

# Extracting the 21cm power spectrum from the EoR

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Kapteyn Institute

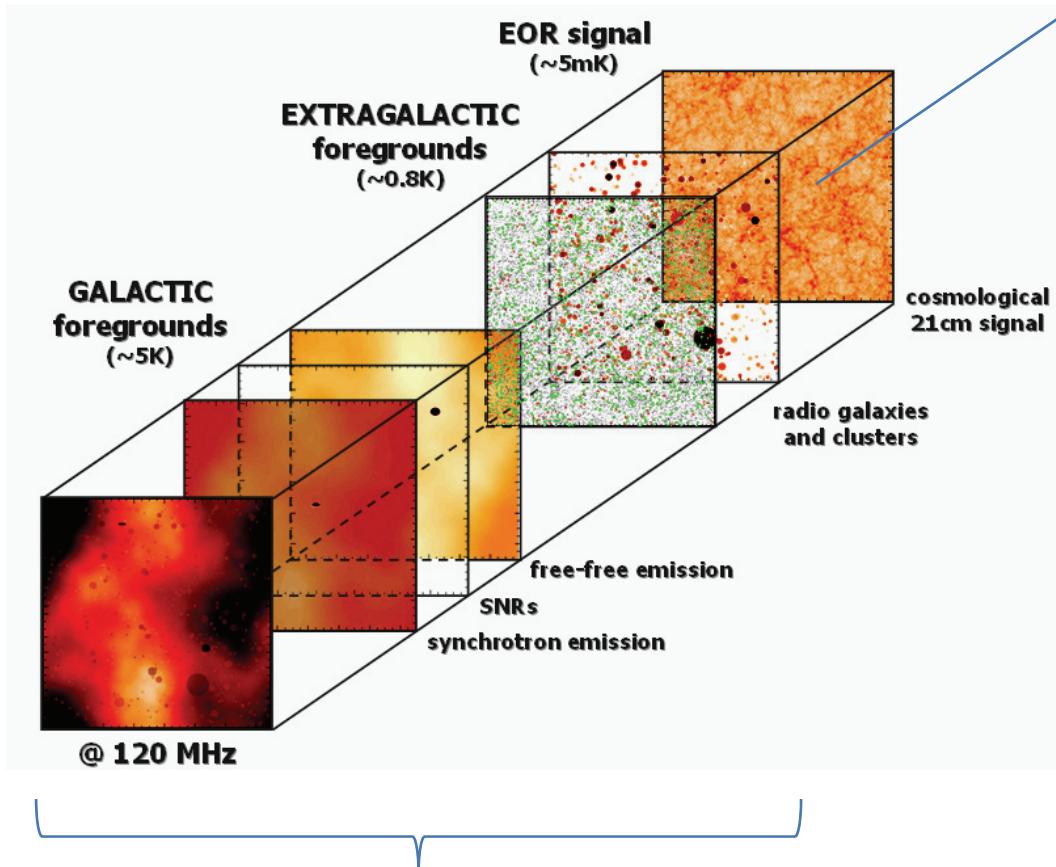
# Motivation (I)

## Information from the power spectrum

$$\frac{\delta T_b}{\text{mK}} = 39h(1 + \delta)x_{\text{HI}} \left(1 - \frac{T_{\text{CMB}}}{T_{\text{spin}}}\right) \left(\frac{\Omega_b}{0.042}\right) \left[\left(\frac{0.24}{\Omega_m}\right) \left(\frac{1+z}{10}\right)\right]^{\frac{1}{2}}$$

- Measure the power spectrum of  $\Delta\delta T_b$ , the difference of  $\delta T_b$  from the mean.
- Contains information on:
  - the growth of structure (through  $1+\delta$ );
  - reionization (through  $x$ ), e.g. growth of bubbles;
  - heating (through dependence on the spin temperature);
  - cosmology;
  - redshift-space distortions.
- Decomposing  $P(k,\mu)$  in powers of  $\mu$  may help disentangle these effects.

# Components of the data cubes



- Cosmological signal here from the f250C simulation of Iliev et al. (2008).
- Foregrounds and cosmological signal are convolved with the instrumental response.
- Uncorrelated noise in the *uv* plane: for one year with one beam, corresponds to an *rms* of 52mK at 150 MHz.
- Need foregrounds which are smooth as a function of frequency.

Foregrounds as in Jelić et al. (2008).

# Wp smoothing: non-parametric foreground fitting

- Model data points  $(x_i, y_i)$  by:

$$y_i = f(x_i) + \varepsilon_i, \quad i = 1, \dots, n$$

- Then we wish to solve the following problem:

$$\min_f \left\{ \sum_{i=1}^n \rho_i(y_i - f(x_i)) + \lambda R[f] \right\}$$

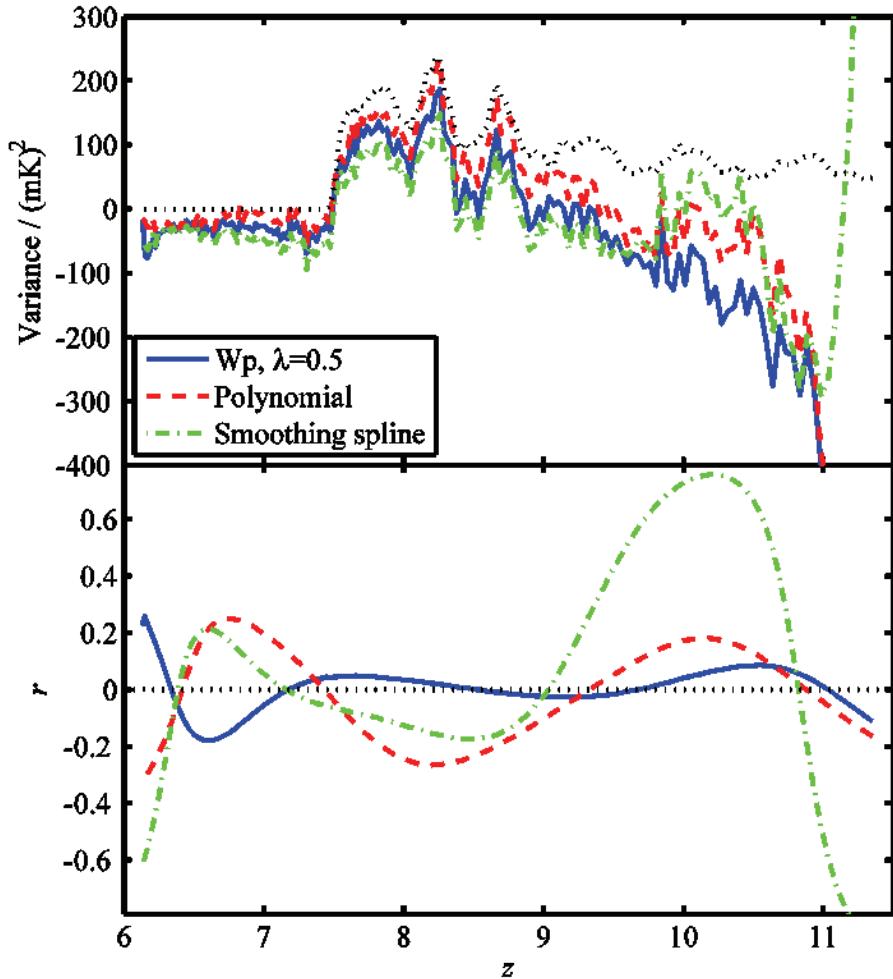


“Least squares”      Roughness penalty

- Here the roughness penalty measures the integrated change in curvature ‘apart from inflection points’; inflection points are the primary measure of roughness.
- The solution of this minimization is the solution of a boundary value problem derived by Mächler.
- ‘Wp’ stands for ‘Wendepunkt’.

