Unveiling the HI power spectrum with MeerKLASS

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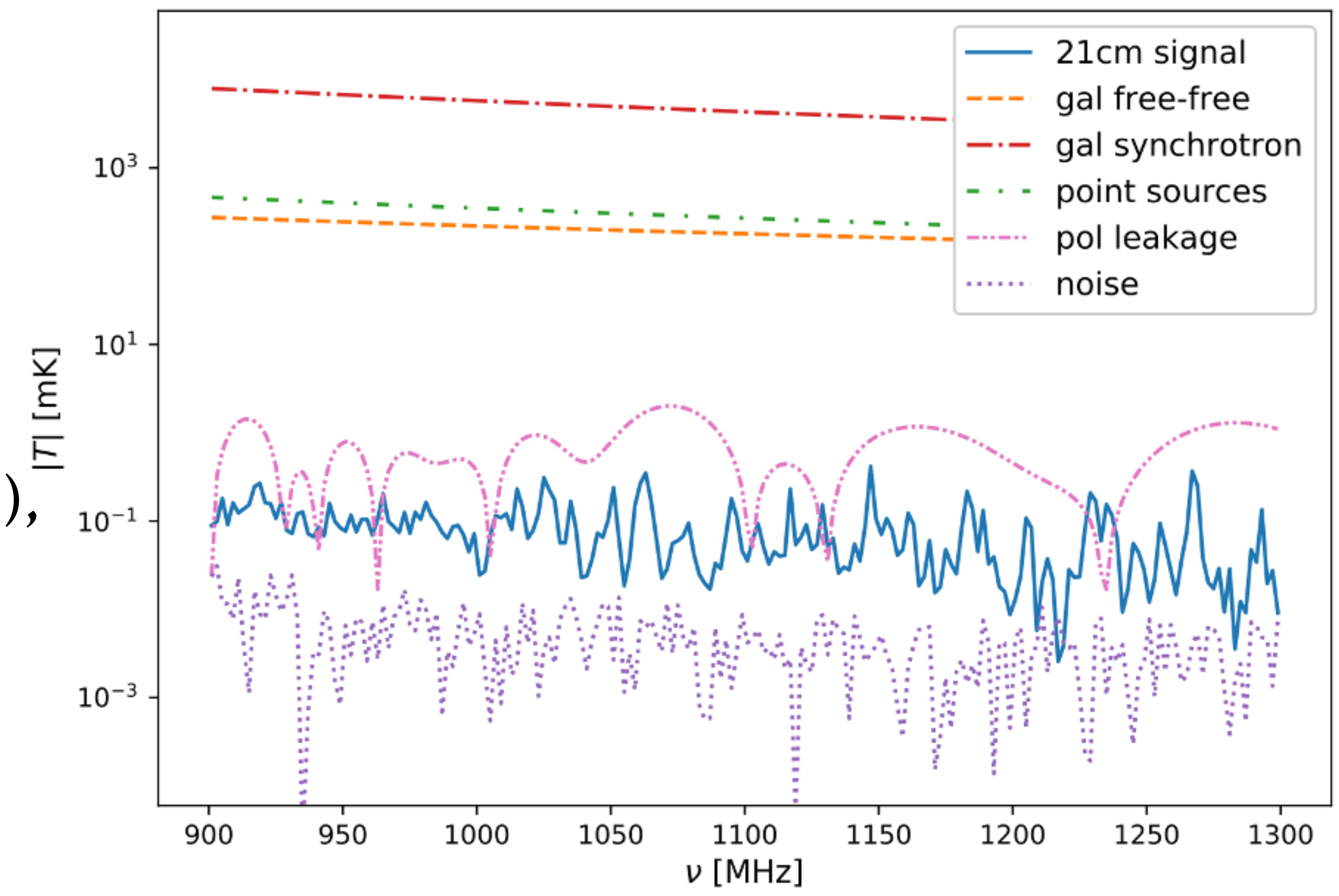
HI intensity mapping

- HI as tracer of the matter distribution
- Emission from the hyperfine transition of HI
- Amplitude of the signal dependent on the clustering of HI
- Wide redshift range
- Not only cosmological signal
  - Astrophysical foregrounds: galactic and extragalactic
  - Contaminants: Radio Frequency Interference (RFI), instrumental contaminations…

[Carucci et al. (2020)]

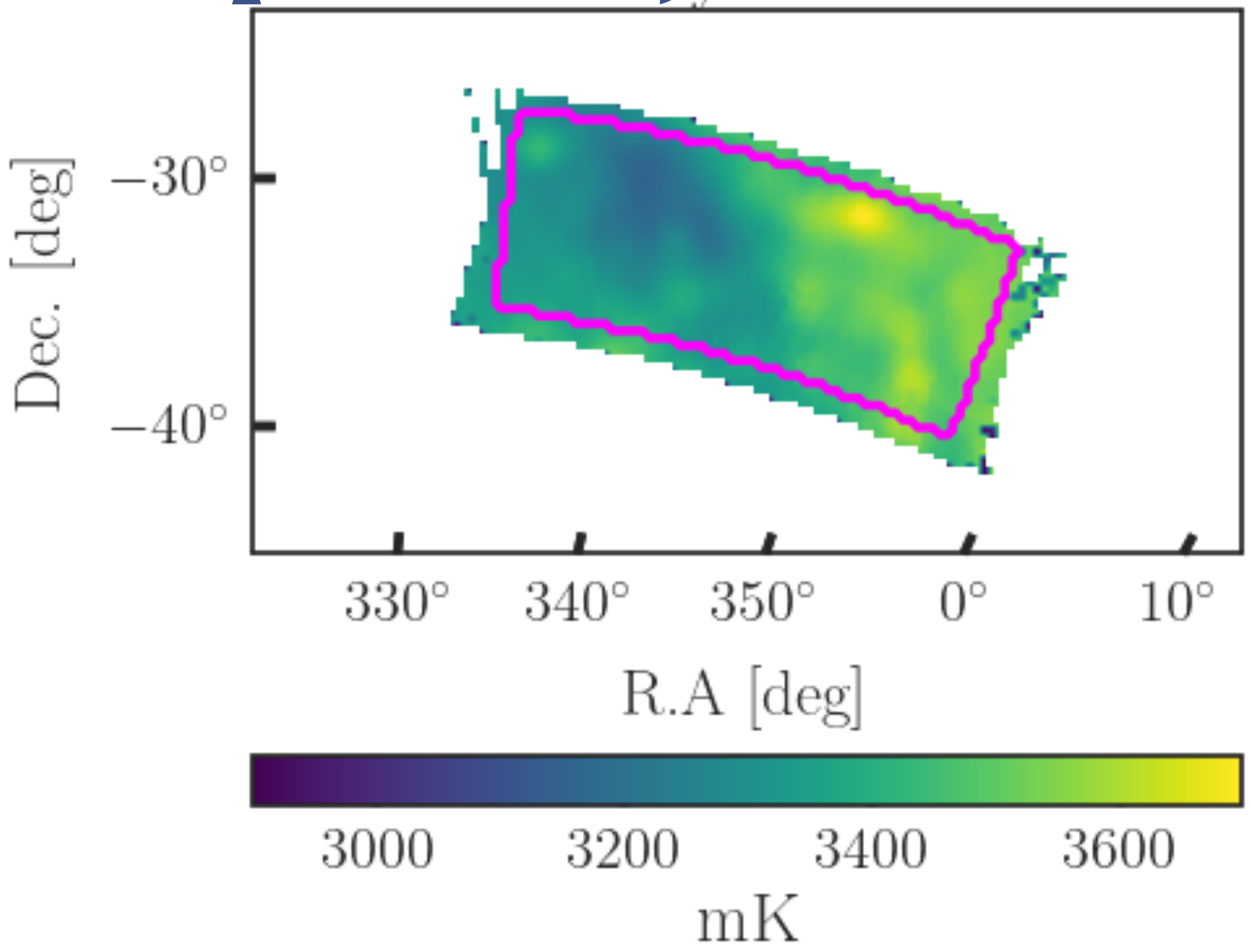


Single dish technique

- All the antennas of the array observe the same region at the same
- Low angular-resolution survey of the total 21cm flux from unresolved sources
- High signal-to-noise ratio (SNR)
- Large cosmic volumes covered

MeerKLASS 2021 deep survey

- MeerKAT Large Area Synoptic Survey
- Observations in single dish mode:
  - Area: 236 deg^2
  - Time: 62 hours (41 scans with 64 dishes)
- Frequency and redshift range
  - 971.2 MHz < ν < 1023.6 MHz → 0.388 < z < 0.463
- Trimming performed to minimise the number of bad pixels
  - 334° < R.A. < 357°
  - -34.5° < dec < -27.5°



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HI cosmological signal detected in cross-correlation with GAMA galaxies

