



Unveiling the HI power spectrum with **M_urKCLASS**

Matilde Barberi Squarotti

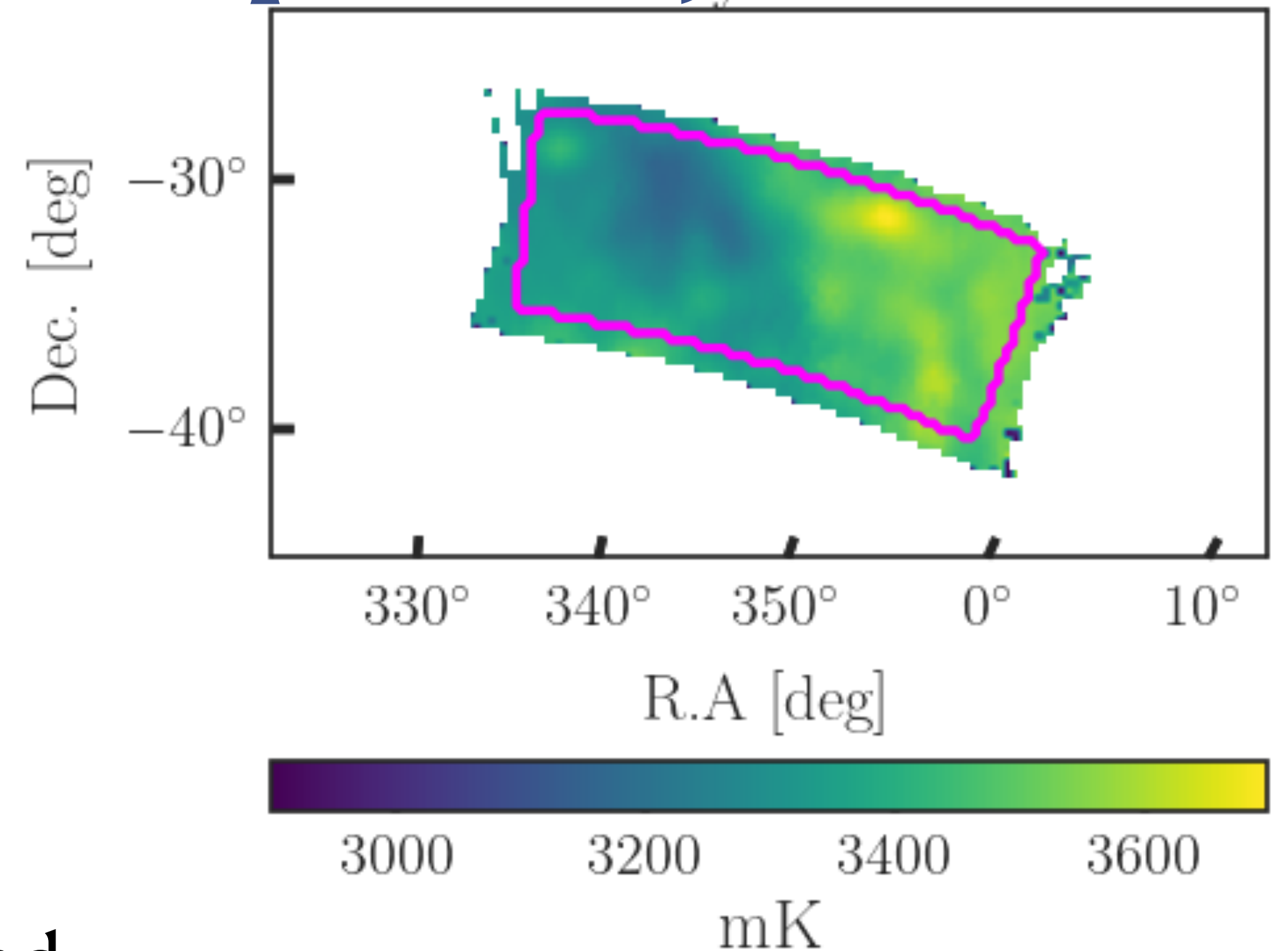
SKAO SWG Cosmology

Görlitz, June 18th 2025



MeerKLASS 2021 deep survey

- MeerKAT Large Area Synoptic Survey
- Observations:
 - Area: 236 deg²
 - Time: 62 hours (41 scans with 64 dishes)
- Frequency and redshift range
 - $971.2 \text{ MHz} < \nu < 1023.6 \text{ MHz} \rightarrow 0.388 < z < 0.463$
- Trimming performed to minimise the number of bad pixels
 - $334^\circ < \text{R.A.} < 357^\circ$
 - $-34.5^\circ < \text{dec} < -27.5^\circ$