# Motivation (II)

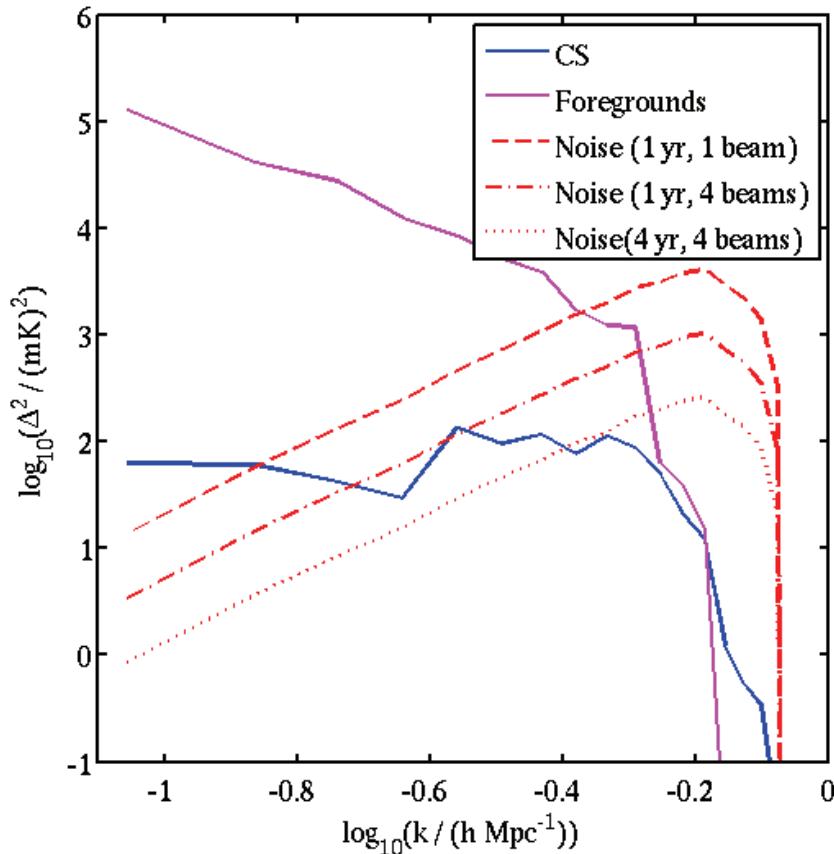
## Step 1: Measure the RMS?



- First aim: establish that we can detect any signal at all from the EoR.
- Seems reasonable to do this using the integrated RMS, which evolves with redshift.
- Unfortunately, polluted by under- and over-fitting, and by edge effects.
- Can using scale-dependence help?

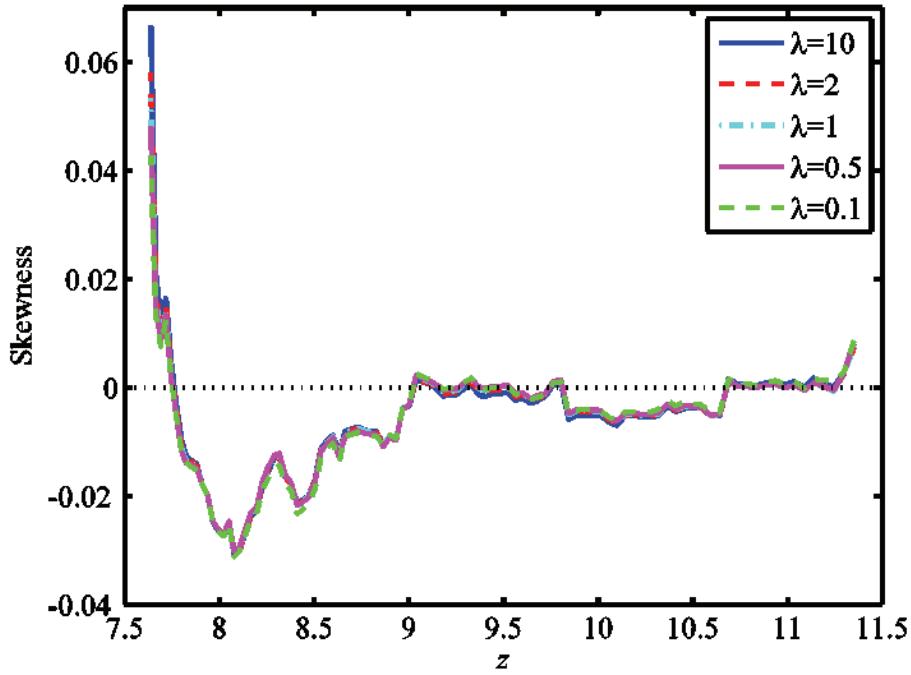
# Scale dependence and size of components of the signal

Power spectra in a slice  $81.602 h^{-1}$  Mpc deep centred at  $z=8.2741$  in f250C



- Noise (receiver noise plus sky noise) dominates on small scales, leading to problems from over-fitting.
- Foregrounds dominate on larger scales, leading to problems from under-fitting.
- All scales contribute to the integrated RMS, but using the whole power spectrum we may be able to pick out the most favourable scales.
- Recovered shape provides a further check.

