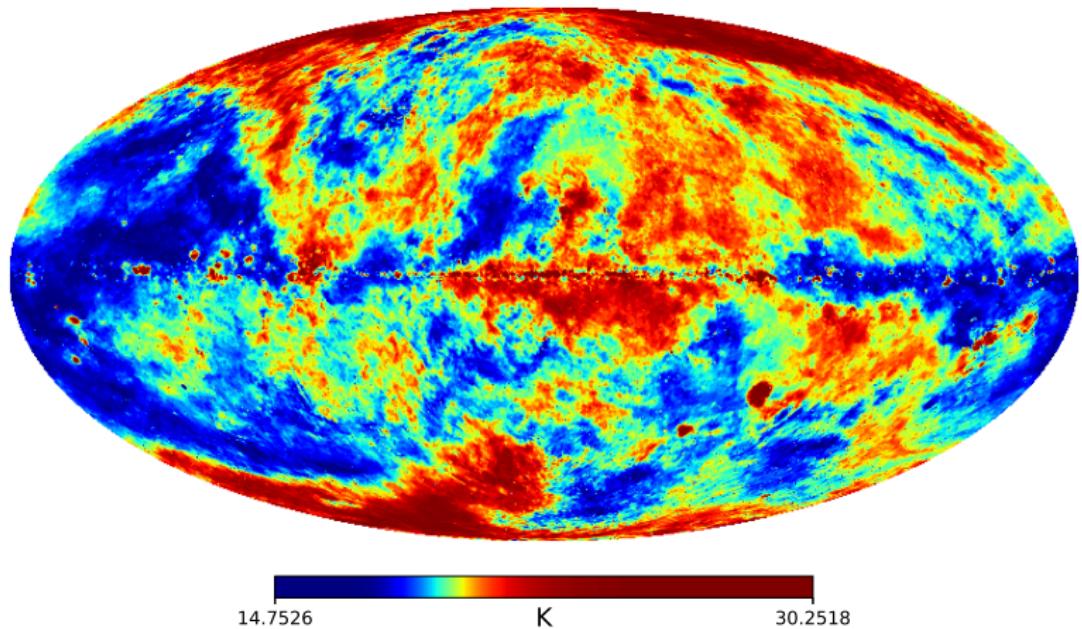
- Comparison with GNILC



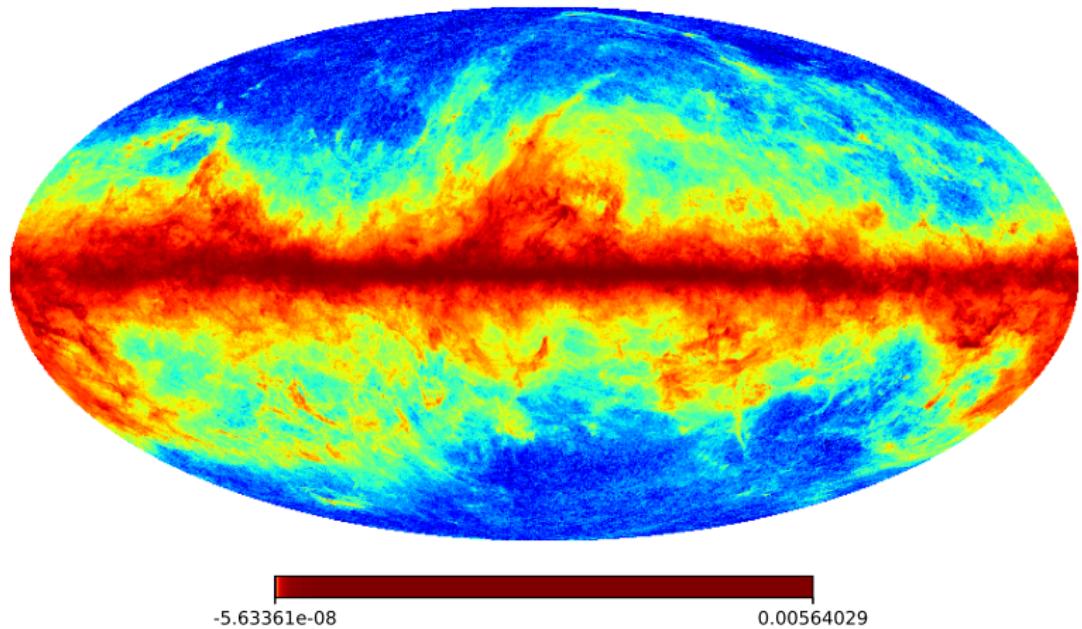
## Full-sky $\beta$ estimate - 5 arcmin



## Full-sky $T$ estimate - 5 arcmin

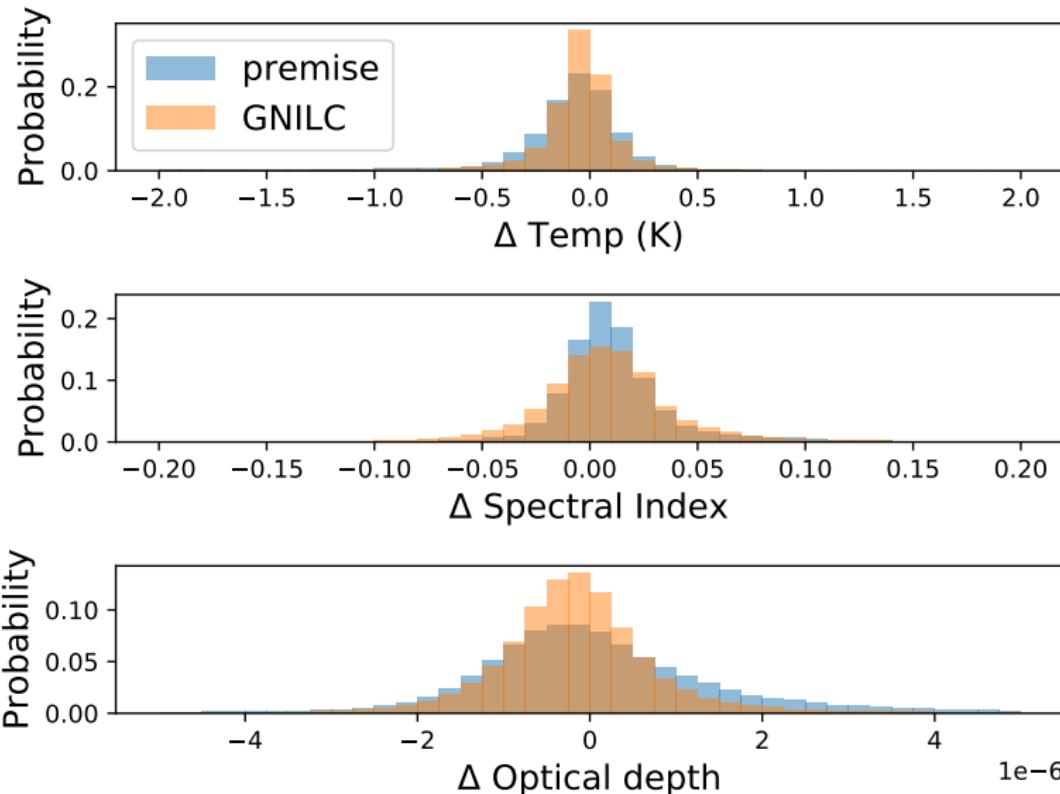