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

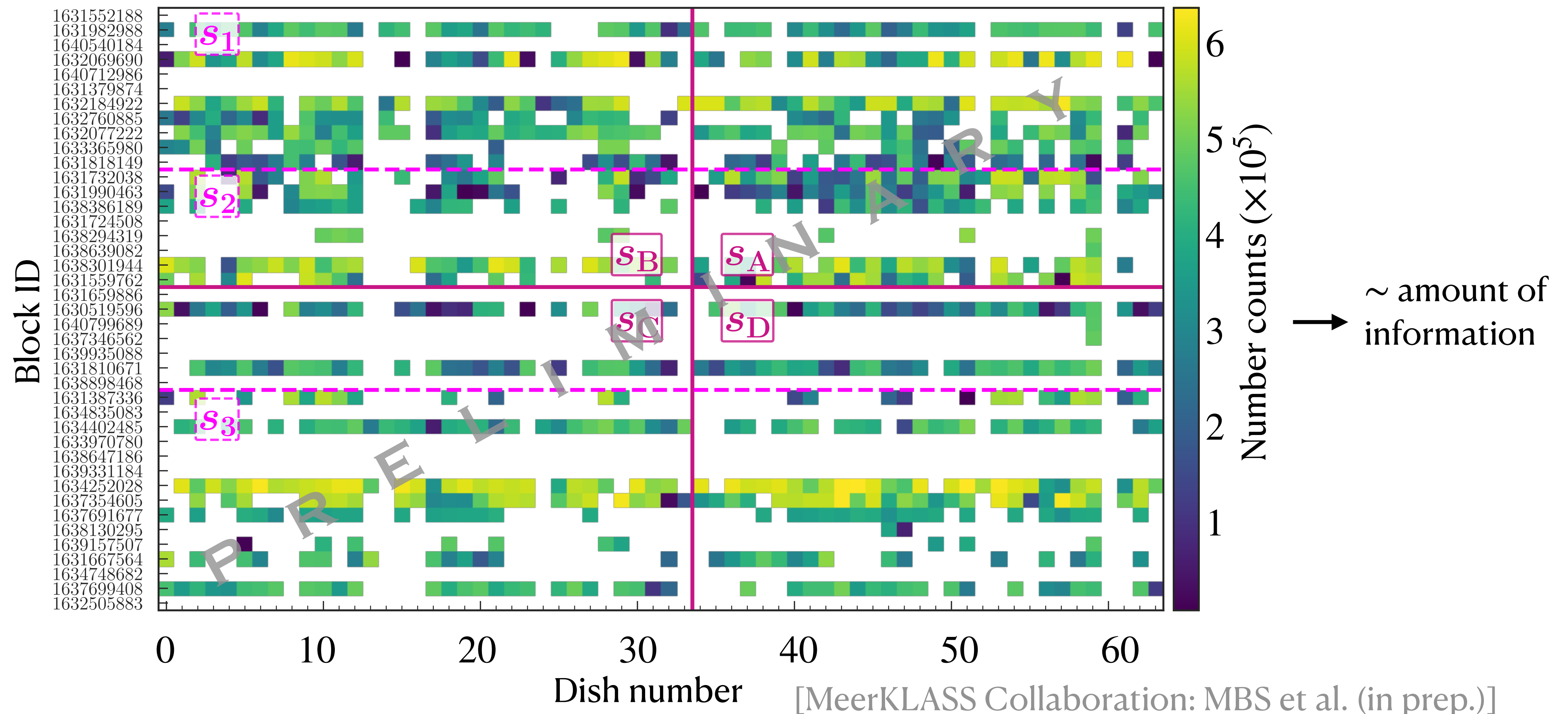
- Building independent data sets from the same survey [Wolz et al. (2021)]
 - Contaminants not correlated between subsets
 - Noise free cross-subset power spectra
- Definition of subset with an equivalent signal-to-noise ratio

Splitting the data set

Chess-board division

Stripe division

- Block- and dish-wise splitting: s_A, s_B, s_C, s_D
- Block-wise splitting: s_1, s_2, s_3