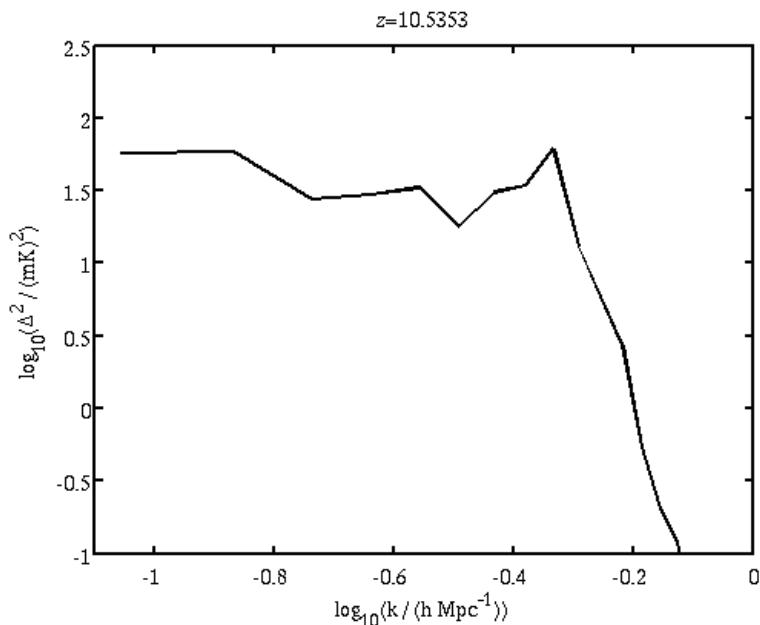
# Motivation (III): using the power spectrum to recover the skewness



- Recovery seems to be robust to changes in the fitting algorithm.

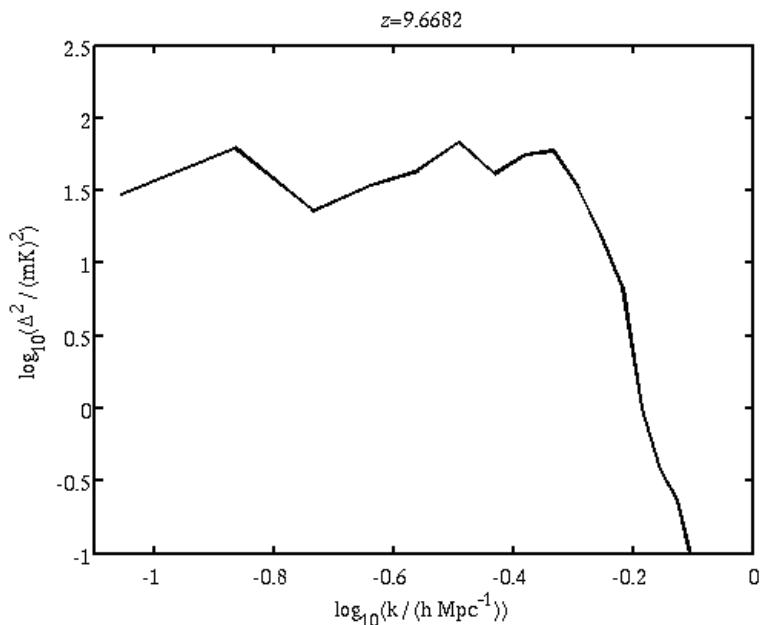
- Redshift evolution of the skewness of residual maps may provide a confirmation of a detection (especially if we see negative skewness).
- Need to deconvolve the maps (e.g. Wiener deconvolution) before calculating the skewness, which requires an estimate of the correlation matrix (and hence angular power spectrum) of the signal.

# Example evolution of the signal power spectrum



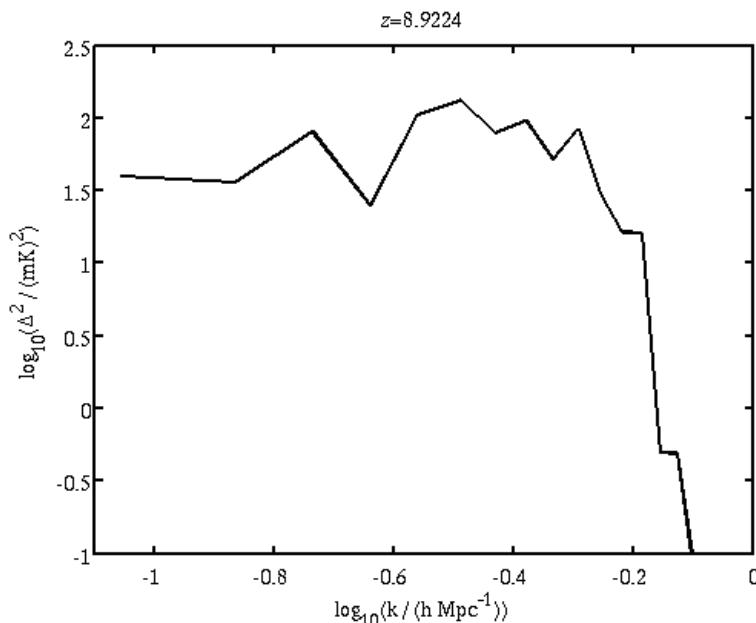
- Spectra here are convolved with the instrumental response (hence high- $k$  cut-off).
- Growth of a feature on small scales due to formation of bubbles.
- Feature broadens and moves to larger scales as bubbles grow.
- At low redshift, signal drops because of a low neutral fraction.