## Full-sky $\tau_{353}$ estimate - 5 arcmin

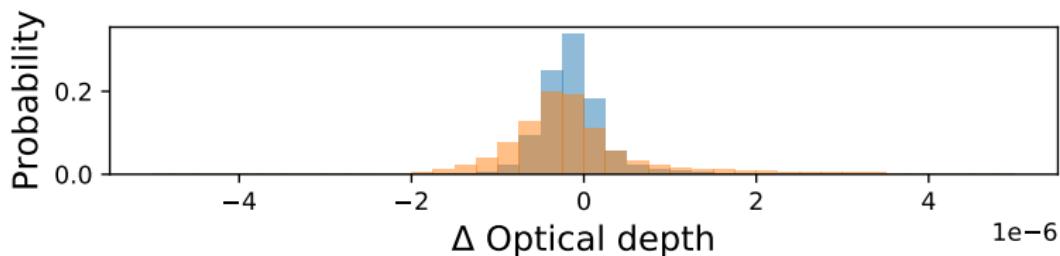
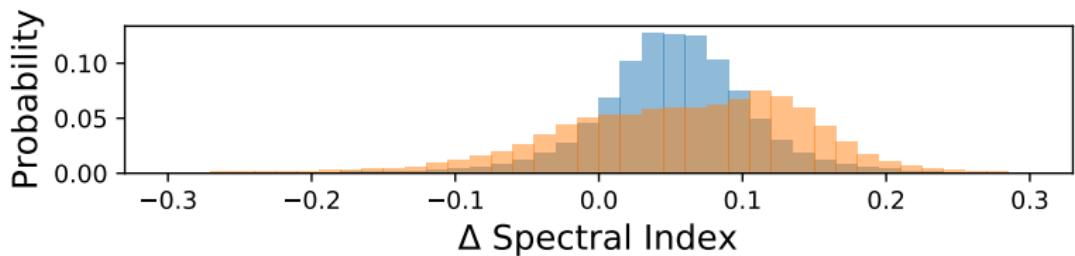
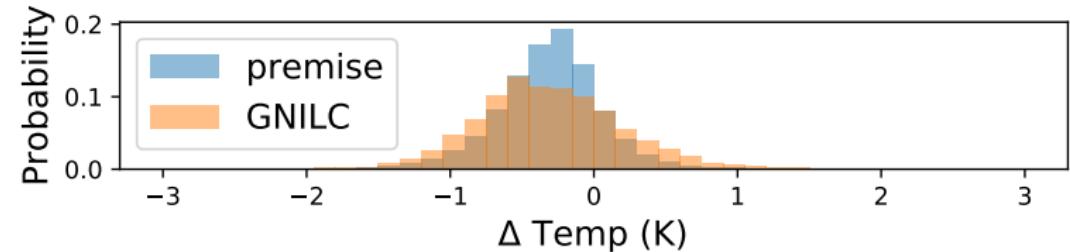


<b>Value</b>	<b>Medium %<math>\Delta</math></b>	<b><math>1\sigma</math> %<math>\Delta</math></b>	<b><math>2\sigma</math> %<math>\Delta</math></b>	<b><math>3\sigma</math> %<math>\Delta</math></b>
Temperature	1.7	2.8	8.0	16.5
Spectral index	3.4	5.7	15.4	25.6
Optical depth (353 GHz)	3.7	7.2	31.2	77.0

