



#### Matilde Barberi Squarotti







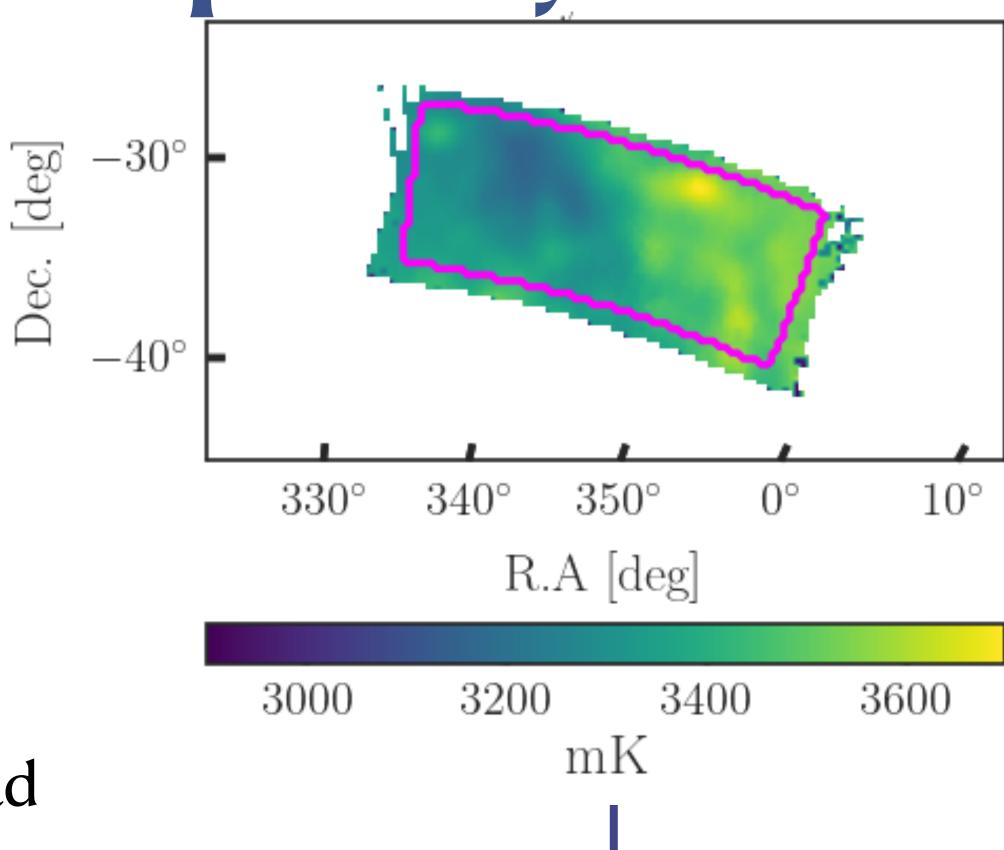






## MeerKLASS 2021 deep survey

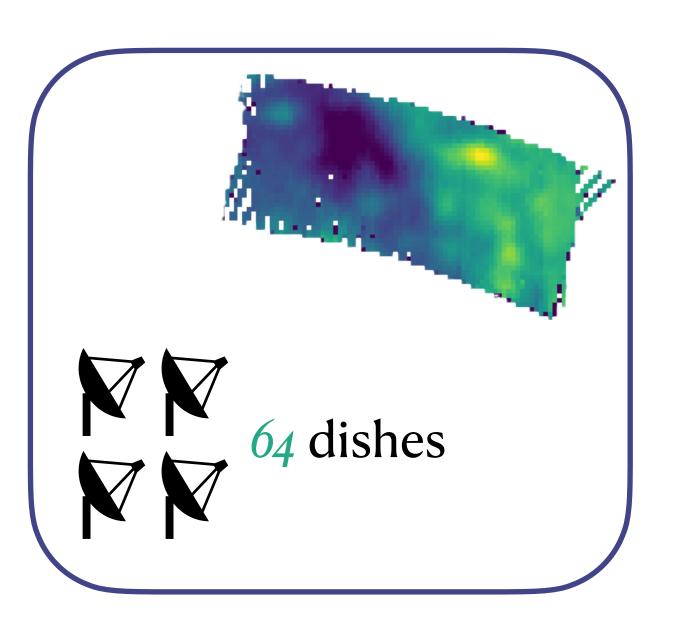
- MeerKAT Large Area Synoptic Survey
- Observations:
  - Area: 236 deg<sup>2</sup>
  - Time: 62 hours (41 scans with 64 dishes)
- Frequency and redshift range
  - 971.2 MHz  $< \nu < 1023.6$  MHz  $\rightarrow 0.388 < z < 0.463$
- Trimming performed to minimise the number of bad pixels
  - $334^{\circ} < R.A. < 357^{\circ}$
  - $-34.5^{\circ} < dec < -27.5^{\circ}$



