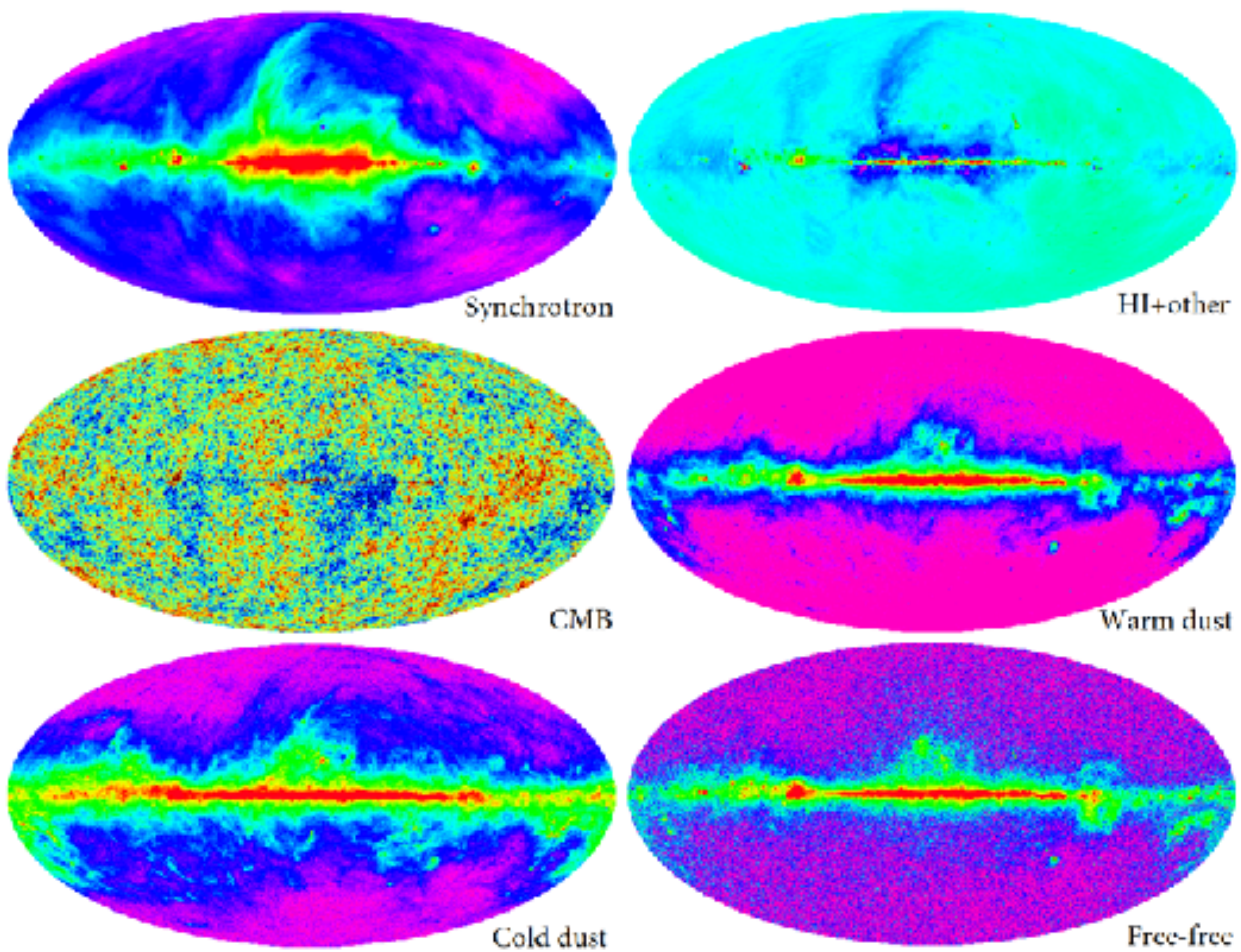
Data, Simulations, and Machine Learning for Foreground Modelling and Signal Extraction



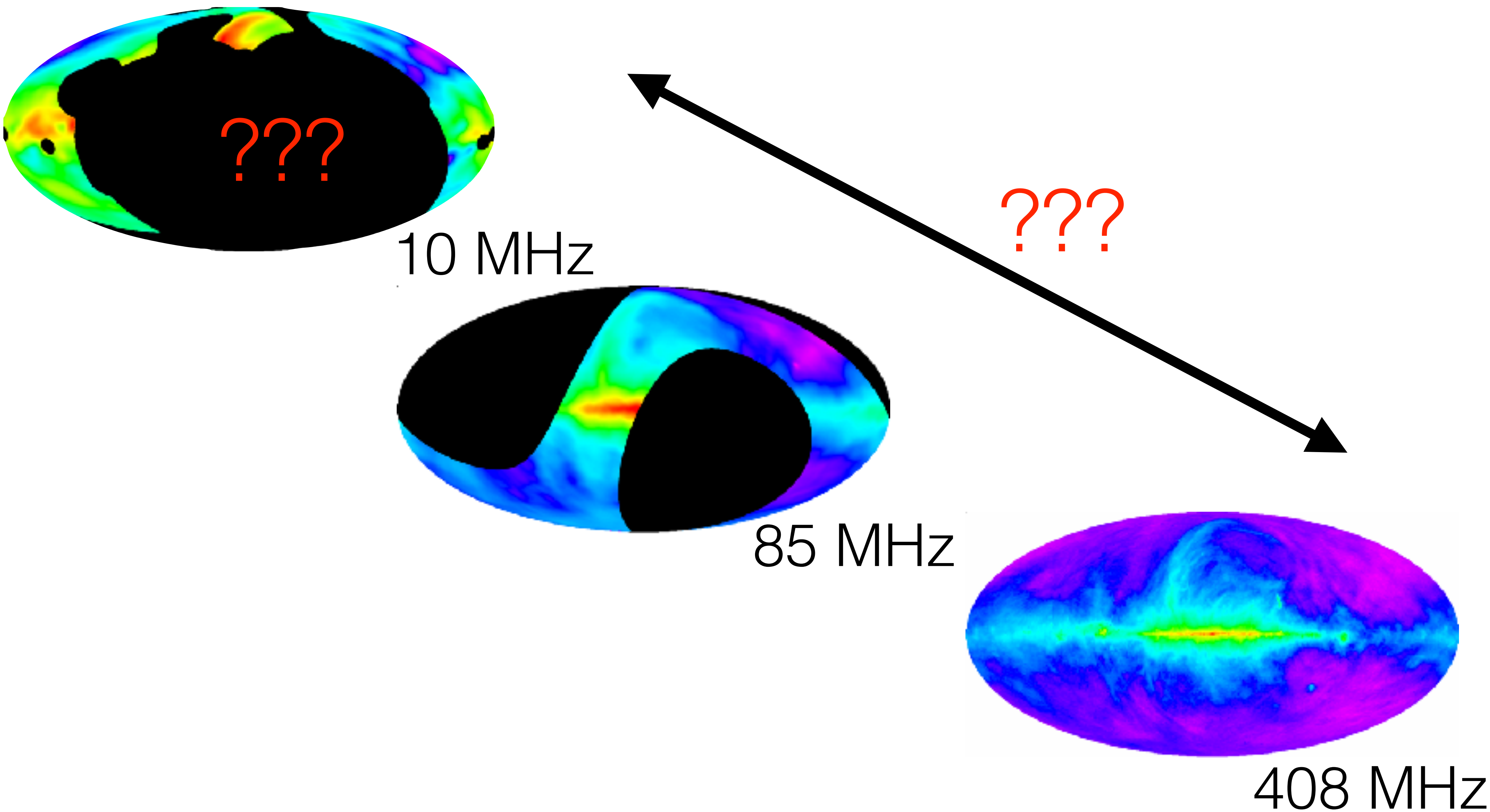
Adrian Liu, UC Berkeley/McGill

Foreground modelling

The extended Global Sky Model (eGSM) project

AL, UC Berkeley/McGill
Doyeon “Avery” Kim, UC Berkeley
Eric Switzer, NASA Goddard
Haoxuan “Jeff” Zheng, MIT/Intel

What does the sky look like in all directions at “all” frequencies?

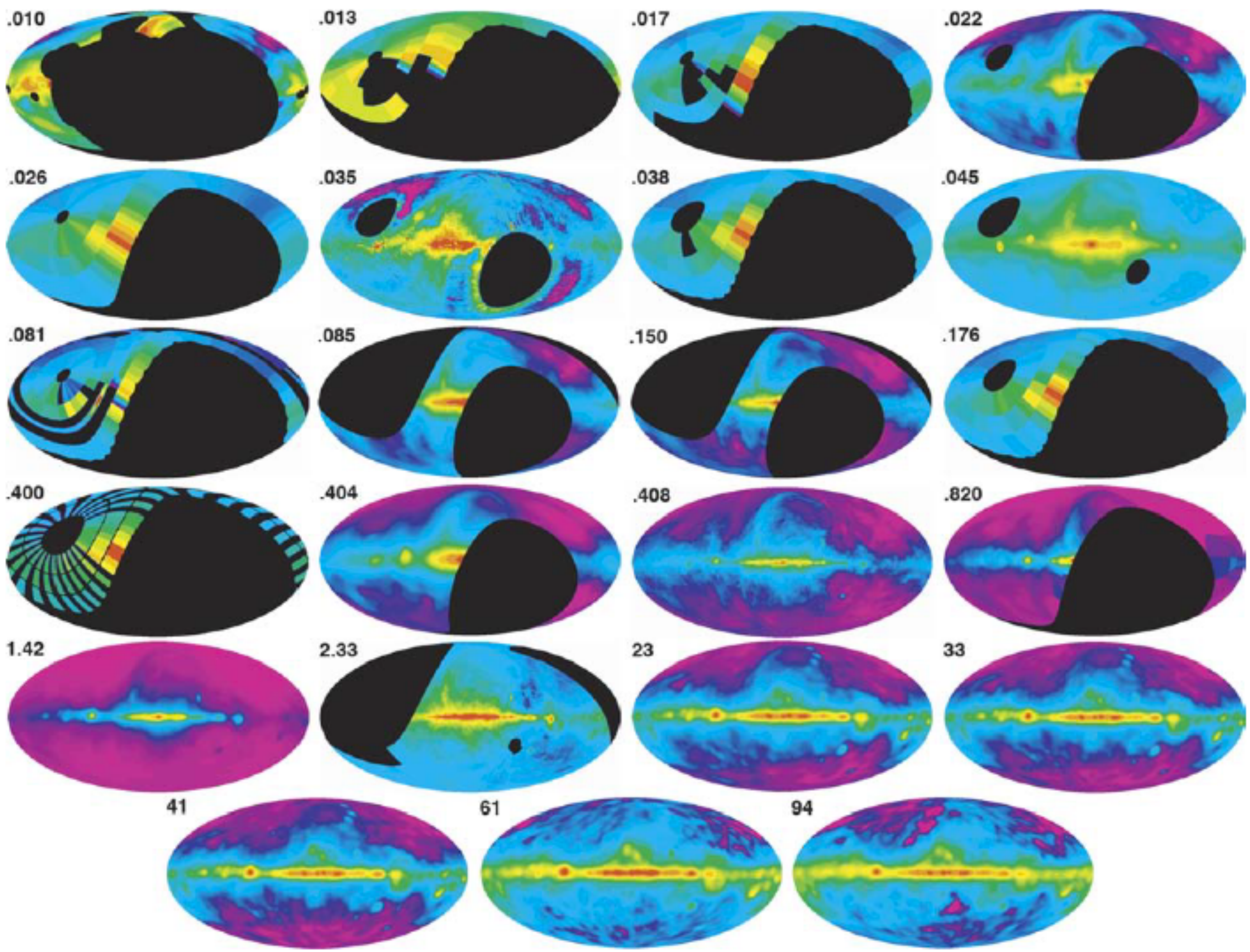


How does one model the sky?

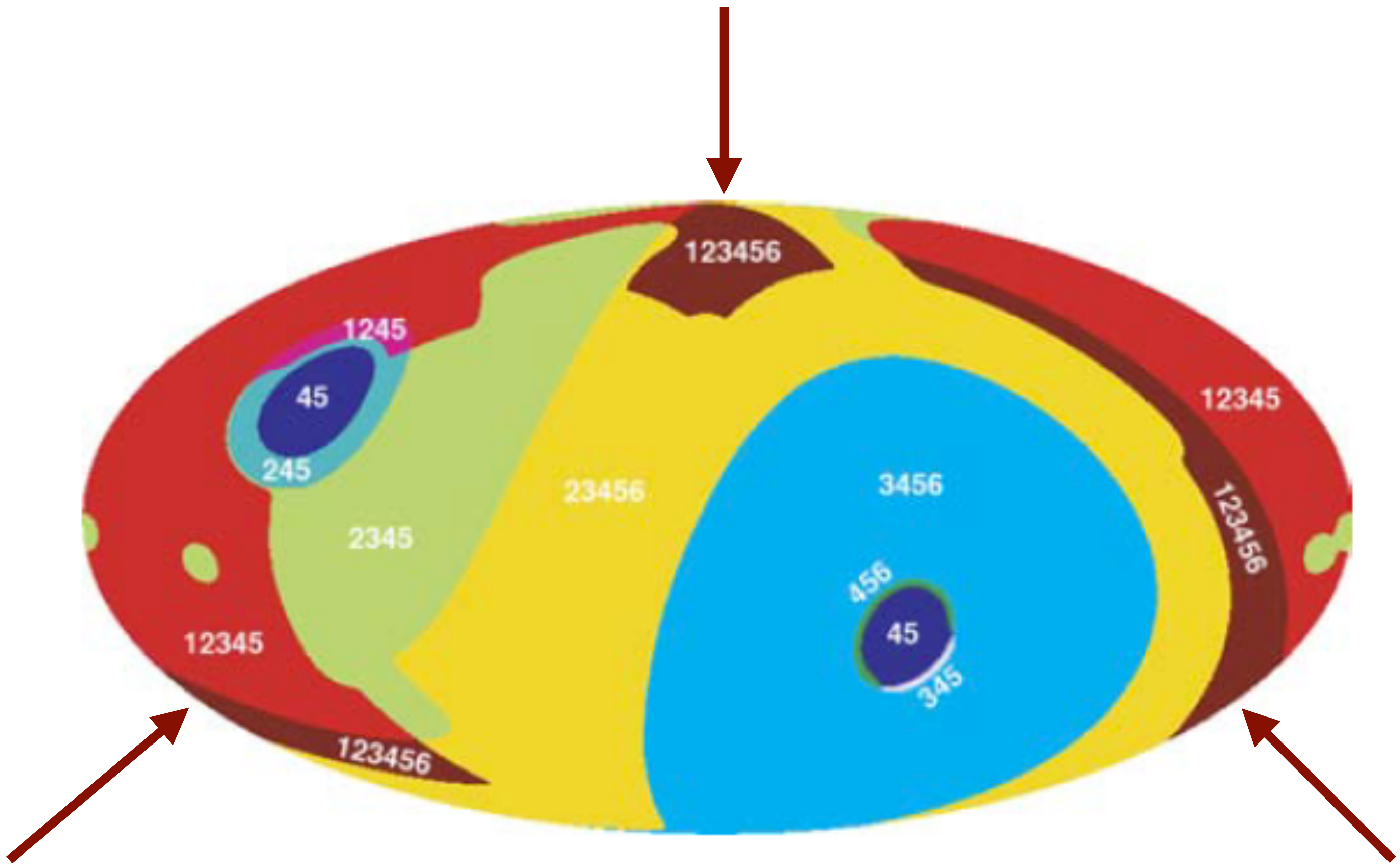
Global Sky Model

(v1: de Oliveira-Costa et al. 2008, MNRAS 388, 247)
(v2: Zheng… Kim, **AL**… et al. 2017, MNRAS 464, 3486)