Foreground cleaning: mPCA

- Blind cleaning method: PCA applied on large and small scales independently
- Scale separation through a wavelet filtering (using starlets) on the observed map of the subset s_i

$$s_i^{\text{obs}} = \overset{\text{Large scale fluctuations}}{s_i^{\text{obs,L}}} + \underset{\text{Small scale fluctuations}}{s_i^{\text{obs,S}}}$$

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

$$\begin{cases} s_i^{\text{clean,L}} = s_i^{\text{obs,L}} - \hat{\mathbf{A}}_{\text{L}} \mathbf{S}_{\text{L}} \\ s_i^{\text{clean,S}} = s_i^{\text{obs,S}} - \hat{\mathbf{A}}_{\text{S}} \mathbf{S}_{\text{S}} \end{cases} \longrightarrow s_i^{\text{clean}} = s_i^{\text{clean,L}} + s_i^{\text{clean,S}}$$

- Successfully adopted for MeerKLASS 2019 L-Band data [Carucci et al. (2024)]
- Optimal cleaning level identified through guidance fits [MeerKLASS Collaboration: MBS et al. (in prep.)]

Power spectrum estimation

- More processing: $s_i^{\text{clean}}(\mathbf{R} . \mathbf{A} . , \text{dec} . , \nu) \xrightarrow{\text{regridding}} s_i^{\text{clean}}(\mathbf{x}) \xrightarrow{\text{FFT}} \tilde{F}_i(\mathbf{k})$

- Power spectrum estimator (applied on the subsets i and j)

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

- Scale range

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

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

Global fits

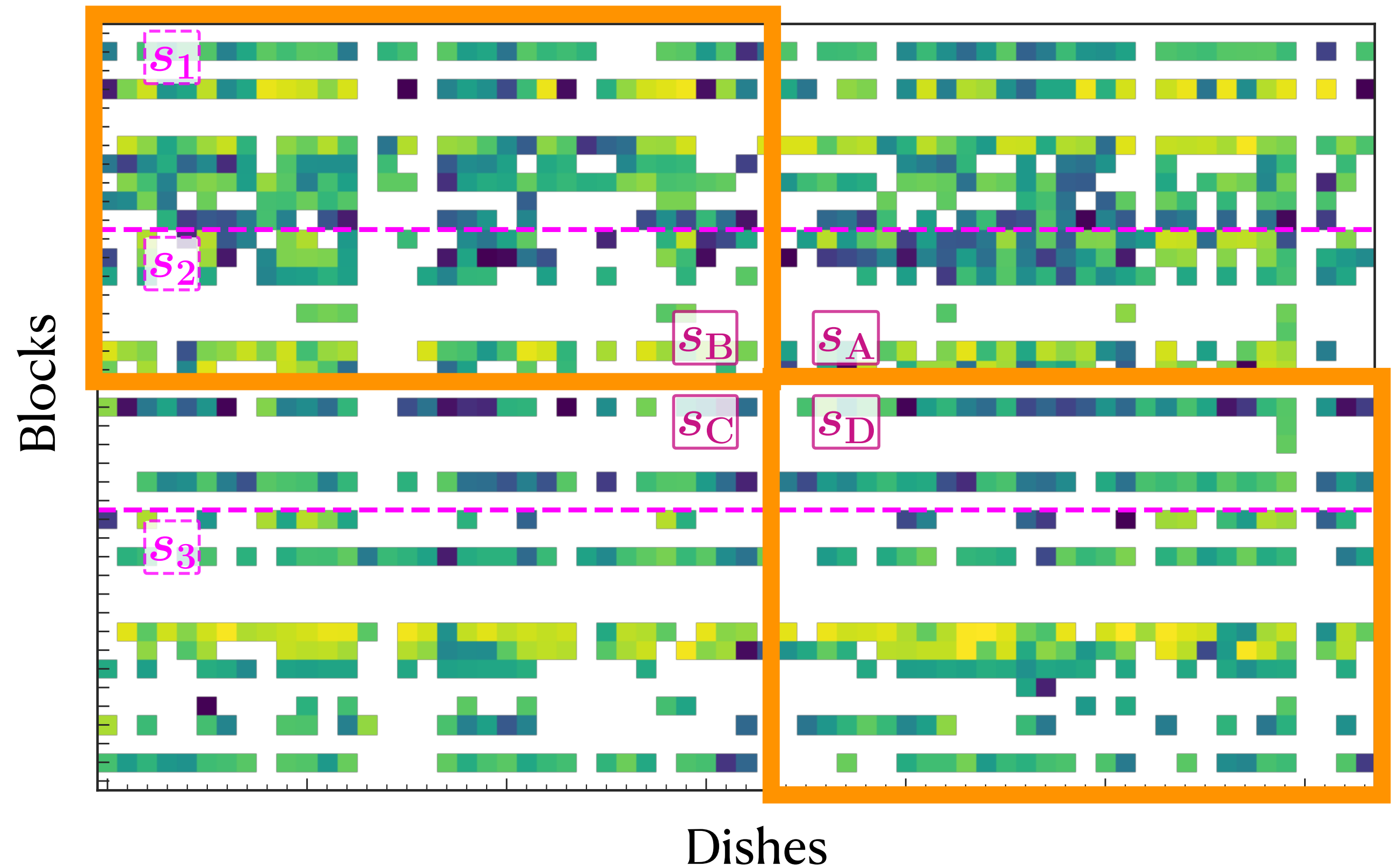
- Multi-tracer formalism translated to the multi-subset formalism to enhance the constraining power and robustness of the analysis
 - Cross- $P_{ij}(k)$ combined in a single data-vector
 - Auto- $P_{ii}(k)$ excluded from the analysis because noise dominated