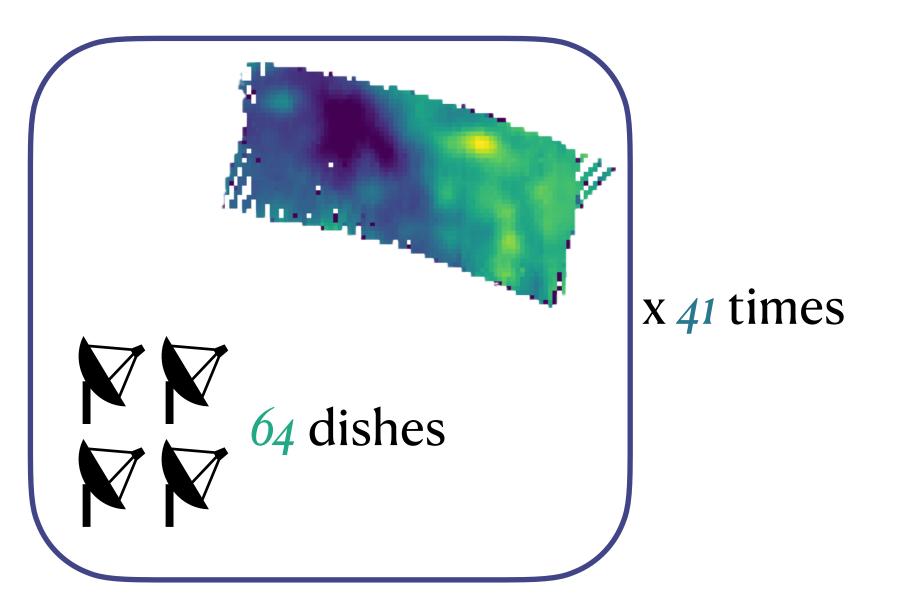
HI cosmological signal detected in cross-correlation with GAMA galaxies

