

Component Separation with Neural Networks



Biuse Casaponsa, on behalf of Radioforegrounds and QUIJOTE collaboration
IFCA, Santander, Spain

CMB Radioforegrounds for B-mode studies,
15-19 October 2018, San Cristóbal de la Laguna, Spain

Outline

1. Neural networks
2. Application to simulations
3. Preliminary results with MFI - Quijote data in combination with Planck

NEURAL NETWORKS.

Introduction

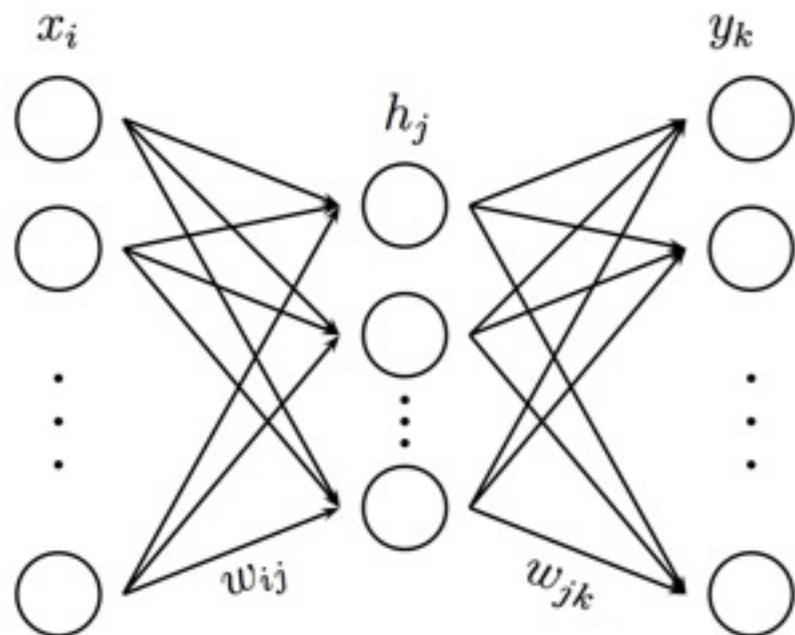
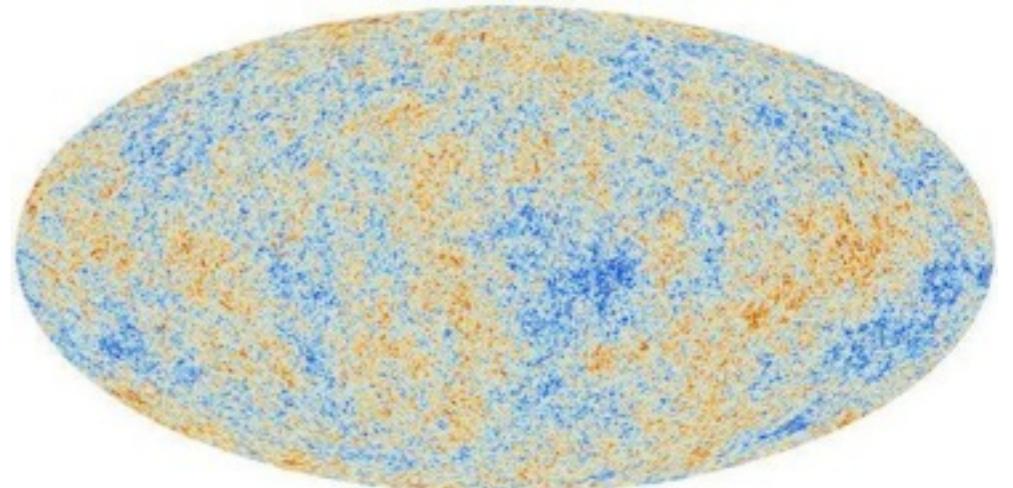


Figure 1. Schematic of a 3-layer feed-forward neural network.

Neural networks are a powerful tool for pattern recognition, predictive modeling, classification, parameter estimation...



In CMB, few applications have been proposed:

Auld et al. 2007, 2008 for cosmological parameters estimation

Casaponsa et al. 2011, 2013 Novaes et al. 2015 for primordial non-Gaussianity analyses.

Norgaard-Nielsen 2008, 2012 for CMB foreground removal

NEURAL NETWORKS.

Introduction

In a one hidden layer network, choosing a tanh activation function, the values on the hidden nodes will be:

$$h_j = \tanh \left(\sum_i w_{ij} x_i \right)$$

and in the output layer with a linear activation function, the output values are:

$$y_k = \sum_j w_{jk} h_j$$

Then we have the outputs as a function of the inputs and the weights

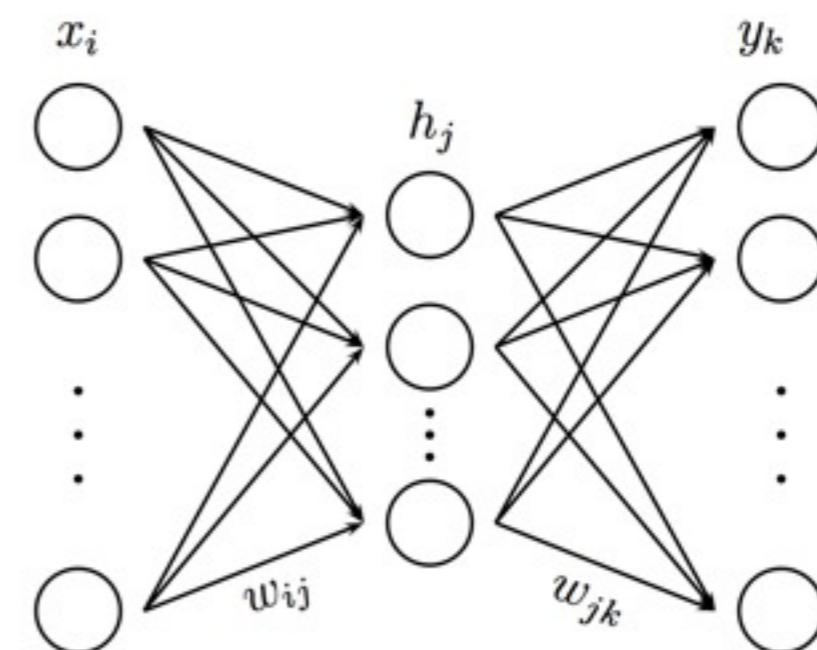


Figure 1. Schematic of a 3-layer feed-forward neural network.

$$y_k = \sum_j w_{jk} \tanh \left(\sum_i w_{ij} x_i \right)$$

NEURAL NETWORKS.

Introduction

General form



$$y_k = g\left(\sum_m w_{nm} \dots f\left(\sum_i w_{ij} x_i + \theta_j\right) + \theta_n\right)$$

To obtain the network parameters ($\vec{w}, \vec{\theta}$): **Training procedure**

We need a **training set**: A set of known inputs
and outputs (called targets) (x, t) .

y_k

NEURAL NETWORKS.

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Once we have x, t for the training set, then we basically do a is a multidimensional fit

minimize loss function:

$$E = \sum_n \sum_k \frac{(t_k^n - y_k^n)^2}{K \times N}$$

NEURAL NETWORKS.

Parametric component separation

POLARIZATION:

What we have

S_i

Q and U values in (μK_{RJ}) at each frequency for Q and U.

What we want

$A_{cmb}^Q, A_{cmb}^U, A_s^Q, A_s^U, \beta_s, A_d^Q, A_d^U, \beta_d, T_d$

NEURAL NETWORKS.

Parametric component separation

POLARIZATION:

Draw random distribution of parameters

What we have

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$A_{cmb}^Q, A_{cmb}^U, A_s^Q, A_s^U, \beta_s, A_d^Q, A_d^U, \beta_d, T_d$

NEURAL NETWORKS.

Parametric component separation

POLARIZATION:

Given a model and some noise
compute de stokes parameters at
each frequency

Draw random distribution of
parameters

What we have

What we want

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Q and U values in (μK_{RJ}) at each
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$$A_{cmb}^Q, A_{cmb}^U, A_s^Q, A_s^U, \beta_s, A_d^Q, A_d^U, \beta_d, T_d$$

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Repeat > 100,000 times

NEURAL NETWORKS.

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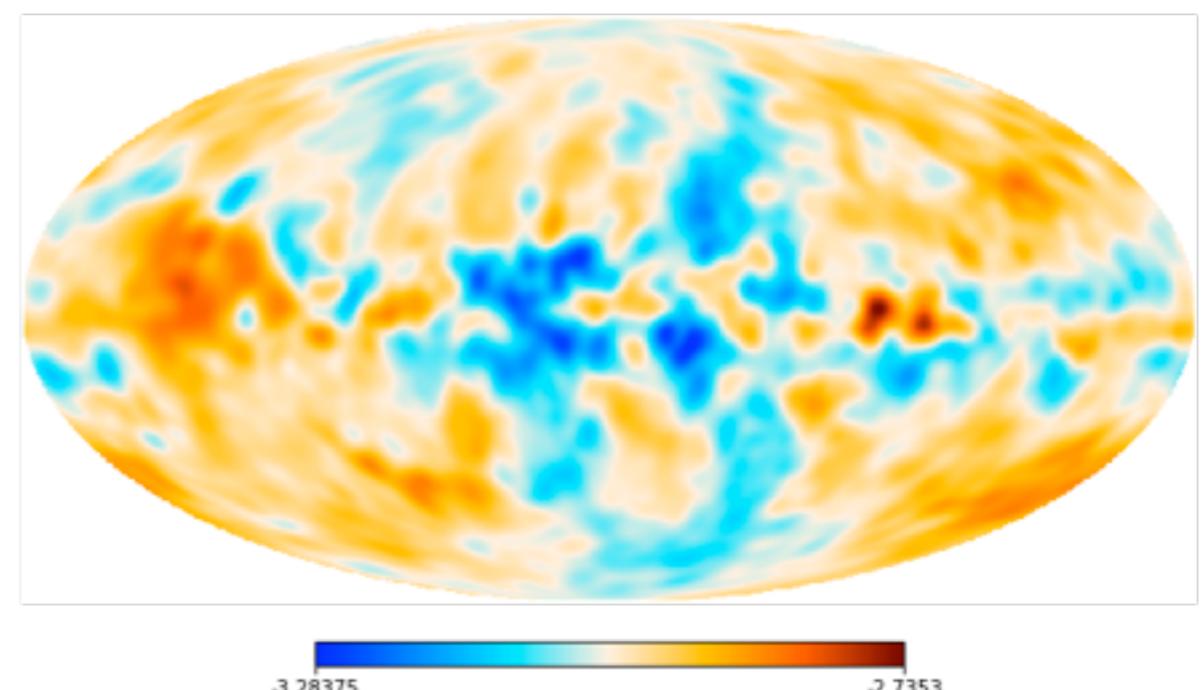
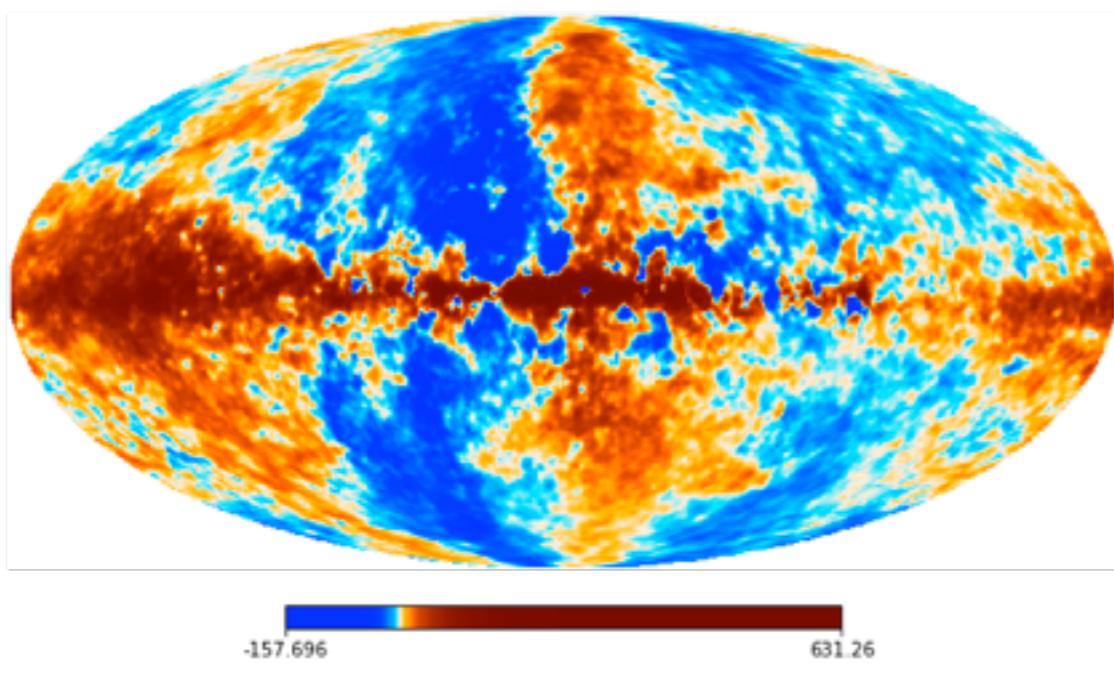
Repeat > 100,000 times