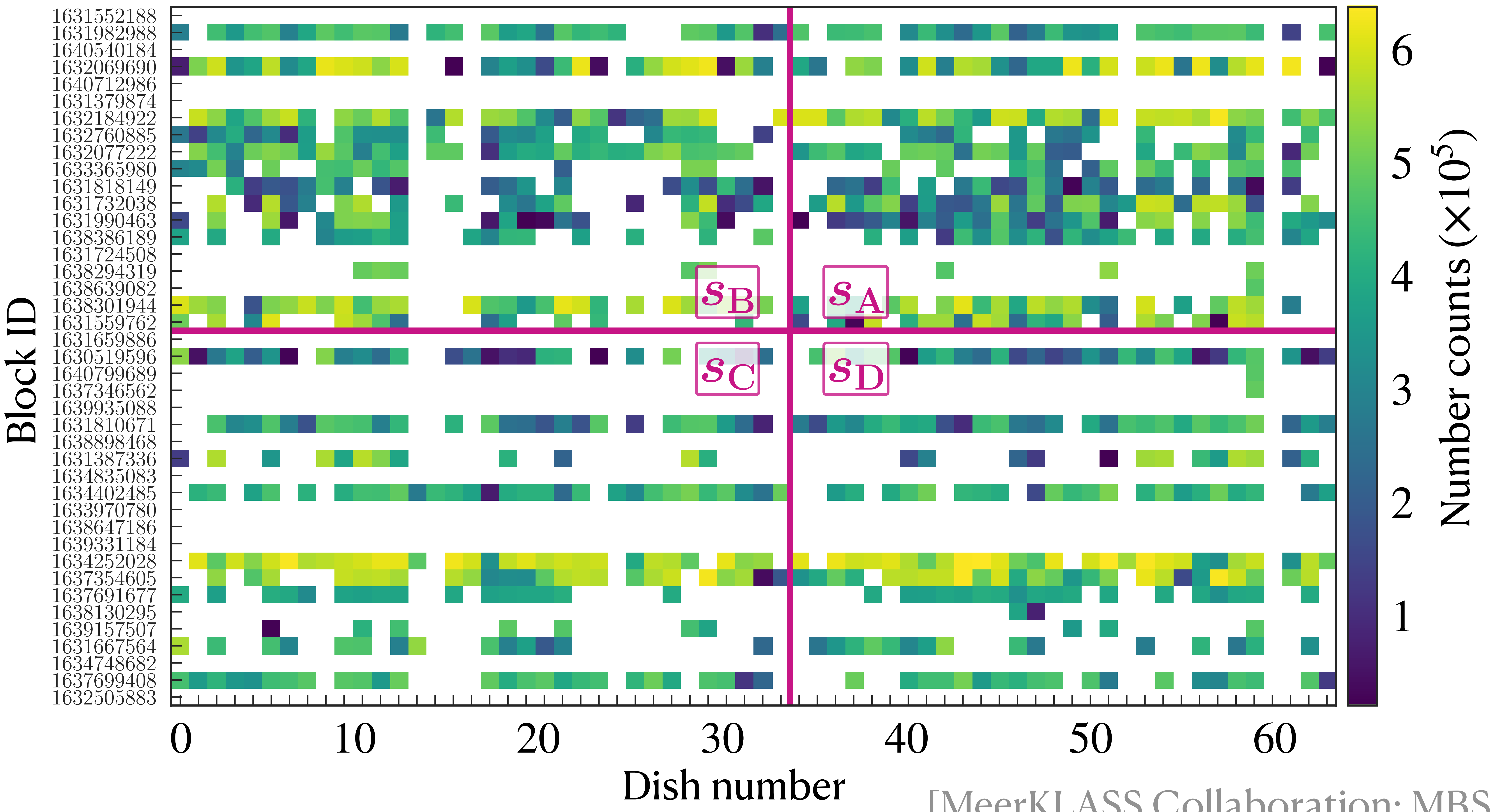
[MeerKLASS Collaboration: Cunnington, Wang et al. (2025)
MeerKLASS Collaboration: MBS et al. (in prep.)]

Splitting the data set

- Building independent data sets from the same survey [Wolz et al. (2021)]
  - Contaminants not correlated between subsets
  - Noise free cross-subset power spectra
- Definition of subset with an equivalent signal-to-noise ratio (SNR)

Splitting the data set

- *Chess-board* division: block- and dish-wise splitting: s_A, s_B, s_C, s_D
- Minimum number of subset (highest SNR) to cover all possible cross-correlations



→ ~ amount of information

[MeerKLASS Collaboration: MBS et al. (in prep.)]

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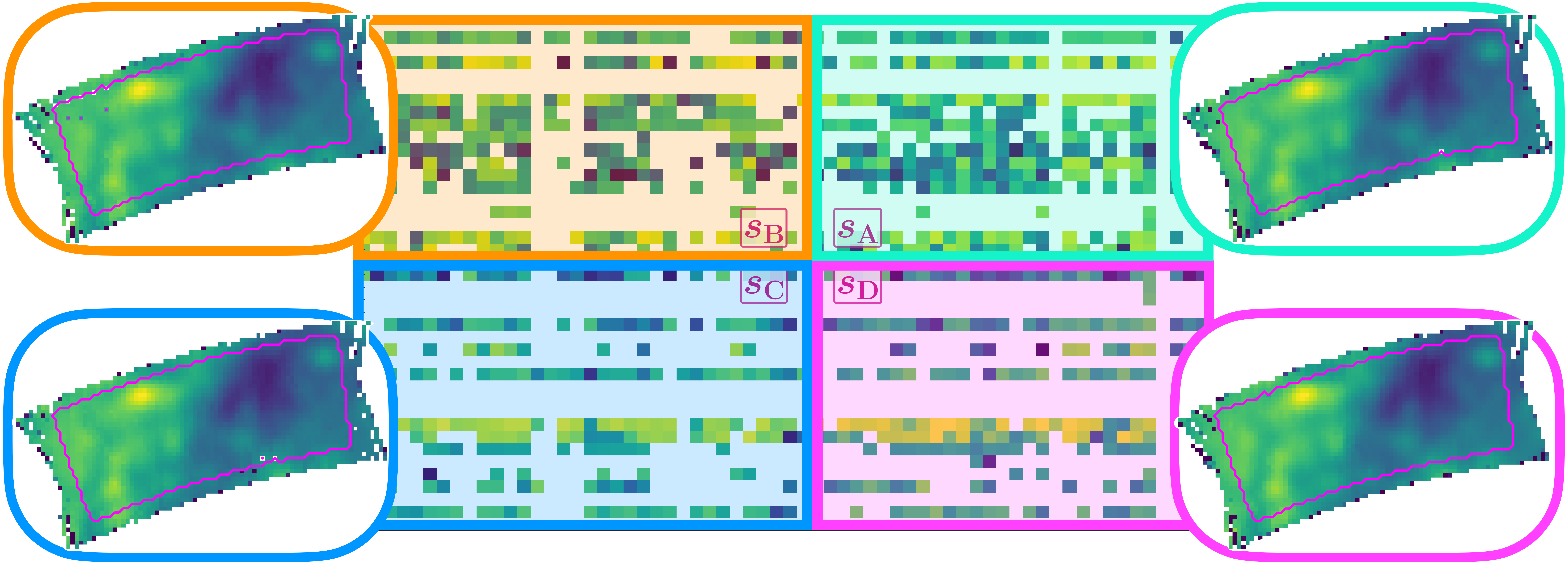

[MeerKLASS Collaboration: MBS et al. (in prep.)]

From intensity maps to power spectra

Foreground cleaning

- mPCA blind cleaning method
- Scale separation through a wavelet filtering on the observed map of the subset s_i

Large – scale map

$$s_i^{\text{obs}} = s_i^{\text{obs,L}} + s_i^{\text{obs,S}}$$

Small – scale map

- PCA analysis of the coarse and fine maps: removal of the first eigenmodes at large and small scales ($N_{\text{fg,L}}$ and $N_{\text{fg,S}}$)

$$s_i^{\text{clean}} = s_i^{\text{clean,L}} + s_i^{\text{clean,S}}$$

- Optimal cleaning level identified through guidance fits

Power spectrum estimation

- Internal cross-correlations

Power spectrum estimator across the subsets i, j

$$\hat{P}_{ij}(\mathbf{k}) = \mathscr{P}\left(s_i^{\text{clean}}, s_j^{\text{clean}}\right) \qquad i \neq j$$

- Scale range
  - $n_k = 9$ k-bins
  - $0.095\,h\,\text{Mpc}^{-1} < k < 0.245\,h\,\text{Mpc}^{-1}$
  - $k_{\parallel,\text{min}} = 0.07\,h\,\text{Mpc}^{-1}$ $\quad k_{\perp,\text{min}} = 0.02\,h\,\text{Mpc}^{-1}$ to avoid the region where signal loss and potential foreground residuals are more prominent

Global fits

- Multi-tracer formalism translated to the multi-subset formalism to enhance the constraining power and robustness of the analysis: cross-$P_{ij}(k)$ combined in a single data-vector
- Multi-subset data vector including only "super" cross-$P_{ij}(k)$
  - Power spectra involving subsets that do not share nor blocks nor dishes
  - Most robust combinations available

[MeerKLASS Collaboration: MBS et al. (in prep.)]