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

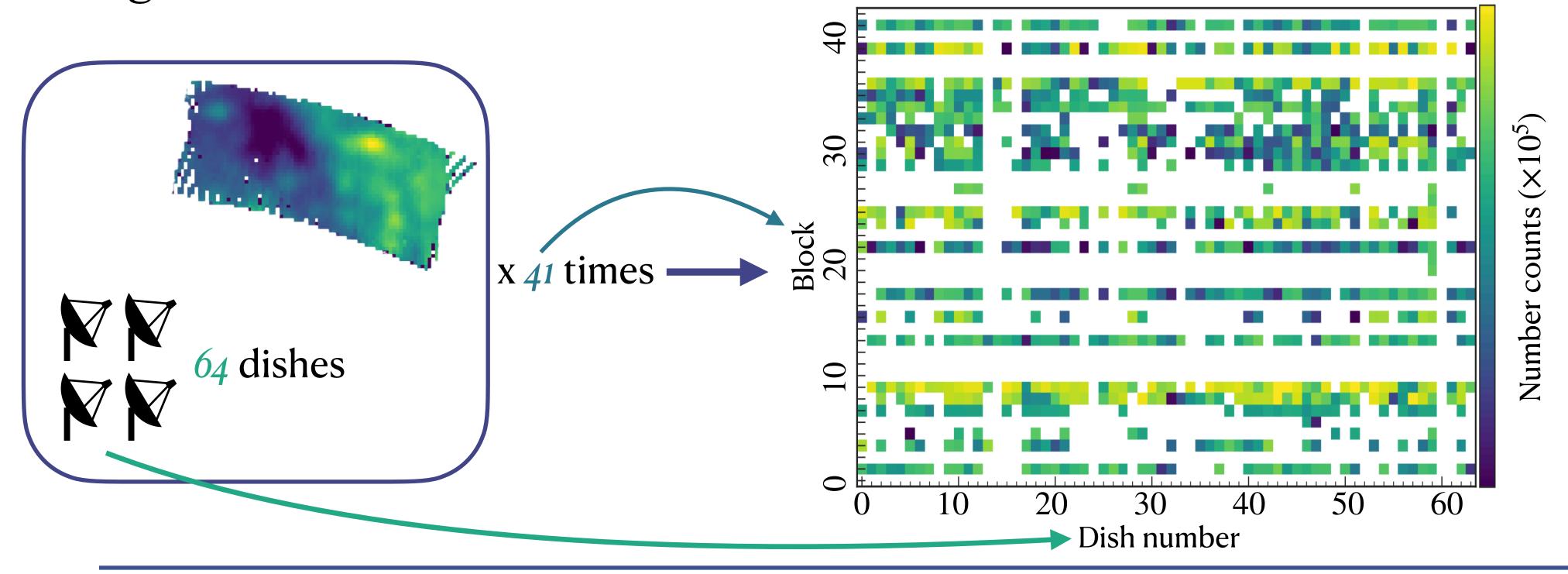
- All the antennas of the array observe the same region at the same
- Low angular-resolution survey of the total 21cm flux from unresolved sources
- High signal-to-noise ratio
- Large cosmic volumes covered



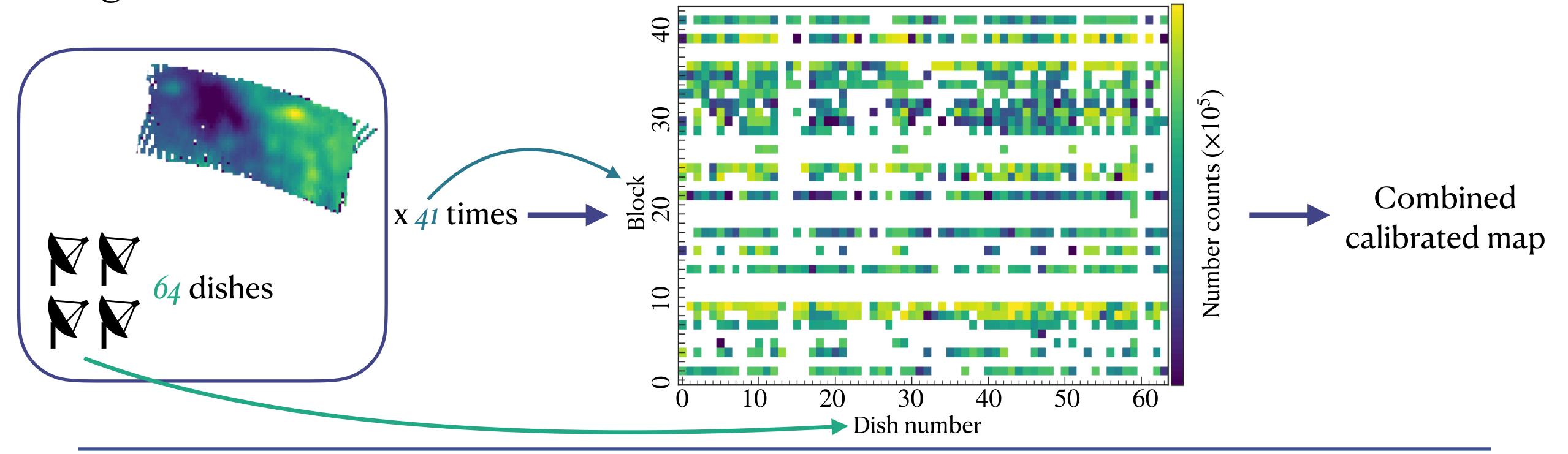
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# Splitting the data set