The training set is ready to learn

APPLICATION TO SIMULATIONS

Once the neural network is trained we have a non-linear function that relates any vector (S_i) to the corresponding parameters $\beta_j = f(S_i)$

and we can apply this function to each pixel of a simulation



APPLICATION TO SIMULATIONS

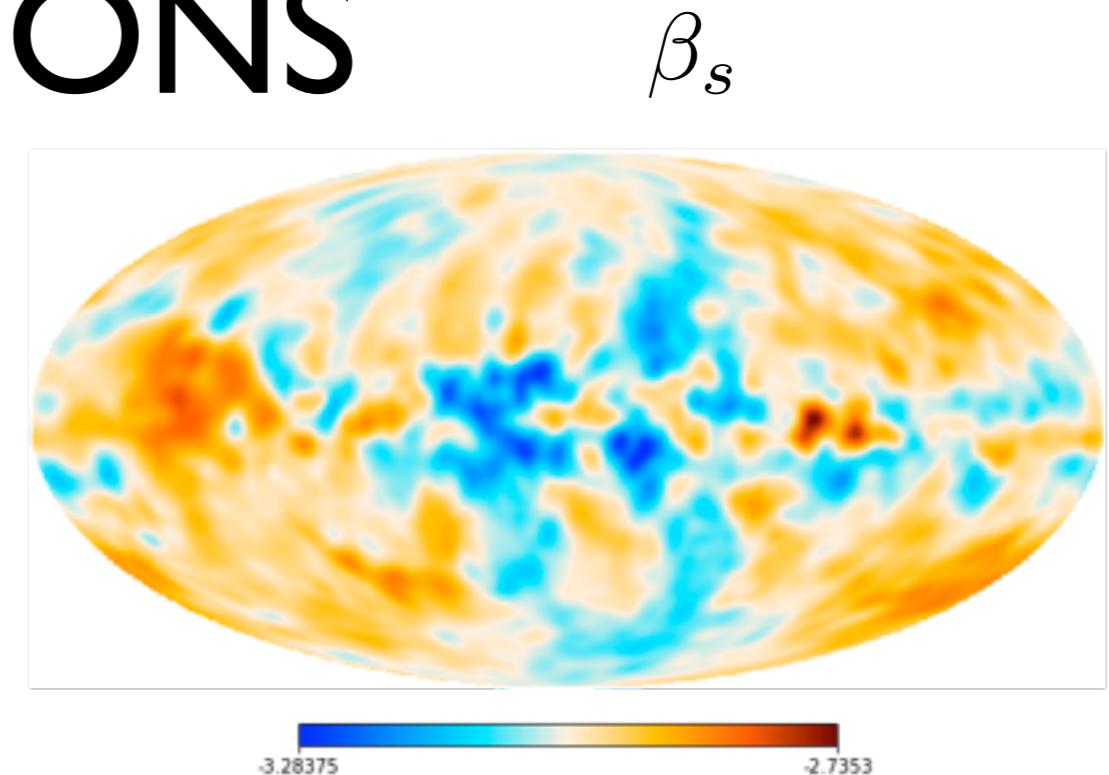
- o Simple cmb + synchrotron + dust simulations with white noise, using PSM amplitudes and spectral indices.
 - o Synchrotron: power law
 - o Dust: one component grey body
- o MFI and Planck channels (11GHz + Planck)
- o 1 set of simulations at 1deg and one set at 10 deg
- o Since we are interested in the low frequency, dust spectral parameters are fixed.

APPLICATION TO SIMULATIONS

If we use a uniform distribution for the spectral index from -4 to -2, the method finds a large bias in PLANCK.

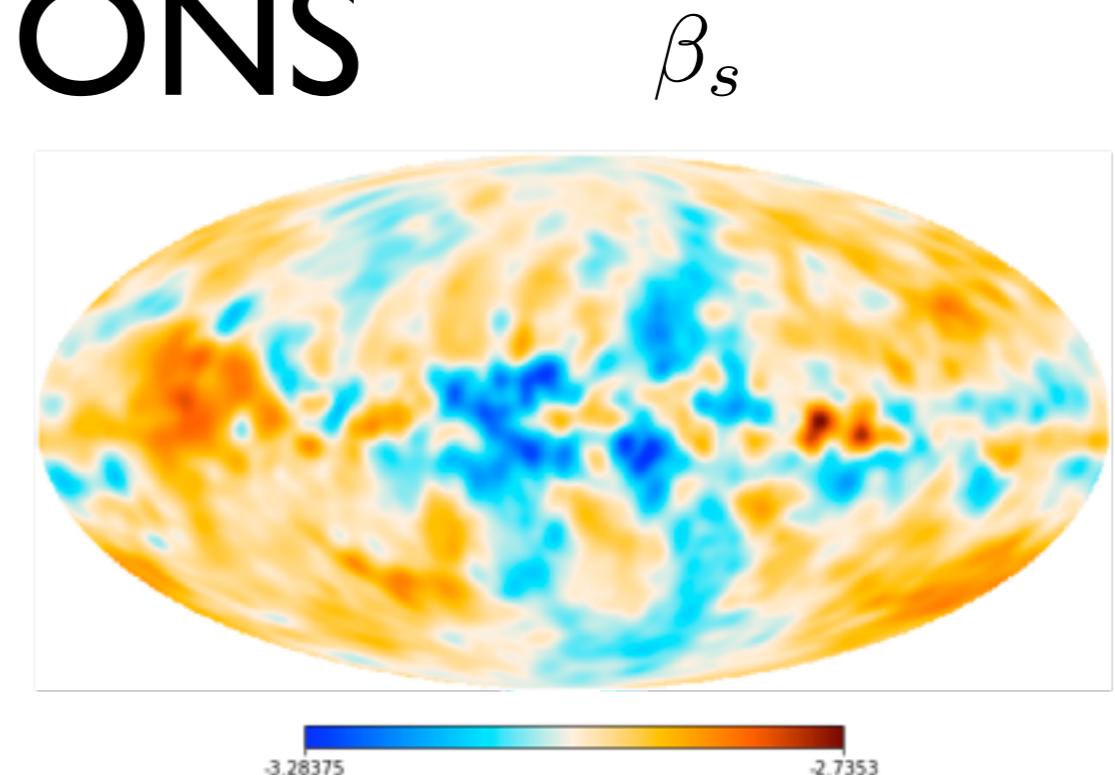
we train 2 networks:

- one with the 7 Planck frequencies
- one with 8 frequencies $\text{II} + \text{Planck}$



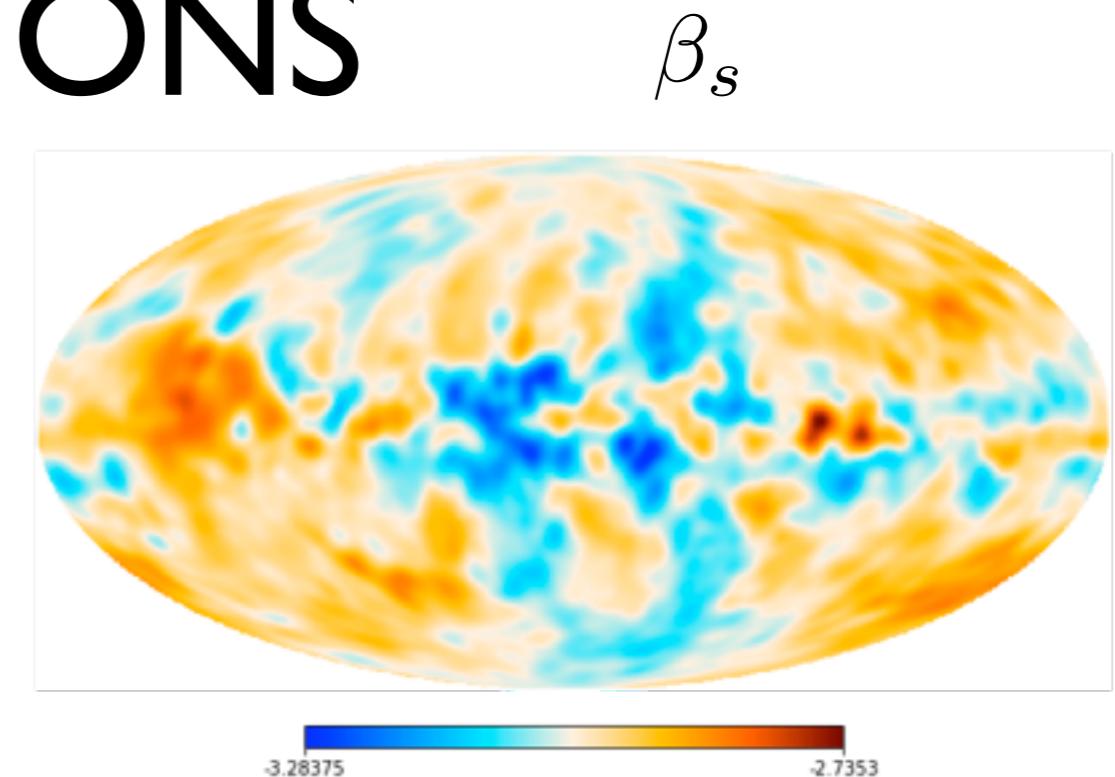
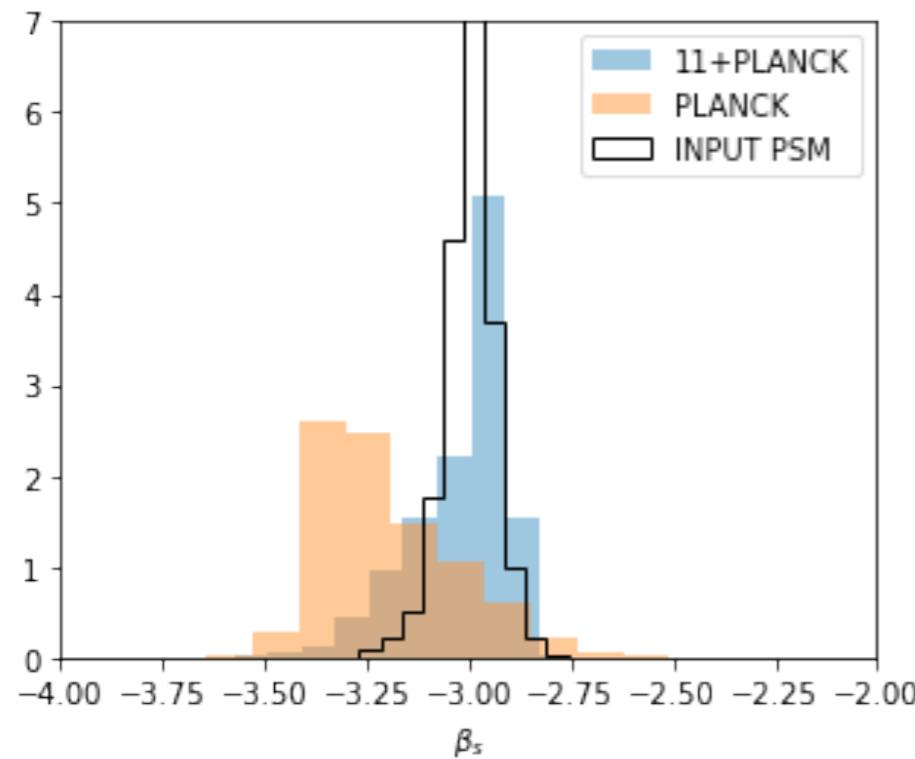
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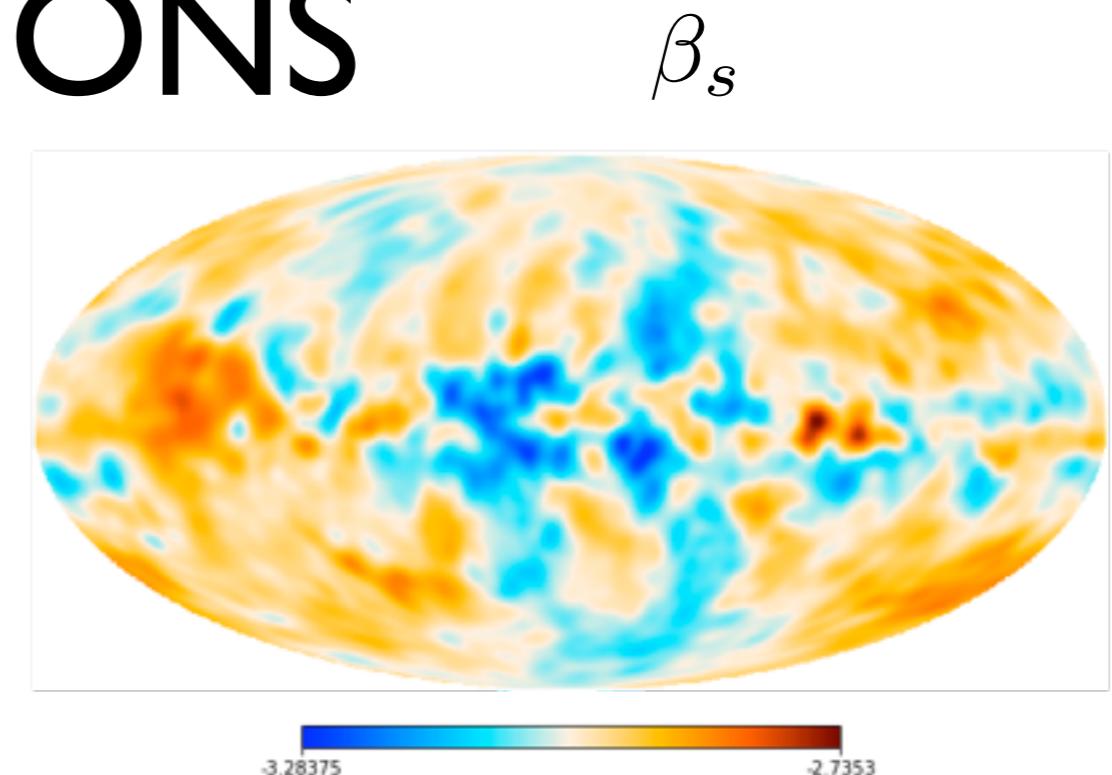
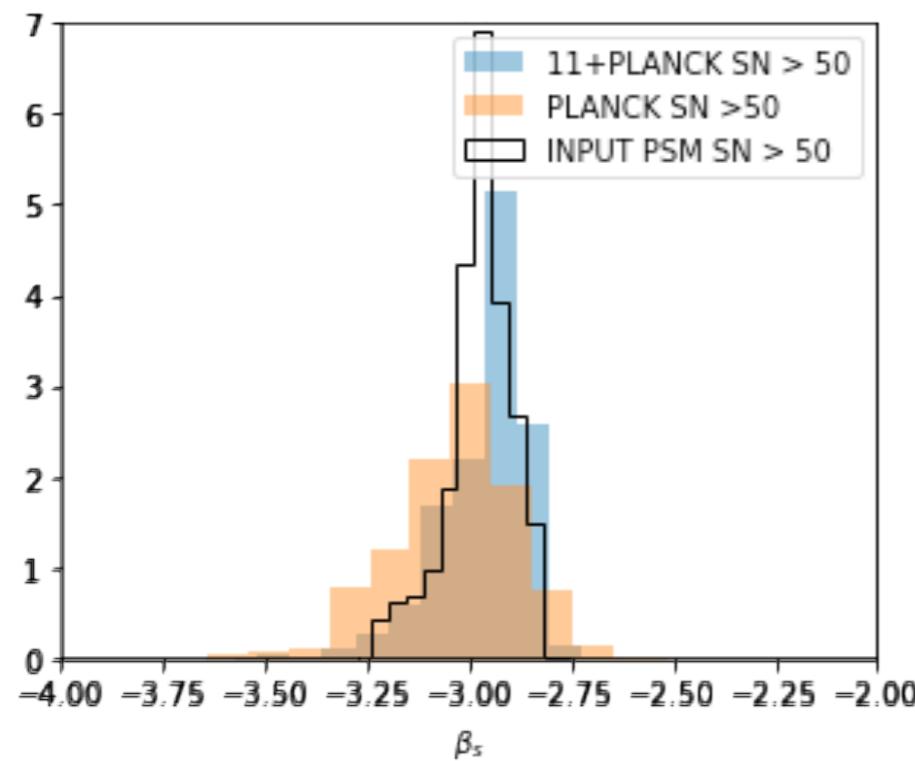
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APPLICATION TO SIMULATIONS