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

Global fits: *Chess-board* division

- 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

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

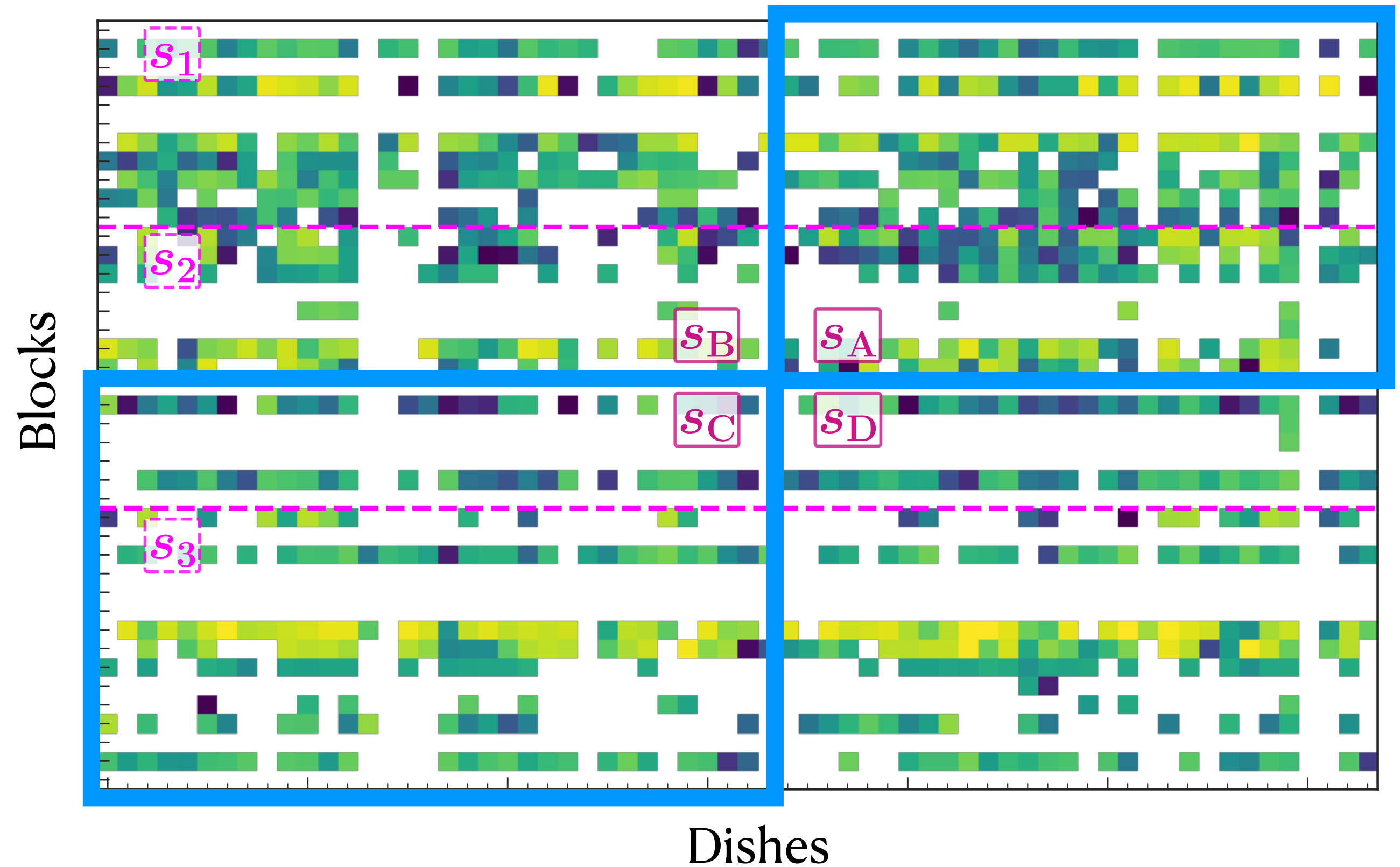