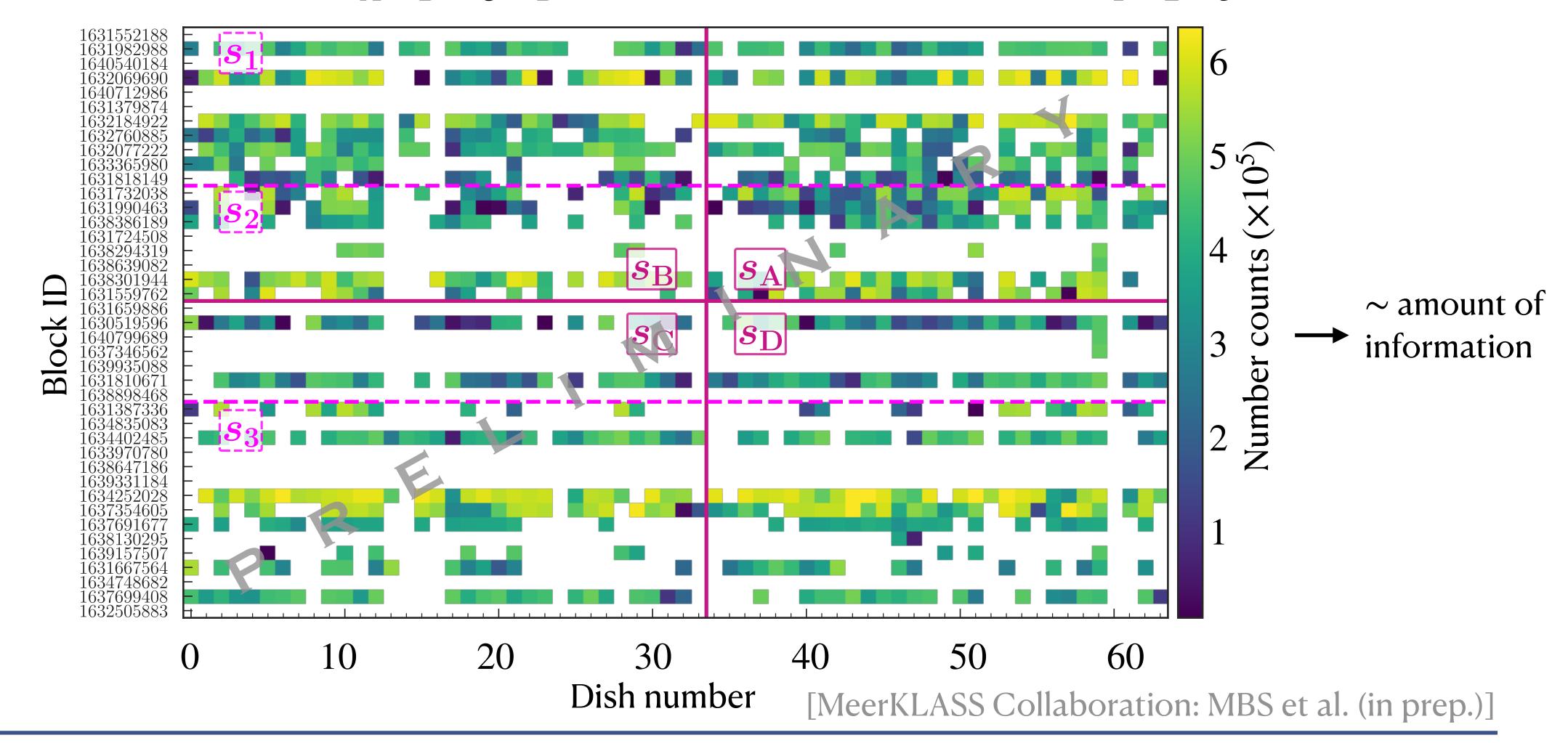
- Building independent data sets from the same survey [Wolz et al. (2021)]
  - Contaminants not correlated between subsets
  - Noise free cross-subset power spectra
- Definition of subset with an equivalent signal-to-noise ratio