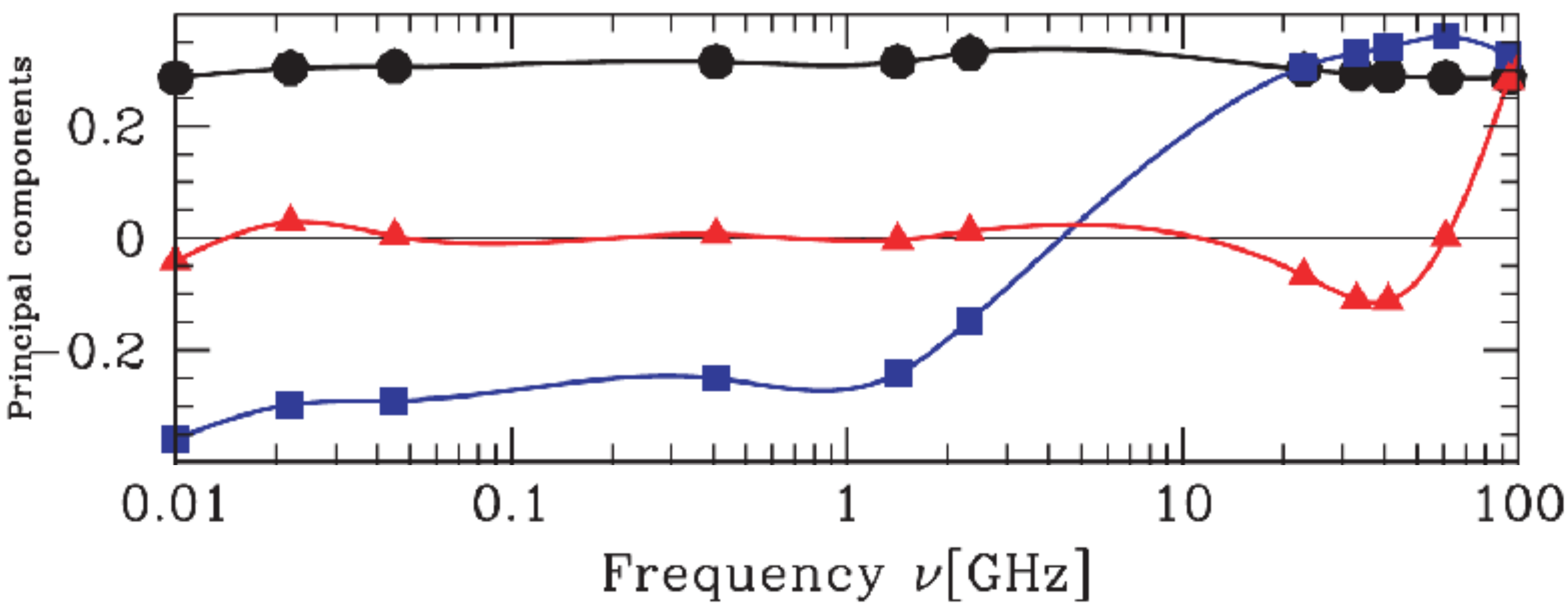
Take a wide selection of survey data…



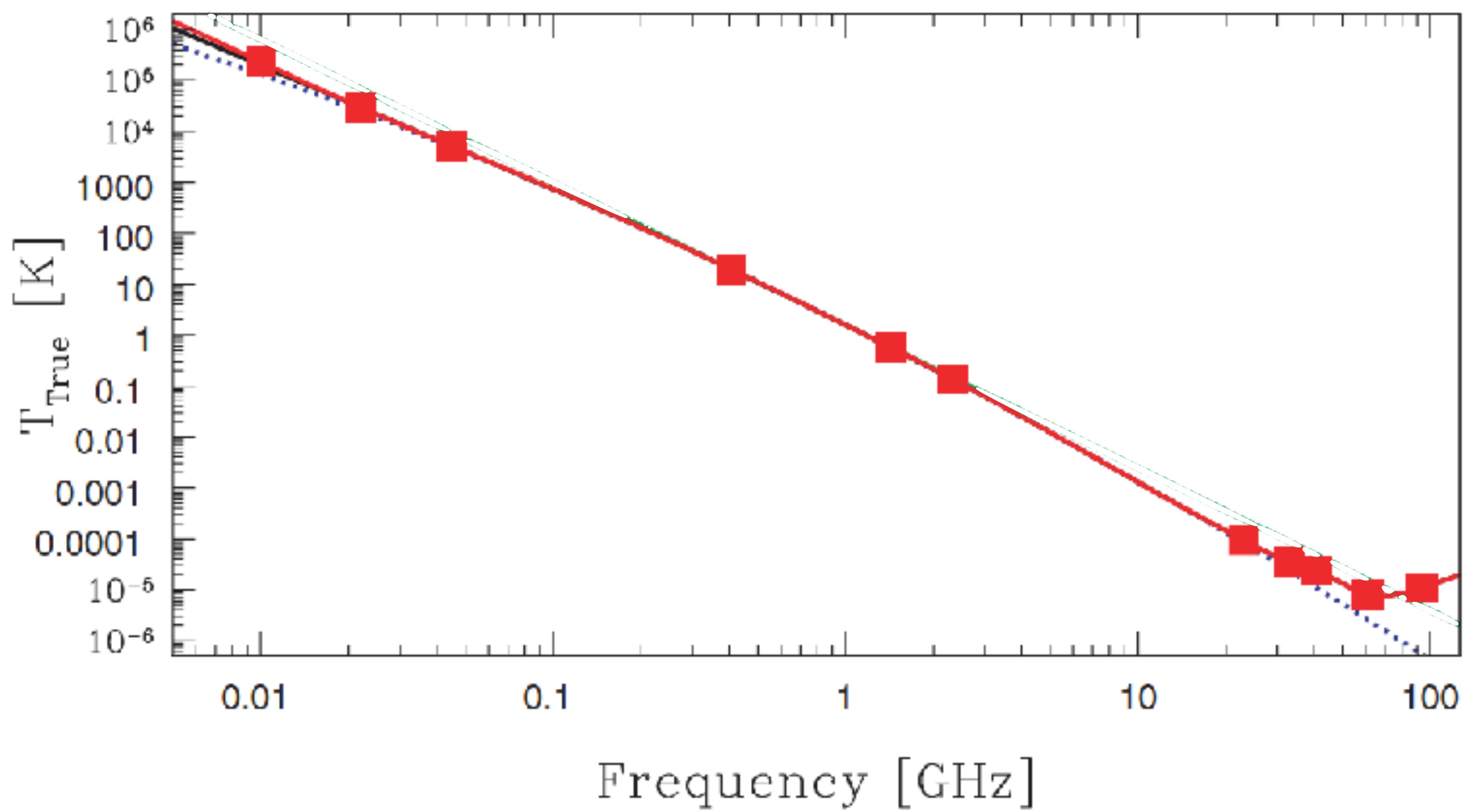
…identify common regions…



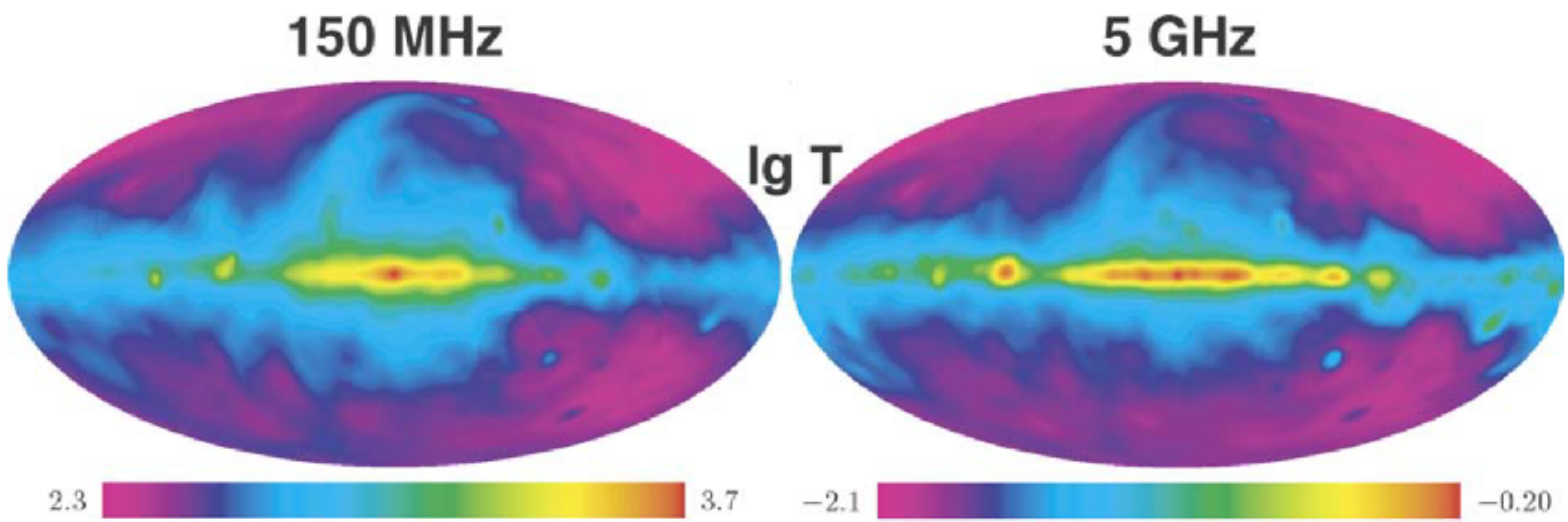
…which are then used to train three (v1) or six (v2) principal component spectral templates…



…that are used to iteratively fit for spectral and spatial information across the whole sky…



…and interpolation allows one to produce maps of the sky at "any" frequency



Global Sky Model v3

(Kim, **AL**, Switzer 2017, in prep.)

The old versions of the GSM
had no error bars!

Solution: construct models for the errors in the input data, and Monte Carlo to get final errors in our predictions