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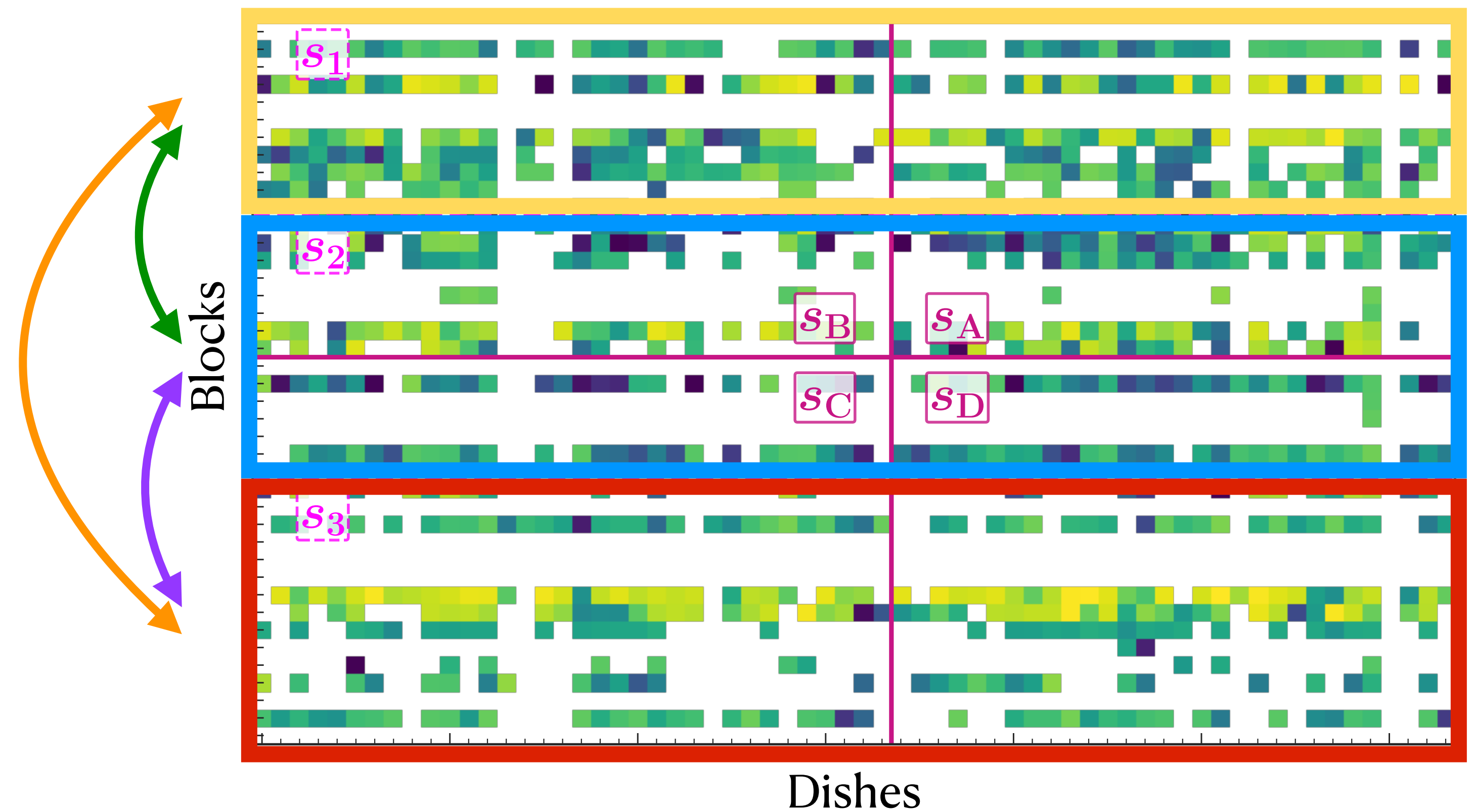
$$C(P_{\text{xchess}}, P_{\text{xchess}}) = \begin{bmatrix} C(P_{BD}, P_{BD}) & C(P_{BD}, P_{AC}) \\ & C(P_{AC}, P_{AC}) \end{bmatrix}$$