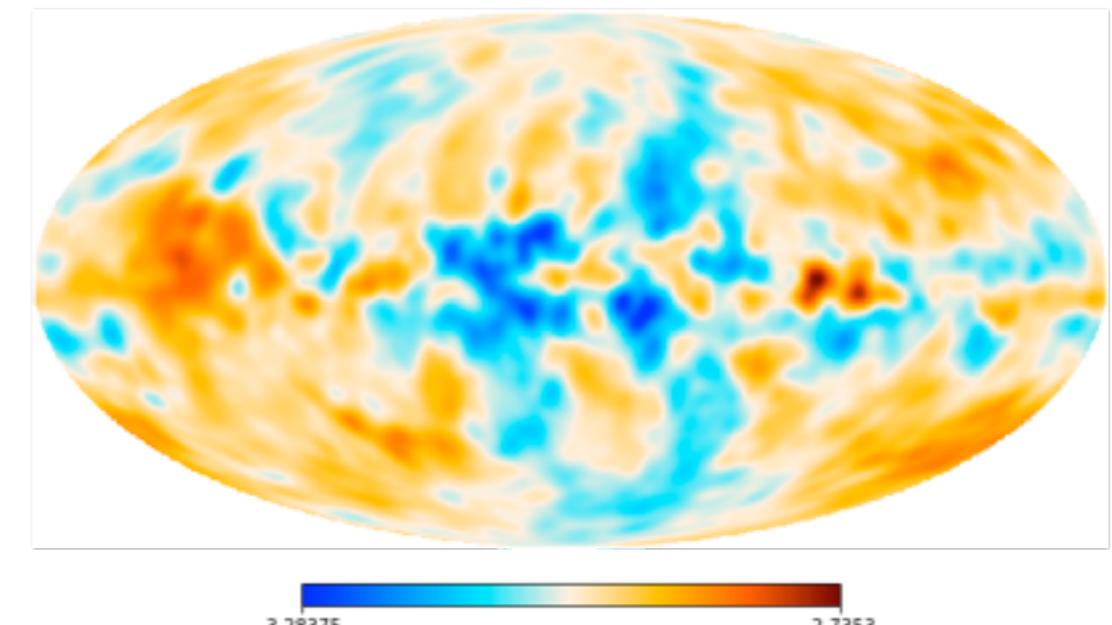
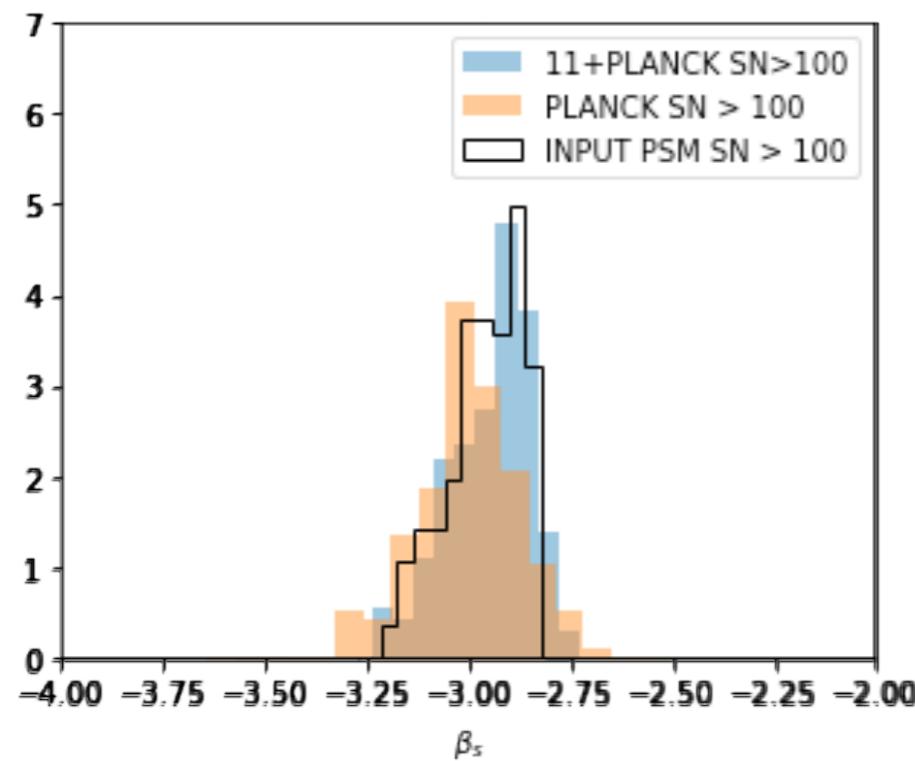
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APPLICATION TO SIMULATIONS

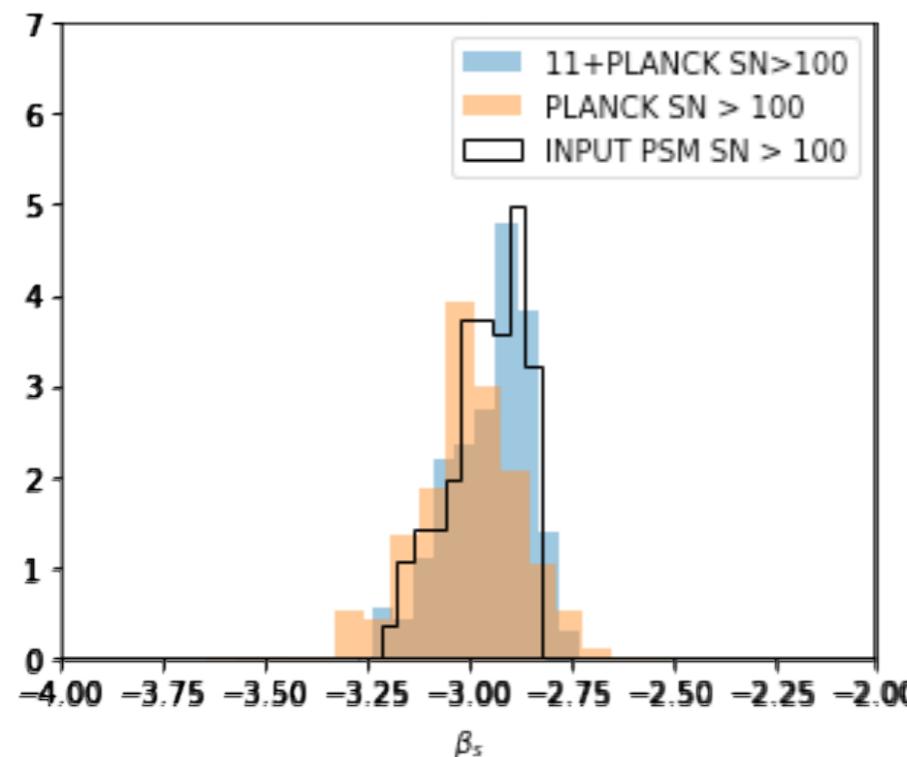
β_s

If we use a uniform distribution for the spectral index from -4 to -2, the method finds a large bias in PLANCK.