# Example evolution of the signal power spectrum



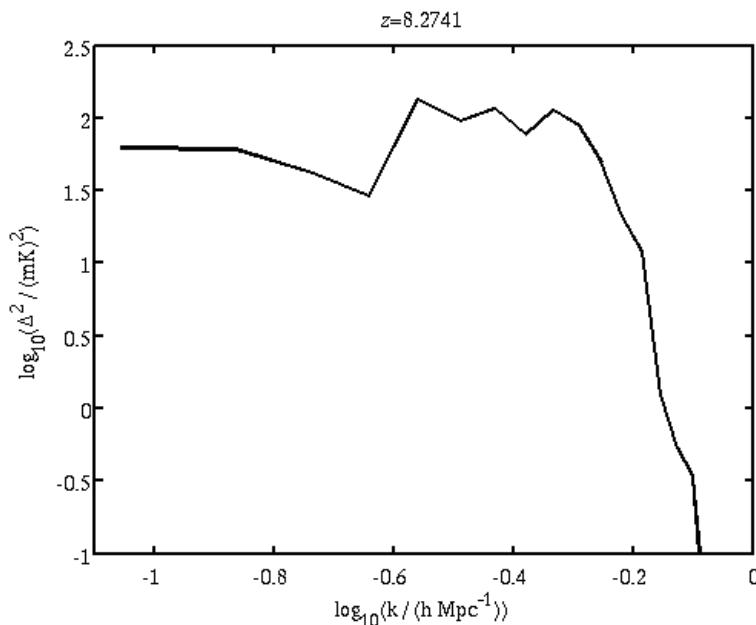
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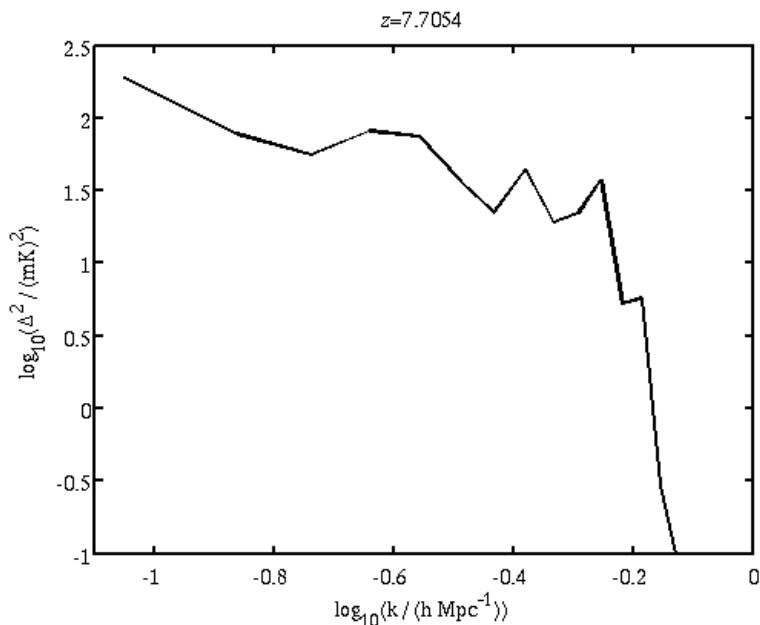
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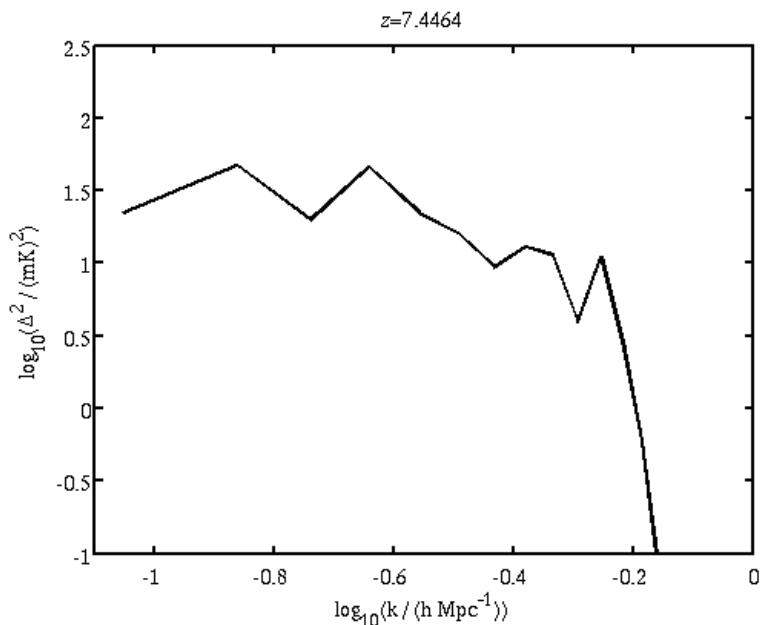
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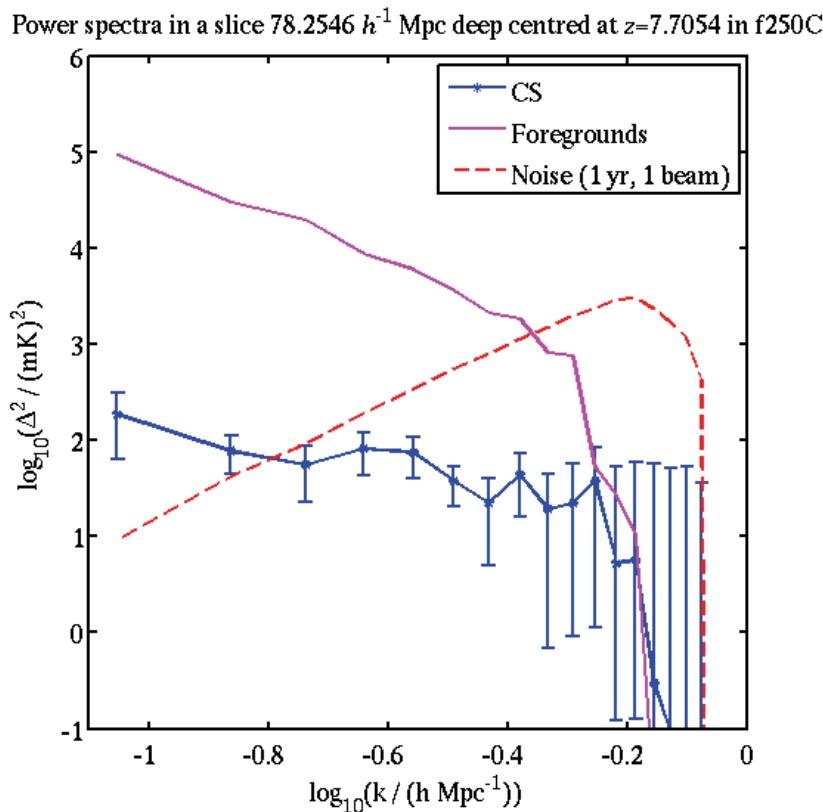
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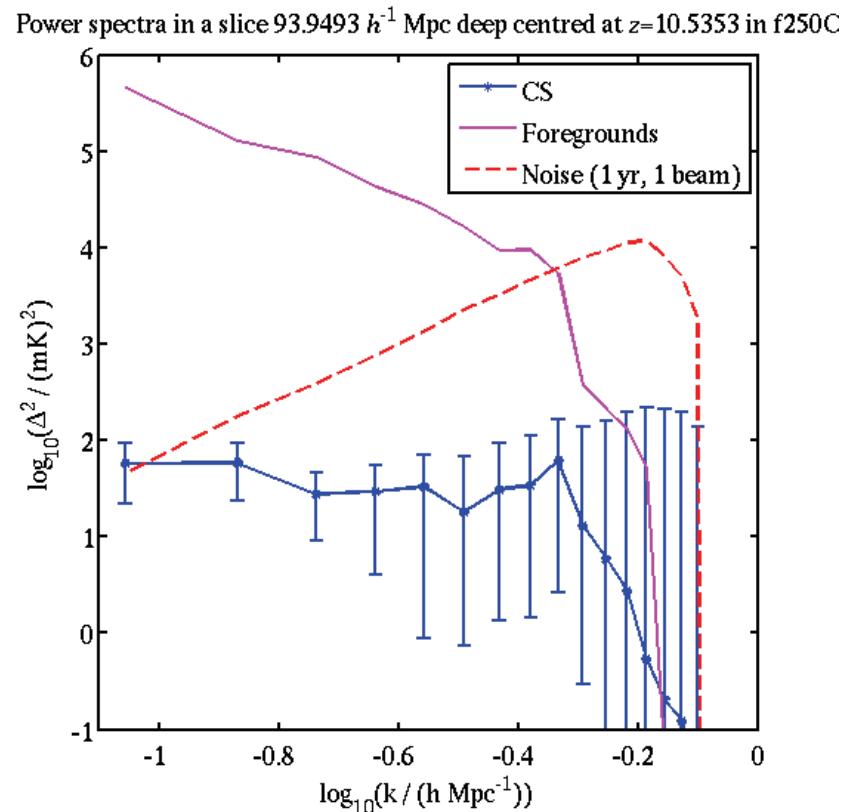
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# Power spectra with perfect foreground subtraction (1 year, 1 beam)