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

Global fits: *Stripes* division

- Multi-subset data vector including all the three available cross- $P_{ij}(k)$
- Potentially more prone to residual (dish-dependent) systematics

$$P_{\text{stripes}} = \{P_{12}, P_{13}, P_{23}\}$$



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

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

Global fits

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

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

- $P_{ij}(\mathbf{k})$ 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.)]

Global fits

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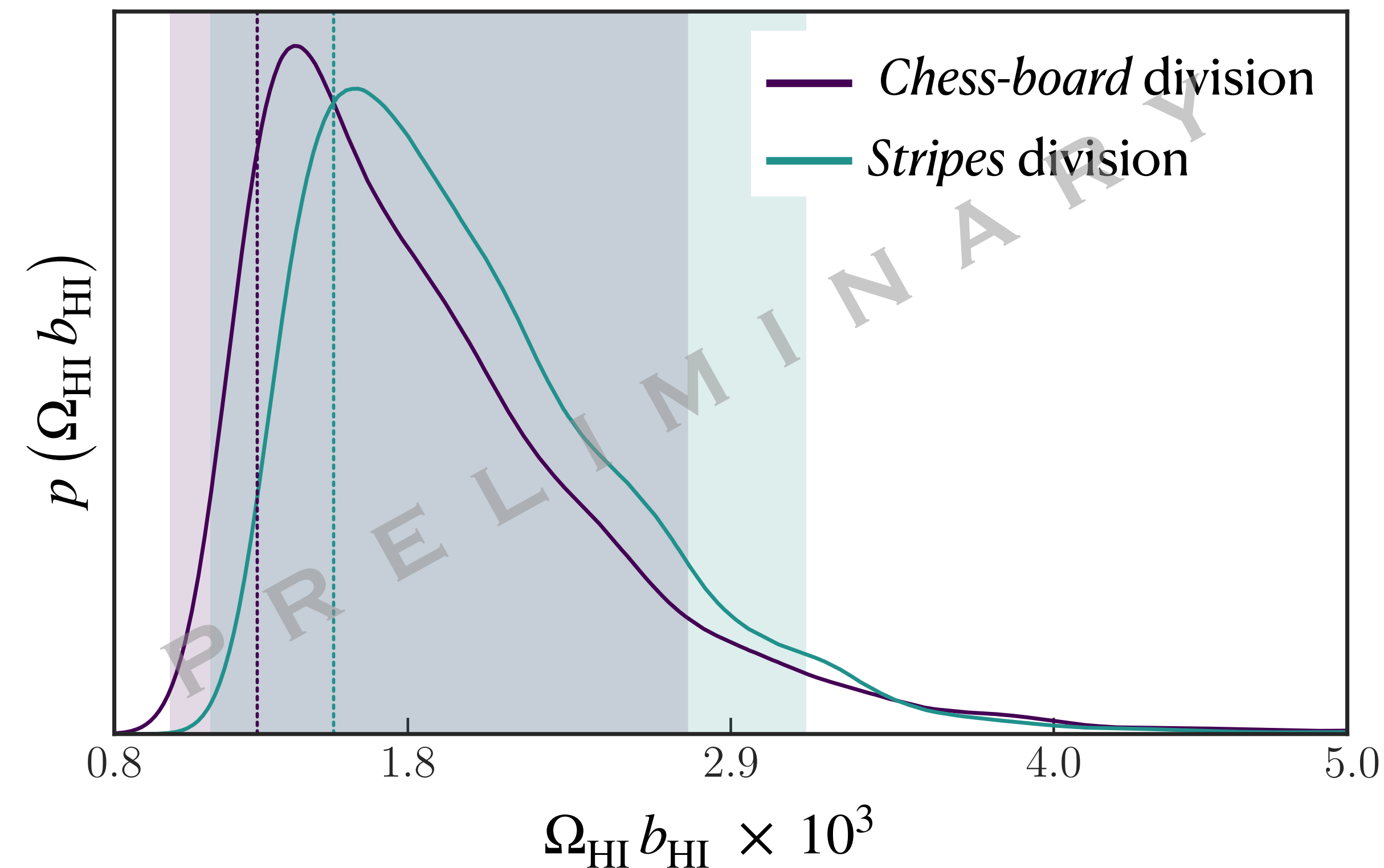
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- $P_{ij}(\mathbf{k})$ spherically averaged $\rightarrow P_{ij}(k)$
- Fit parameters
 - $\Omega_{\text{HI}} b_{\text{HI}}$ common to all cross- $P_{ij}(k)$
 - One nuisance β for each cross- $P_{ij}(k)$ in the data vector
- Jackknife covariance matrix