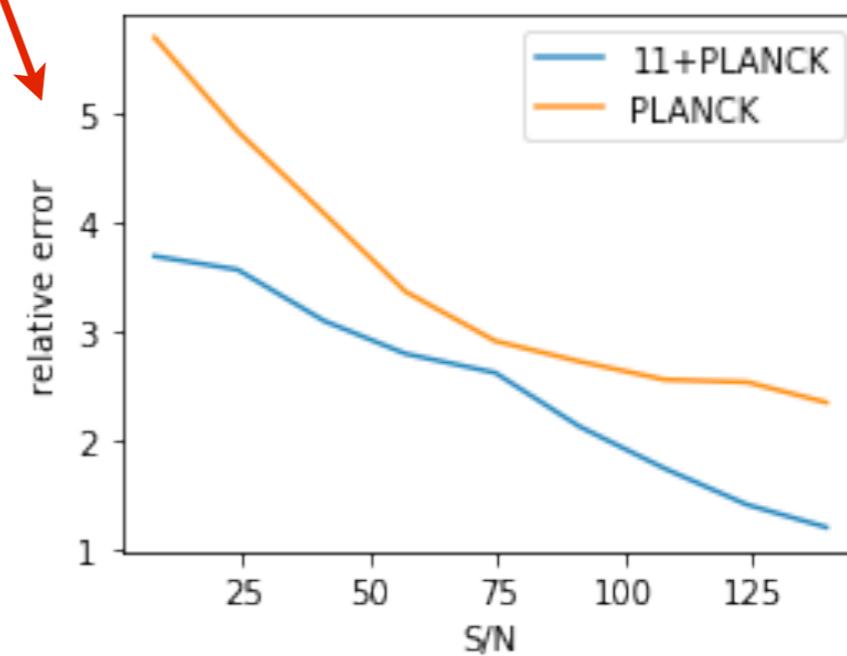
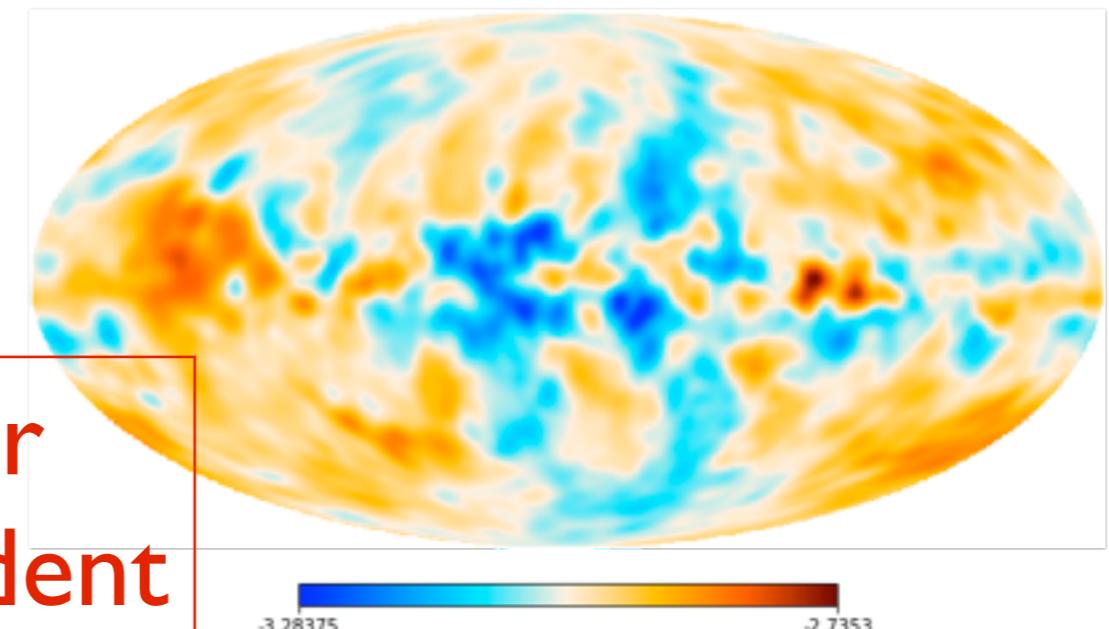


APPLICATION TO SIMULATIONS

If we use a uniform distribution for the spectral index from -4 to -2, the method finds a large bias in PLANCK.



Prior
dependent



Besides that, we see a bias also in the 11+PLANCK estimation for low SN if we shift the training distribution

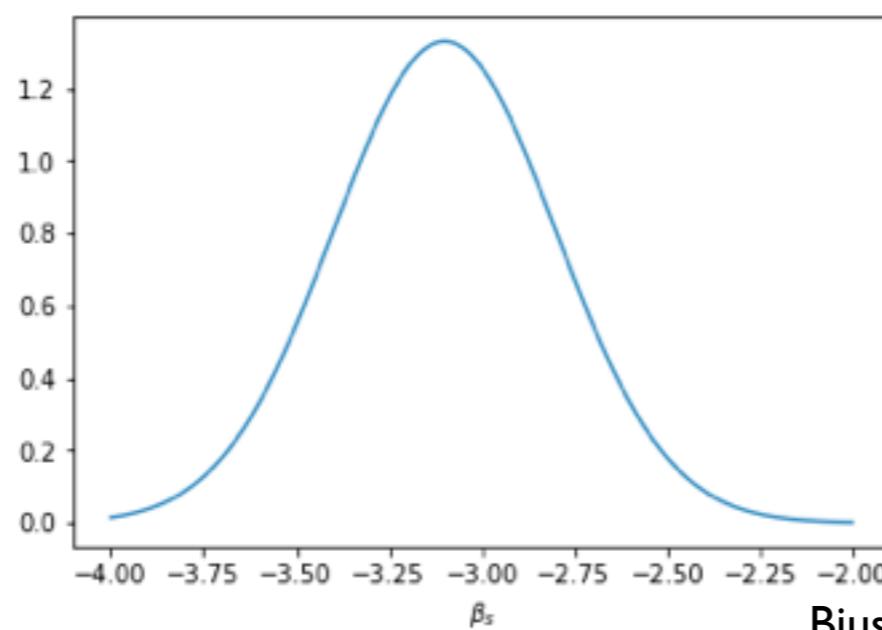
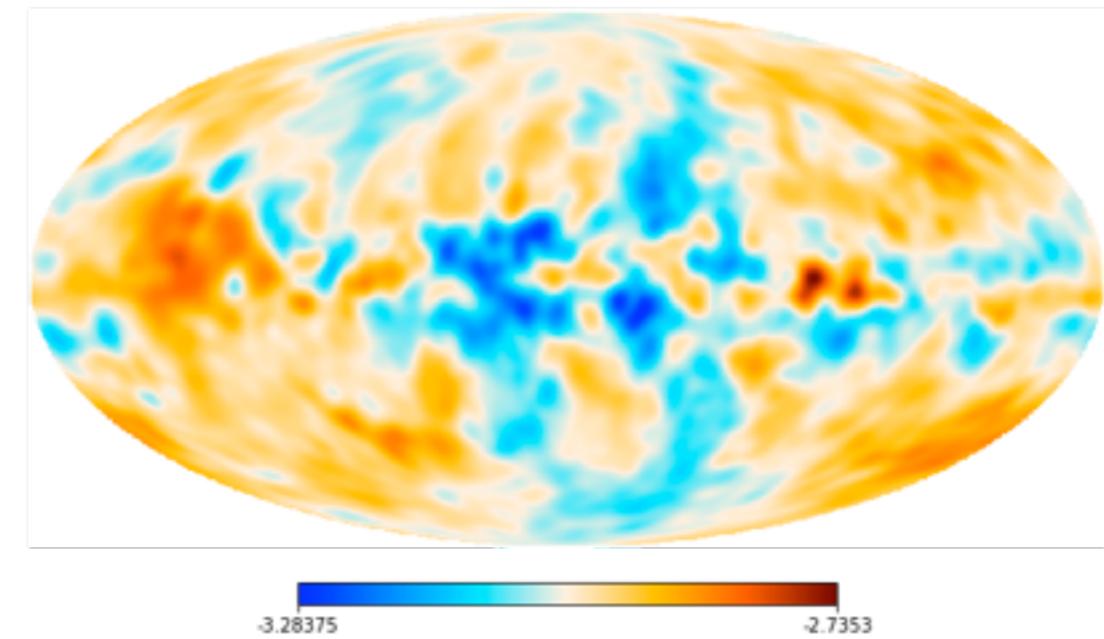
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APPLICATION TO SIMULATIONS

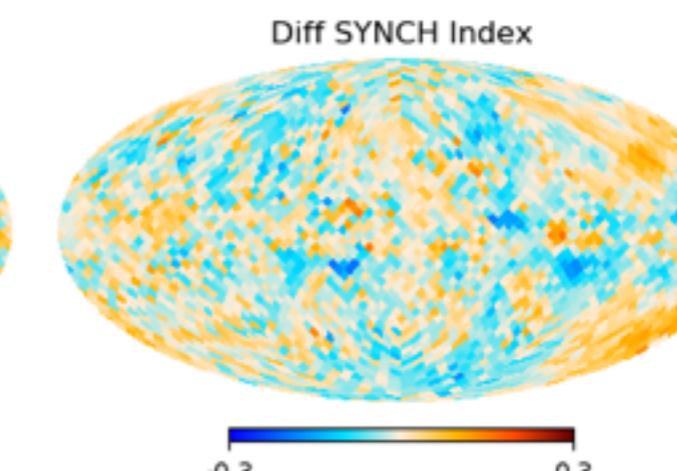
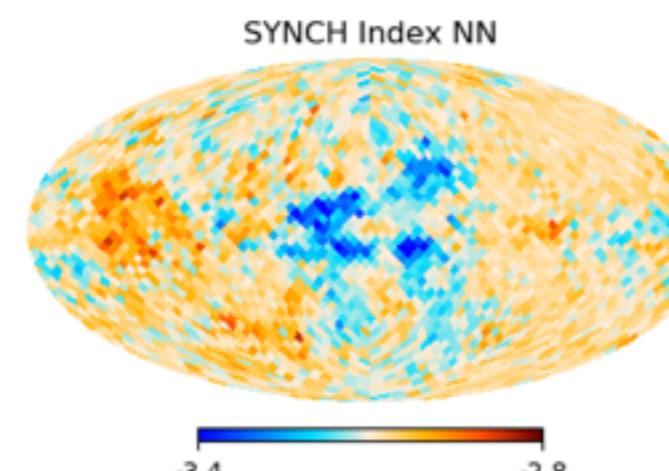
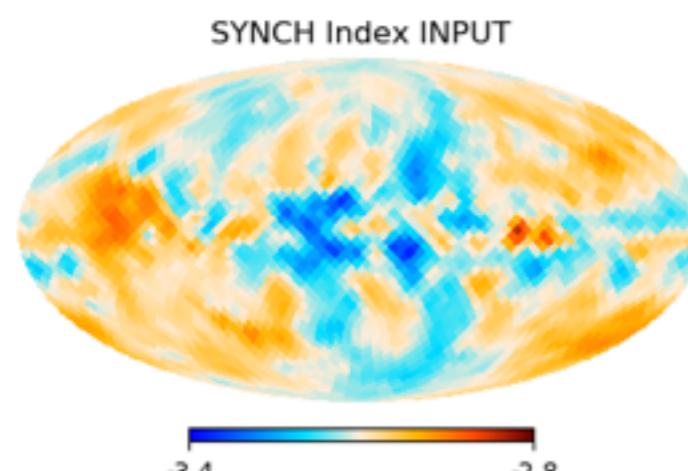
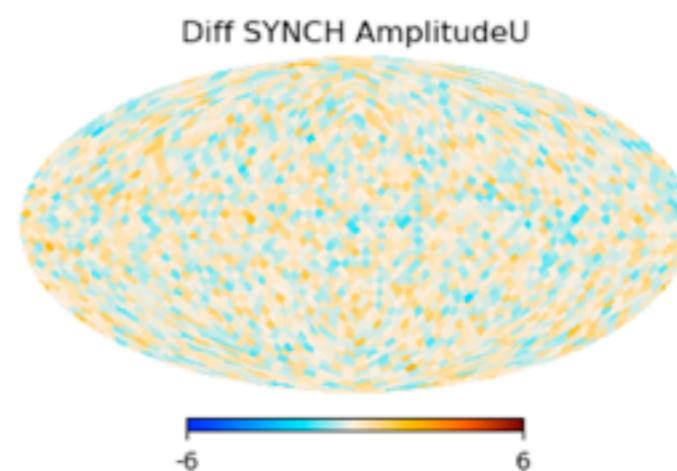
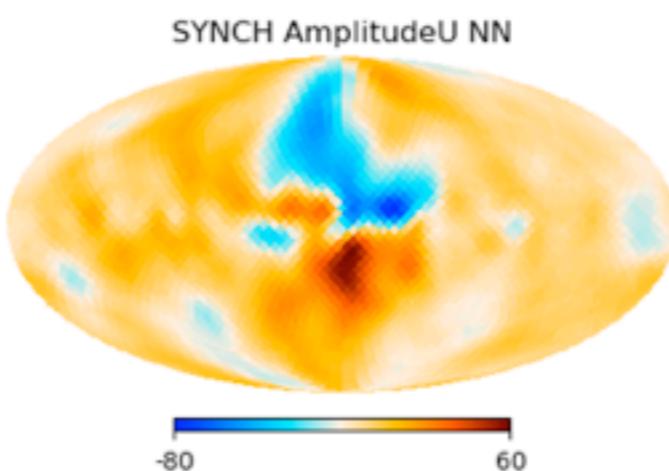
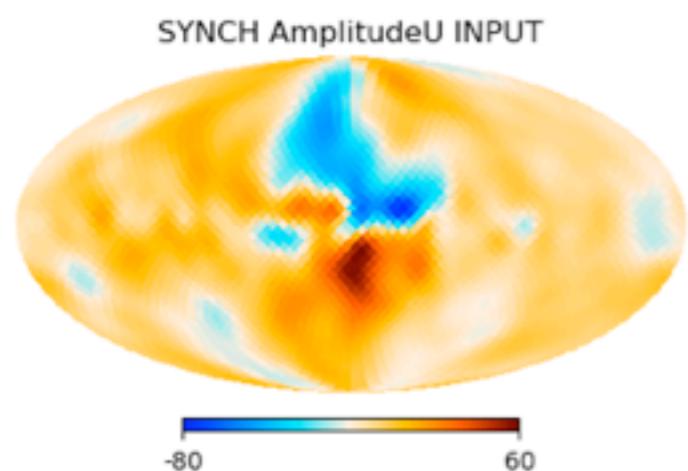
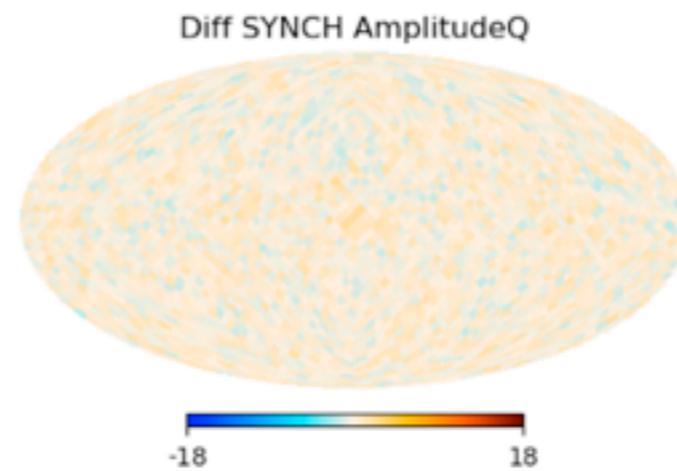
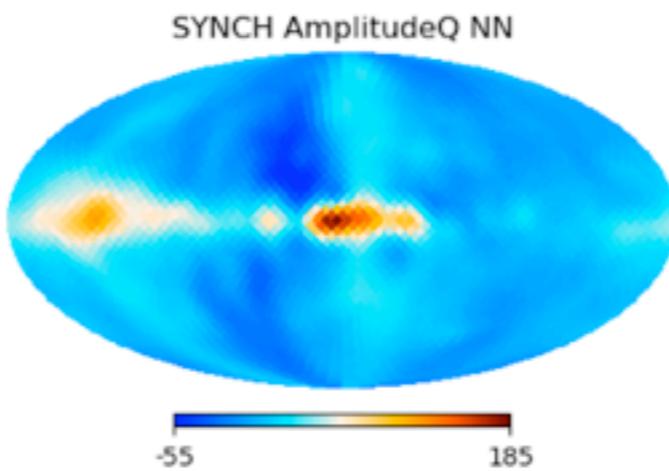
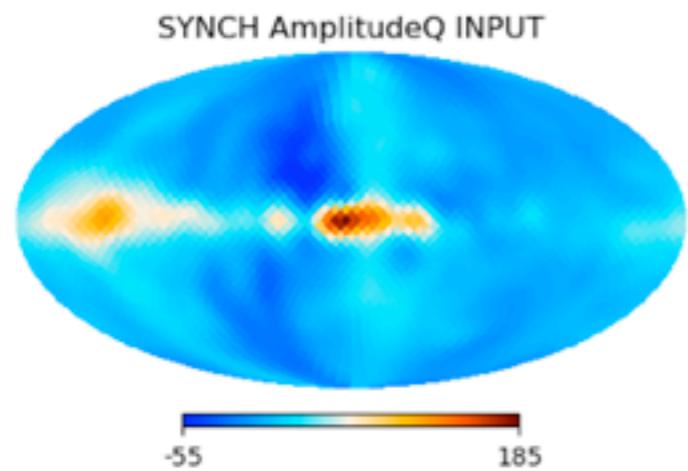
to increase SN:

- Work at lower resolution
- Add more data
- Keep doing observations

When we can't, we use a tight Gaussian distribution to perform a component separation at high latitudes



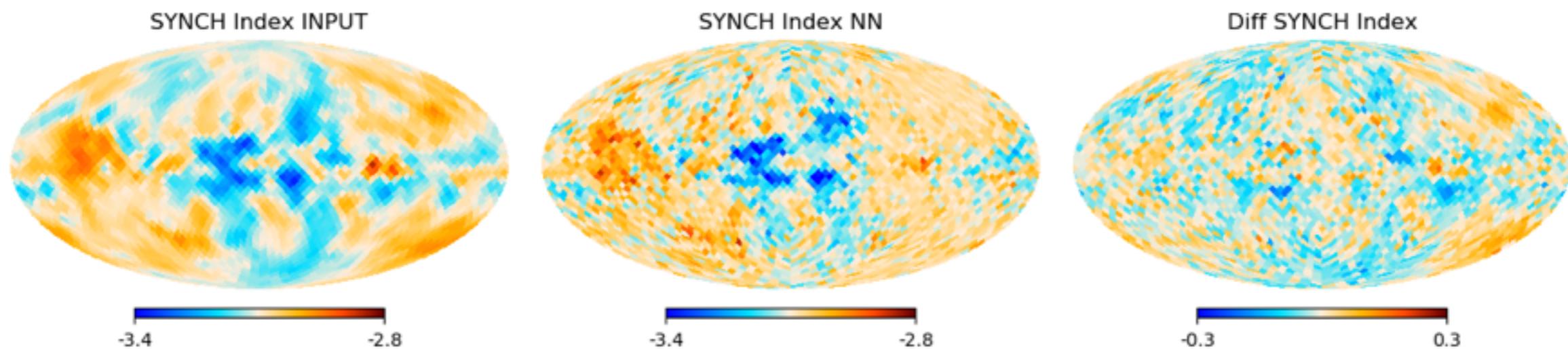
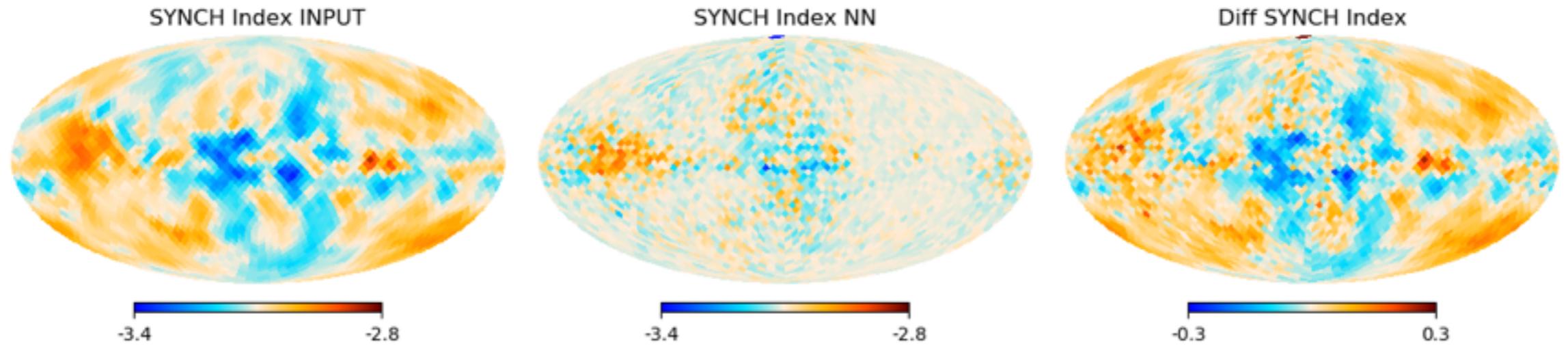
APPLICATION TO SIMULATIONS. SYNCHROTRON



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APPLICATION TO SIMULATIONS. SYNCHROTRON

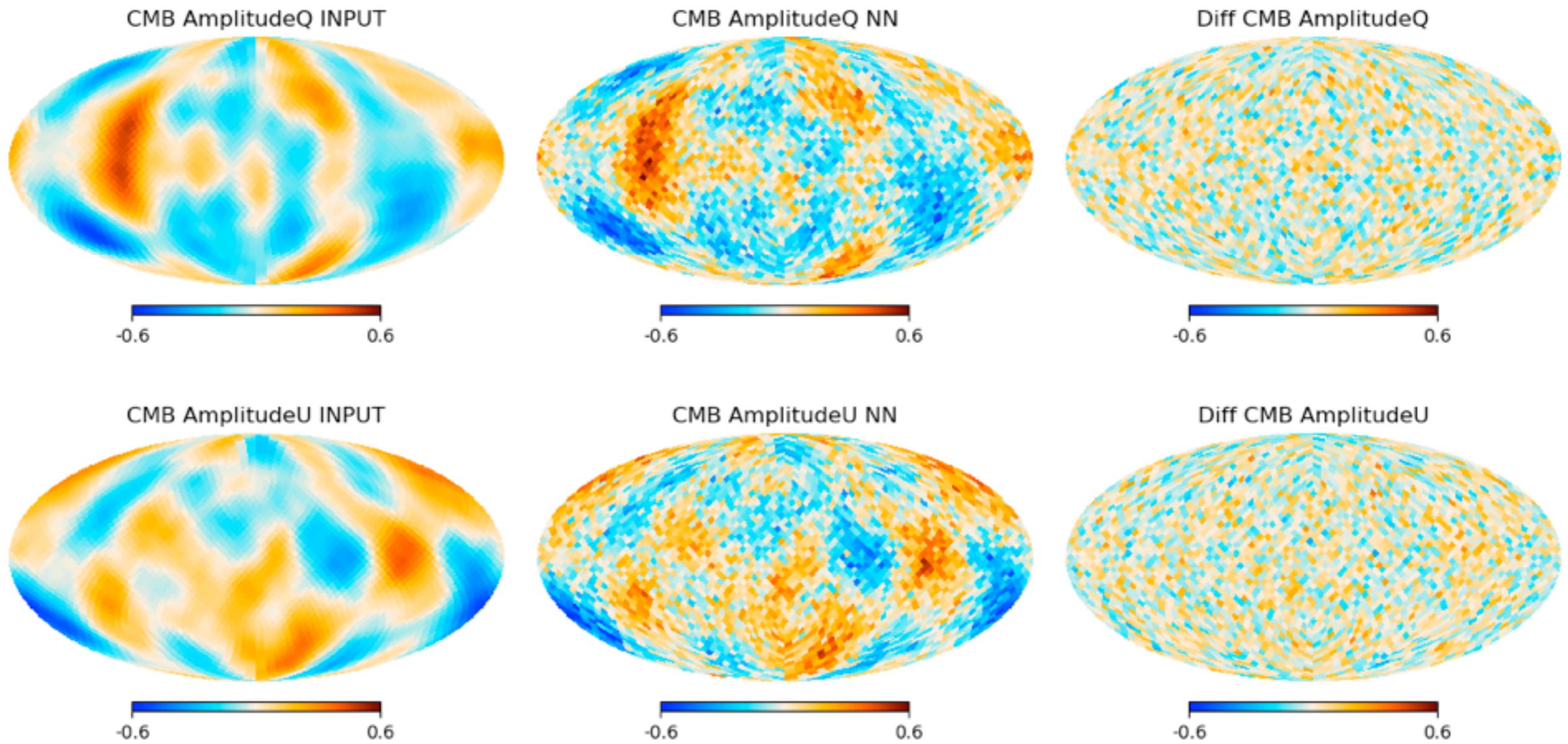
Only Planck frequencies



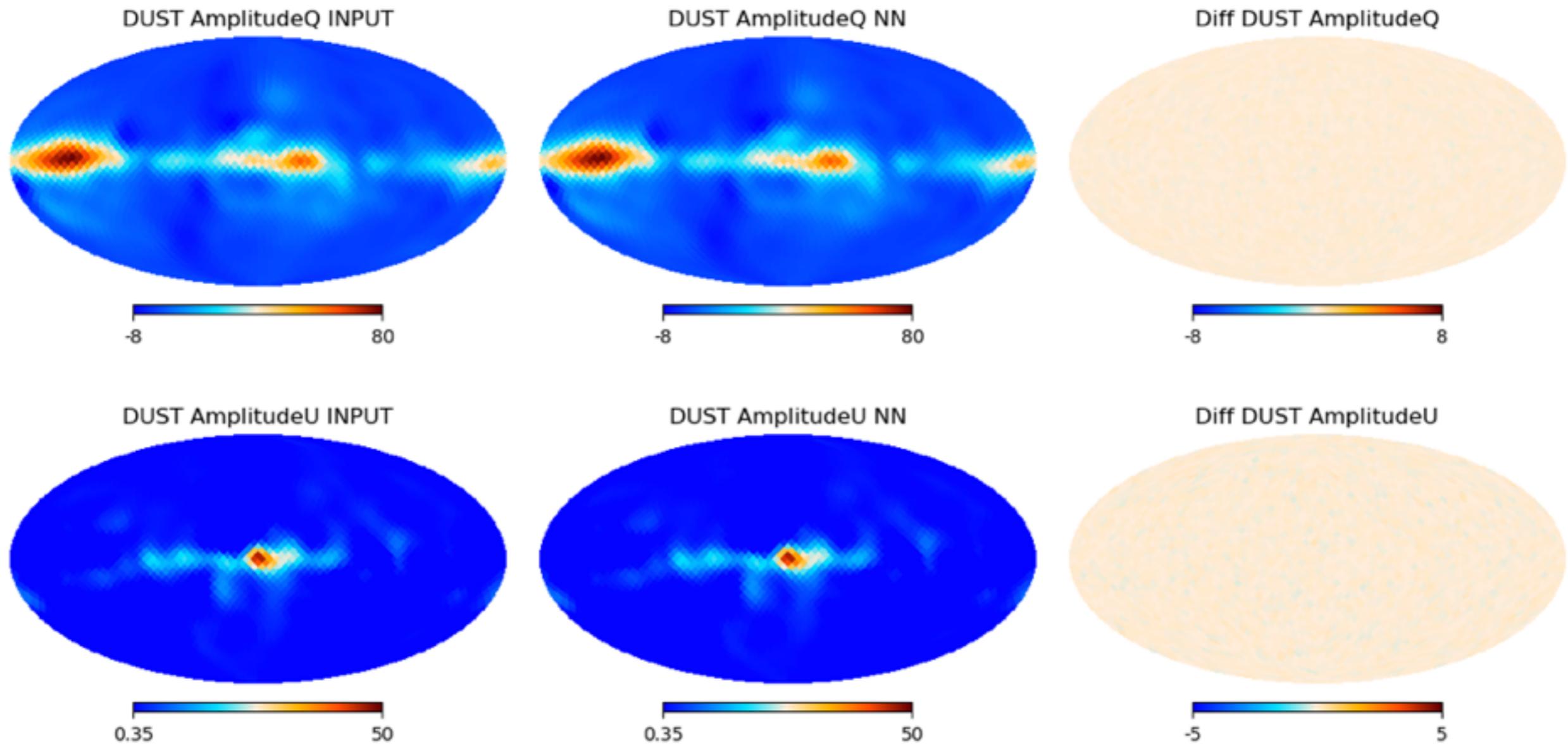
MFI + Planck frequencies

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APPLICATION TO SIMULATIONS. CMB