## Low redshift

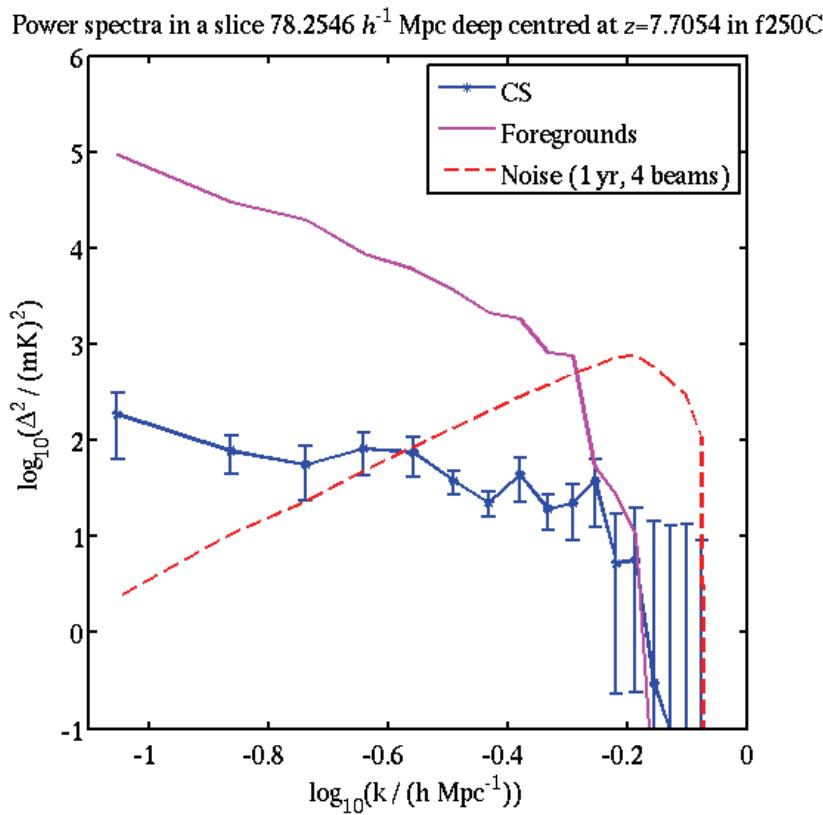


## High redshift

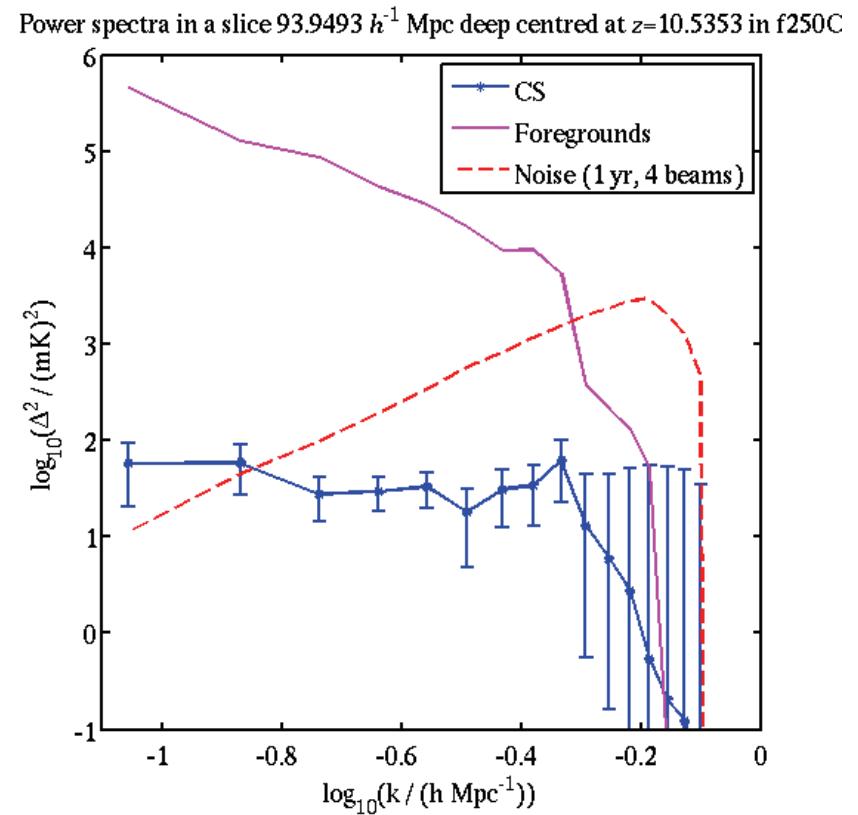


# Power spectra with perfect foreground subtraction (1 year, 4 beams)

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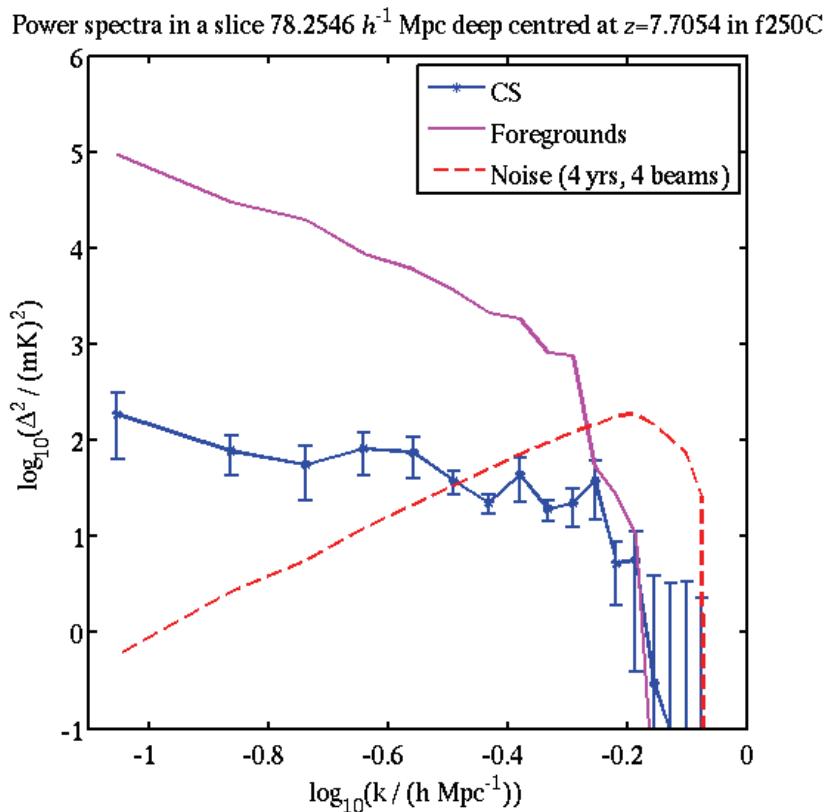