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

Results

- High detection significance
- Good internal consistency (but *chess-board* division confirmed to be more robust than the *stripe* division)
- 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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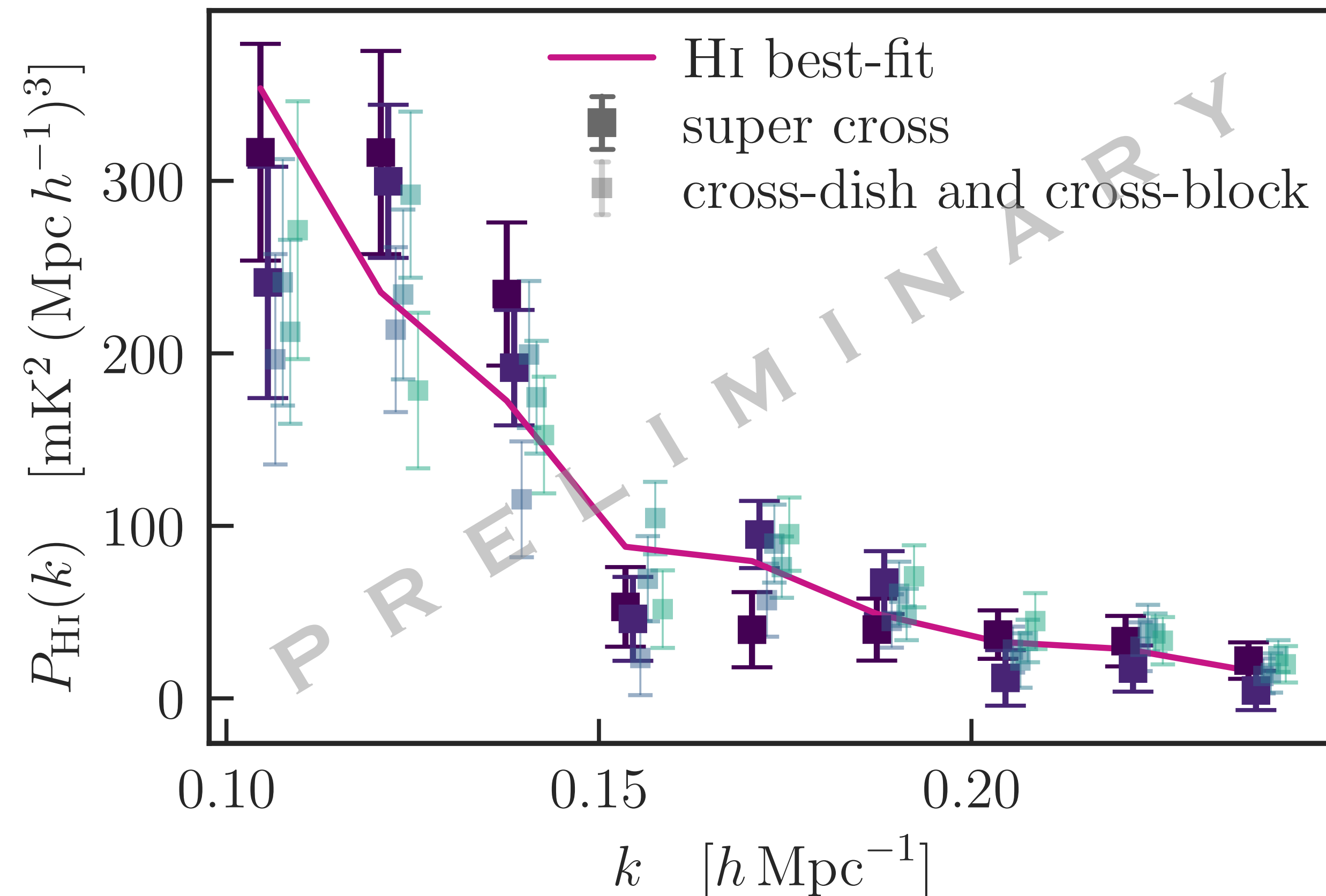
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Focus on the *chess-board* division