## 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  $s_i$

Large scale fluctuations

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

Small scale fluctuations

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

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

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

## Power spectrum estimation

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

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

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

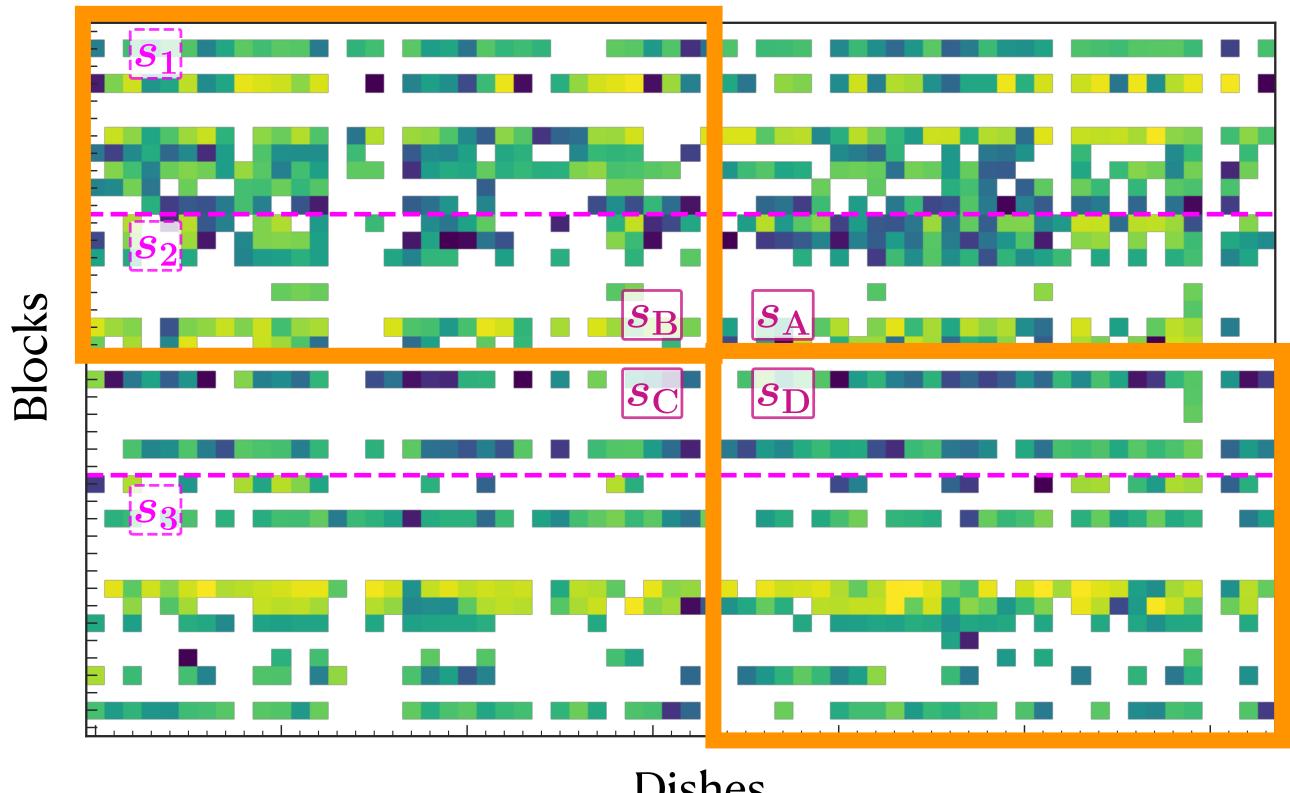
#### Global fits

- 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

#### Global fits: Chess-board division

- Multi-subset data vector including only "super" cross- $P_{ii}(k)$ 
  - Power spectra involving subsets that do not share nor blocks nor dishes
  - Most robust combinations available