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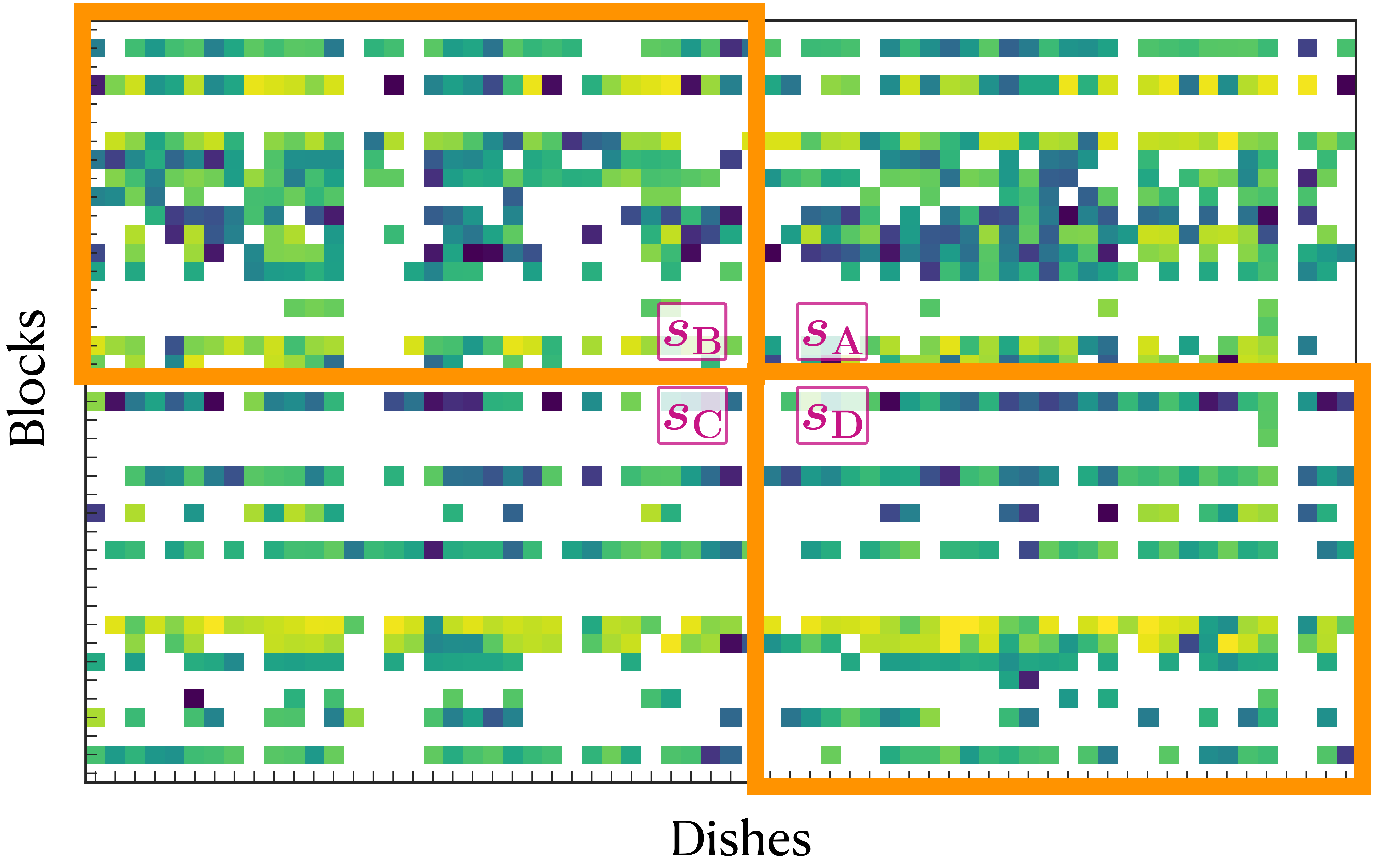
$$P_{\text{xchess}} = \{P_{BD}, P_{AC}\}$$



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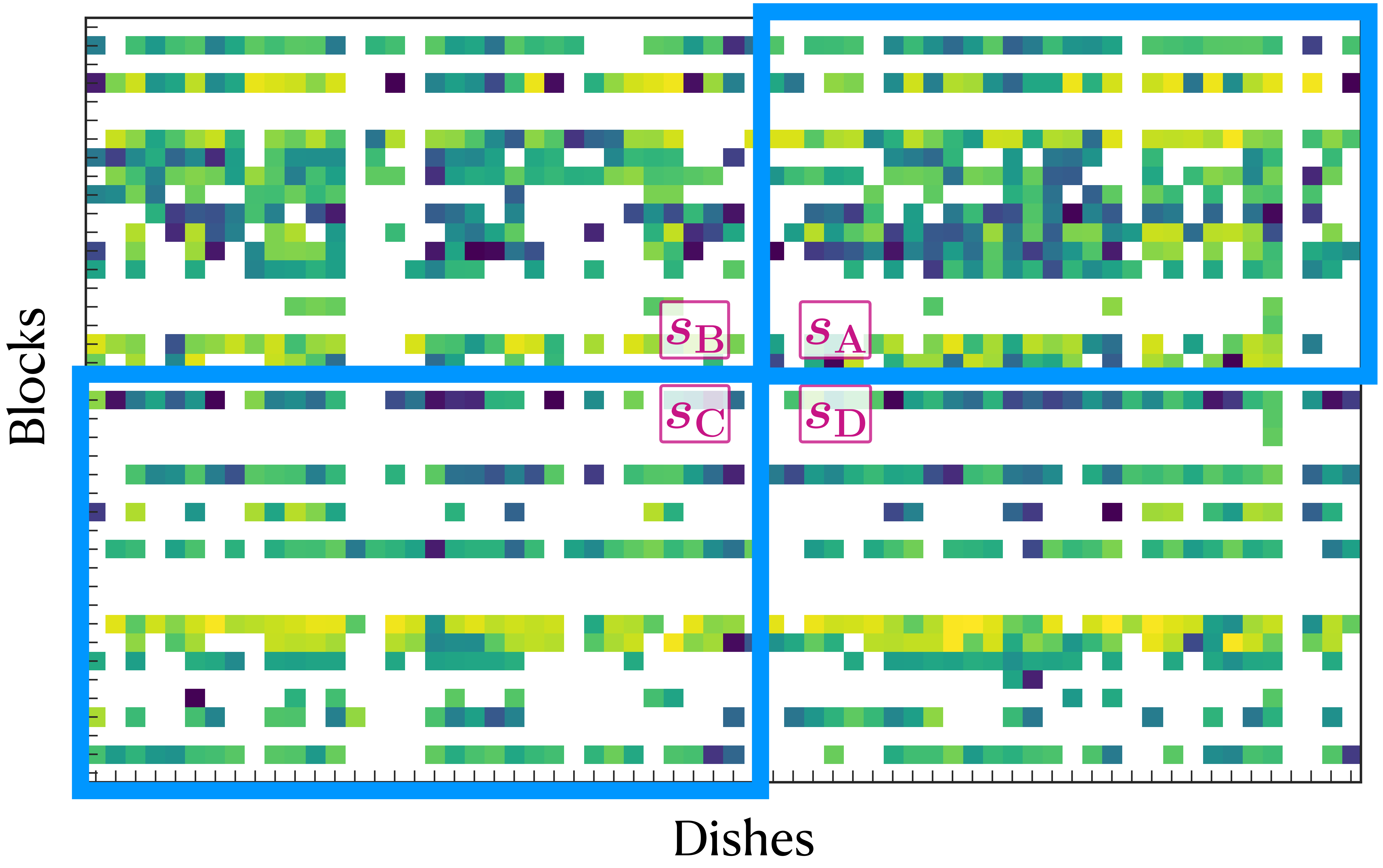

[MeerKLASS Collaboration: MBS et al. (in prep.)]

Global fits

- MCMC fits of the multi-subsets data vectors against the model

$$P_{ij}(\mathbf{k}) = \mathcal{D}_{\rm sl}(k)\left[\mathcal{B}^2(\mathbf{k})T_{\rm HI}^2 b_{\rm HI}^2\left(1+f\mu^2\right)^2 P_{\rm m}(k)\right] \quad \text{where} \quad \begin{cases} T_{\rm HI}^2 b_{\rm HI}^2 = \text{HI brightness temperature } (\propto \Omega_{\rm HI}) \\ \quad\quad\quad\quad \text{and linear bias} \\ \mathcal{B}^2(\mathbf{k}) = \text{instrumental damping (mostly beam)} \\ \mathcal{D}_{\rm sl}(k) = \left(\frac{k}{h\,{\rm Mpc}^{-1}}\right)^{\beta} = \text{signal loss damping} \end{cases}$$

- $P_{ij}(\mathbf{k})$ spherically averaged $\rightarrow$ $P_{ij}(k)$
- Signal loss taken into account with a forward model approach
  - No reconstruction of the signal at the power spectrum level
  - Extra nuisance parameter in the model: β

[MeerKLASS Collaboration: MBS et al. (in prep.)]

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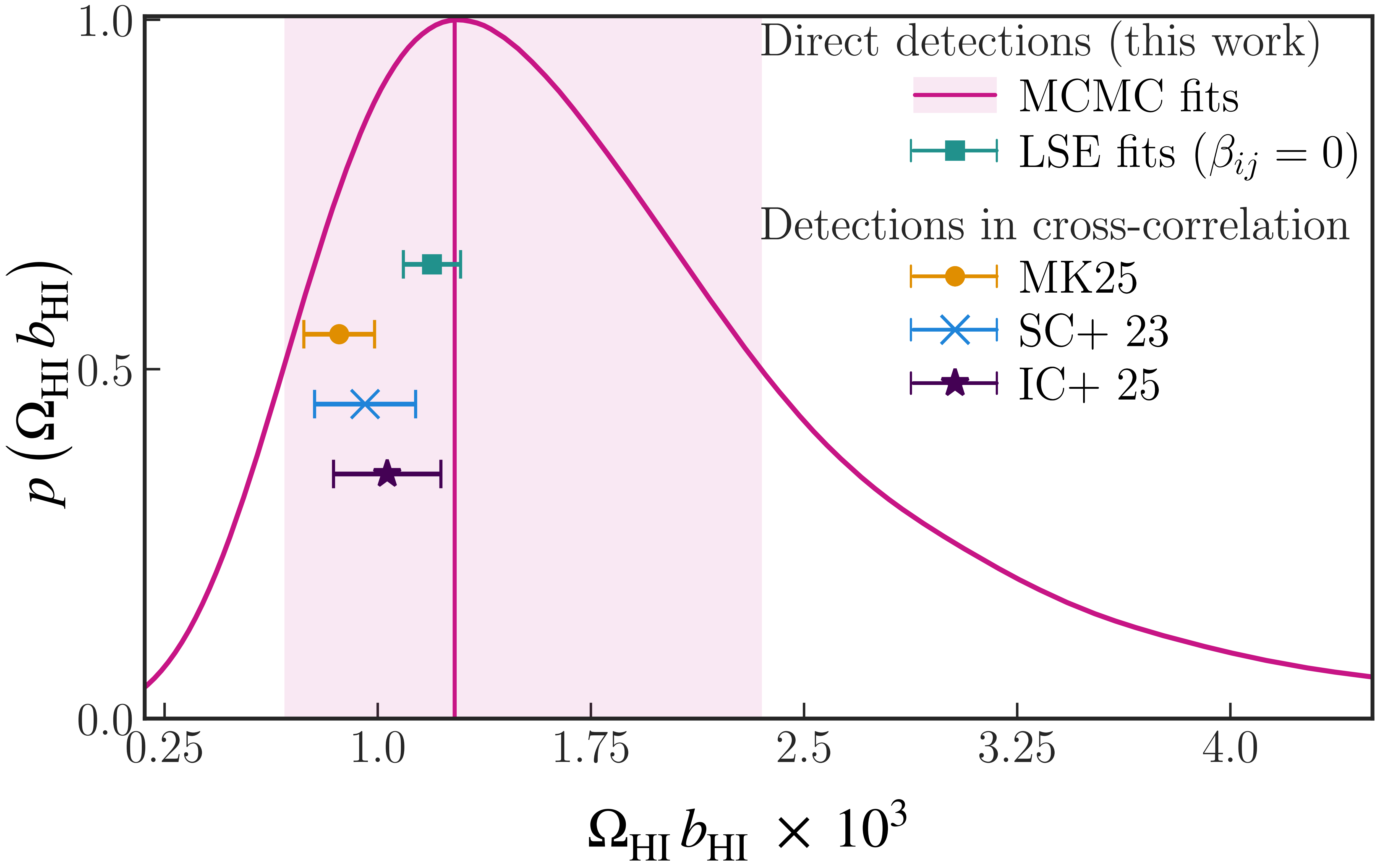
- $P_{ij}(\mathbf{k})$ spherically averaged $\rightarrow$ $P_{ij}(k)$
- Fit parameters
  - $\Omega_{\rm HI} b_{\rm HI}$ common to all cross-$P_{ij}(k)$
  - One nuisance β for each cross-$P_{ij}(k)$ in the data vector
- Jackknife covariance matrix