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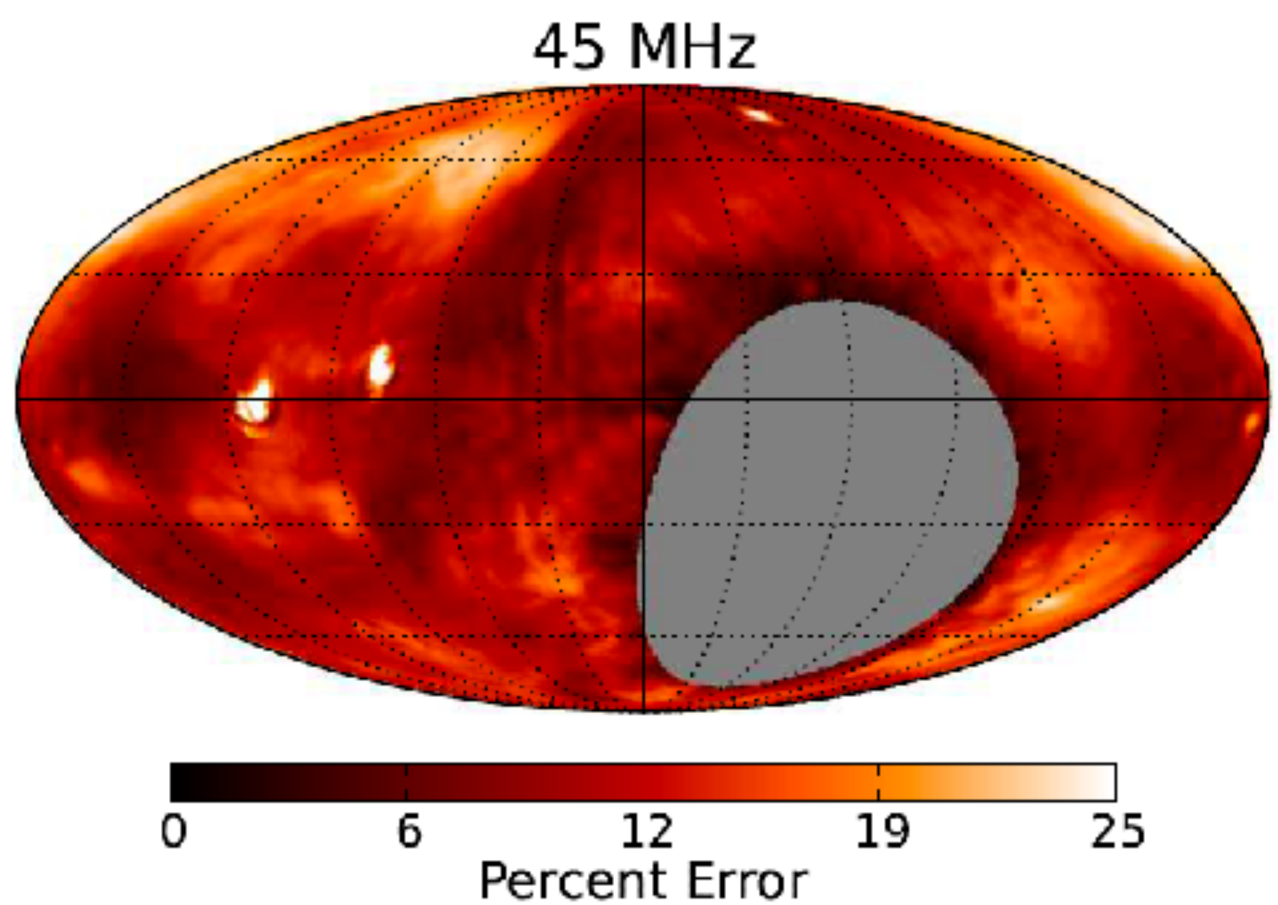
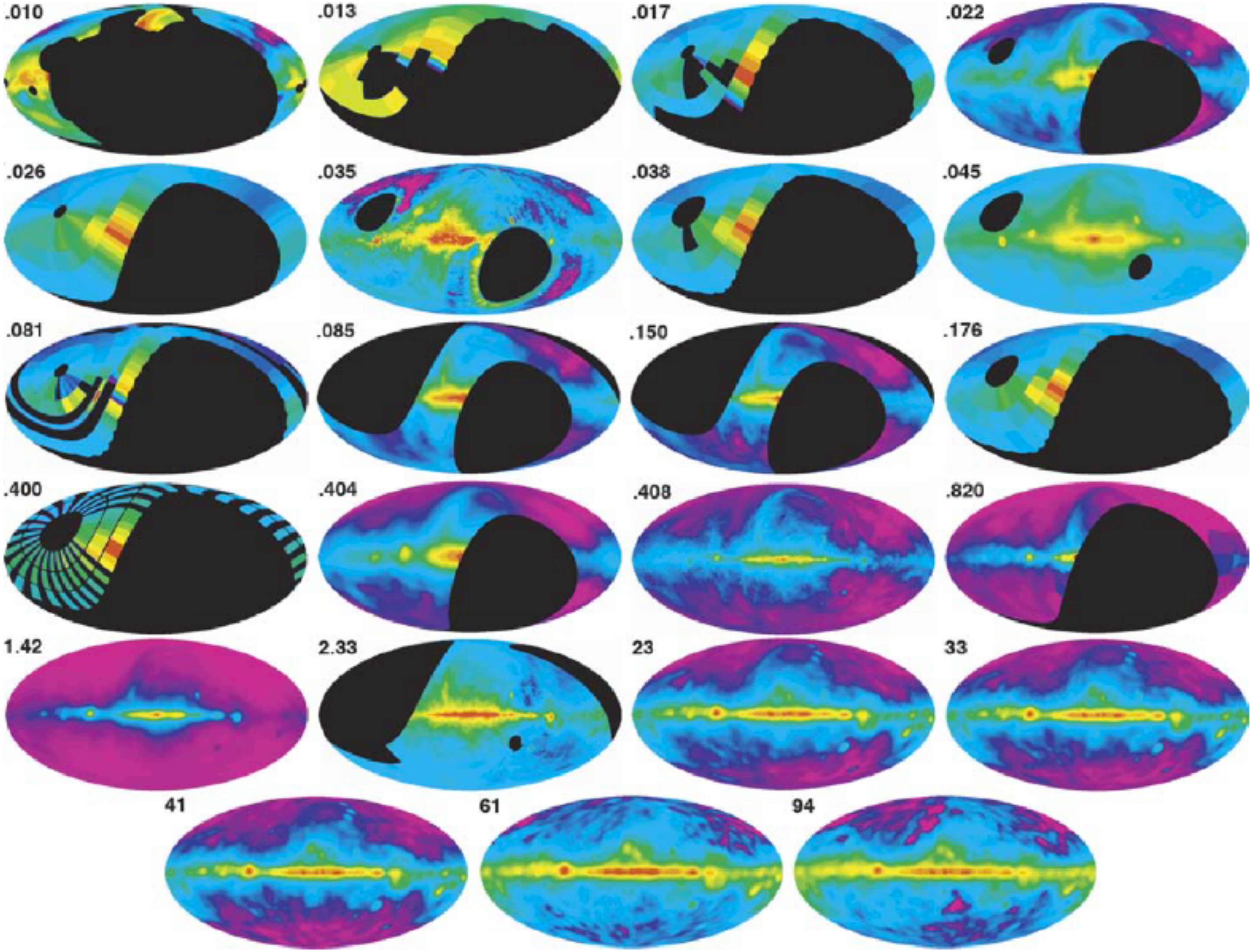
- Where available, use provided estimates of errors and covariances

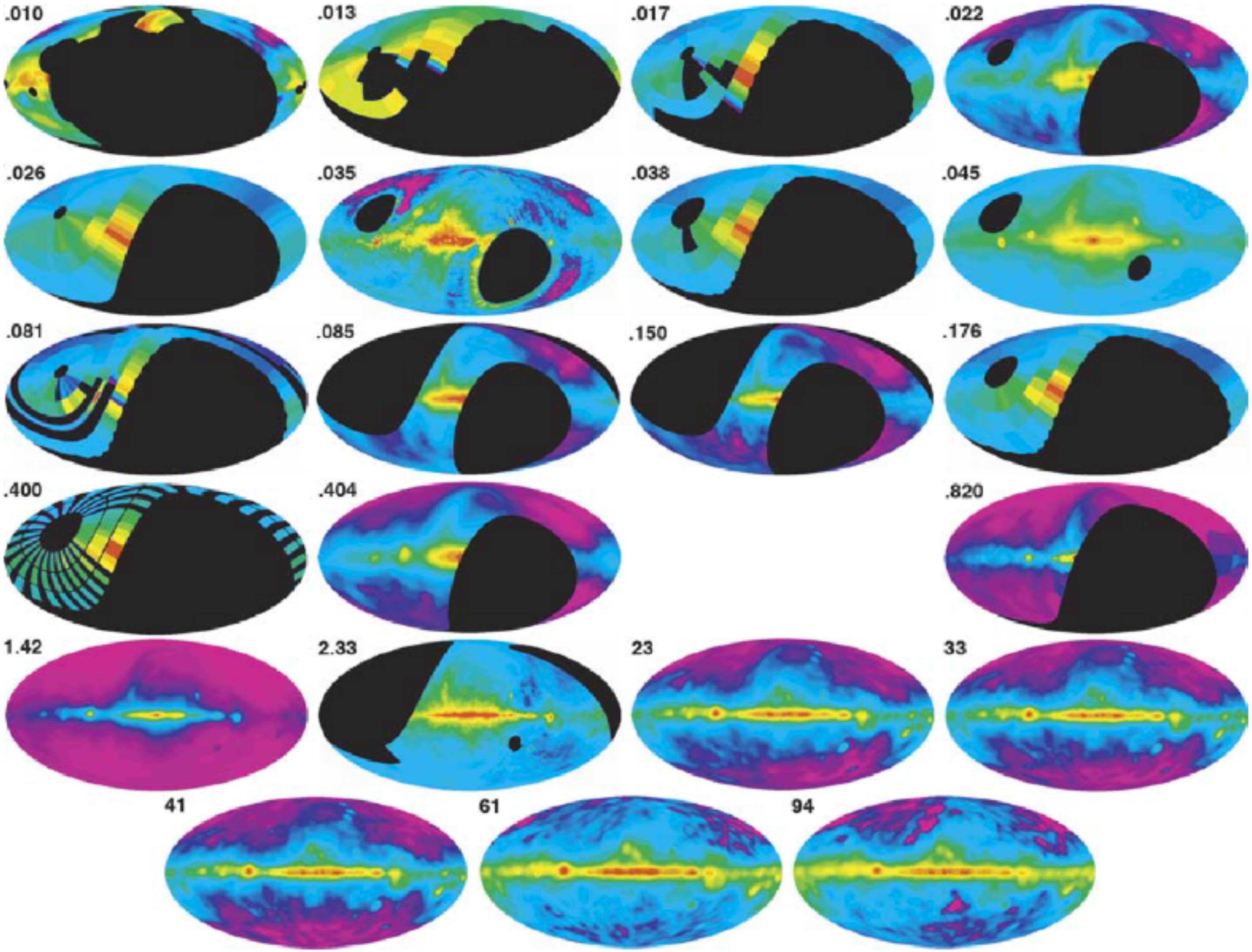


LWA 74 MHz, Dowell et al. (2017)

Solution: construct models for the errors in the input data, and Monte Carlo to get final errors in our predictions

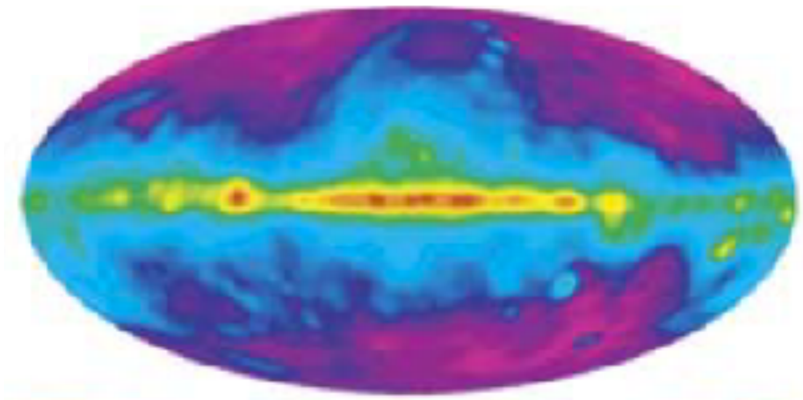
- Where available, use provided estimates of errors and covariances
- Errors in the model itself modelled empirically


.010
.013
.017
.022
.026
.035
.038
.045
.081
.085
.150
.176
.400
.404
.408
.820
1.42
2.33
23
33
41
61
94



Run model again with an input map removed, making a prediction for the missing map

Prediction **Data**



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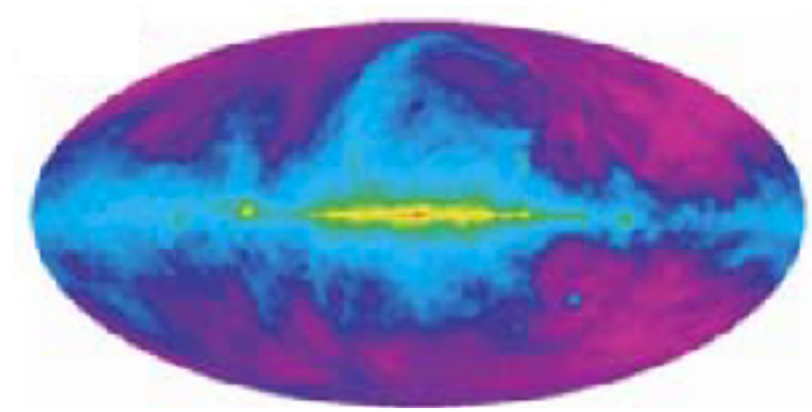
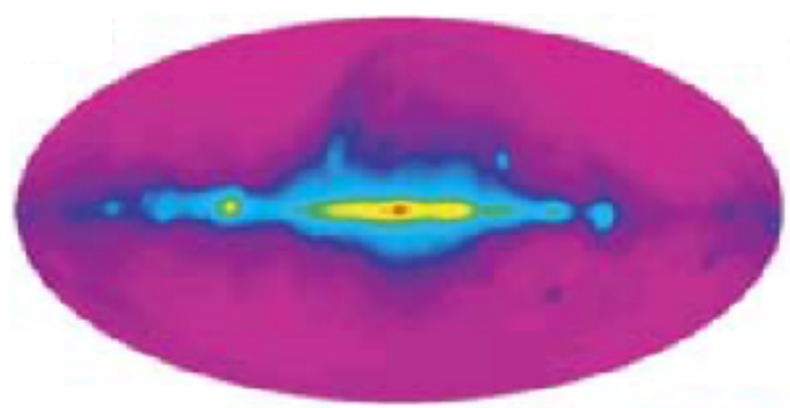


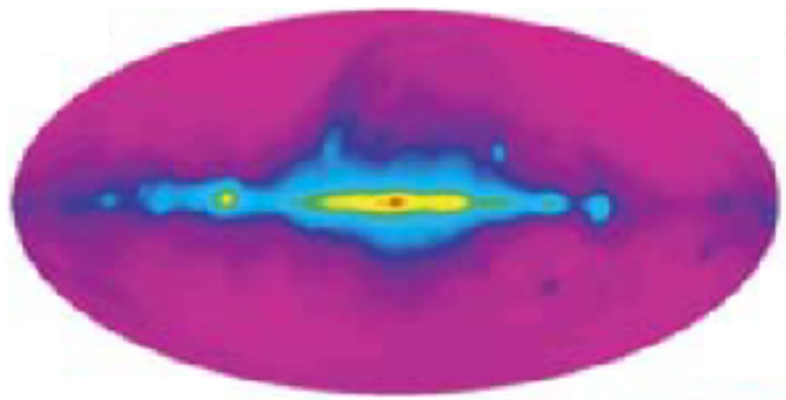
“Error”

=



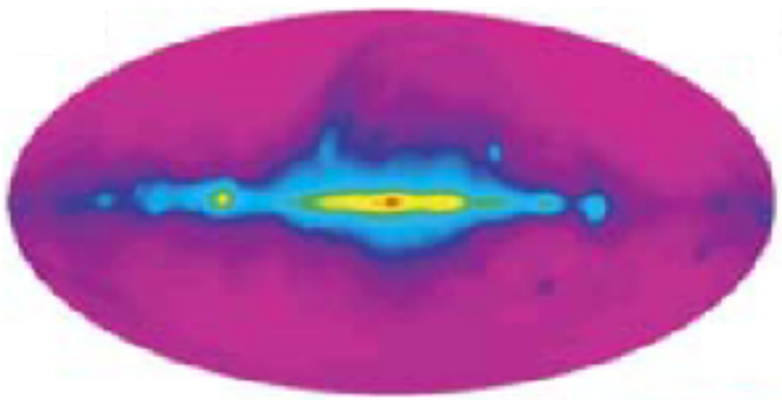
Subtract the new predicted map from the observed data