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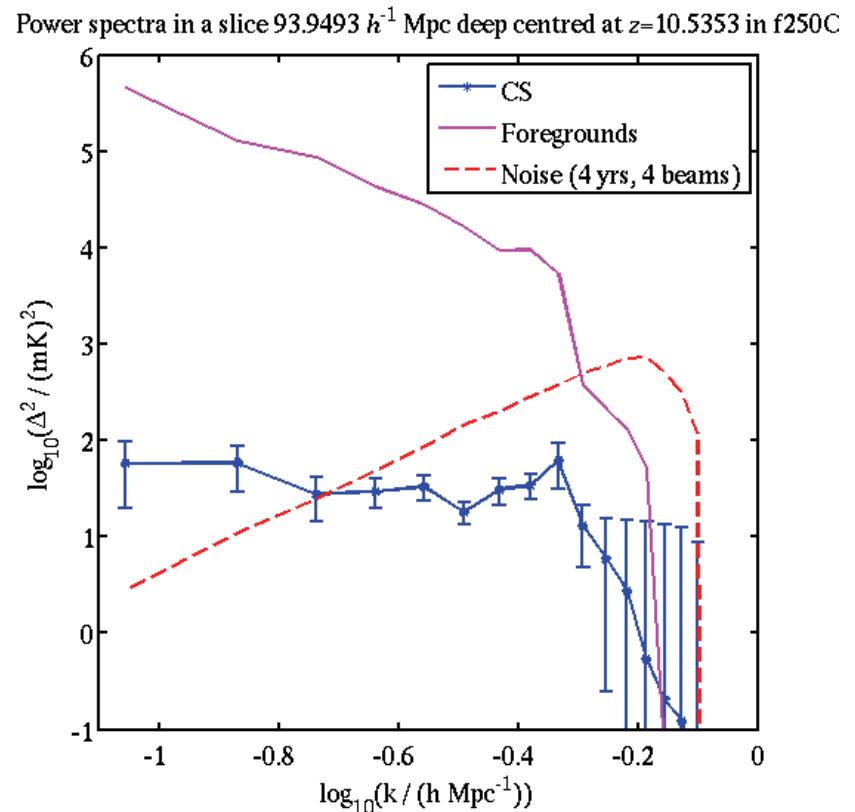