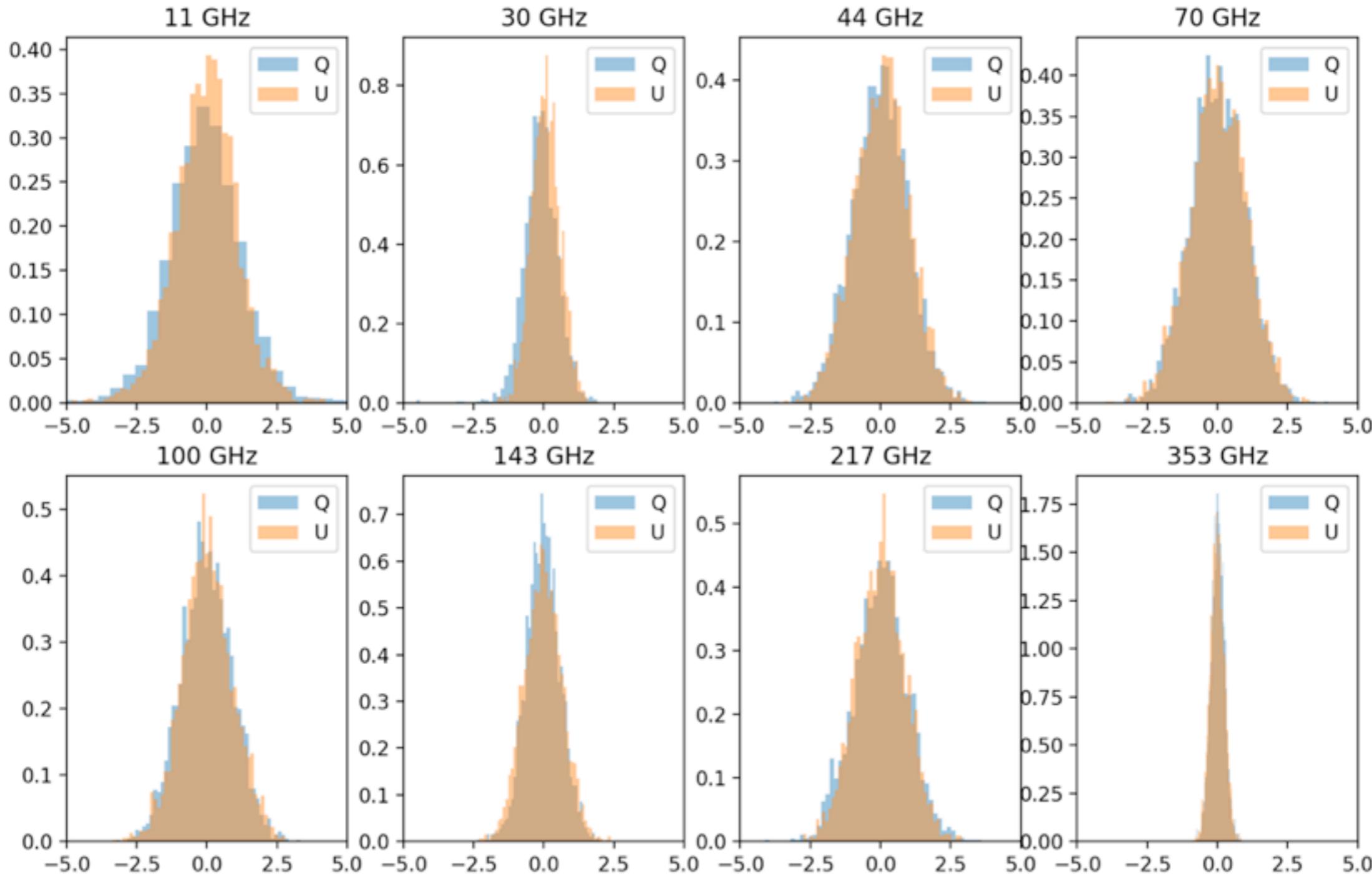
APPLICATION TO SIMULATIONS. DUST



APPLICATION TO SIMULATIONS. Correlations coefficients NN vs Input

- CMB $r \sim 0.83$
- Synchrotron Amplitude $r > 0.999$
- Synchrotron Index $r \sim 0.69$
(SN > 50 $r \sim 0.89$)
- Dust Amplitudes $r > 0.9999$

APPLICATION TO SIMULATIONS. Residuals



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APPLICATION TO THE DATA. **MFI QUIJOTE channels**

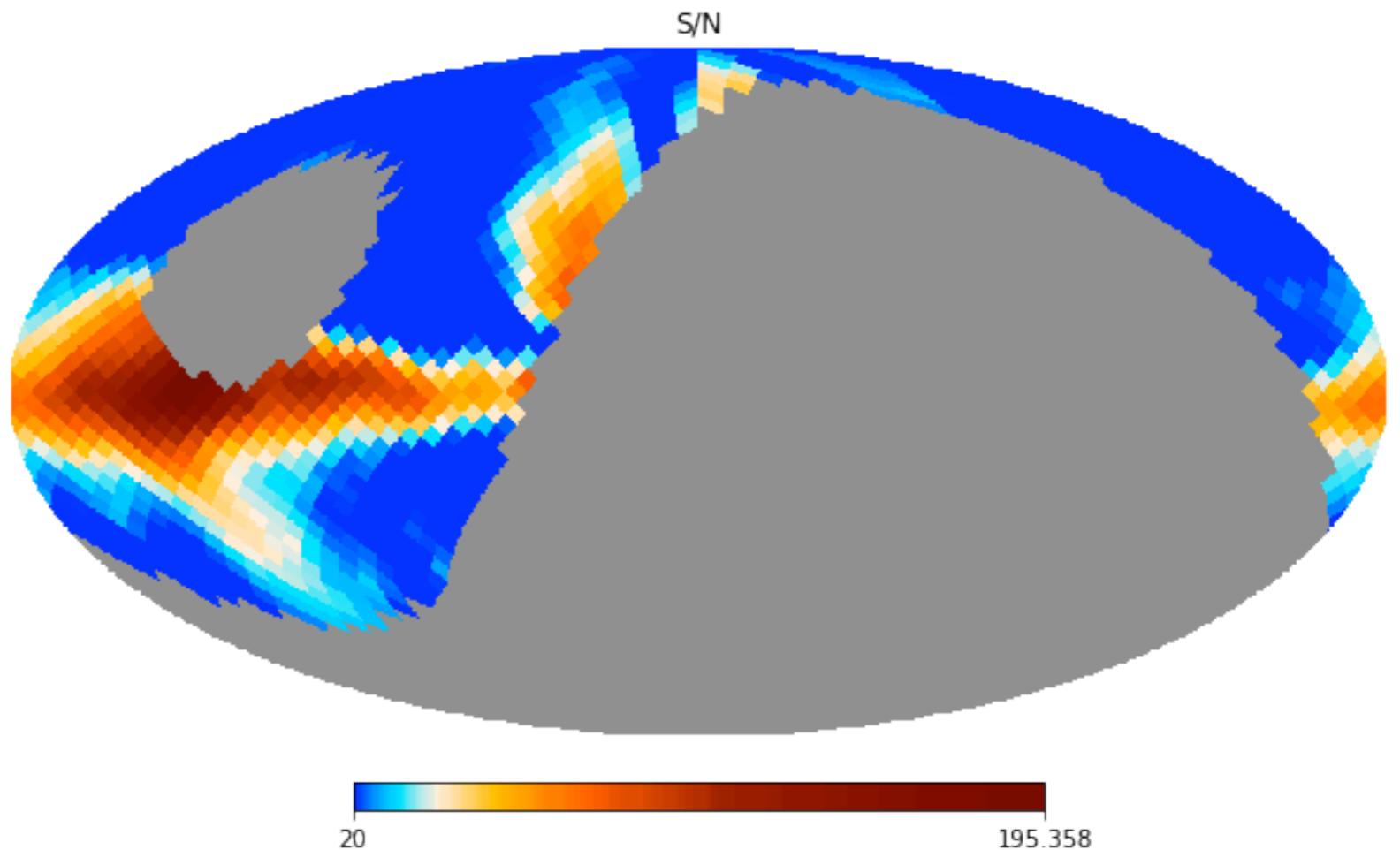
- Planck 2018 release polarization maps and 11GHz+QUIJOTE internal release at nside =256 with a common resolution of 1deg.
- Spectral index is recovered at 10 degrees resolution and this is udgraded to nside=256 to recover the amplitudes of the components at 1 deg resolution
- T_d and β_d fixed to the COMMANDER estimation (Planck collaboration IV, 2018)

PREPARING TO APPLY THE METHOD TO DATA

For the full sky component separation we are using a tighter distribution for beta_s : -3.5 to -2.6

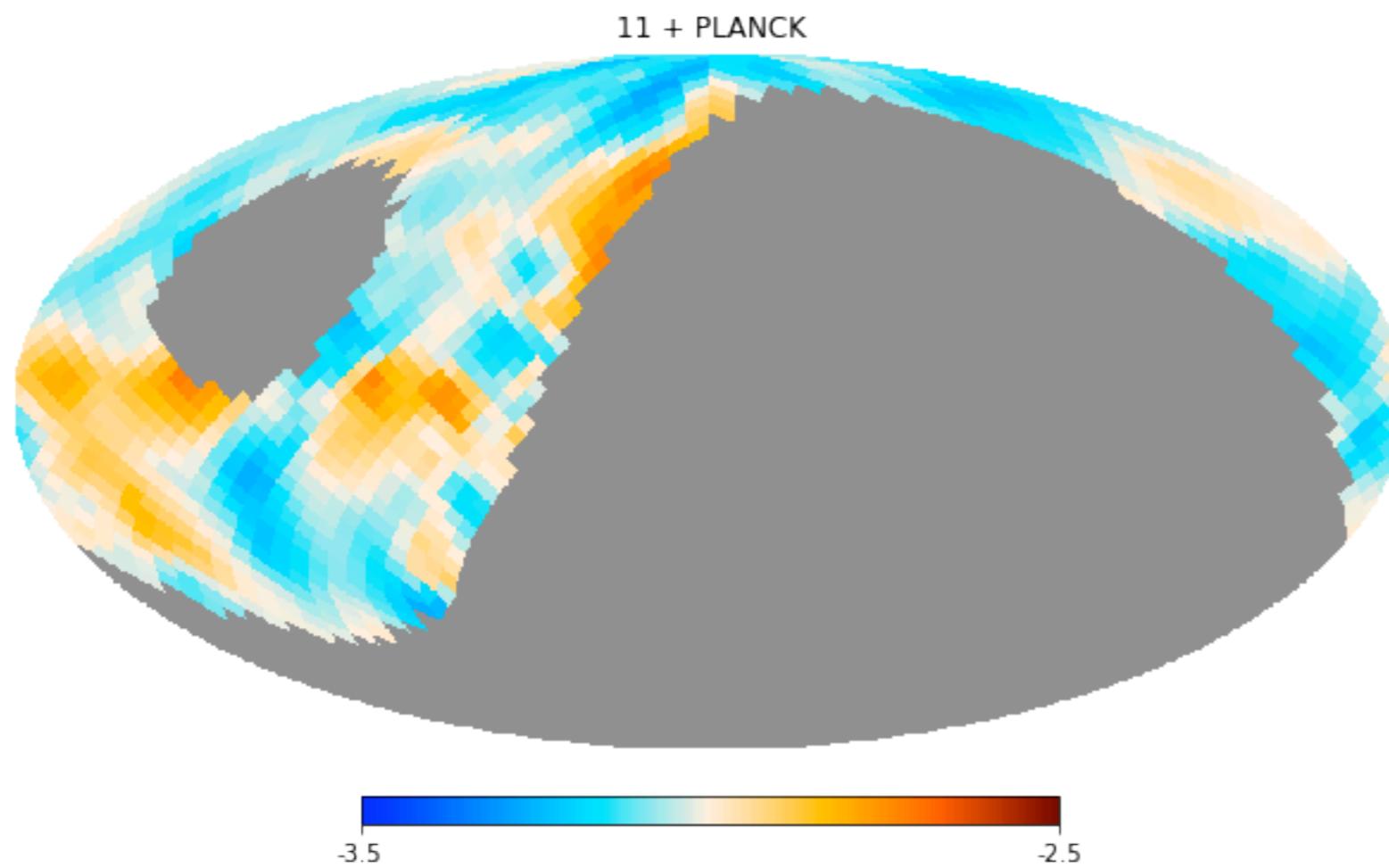
Given what we know with simulation the S/N of the data, we can know which areas we can trust.