“Error”



Error model

“Error”

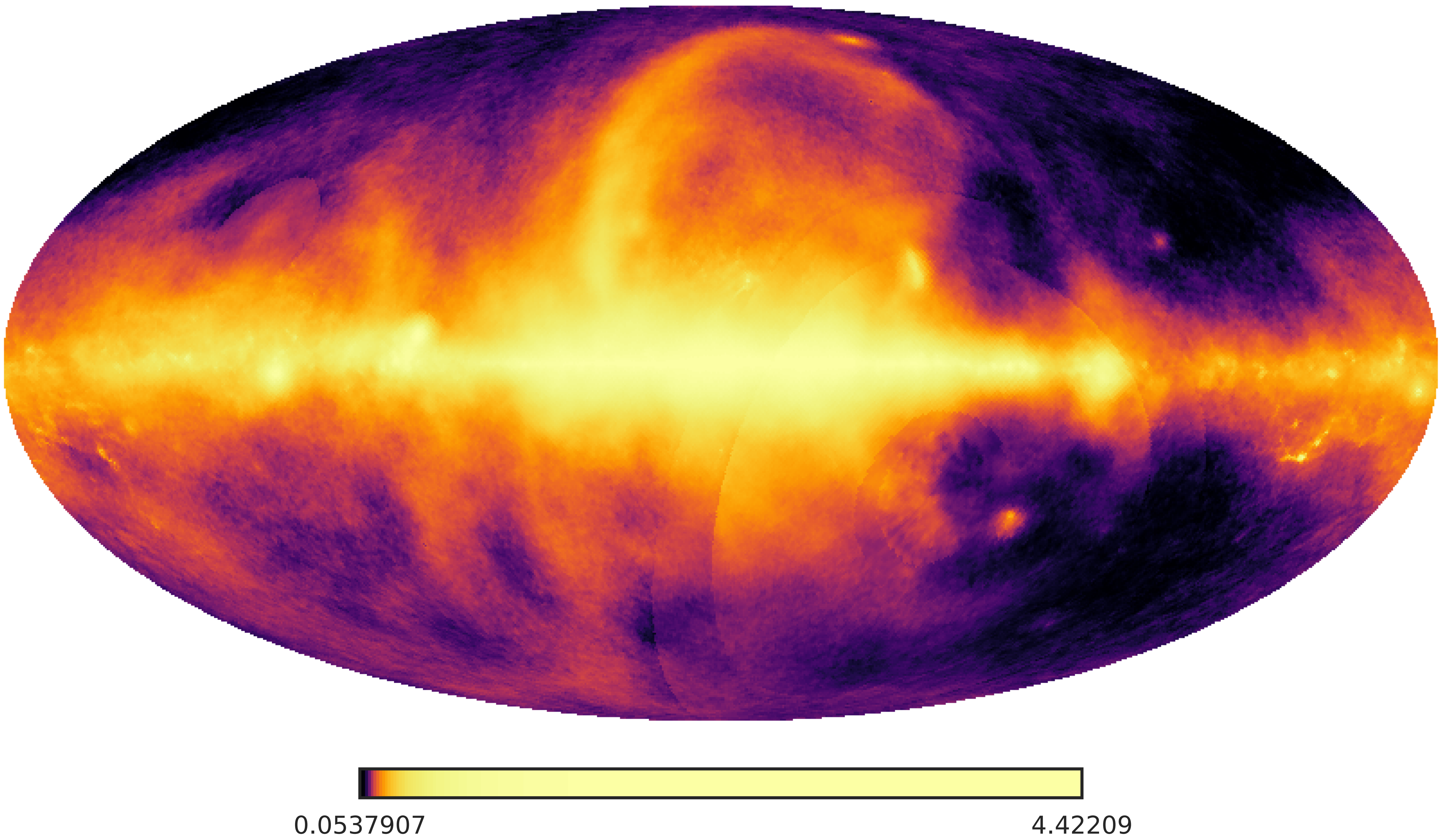


Ansatz for harmonic space: determined by C_l of whitened error map

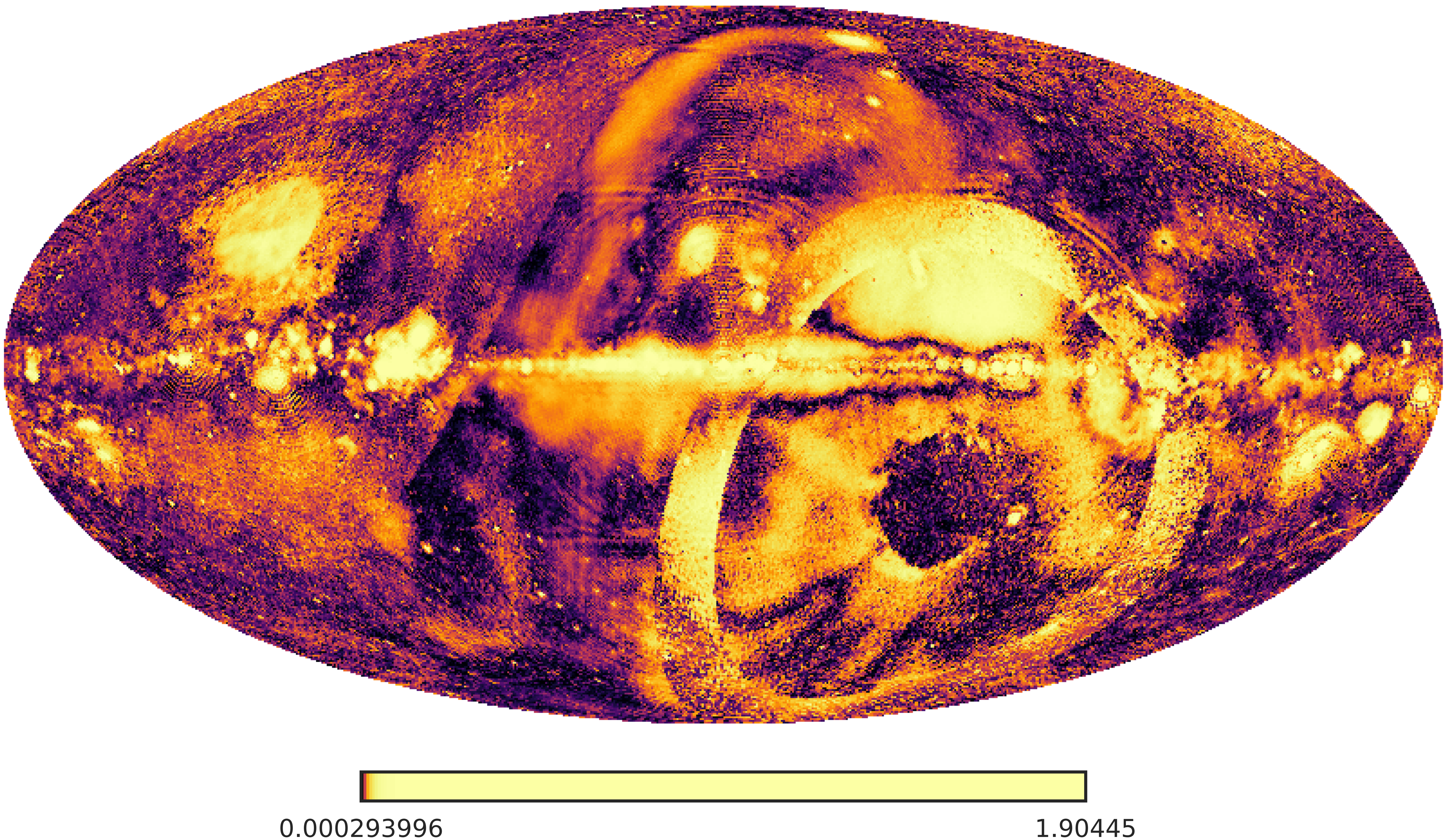
Ansatz for errors in image space: proportional to error map

Error model

An example 408 MHz prediction



Errors on the 408 MHz prediction

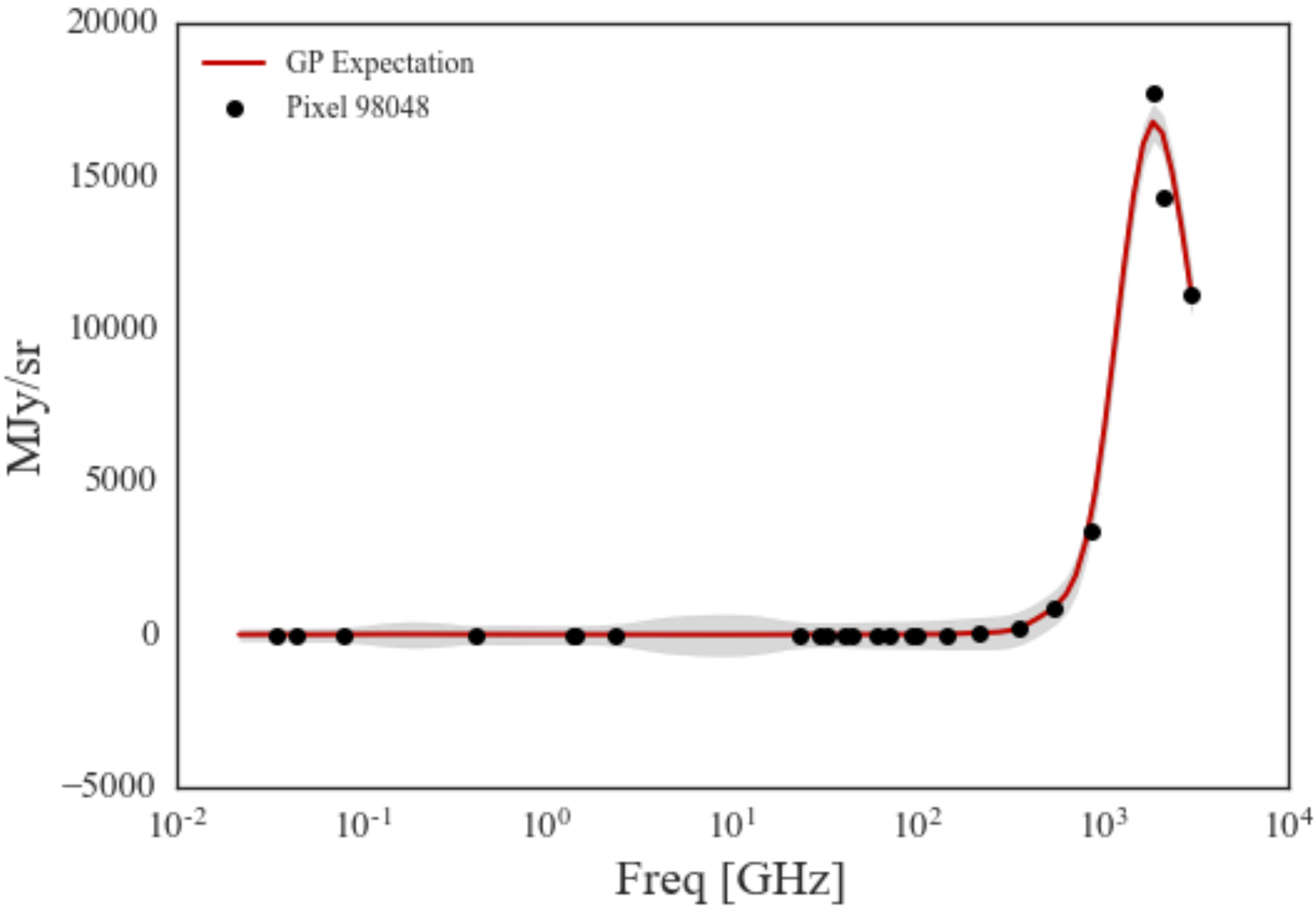


Solution: construct models for the errors in the input data, and Monte Carlo to get final errors in our predictions

- Where available, use provided estimates of errors and covariances

- Errors in the model itself modelled empirically

- Interpolation errors accounted for using Gaussian Process regression.



GP Expectation
Pixel 98048
20000
15000
10000
5000
0
−5000
MJy/sr
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}
10^{4}
Freq [GHz]

Lots more coming soon to a Github repo near you!

- Position-dependent number of components.
- Error bars in output maps.
- Framework for incorporating monopole measurements.
- Inclusion of new map data.