[MeerKLASS Collaboration: MBS et al. (in prep.)]

Results

- High detection significance
- Good internal consistency
- Positive outcomes from stress tests performed
- Agreement with previous detections:
  - MeerKLASS 2019 L-band survey in cross-correlation with WiggleZ galaxies [Cunnington, Li et al. (2022), Carucci et al. (2024)]
  - MeerKLASS 2021 L-band survey in cross-correlation with GAMA galaxies [MeerKLASS Collaboration: Cunnington, Wang et al. (2025)]



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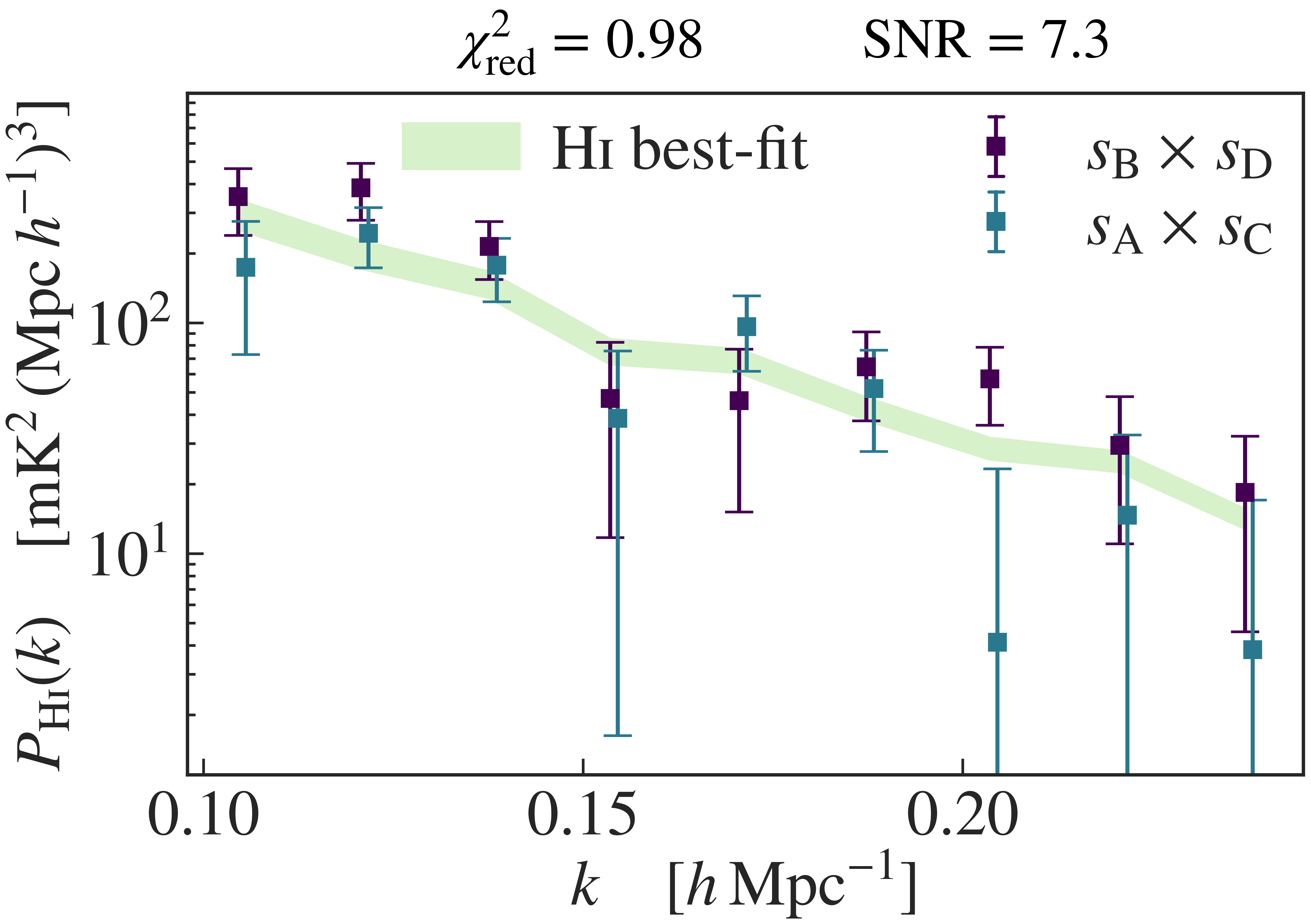
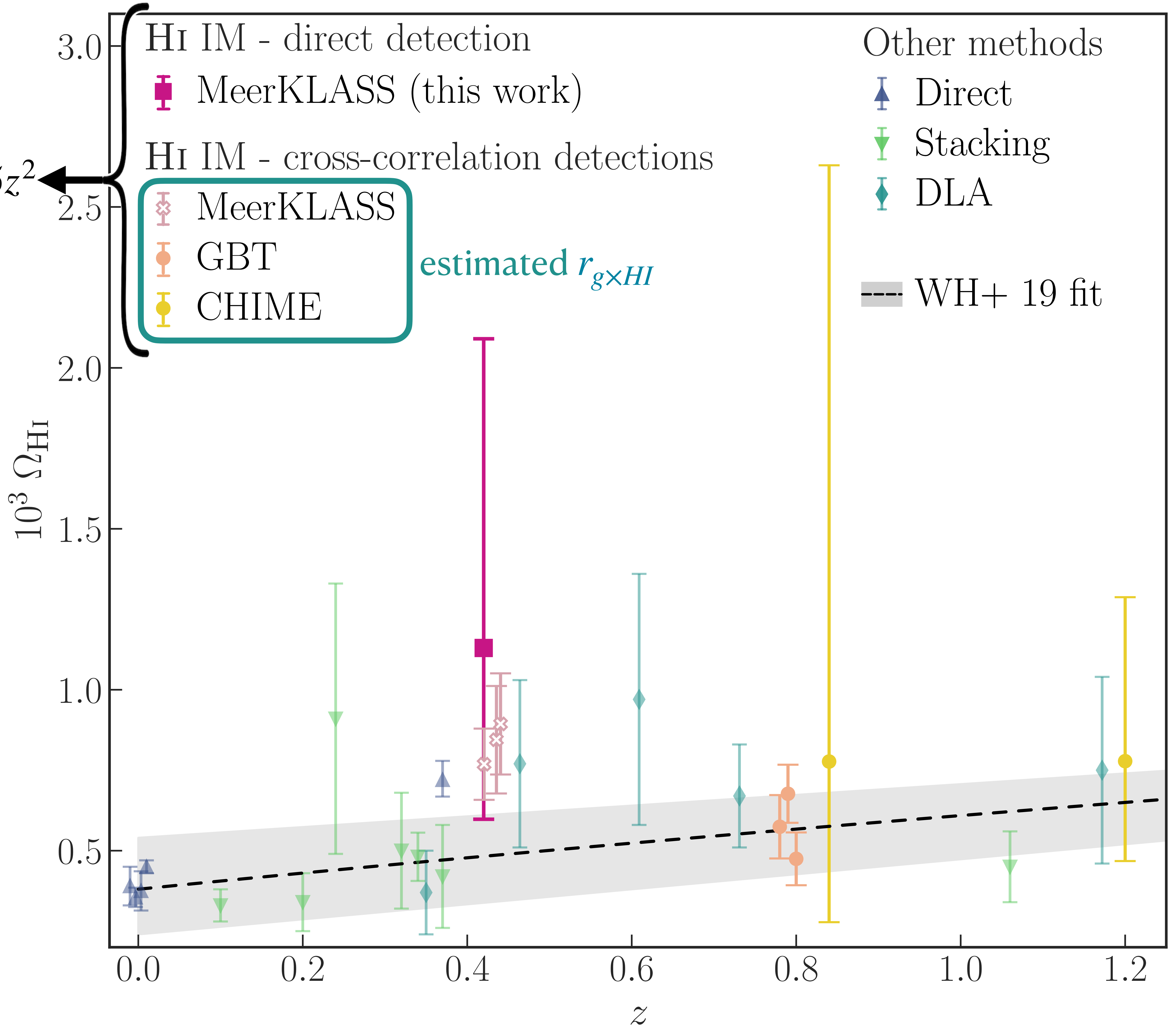


[MeerKLASS Collaboration: MBS et al. (in prep.)]