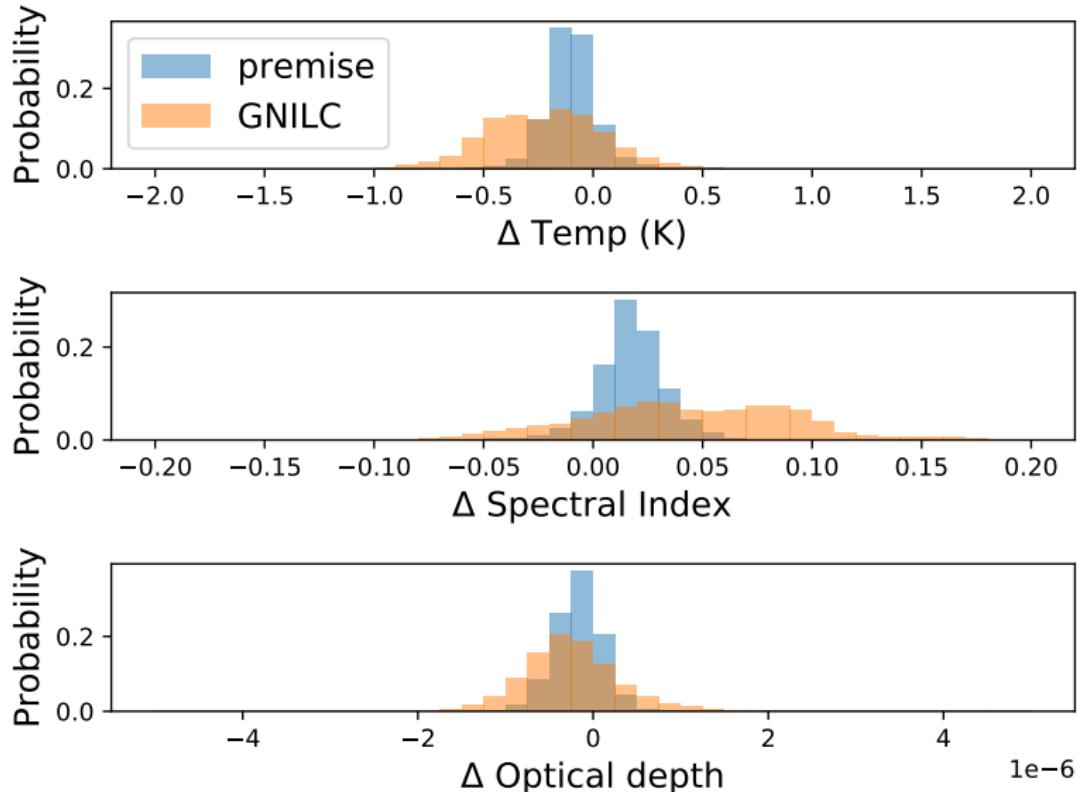
## Region 1 - High SNR



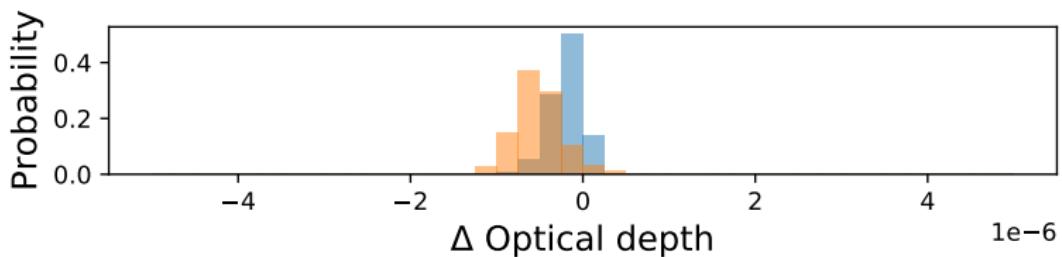
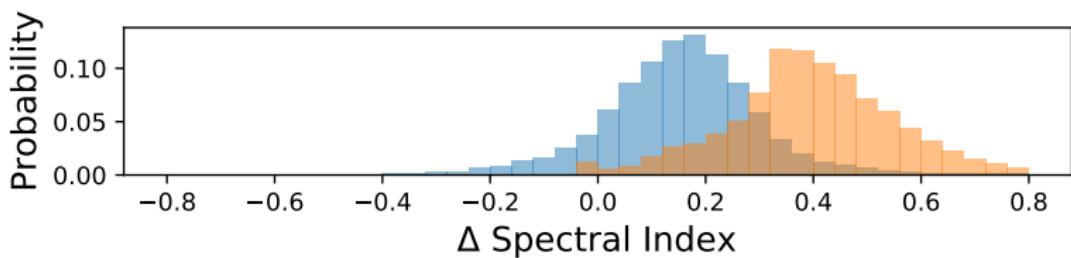
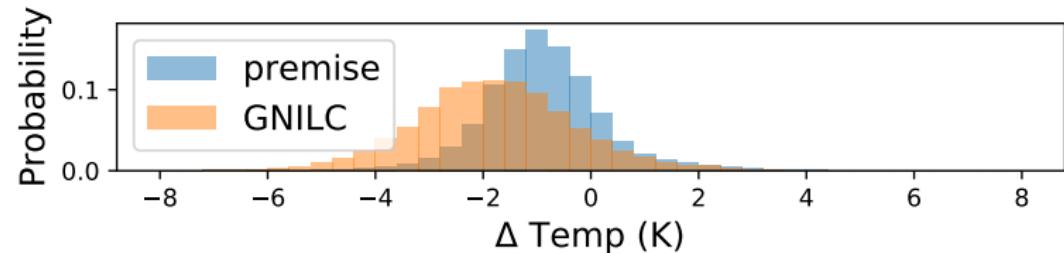
## Region 2 - Medium SNR



## Region 3 - Medium SNR



## Region 4 - Low SNR



## Conclusion

- Thermal dust parameters - 5 armcm
- Sparsity replaces smoothing
- Fast ( $\sim 2$  days)
- Improvement within low SNR