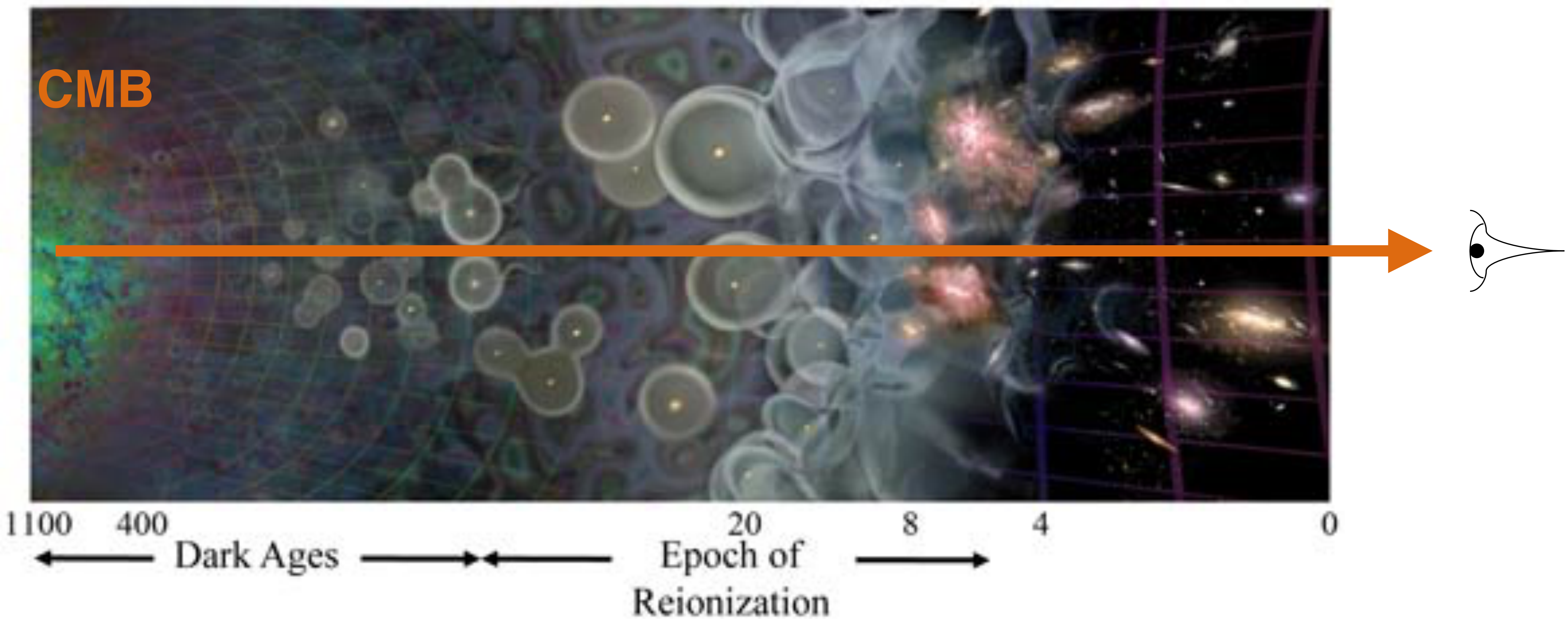
Lots more coming soon to a Github repo near you!

- Position-dependent number of components.

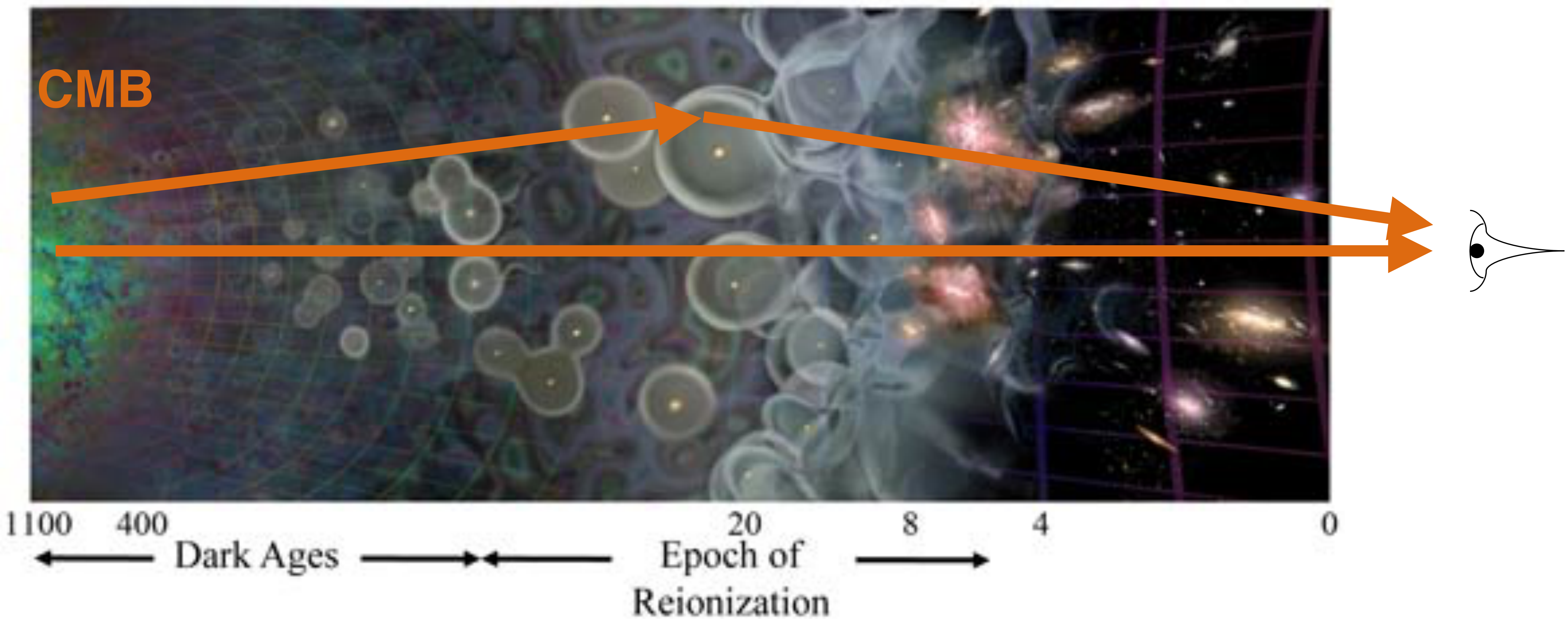
End goal: a publicly hosted, self-updating, best-guess model of the sky

Signal extraction using machine learning

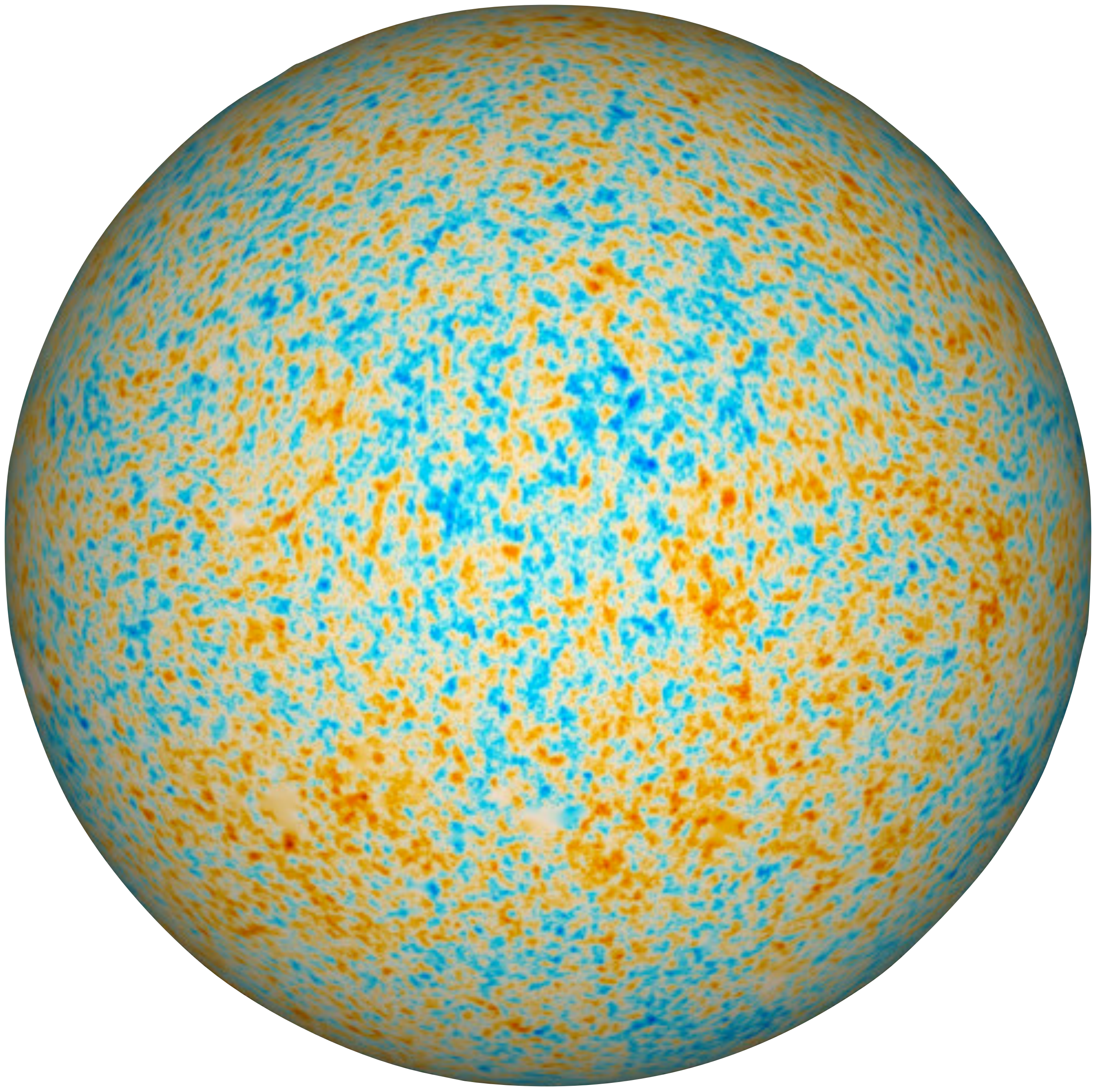
Reionization is a nuisance for CMB measurements

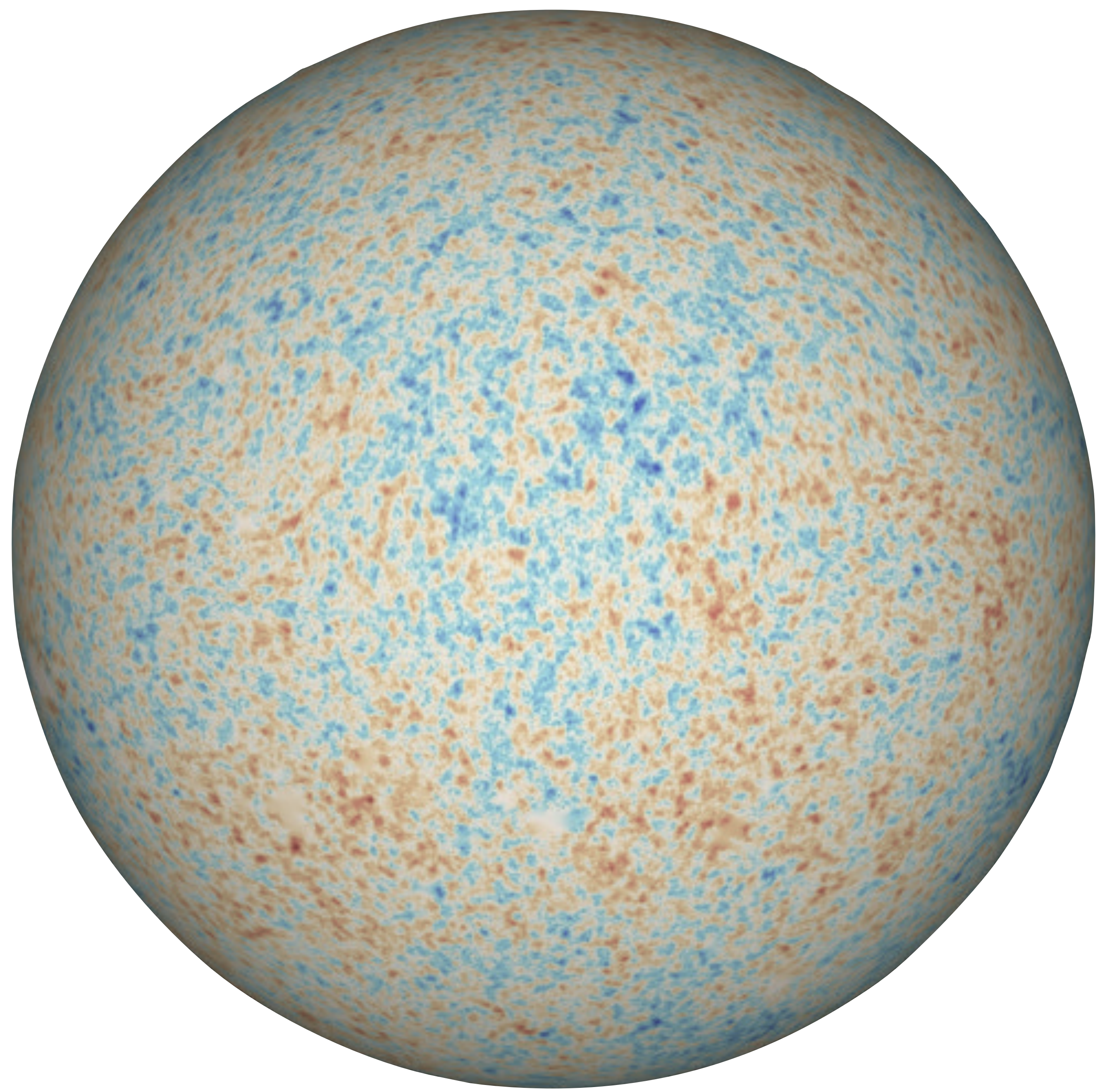


Reionization is a nuisance for CMB measurements



Extra optical depth parameter: $\tau \propto \int \langle x_i \rho_b \rangle dz$



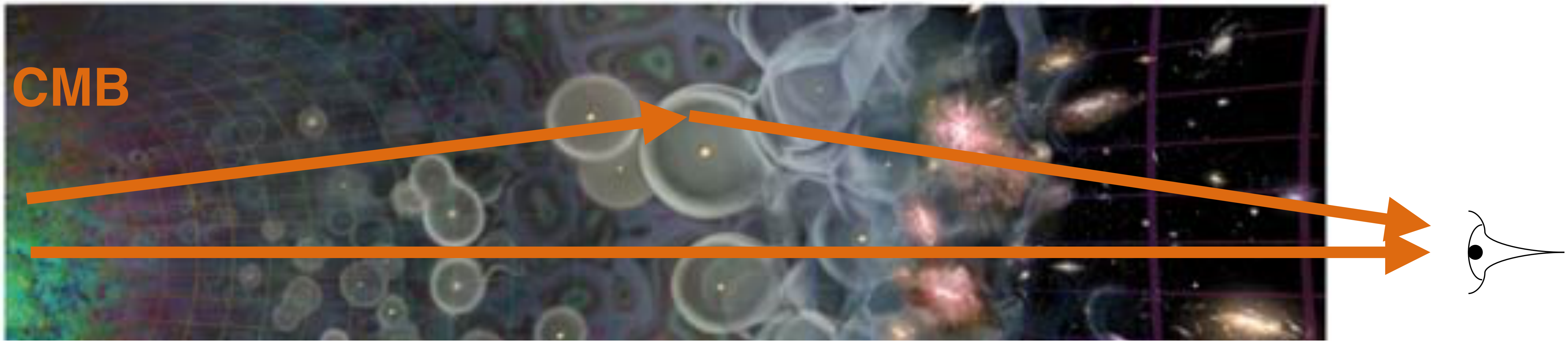


Scattering → Reduces amplitude of density fluctuations

- Early reionization (higher optical depth) + Large primordial fluctuations A_s

VS

- Late reionization (lower optical depth) + Small primordial fluctuations A_s

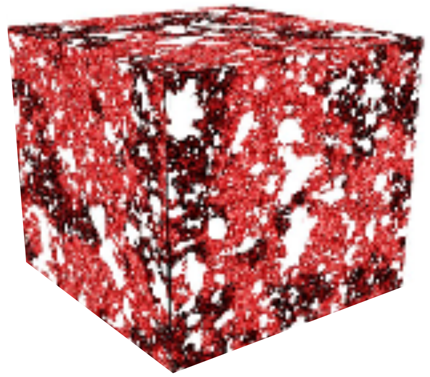


- Early reionization (higher optical depth)
  + Large primordial fluctuations A_s