MeerKLASS in the HI landscape

- A comparison with other measurements of the abundance of HI

$b_{HI}(z) = 0.89 + 0.69z - 0.05z^2$



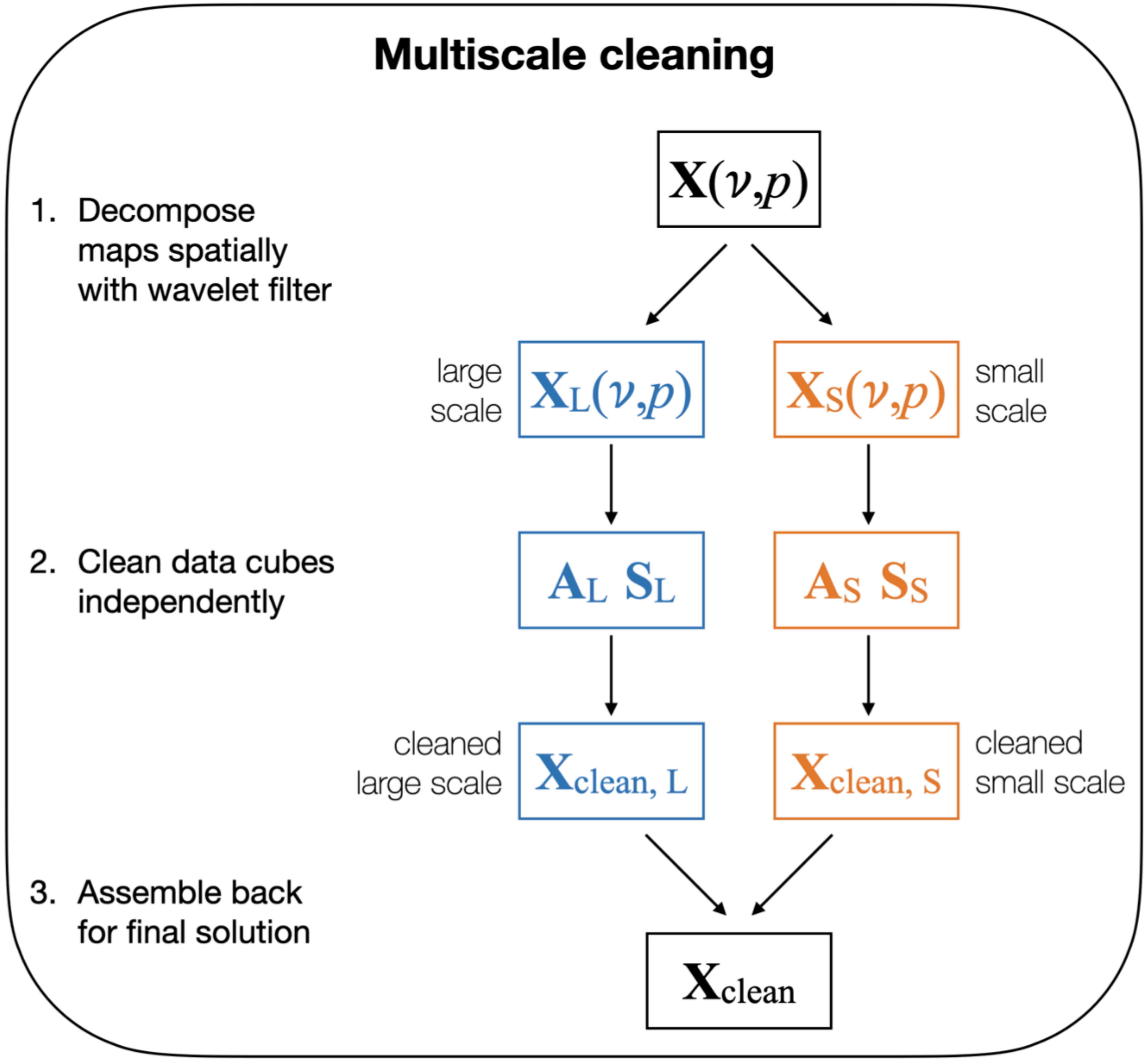
[MeerKLASS Collaboration: MBS et al. (in prep.)]

Conclusions

- **21 cm intensity mapping** is challenging but it has a **great potential** for probing the large scale structure of the Universe
- The **MeerKLASS collaboration** is demonstrating the feasibility of this technique
  - Development of calibration pipelines [Wang et al. (2021), MeerKLASS Collaboration: Cunnington, Wang et al. (2025)], optimized foreground cleaning techniques [Carucci et al. (2024)] and methods to extract the information embedded in the data [Cunnington et al. (2023), Chen et al. (2025), ...]
  - Detections of the HI signal in cross-correlation with galaxies [Cunnington, Li et al. (2022), Carucci et al. (2024), MeerKLASS Collaboration: Cunnington, Wang et al. (2025)]
  - First data release (2019 L-band pilot survey): meerklass.org/data
  - **Detection of the HI signal independently on external tracers** [MeerKLASS Collaboration: MBS et al. (in prep.)]

Backup slides

Foreground cleaning: mPCA



Foreground cleaning: PCA

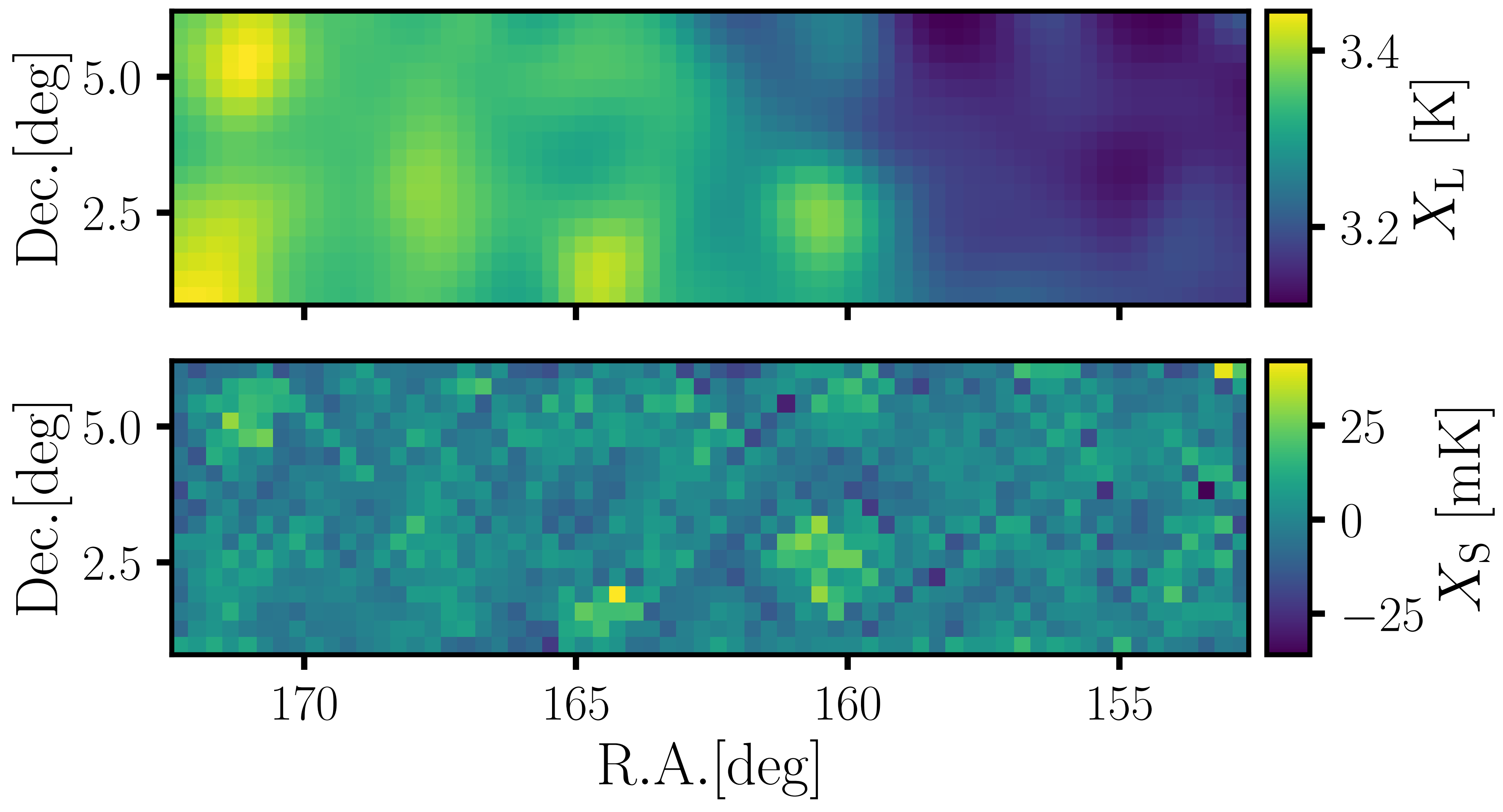
Why multi-scale?

- PCA better performs when dealing with smooth components
- Large scale components (smoother) better identified when separated from the small scale fluctuations
- Small scale (and smaller in amplitude) components captured independently to refine the cleaning
- Fits look better

Why mPCA and other choices?