$$\chi^2_{\text{red}} = 1.07$$

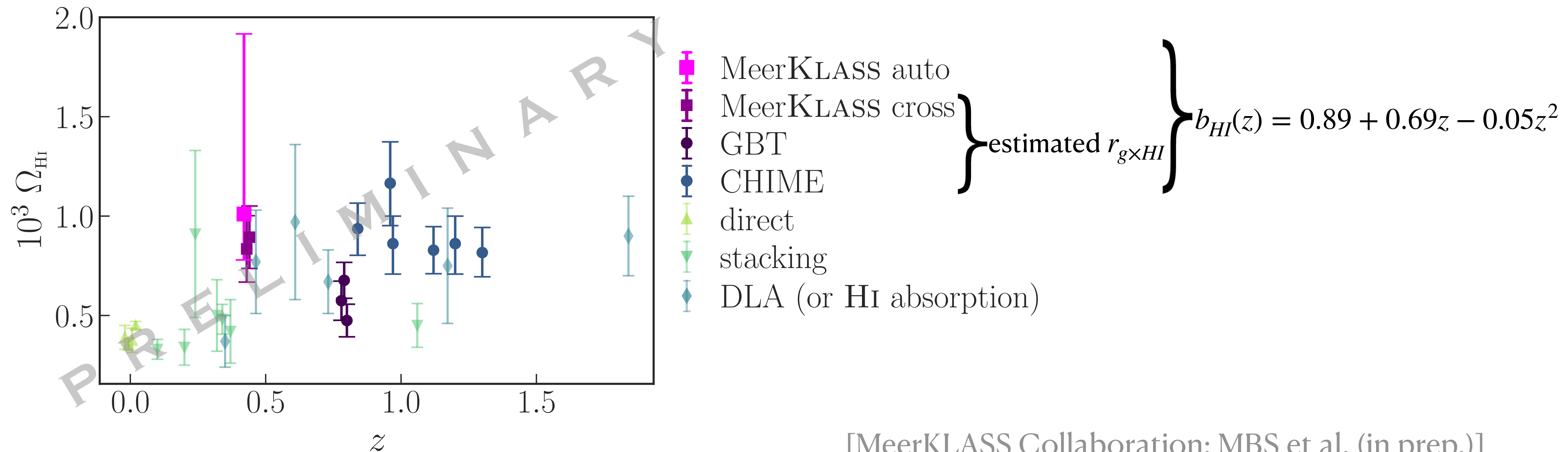
$$\text{SNR} = 10.13$$



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

MeerKLASS in the HI landscape

- A comparison with other measurements of the abundance of HI
 - Other intensity mapping measurements (but in cross correlation with galaxies) $\rightarrow \Omega_{\text{HI}} b_{\text{HI}} r_{g \times \text{HI}}$
 - Direct measurements $\rightarrow \Omega_{\text{HI}}$
 - Staking measurements $\rightarrow \Omega_{\text{HI}}$
 - Damped Lyman- α measurements $\rightarrow \Omega_{\text{HI}}$



[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 successfully demonstrating the feasibility of such a technique, **paving the way for SKAO**
- Development of calibration pipelines [Wang et al. (2021), MeerKLASS Collaboration: Cunnington, Wang et al. (2025)]
- Development of 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 H I signal in cross-correlation with galaxies [Cunnington, Li et al. (2022), Carucci et al. (2024), MeerKLASS Collaboration: Cunnington, Wang et al. (2025)]
- **Detection of the H I signal independently on external tracers** [MeerKLASS Collaboration: MBS et al. (in prep.)]