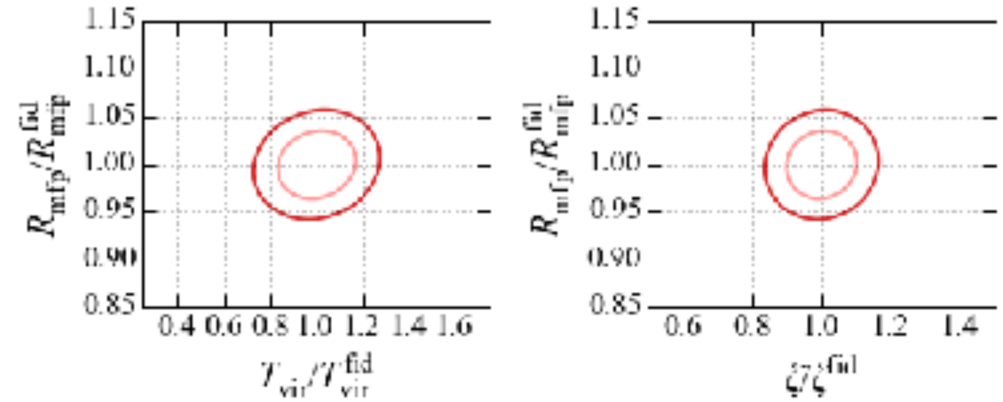
vs

- Late reionization (lower optical depth)
  + Small primordial fluctuations A_s

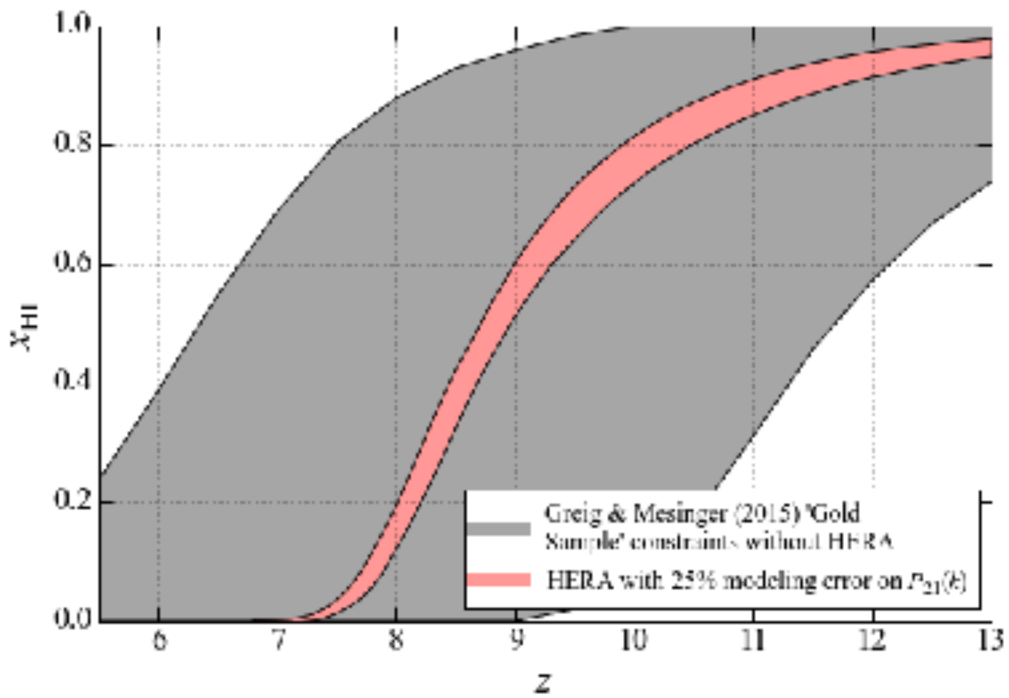
Understanding reionization (especially the CMB optical depth) can improve constraints on other cosmological parameters



Observations



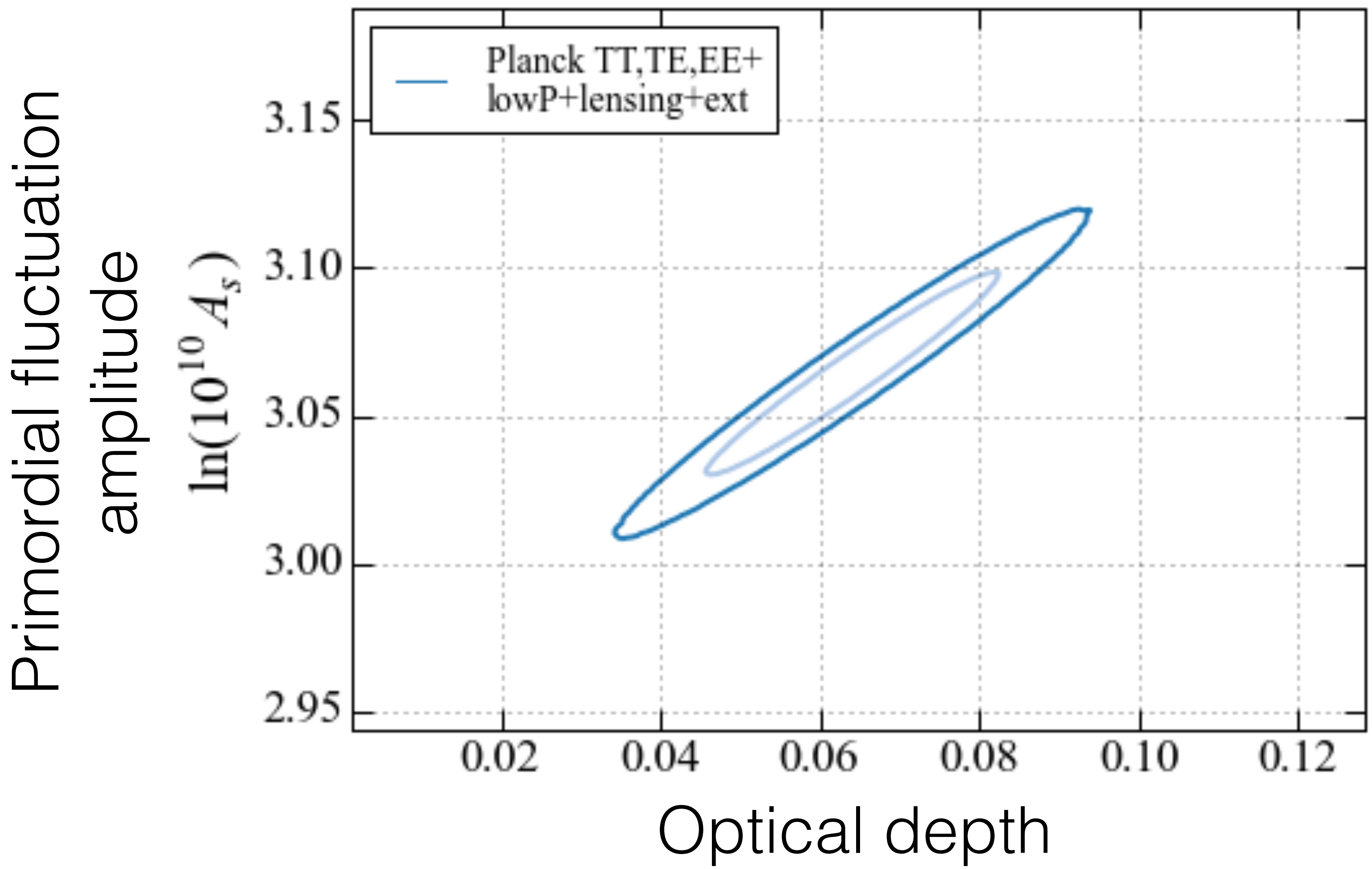
Model parameters
via power spectrum



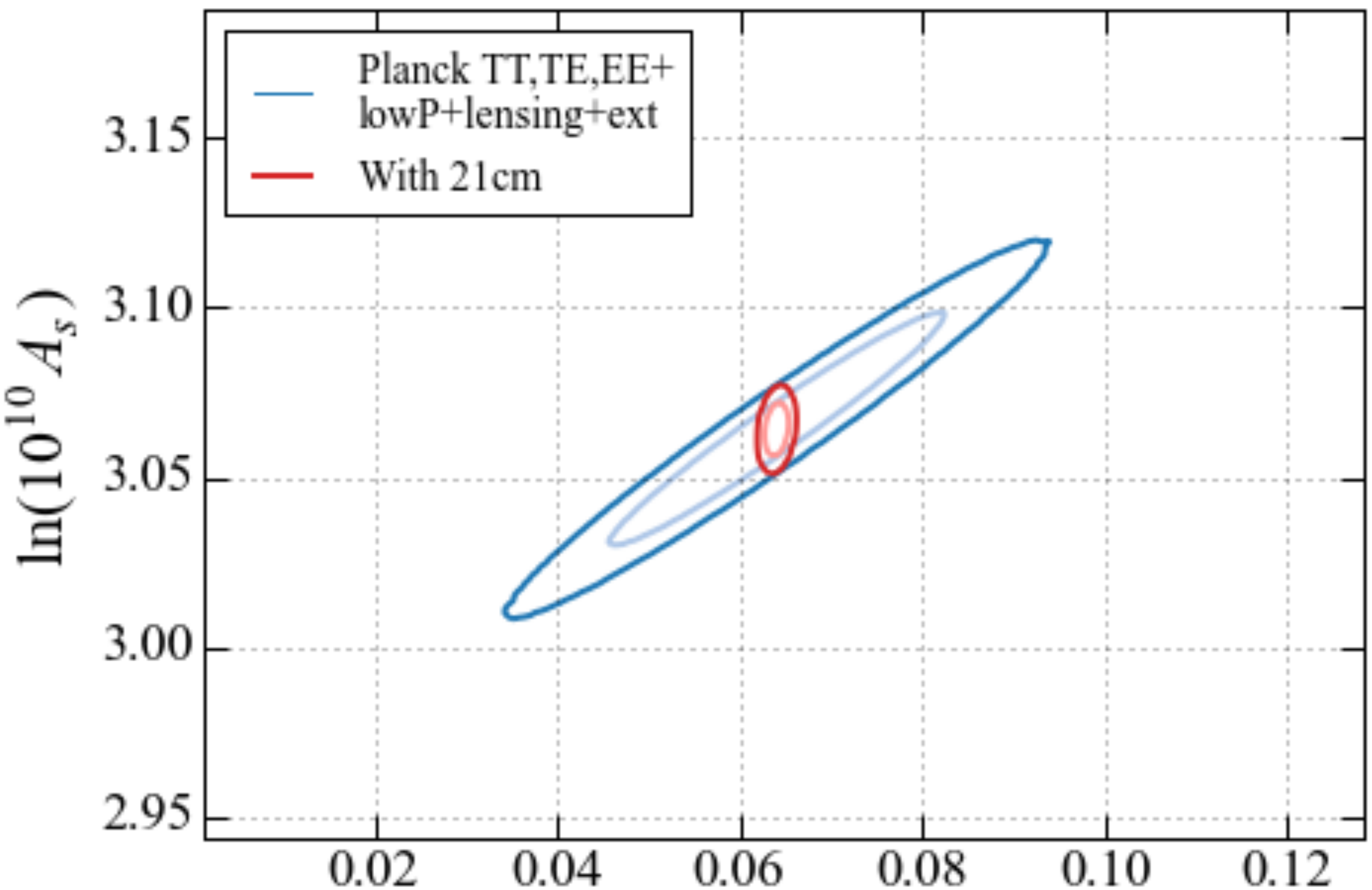
Theory prediction

τ

21cm information breaks the degeneracy between the amplitude of fluctuations and the optical depth



21cm information breaks the degeneracy between the amplitude of fluctuations and the optical depth