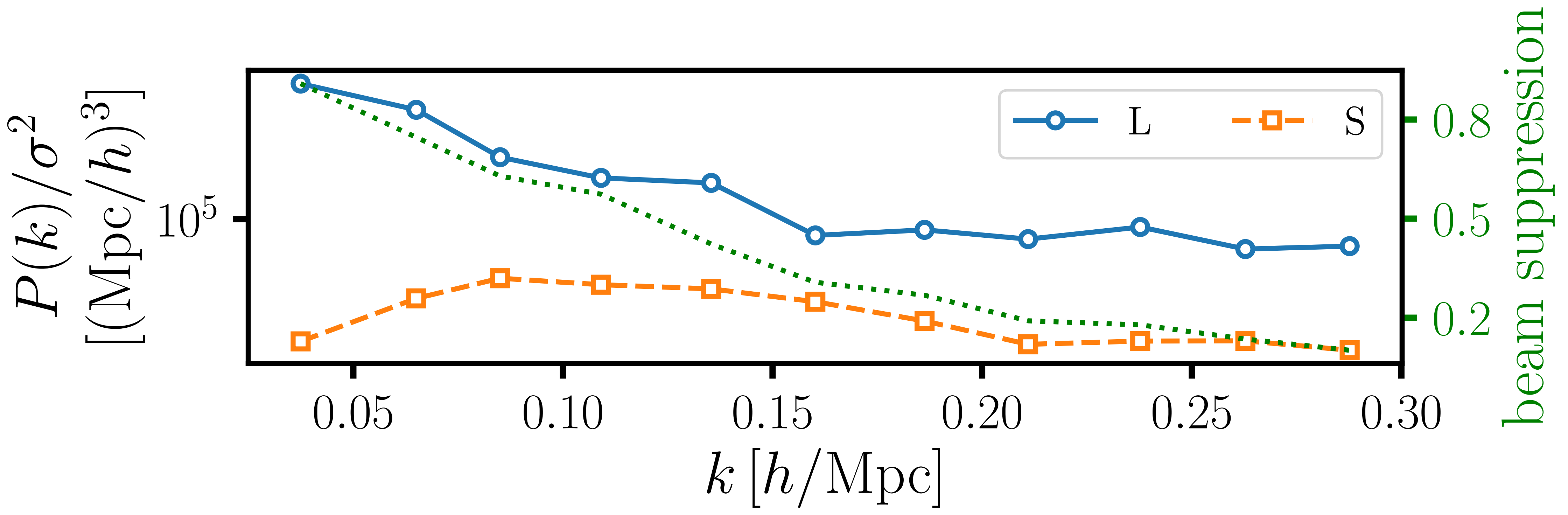
- It works with simulations [Carucci et al. (2020)]
- It works with MeerKLASS data [Carucci et al. (2025)]
  - More diagonal frequency-frequency correlation matrix
  - Stability against larger $k_{\rm eff}$
- Wavelets are stable and fast
- Starlets already tested with CMB and with simulations

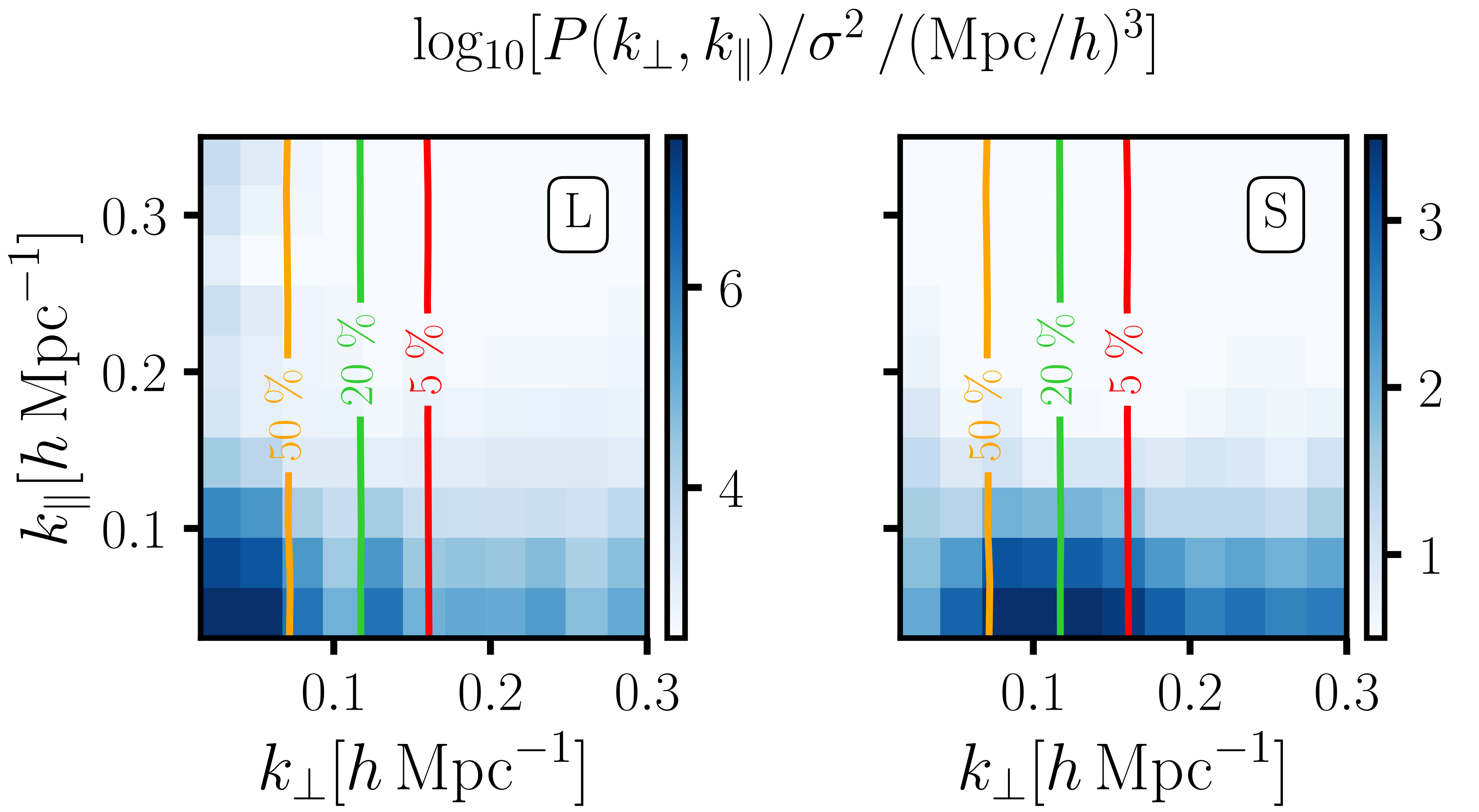
Foreground cleaning: PCA



what Large and Small scale version of 2019 L-band data look like

The division is 2D: separation mostly visible in $k_\perp$





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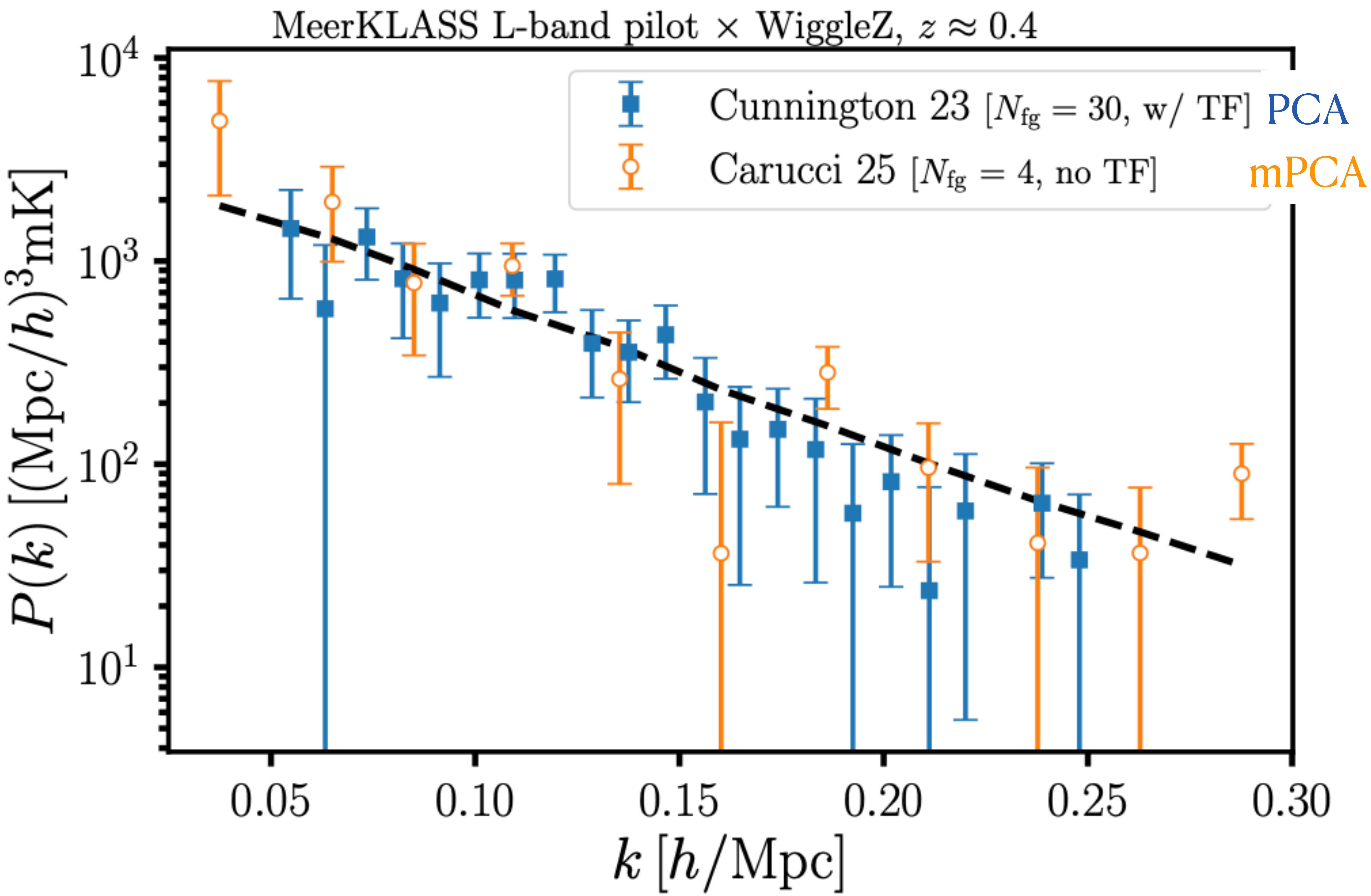