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

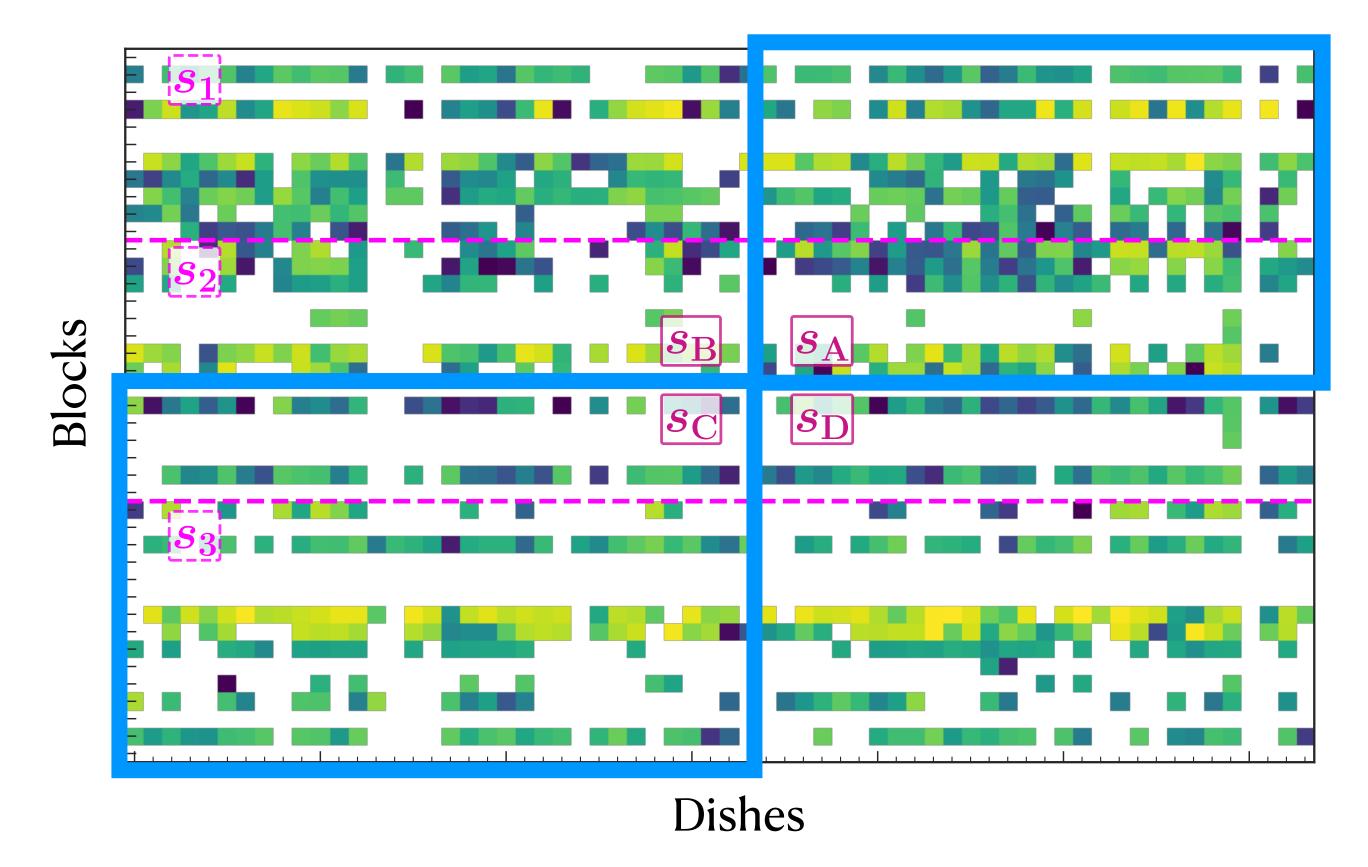


Dishes

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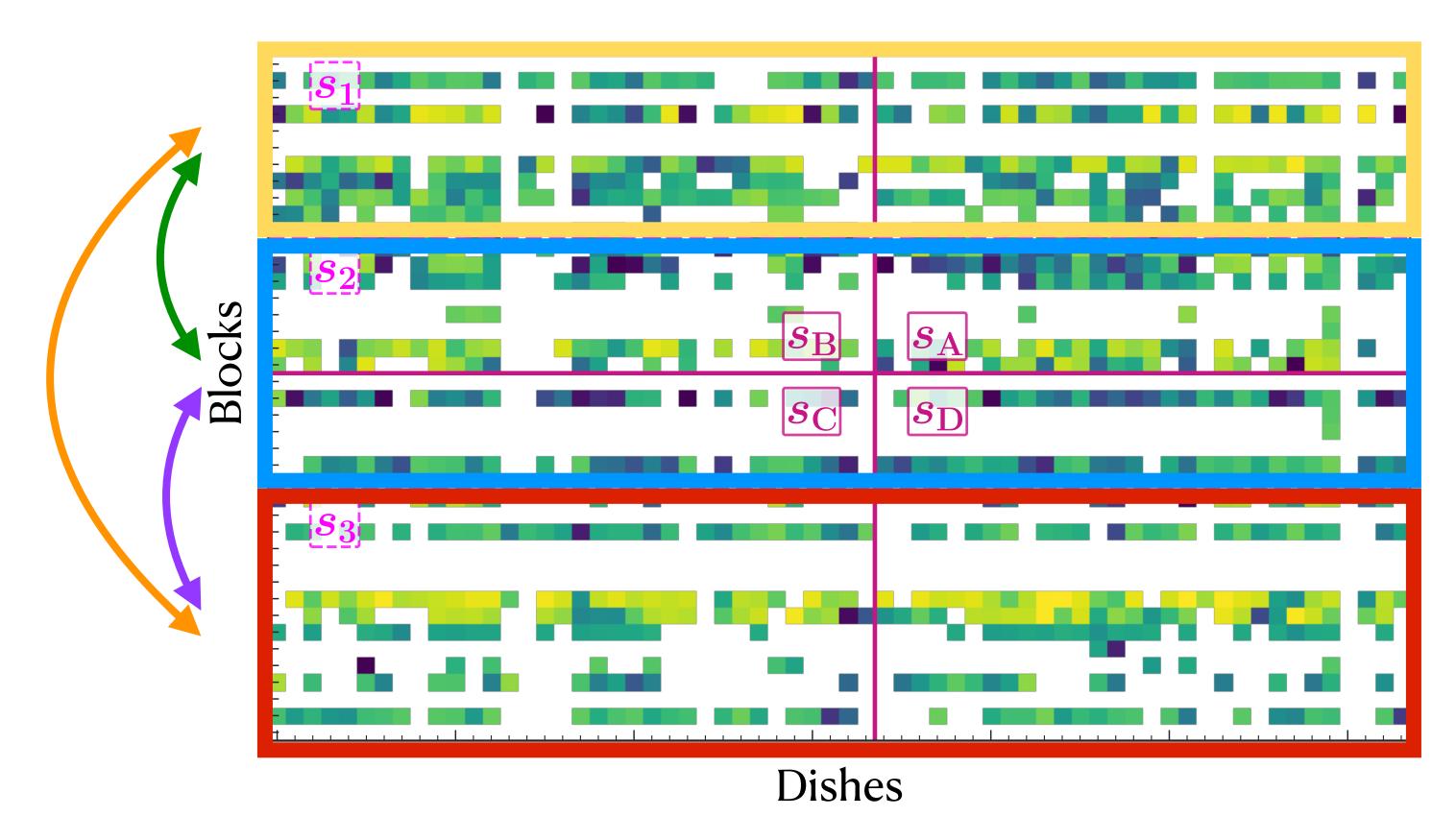
$$P_{\text{xchess}} = \{P_{BD}, P_{AC}\}$$

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

## 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

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



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#### Global fits

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

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

- $P_{ij}(\mathbf{k})$  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:  $\beta$