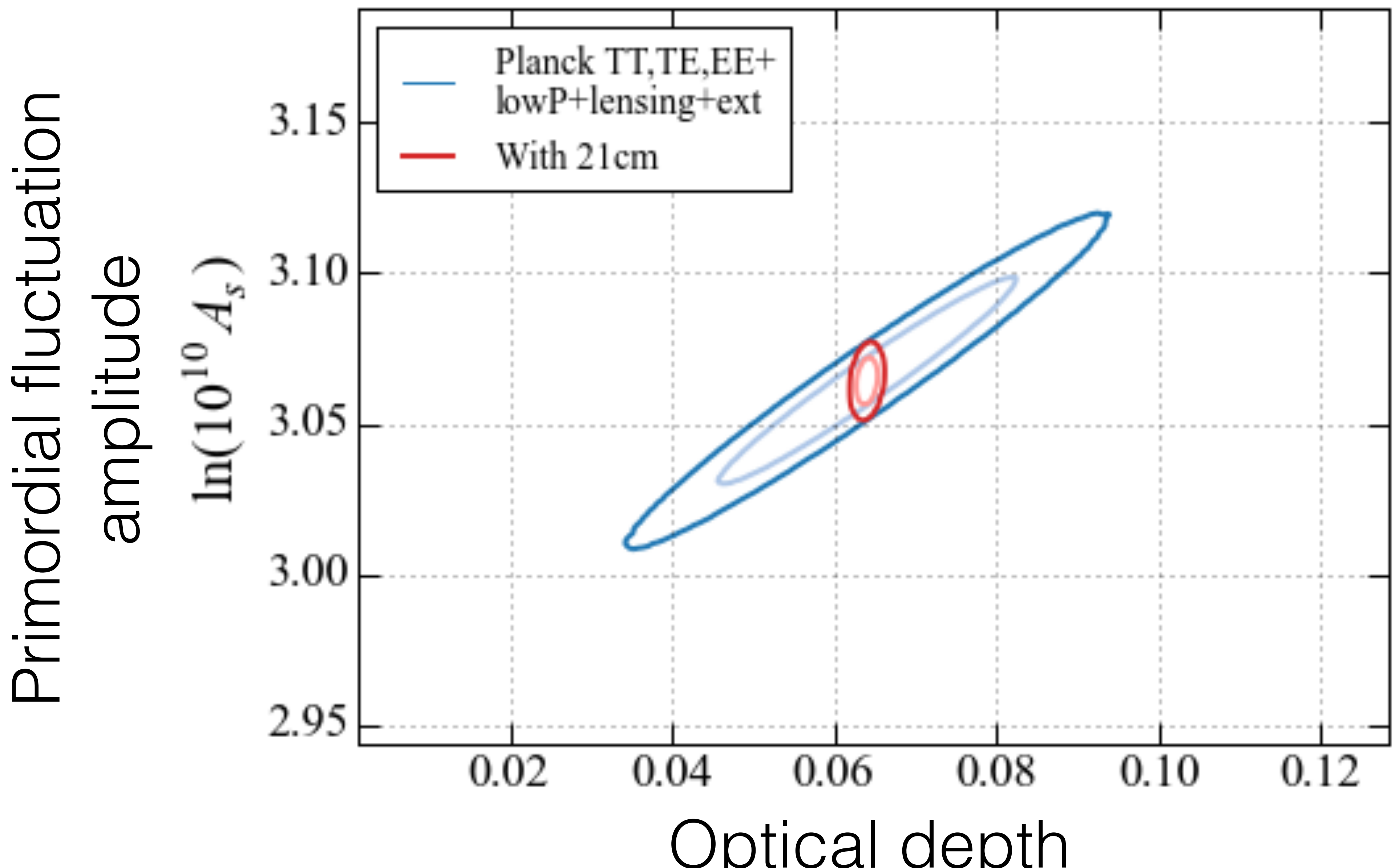


Primordial fluctuation amplitude

Optical depth

AL et al. (2015a)

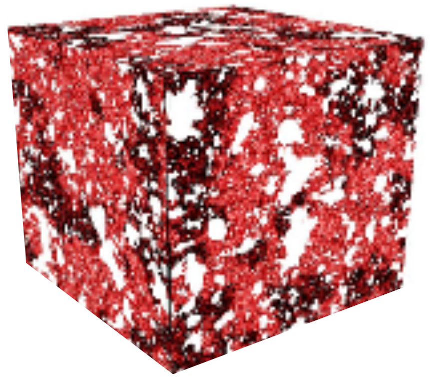
21cm information breaks the degeneracy between the amplitude of fluctuations and the optical depth



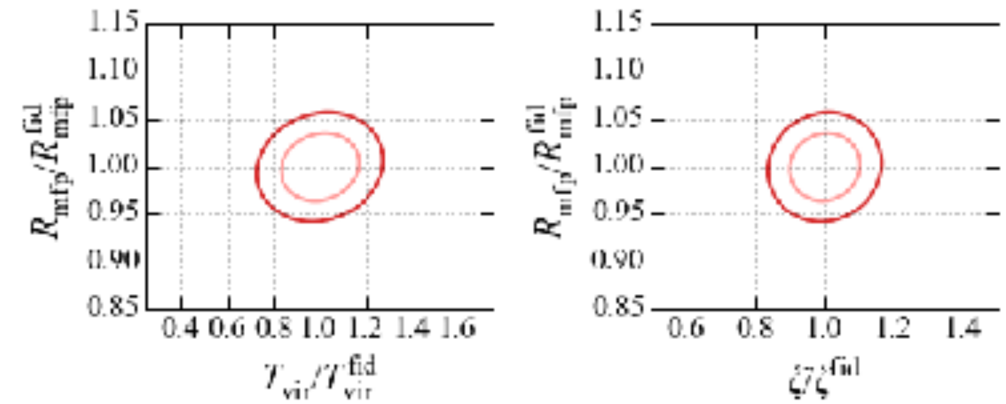
AL et al. (2015a)

$$\Delta \ln(10^{10} A_s) = \pm 0.023 \longrightarrow \pm 0.0053$$

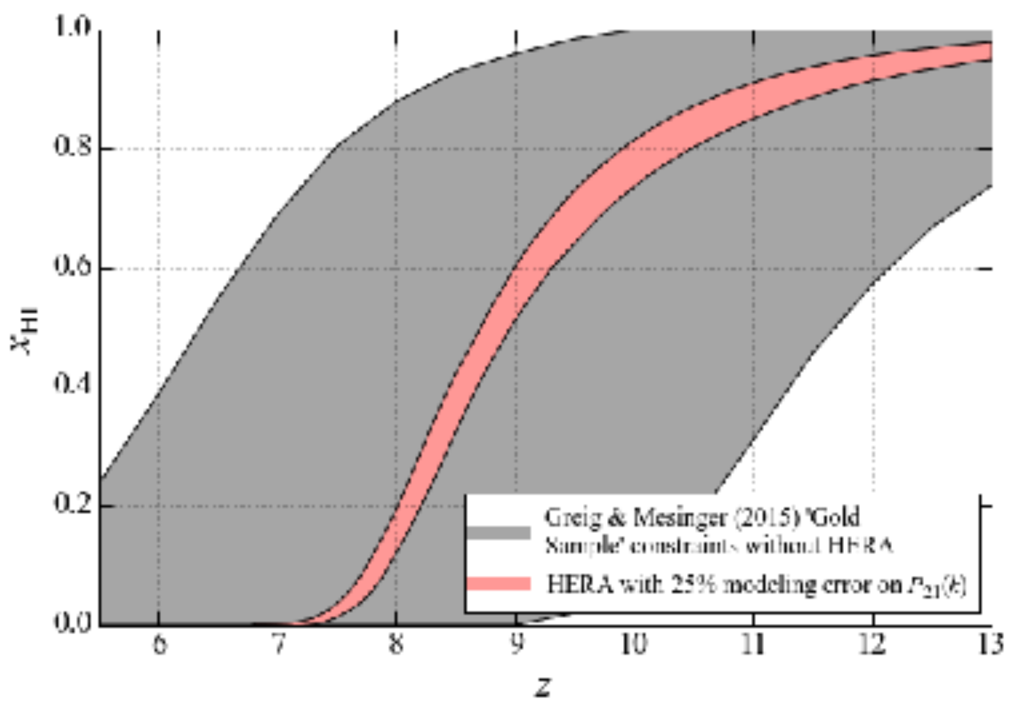
Isn't this awfully indirect and model-dependent?



Observations

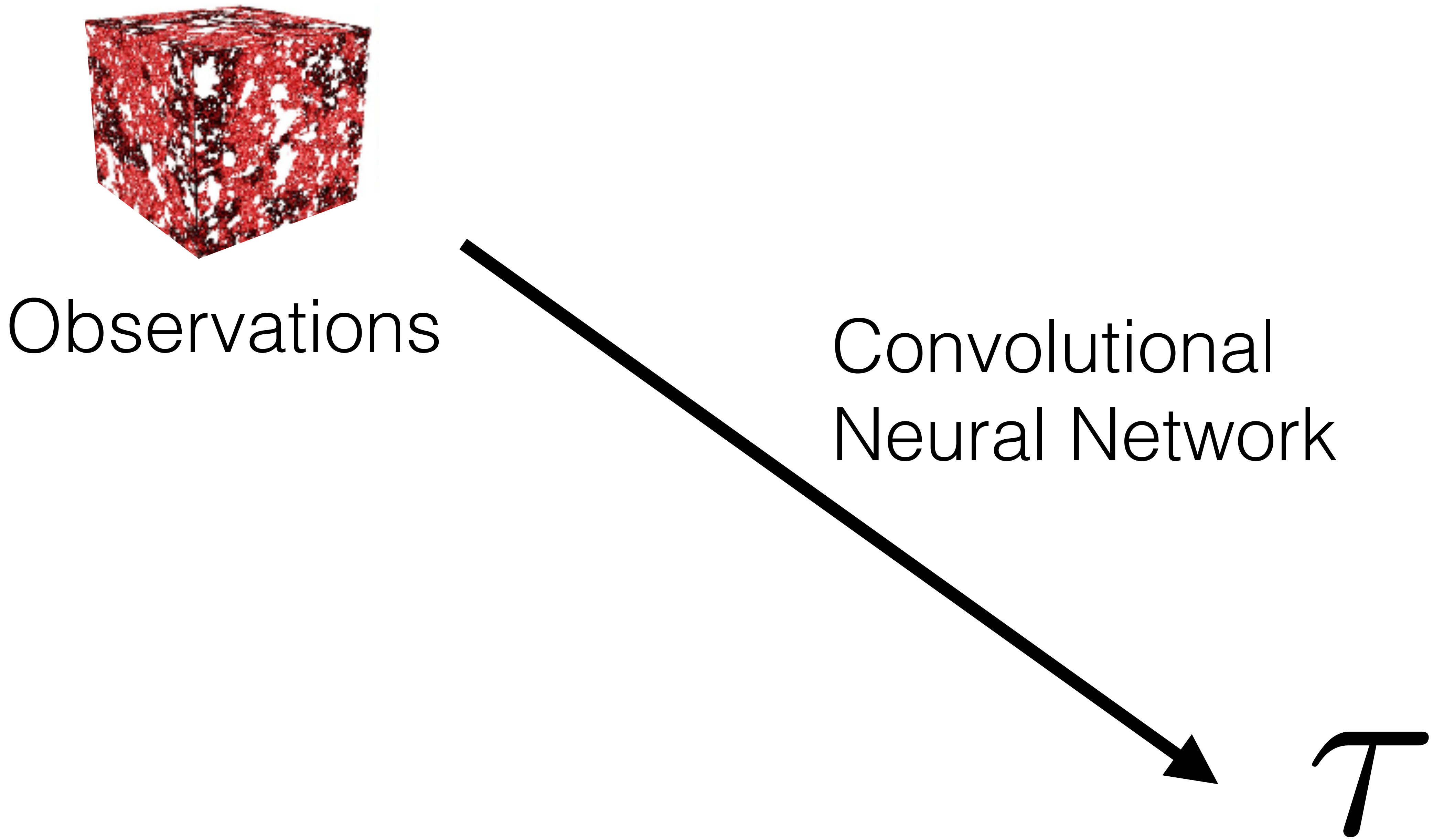


Model parameters via power spectrum

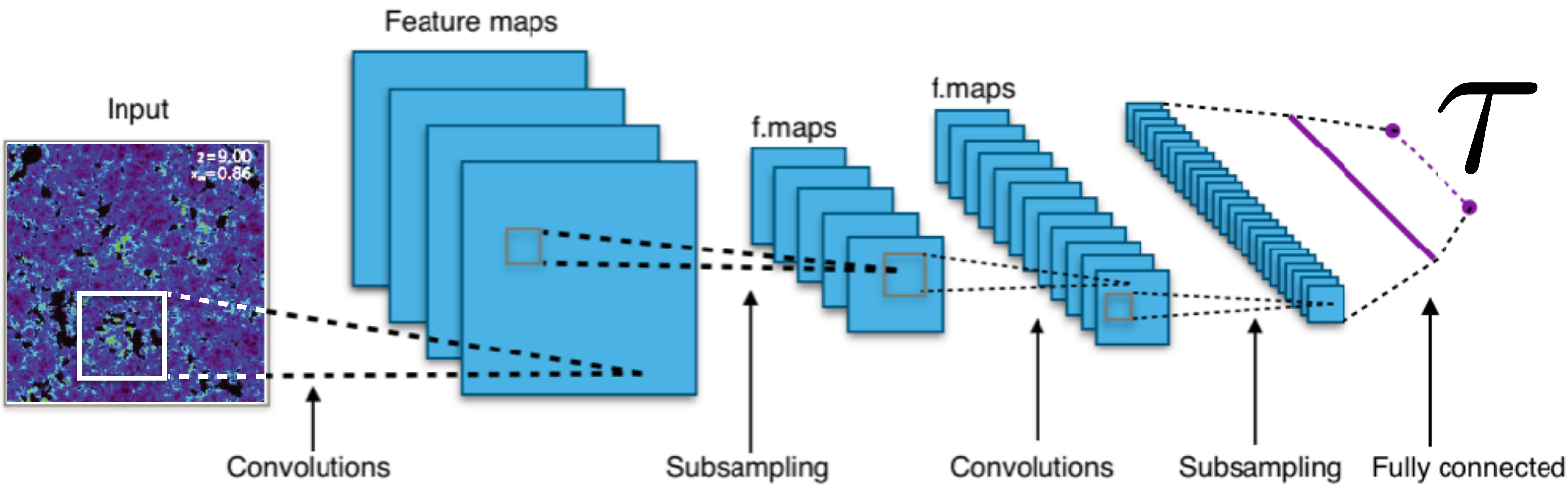


Theory prediction

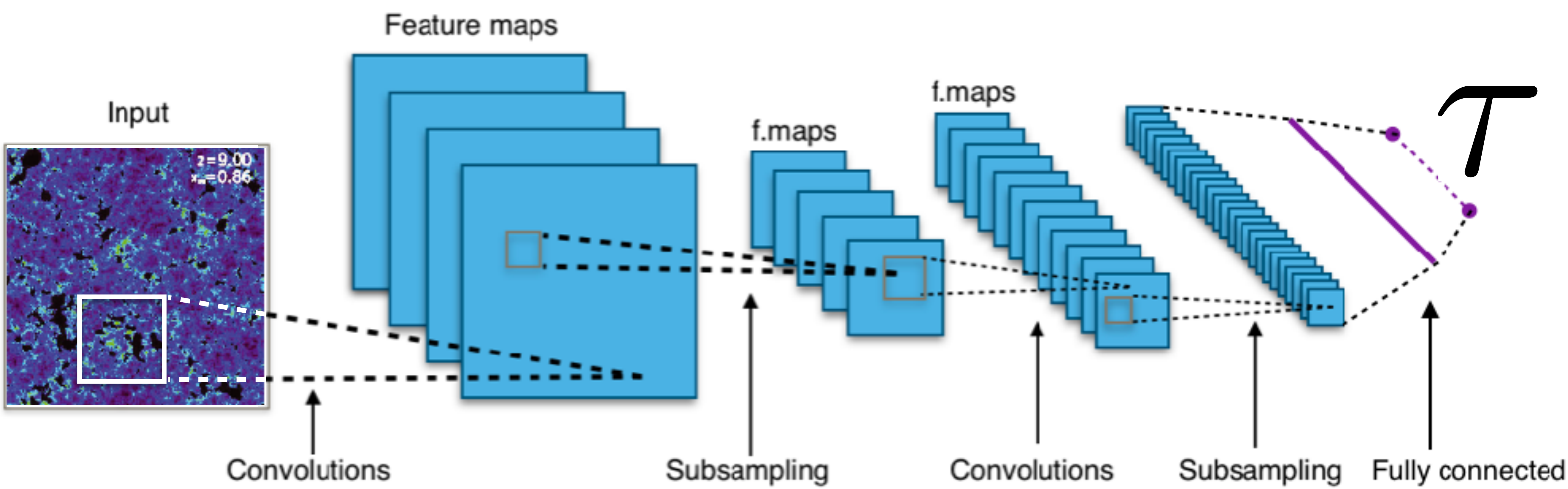
τ


Observations
Convolutional
Neural Network
τ

Convolutional neural nets process data through a series of convolutions, thresholdings, and averages