Power spectrum estimation

- More processing: $s_i^{\rm clean}({\rm R.A.}, {\rm dec.}, \nu) \xrightarrow{\text{regridding}} s_i^{\rm clean}(\mathbf{x}) \xrightarrow{\text{FFT}} \tilde{F}_i(\mathbf{k})$
- Power spectrum estimator (applied on the subsets i and j)

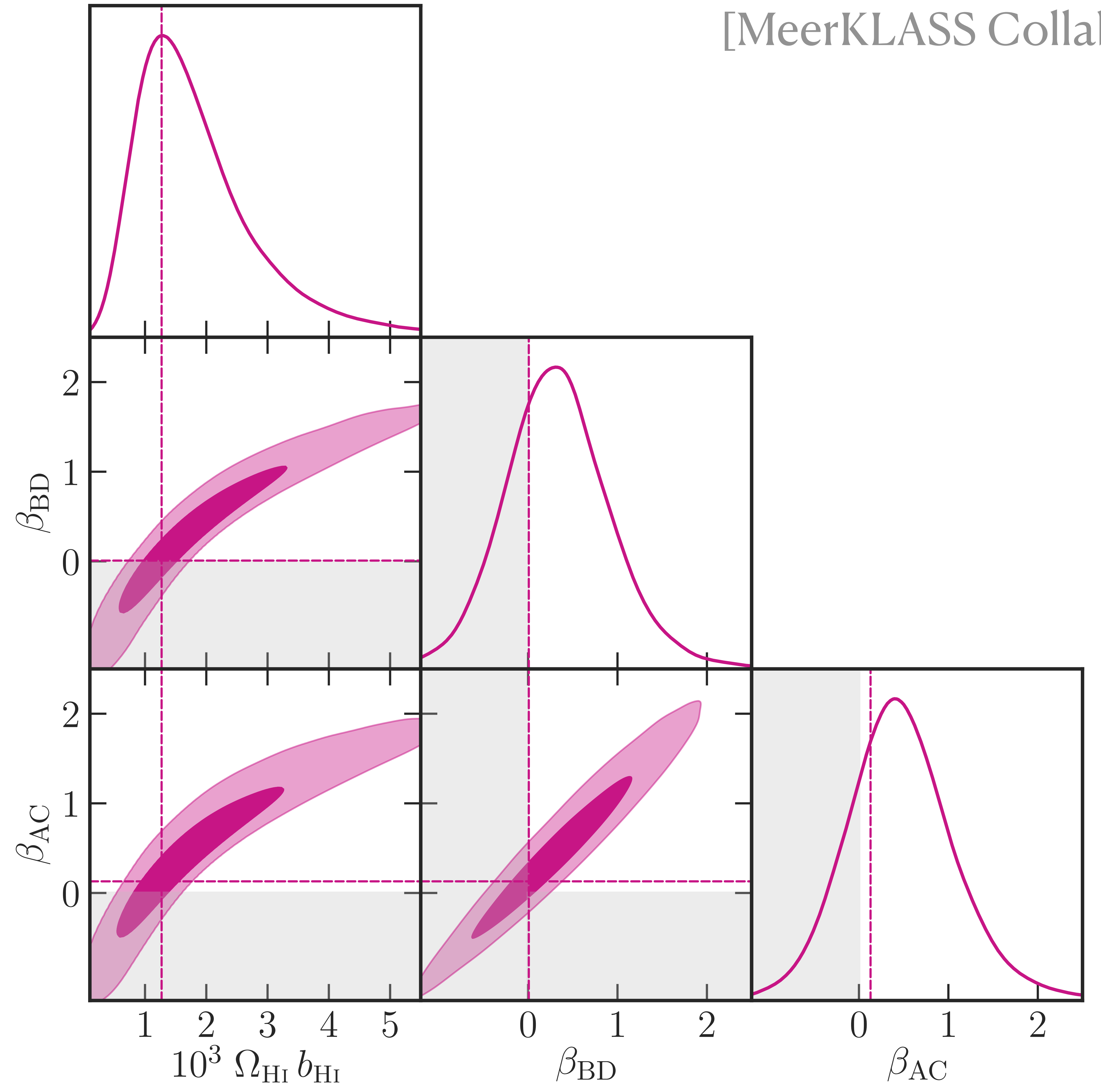
$$\hat{P}_{ij}(\mathbf{k}) = \frac{V_{\rm cell}}{\sum_{\mathbf{x}} w_i(\mathbf{x}) w_j(\mathbf{x})} \mathrm{Re}\left\{ \tilde{F}_i(\mathbf{k}) \tilde{F}_j^*(\mathbf{k}) \right\}$$

- Scale range
  - $n_k = 9$ k-bins
  - $0.095\, h\,{\rm Mpc}^{-1} < k < 0.245\, h\,{\rm Mpc}^{-1}$
  - $k_{\parallel,{\rm min}} = 0.07\, h\,{\rm Mpc}^{-1}$ $k_{\perp,{\rm min}} = 0.02\, h\,{\rm Mpc}^{-1}$ to avoid the region where signal loss and potential foreground residuals are more prominent

[MeerKLASS Collaboration: MBS et al. (in prep.)]

Full posterior distribution

[MeerKLASS Collaboration: MBS et al. (in prep.)]



Theoretical error bars

- Diagonal covariance matrix for Gaussian error bars

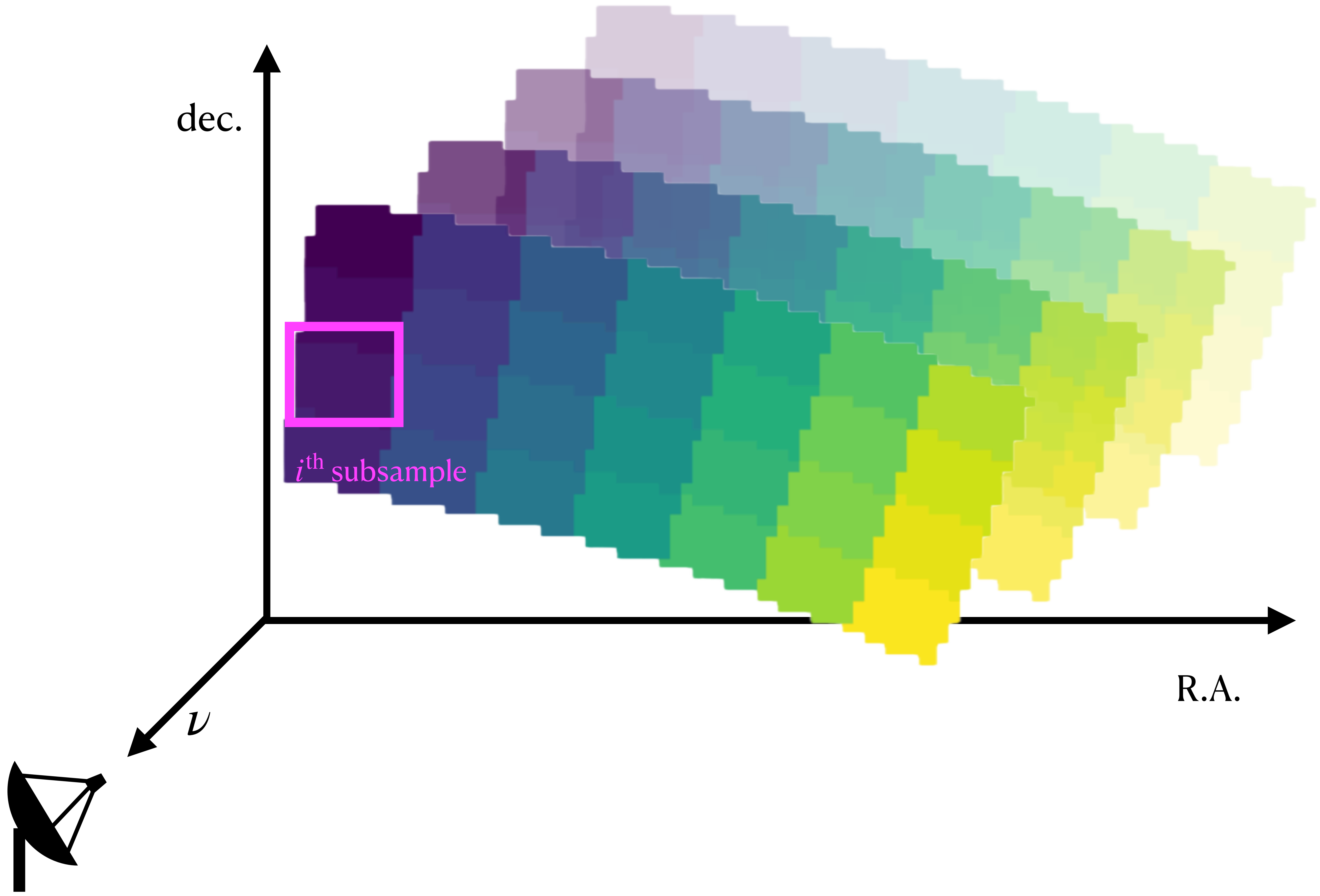
$$\Delta P_{ij}(k) = \sqrt{\frac{1}{2N_{\rm m}(k)}\left[\hat{P}_{ii}(k)\hat{P}_{jj}(k) + \hat{P}_{ij}(k)\hat{P}_{ij}(k)\right]}$$

Number of independent modes
(taking into account the partial
coverage of the grid)

[MeerKLASS Collaboration: MBS et al. (in prep.)]