Blue area values are highly dependent on the distribution of the training set.



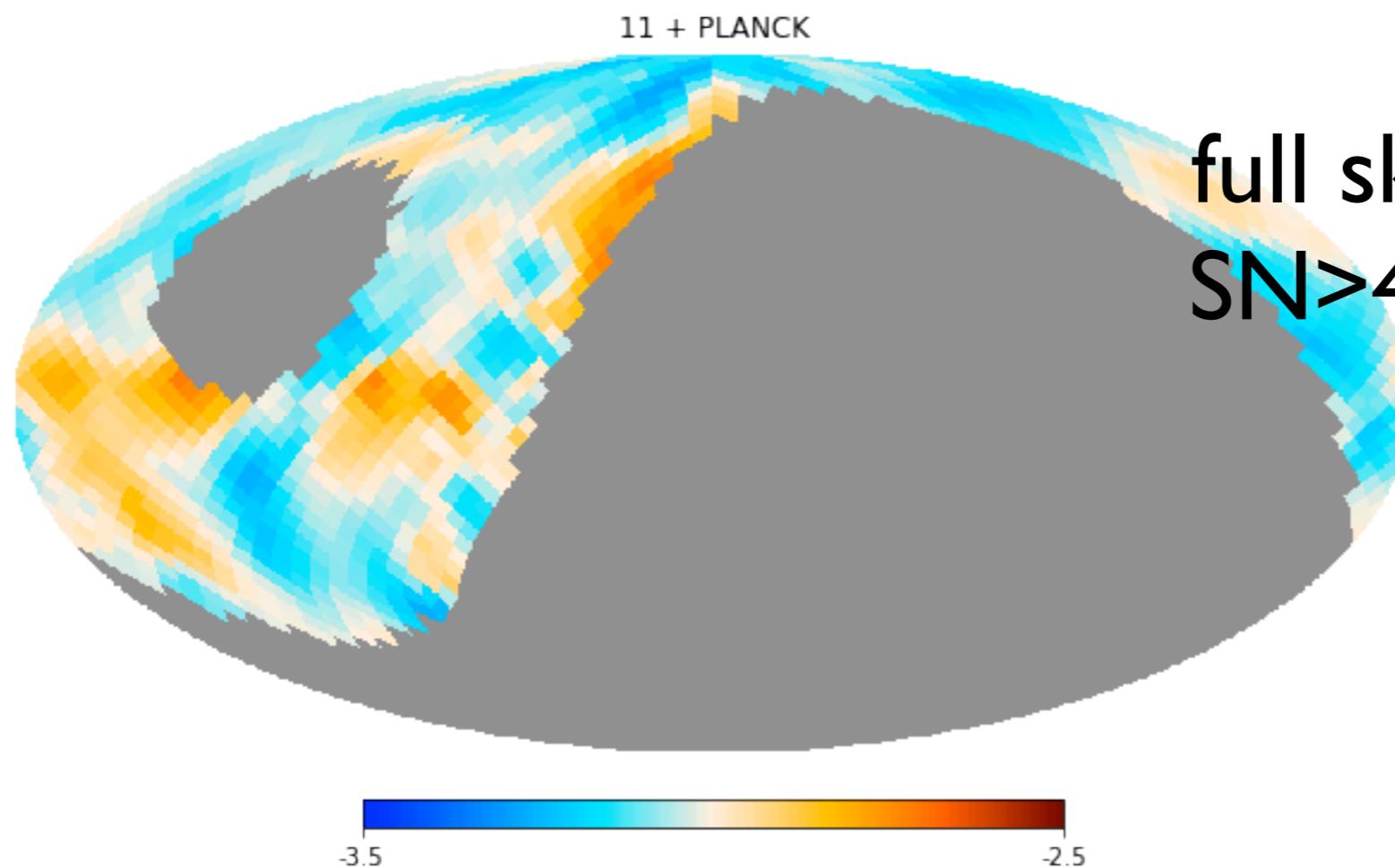
APPLICATION TO THE DATA. Synchrotron spectral index

PRELIMINARY

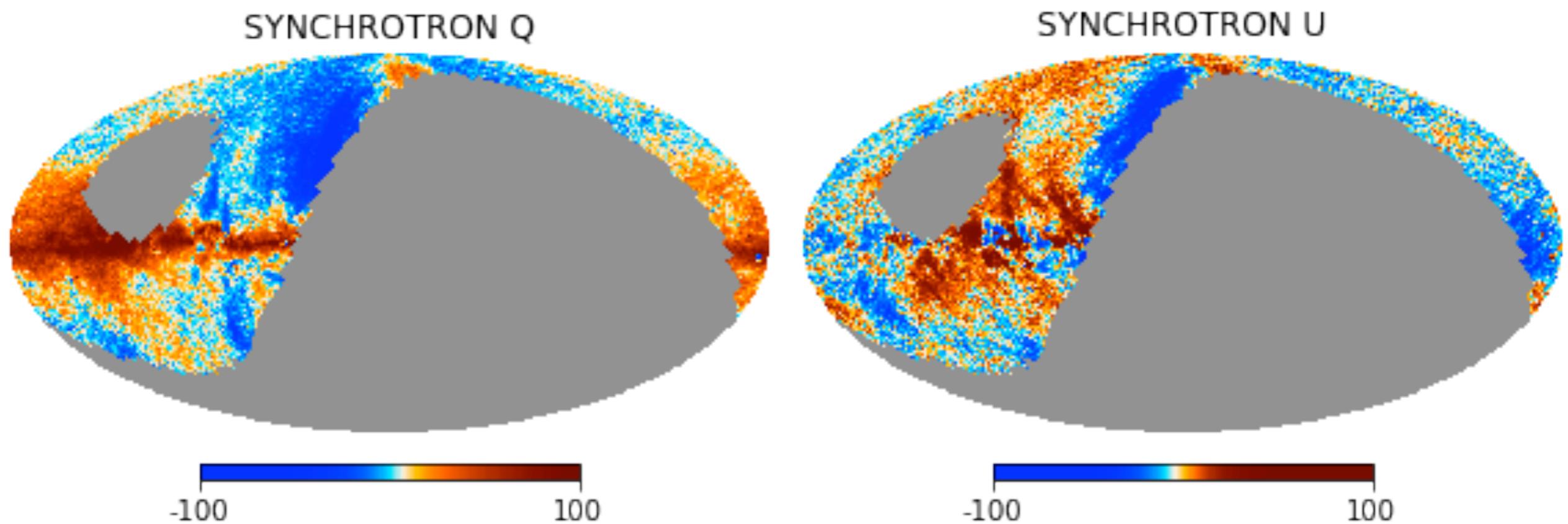


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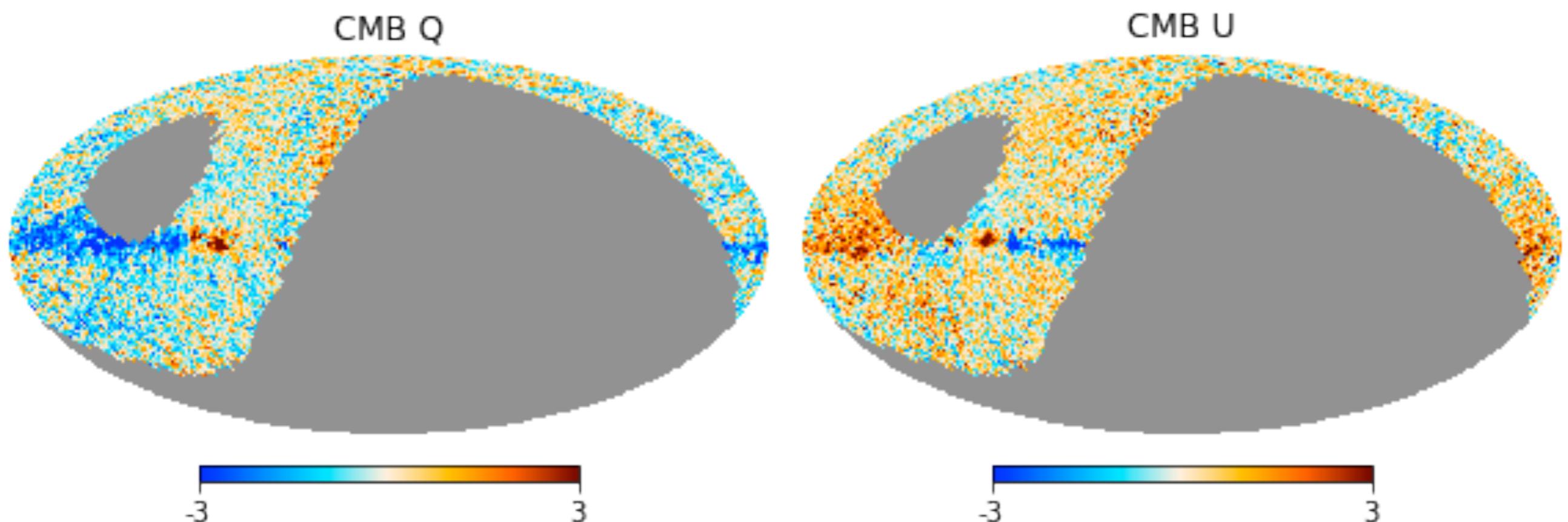


APPLICATION TO THE DATA. Synchrotron at 23GHz in uKRJ



PRELIMINARY

APPLICATION TO THE DATA. CMB

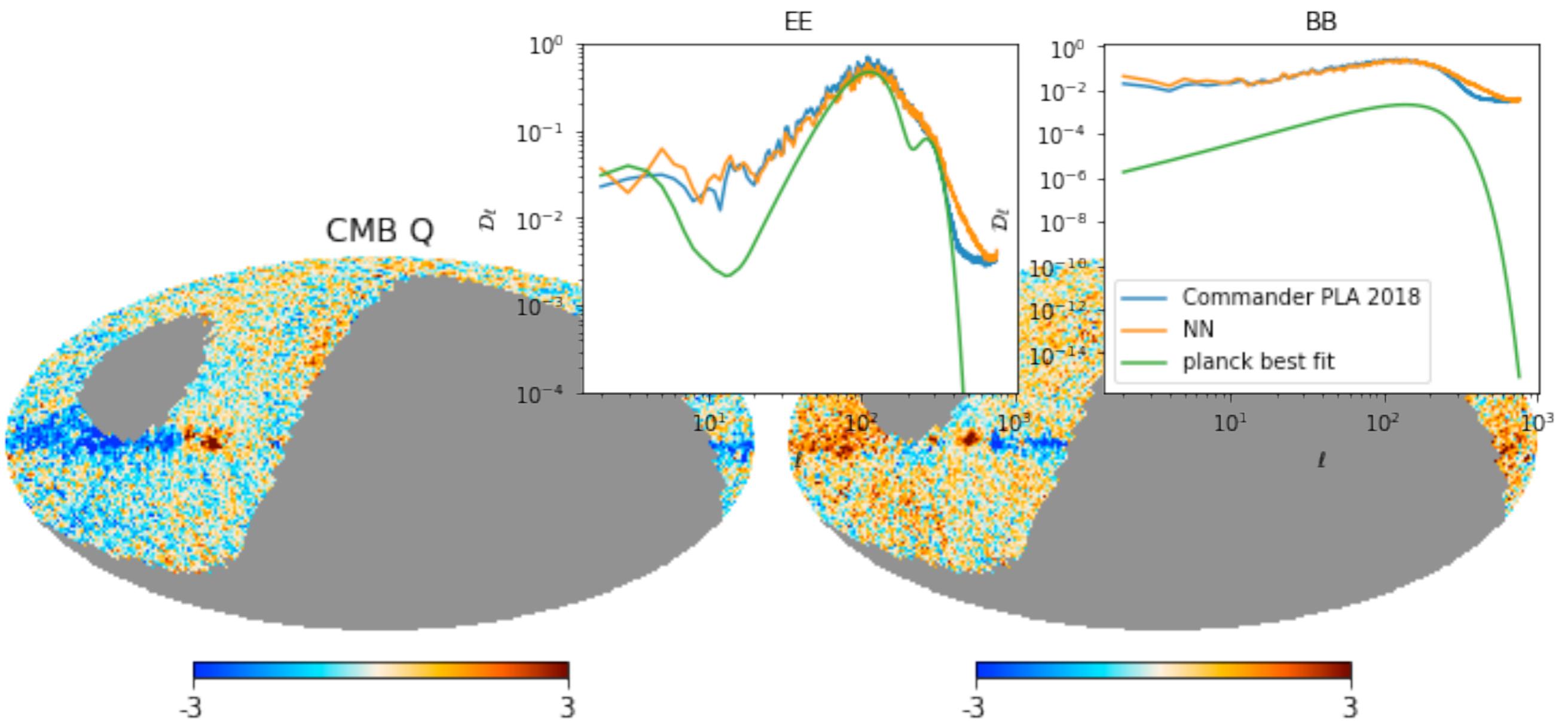


PRELIMINARY

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APPLICATION TO THE DATA. CMB