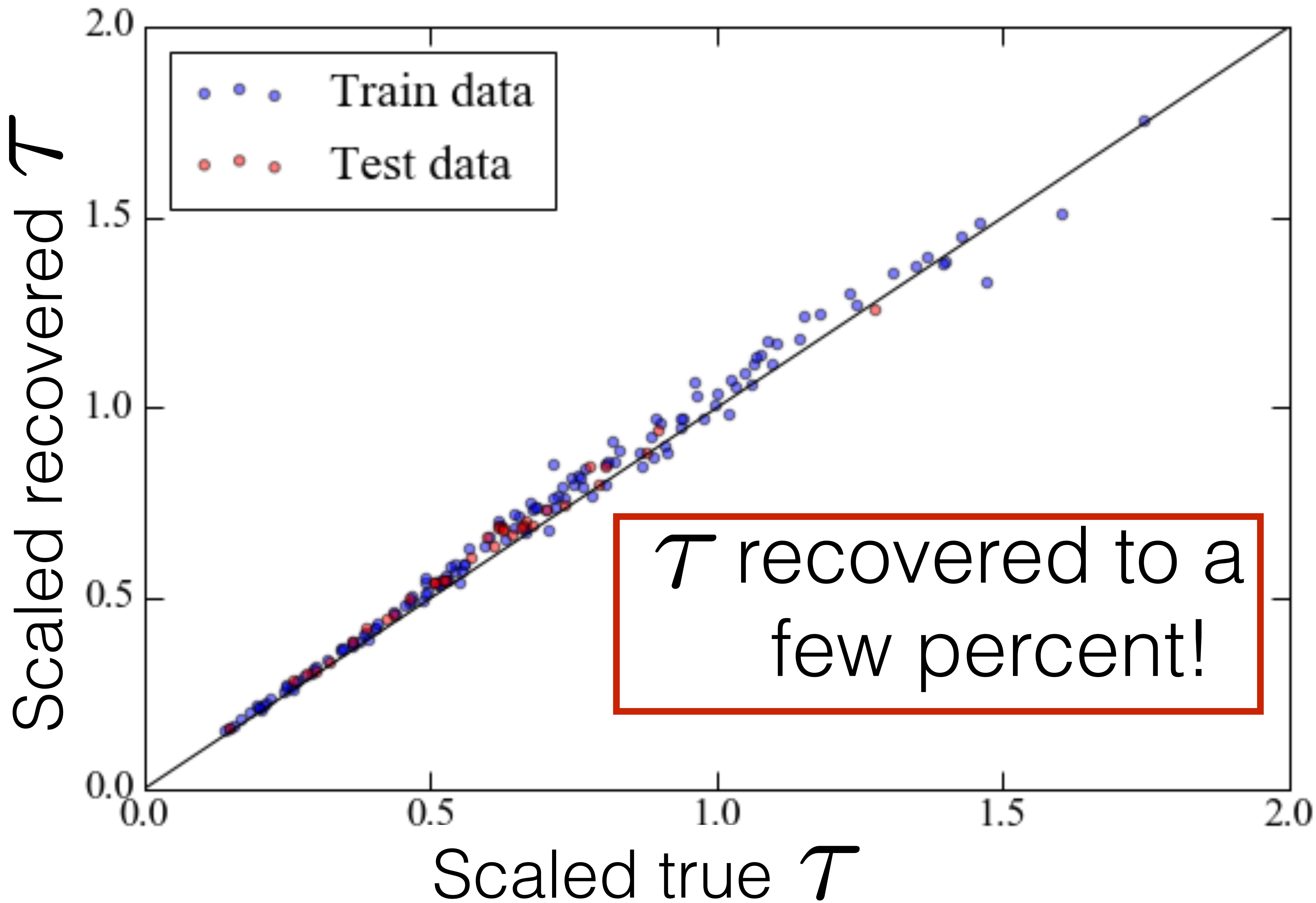


Convolutional neural nets process data through a series of convolutions, thresholdings, and averages



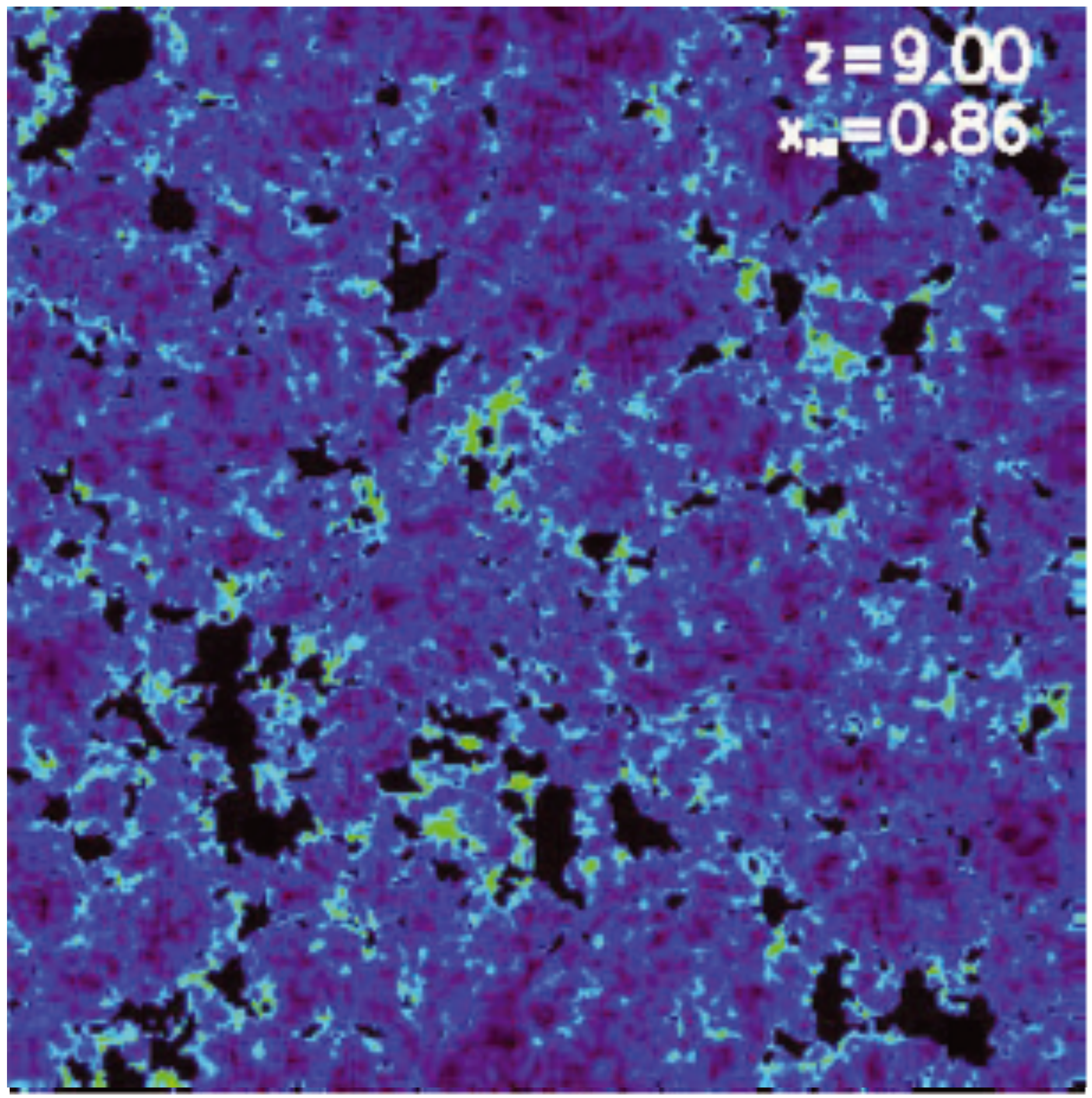
Repeated exposure to training data allows the optimization of the convolution kernels for extracting parameters of interest

Initial results suggest that CNNs can extract the optical depth



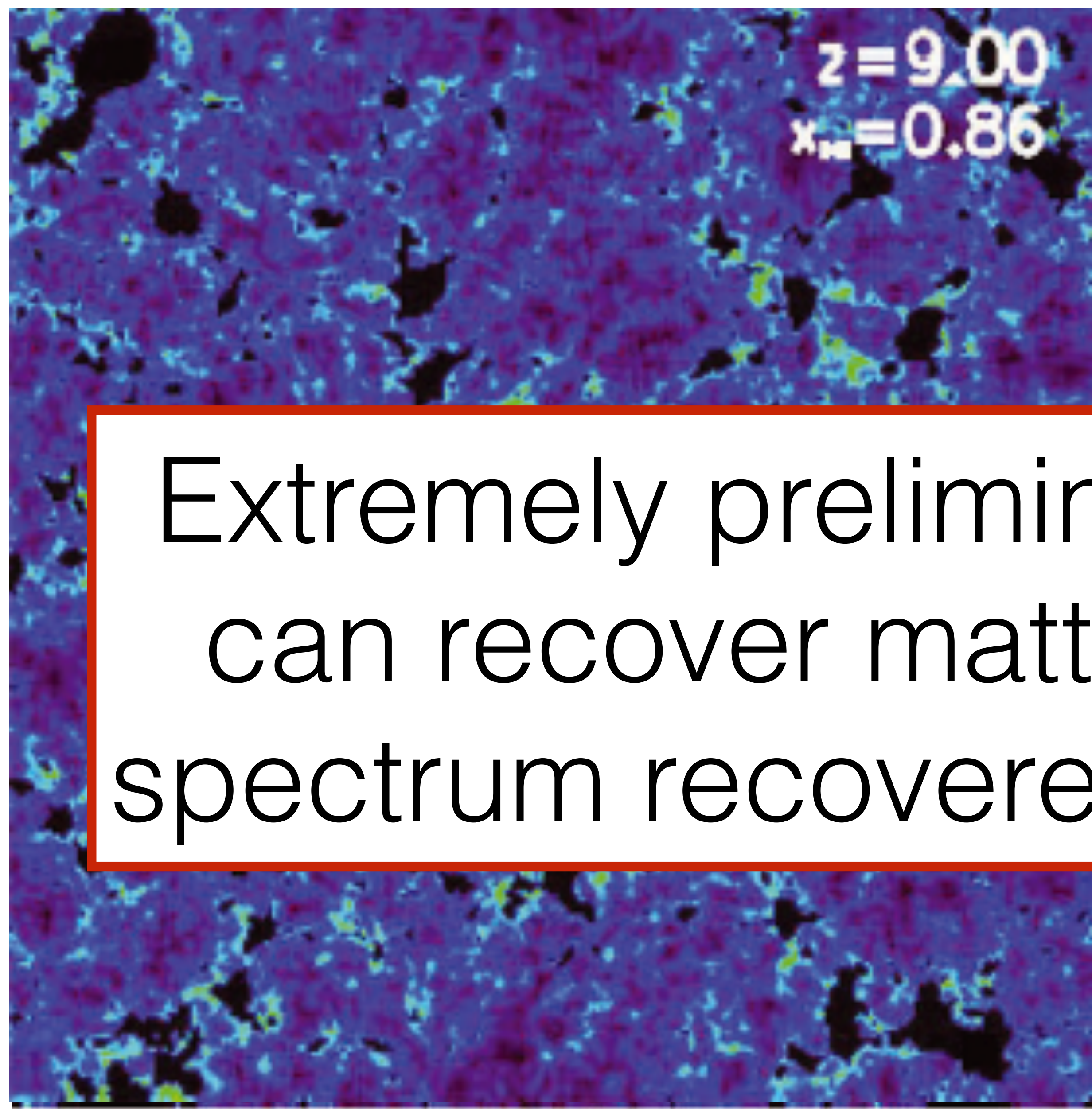
AL et al., in prep.

Descriptions of reionization hinge crucially on the correlation between the density field and the ionization field



21cm field
Mesinger et al. (2010)

Descriptions of reionization hinge crucially on the correlation between the density field and the ionization field



Extremely preliminary: CNN can recover matter power spectrum recovered to ~10%

21cm field
Mesinger et al. (2010)

Take home messages

- Latest version of the data-driven GSM outputs errors in addition to best-guess sky models.
- Convolutional Neural Networks allow simulated training sets to teach us how to leverage non-Gaussianity for parameter constraints.