Jackknife covariance

- Jackknife replicates of the original map: each one is built removing one of the N_{jack} sub-samples of the map at a time



Jackknife covariance

- Jackknife replicates of the original map: each one is built removing one of the $N_{\rm jack}$ sub-samples of the map at a time
- Full non-Gaussian covariance matrix using 224 jackknife replicates

Volume factor

$J^{\rm th}$ jackknife power spectra

$$\mathrm{Cov}\left(P_{ij}^{(k,k')}\right) = \frac{N_{\rm jack}-1}{N_{\rm jack}-n_{\rm k}-2}\frac{N_{\rm jack}-1}{N_{\rm jack}}\sum_{J=1}^{N_{\rm jack}}\left[P_i^J(k)-\bar{P}_i^J(k)\right]\left[P_j^J(k')-\bar{P}_j^J(k')\right]$$

Hartlap factor

[MeerKLASS Collaboration: MBS et al. (in prep.)]

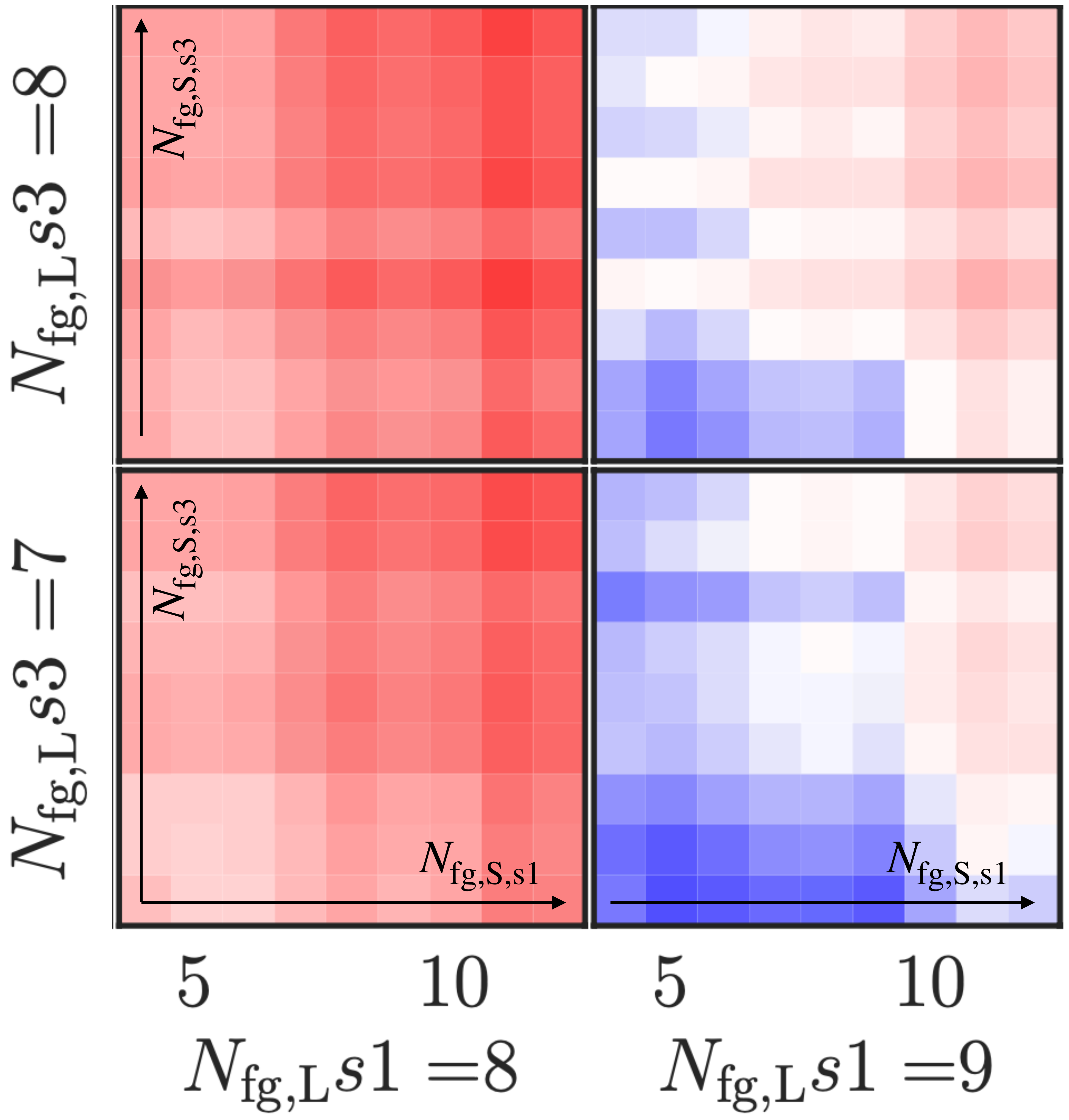
Guidance fits

- Fit of each cross power spectrum against the model

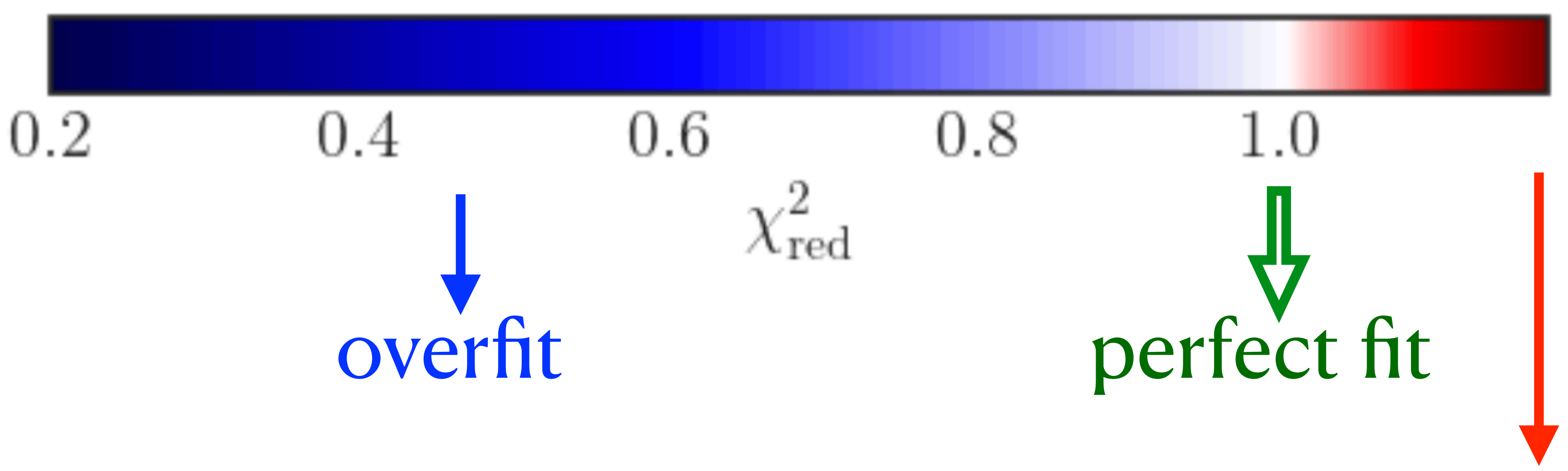
$$P_{ij}(\mathbf{k}) = \mathscr{B}^2(\mathbf{k}) T_{\rm HI}^2 b_{\rm HI}^2 \left(1 + f\mu^2\right)^2 P_{\rm m} \qquad \text{where} \quad \mathscr{B}(\mathbf{k}) = \mathscr{B}_{\rm beam}(\mathbf{k})\, \mathscr{B}_{\rm pix}(\mathbf{k})\, \mathscr{B}_{\rm chan}(\mathbf{k})$$

- Least Square Error method to constrain the overall amplitude (parameterized by $\Omega_{\rm HI} b_{\rm HI}$)
- Jackknife covariance matrix
- Best cleaning identified according to the quality of the fit (the metric is the reduced χ^2) [Carucci et al. (2020)]
  - Too mild cleaning → residuals contributing to the power spectra with a different trend compared to the cosmological clustering → fit fails
  - Too aggressive cleaning → the signal is almost completely erased → fit fails

Guidance fits



- Columns: cleaning of the large scales in one of the subsets
- Rows: cleaning of the large scales in one of the subsets
- Block axes: cleaning of the small scales
- Color map:



Threshold for being in the region of the 68% confidence level

[MeerKLASS Collaboration: MBS et al. (in prep.)]

Robustness tests

- Null tests: reshuffling the maps (and then computing the power spectra)
  - Along radial direction
  - In pixel space
- Scale-independence tests: repeating the fits removing 1 to 3 bins at large/small scales
- Map cuts: repeating the fits after splitting the maps at the mean R.A.
- Radial power spectra: test of the presence of residual contaminants after the foreground cleaning
- Leakage power spectra: test of the presence of residual contaminants after the foreground cleaning
- Signal injection test: assessment of the impact of signal loss
- ...

[MeerKLASS Collaboration: MBS et al. (in prep.)]

Validating the signal loss kernel

- Tested on simulations and on data
- Power laws fitted to the estimated transfer functions