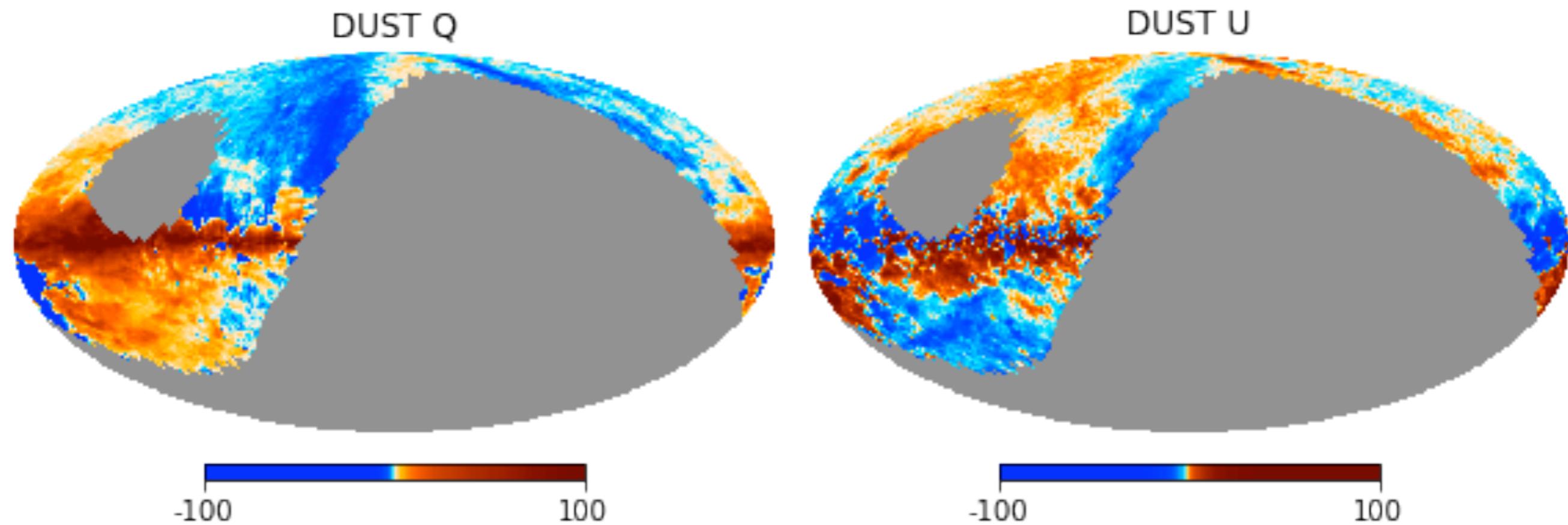


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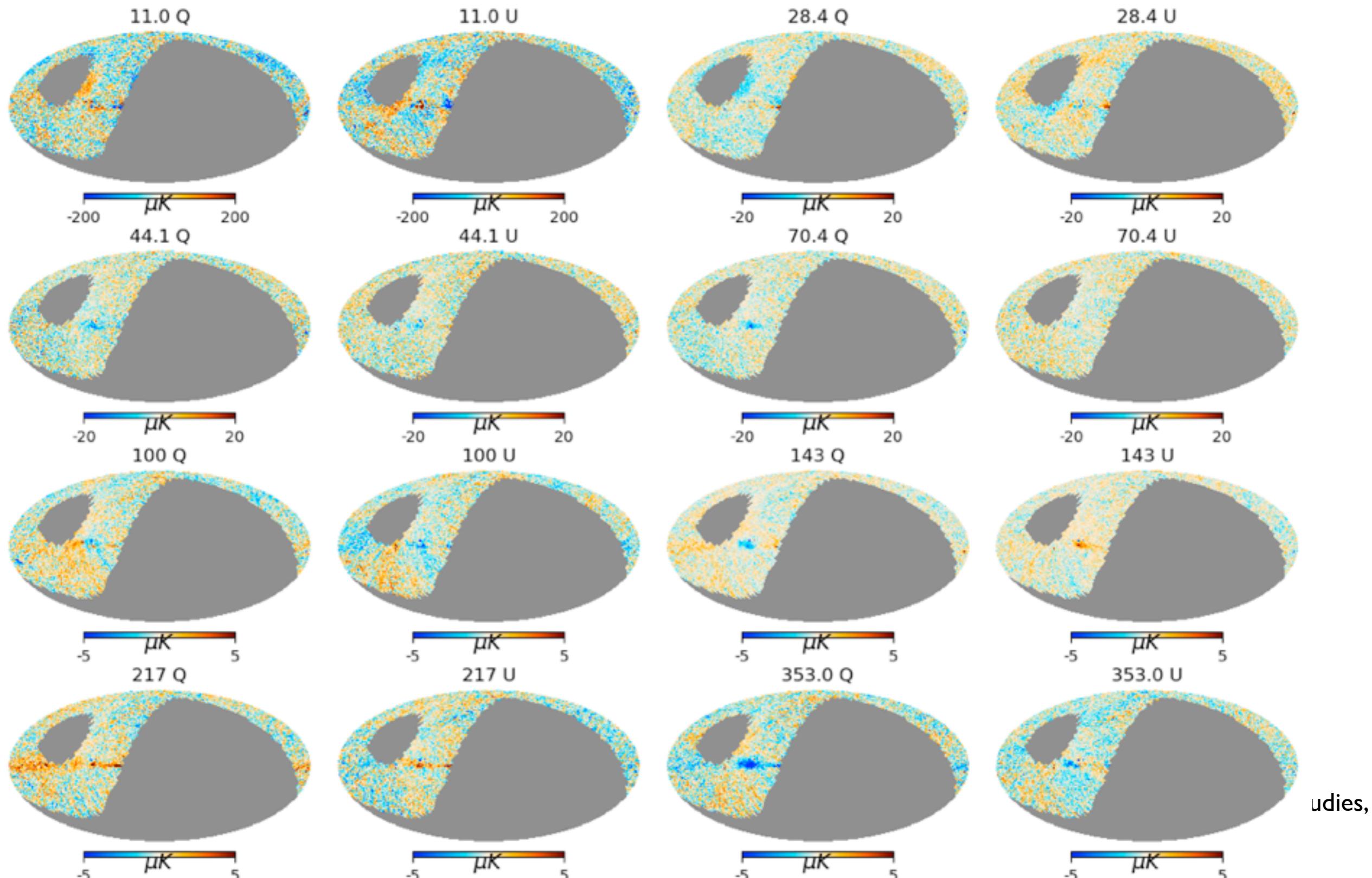
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APPLICATION TO THE DATA. **DUST at 353GHz** in uKRJ



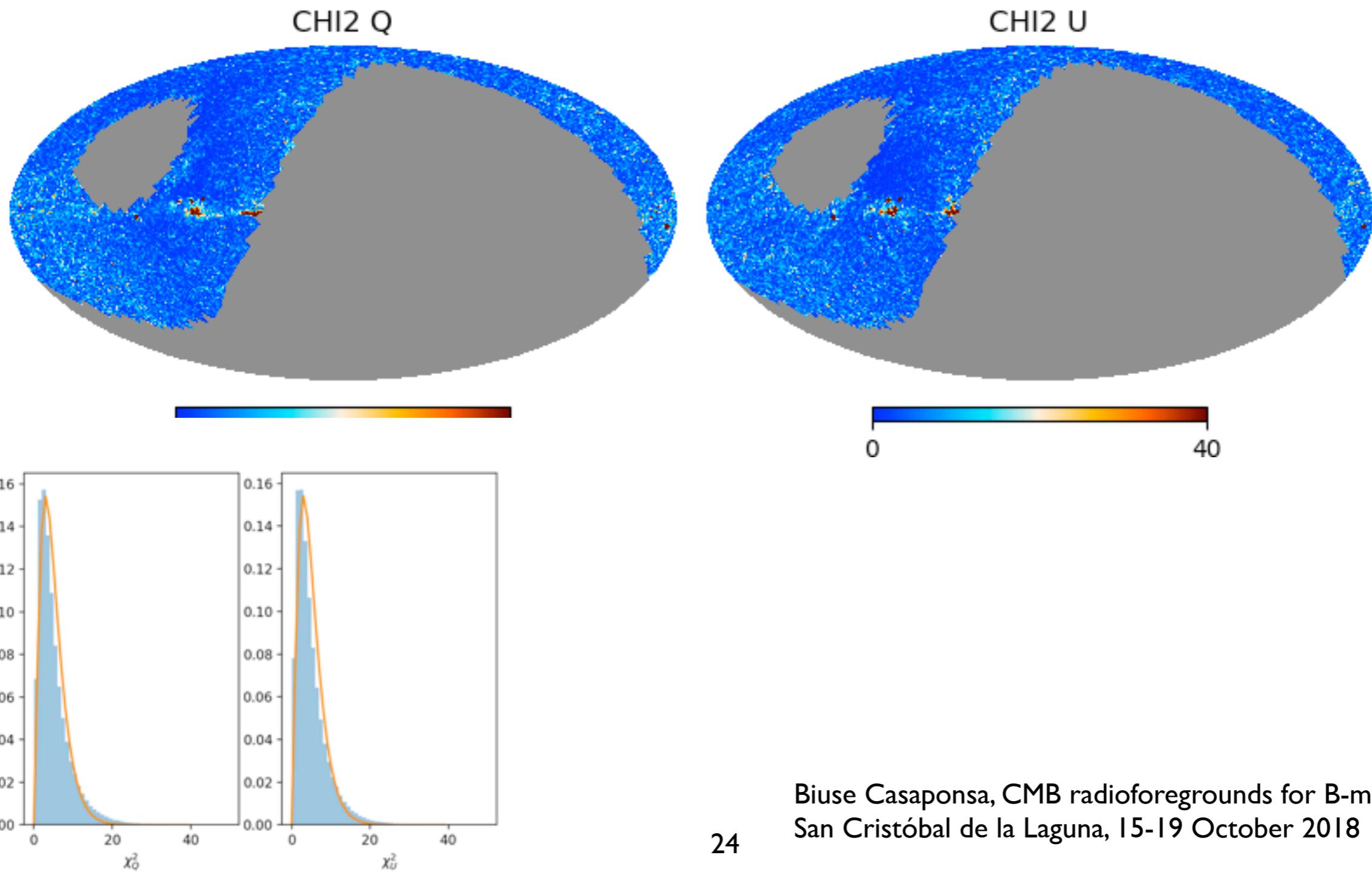
APPLICATION TO THE DATA. Residual maps



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APPLICATION TO THE DATA.

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Conclusions and ongoing work

- The NN are a useful tool to perform component separation. Main advantage: fast, Main handicap: new method, tests on simulations to fully understand it at low SN are still in place (Casaponsa et al. in preparation)
- MFI channels help to the reconstruction of the synchrotron, we need to reduce the noise for high latitudes spectral index estimation
- Several improvements of the method are in mind
 - work at native resolutions
 - use multi-resolution information
 - train with more realistic simulations (foreground correlations, bandpass, correlated noise,...)
- Include more low frequency data
- Temperature analyses ongoing
-

Thanks!