# Power spectra with perfect foreground subtraction (4 years, 4 beams)

## Low redshift

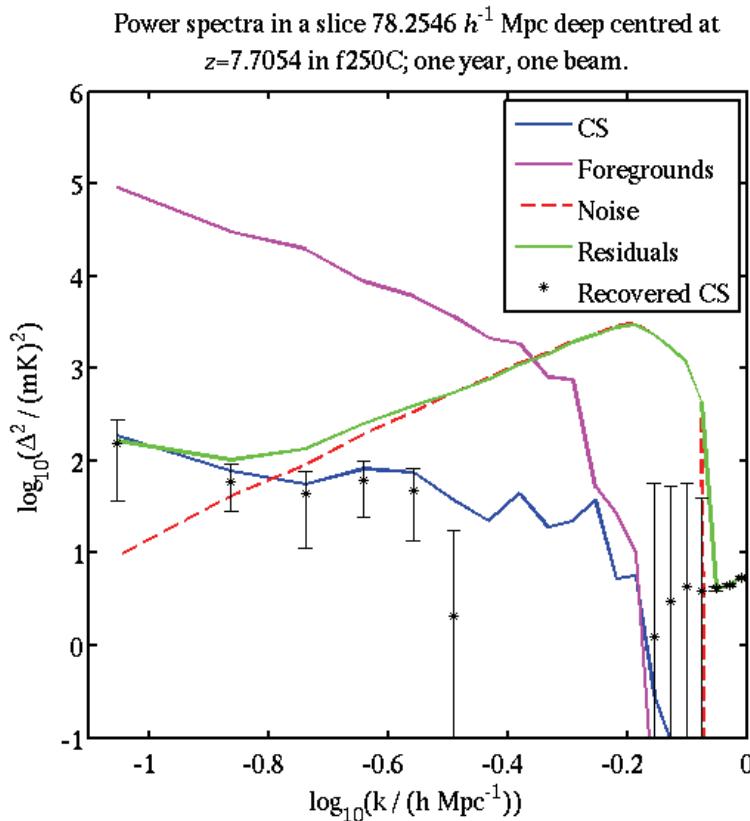


## High redshift

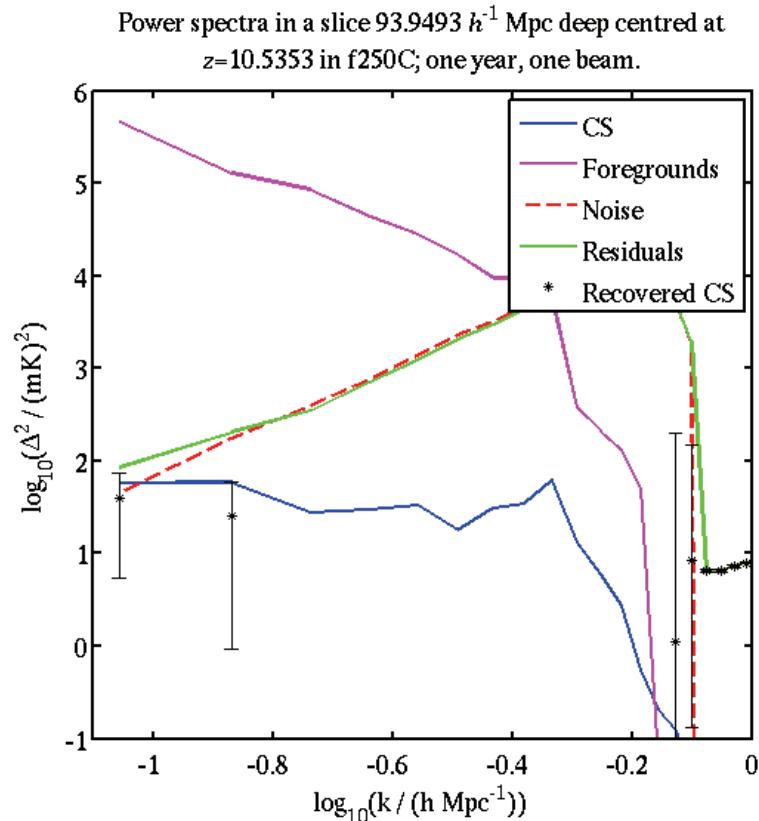


# Results using Wp smoothing for foreground subtraction (1 yr, 1 beam)

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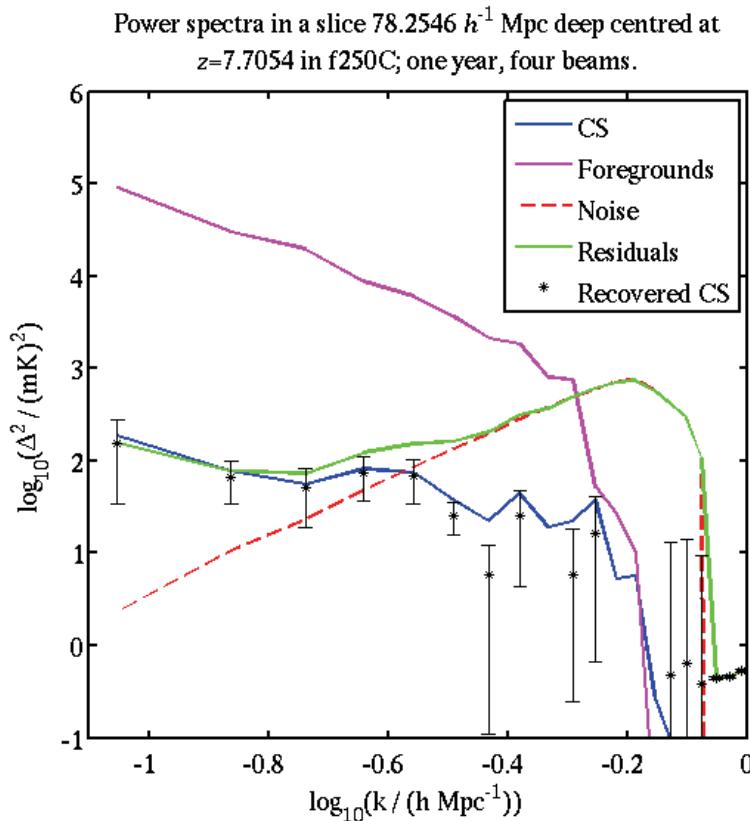


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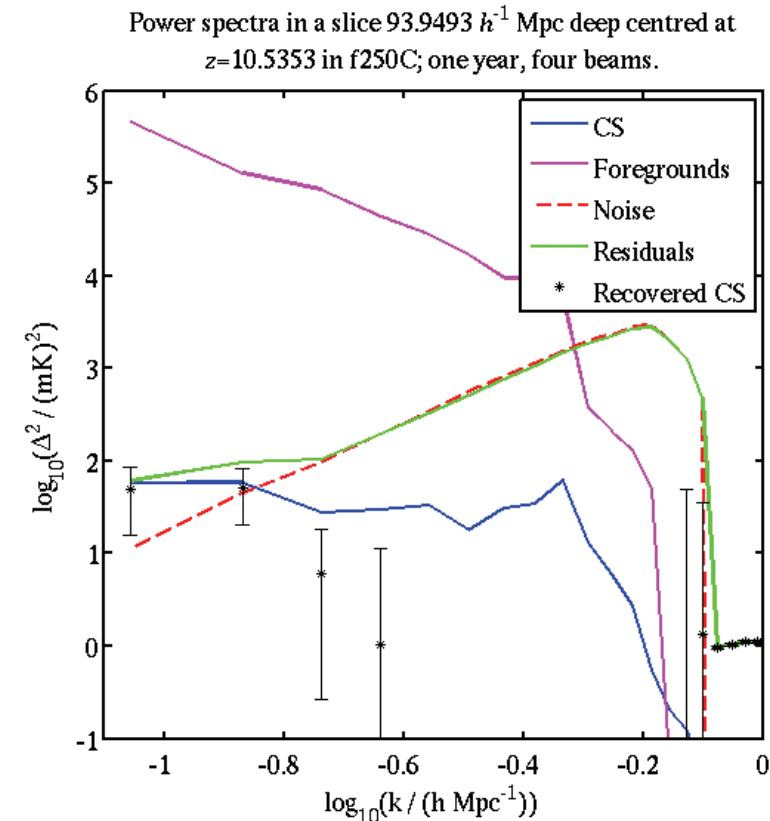


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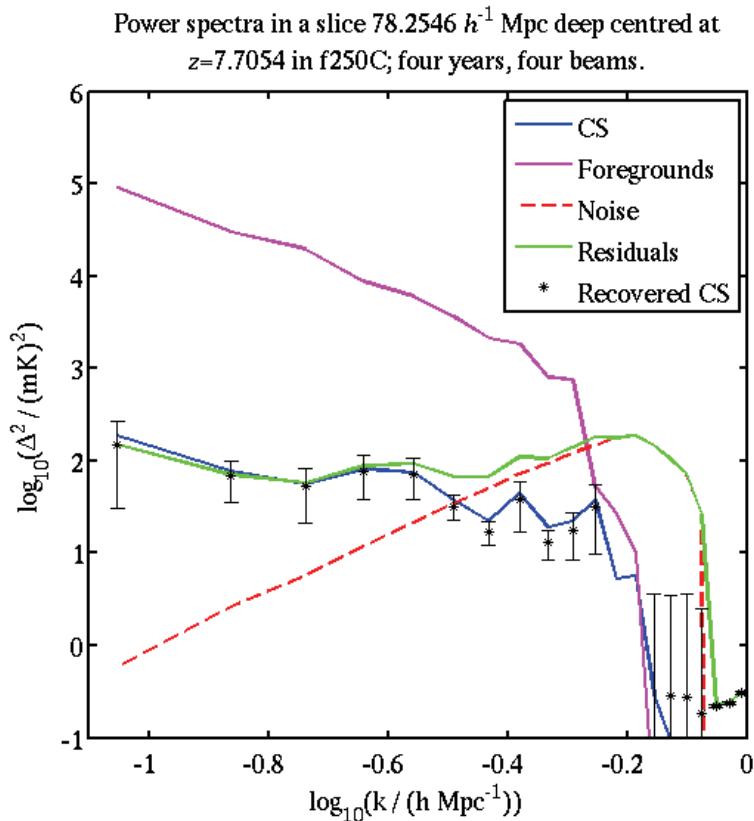


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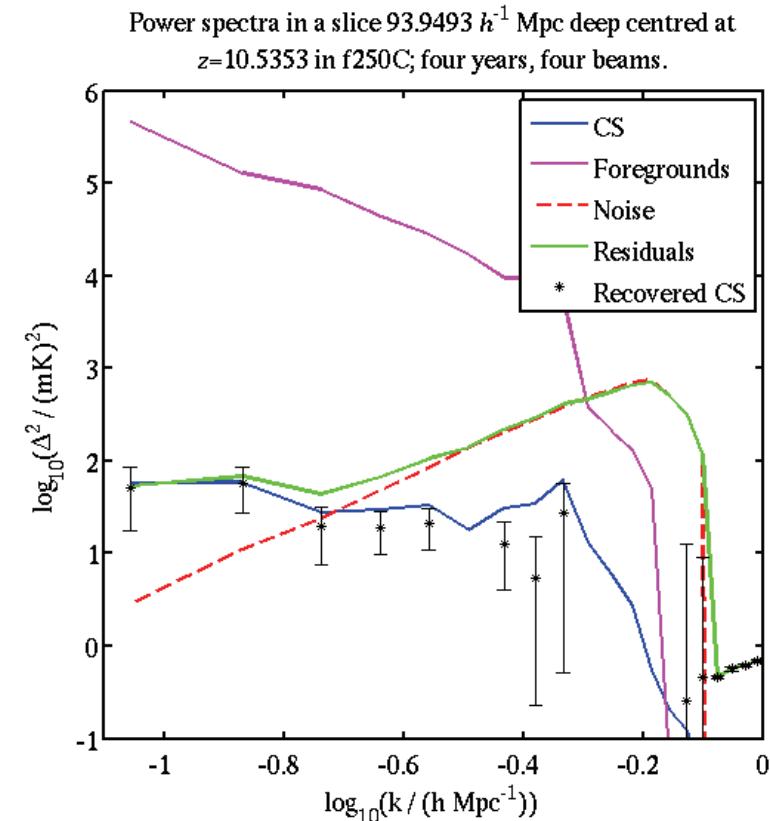


# Results using Wp smoothing for foreground subtraction (4 yr, 4 beams)

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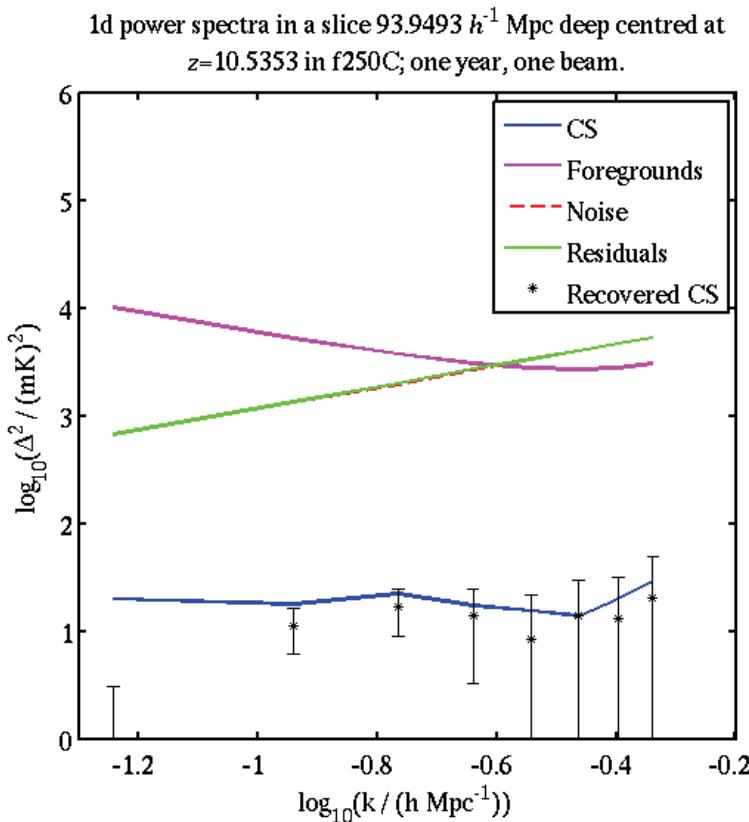


## High redshift

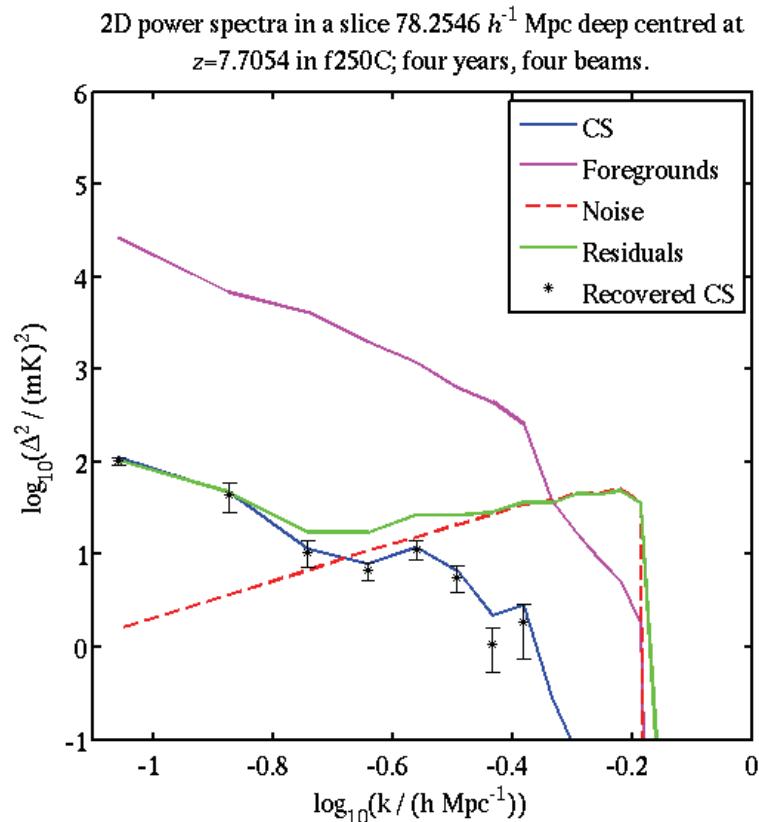


# 1D and 2D power spectra

## 1D power spectrum – high z, 1 yr, 1 beam



## 2D power spectrum – low z, 4 yrs, 4 beams



# Comments and conclusions

- The power spectrum is a rich source of physical information.
- The different scale-dependence of the foregrounds, noise and cosmological signal may help in extracting the signal.
- Only a rough estimate of the power spectrum is required to extract the evolution of the skewness (after Wiener filtering).
- Foreground fitting is unlikely to be a bottleneck in extraction: we can afford something sophisticated even if it's computationally expensive.
- Realistic levels of noise and diffuse foregrounds do not, in themselves, seem to be a deal-breaker for power spectrum subtraction...
- ...but the fitting process introduces biases: can they be corrected for using simulation results?
- As the integration time increases, we can expect continued qualitative improvements in what can be inferred from the data.

# Future work

- How accurately can we really estimate the power spectrum of the noise? Probably need to use the data before they're binned in time and frequency to give a final data cube.
- How is the ‘separation of powers’ (of  $\mu$ ) affected by the fitting and extraction process?
- Continue to integrate improved models of the instrument, foregrounds, noise and a variety of signal models incorporating larger scales.
- Effect of other error sources: ionosphere, polarization calibration, point source subtraction errors...
- Incorporate signal correlations and a systematic way of choosing the amount of smoothing in the foreground fitting.
- Can we gain from mismatched spatial and frequency resolution?
- Effect of power spectrum errors on recovery of evolution of skewness.
- Full error analysis including cosmic variance; effect of multiple windows.