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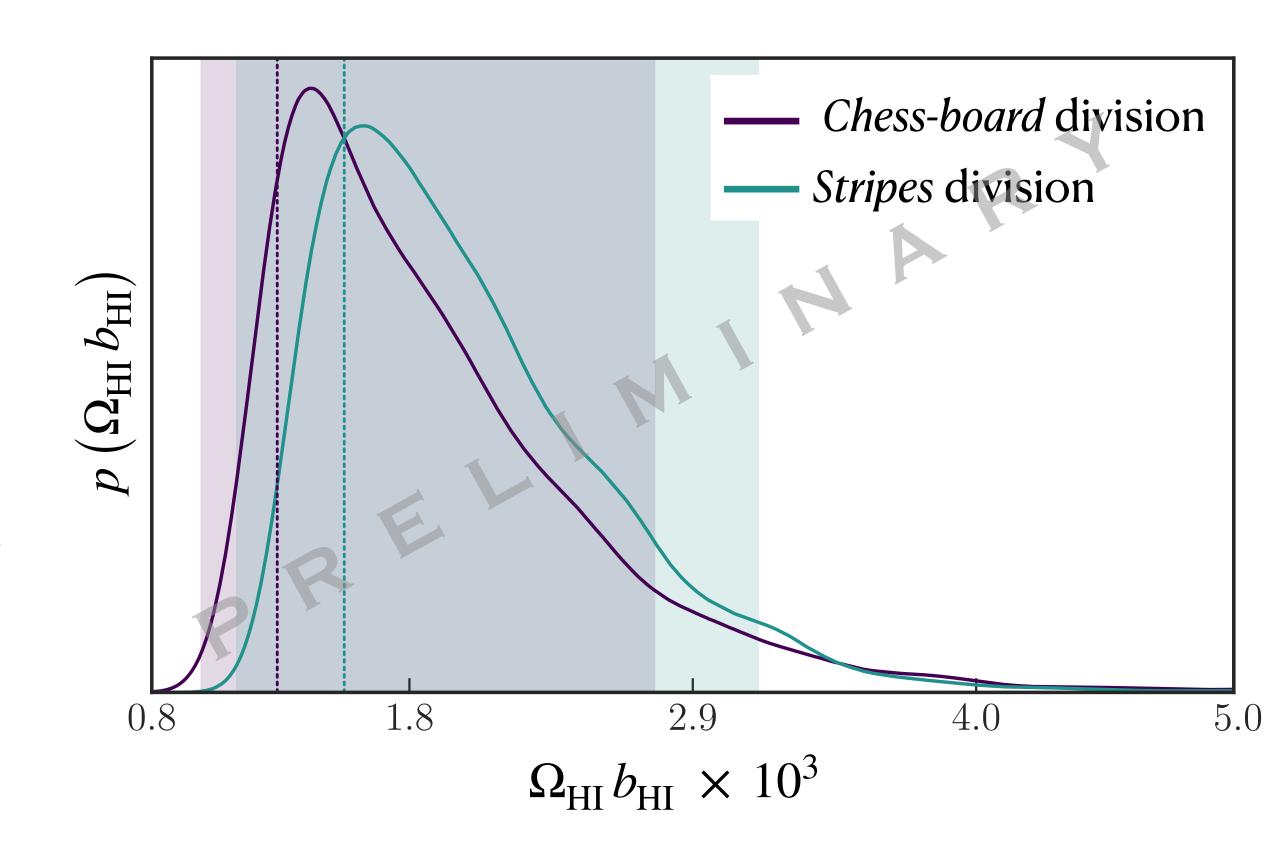
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- $P_{ii}(\mathbf{k})$  spherically averaged  $\rightarrow P_{ij}(k)$
- Fit parameters
  - $\Omega_{\rm HI}b_{\rm HI}$  common to all cross- $P_{ii}(k)$
  - One nuisance  $\beta$  for each cross- $P_{ii}(k)$  in the data vector
- Jackknife covariance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

#### 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 crosscorrelation 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)]



### Results

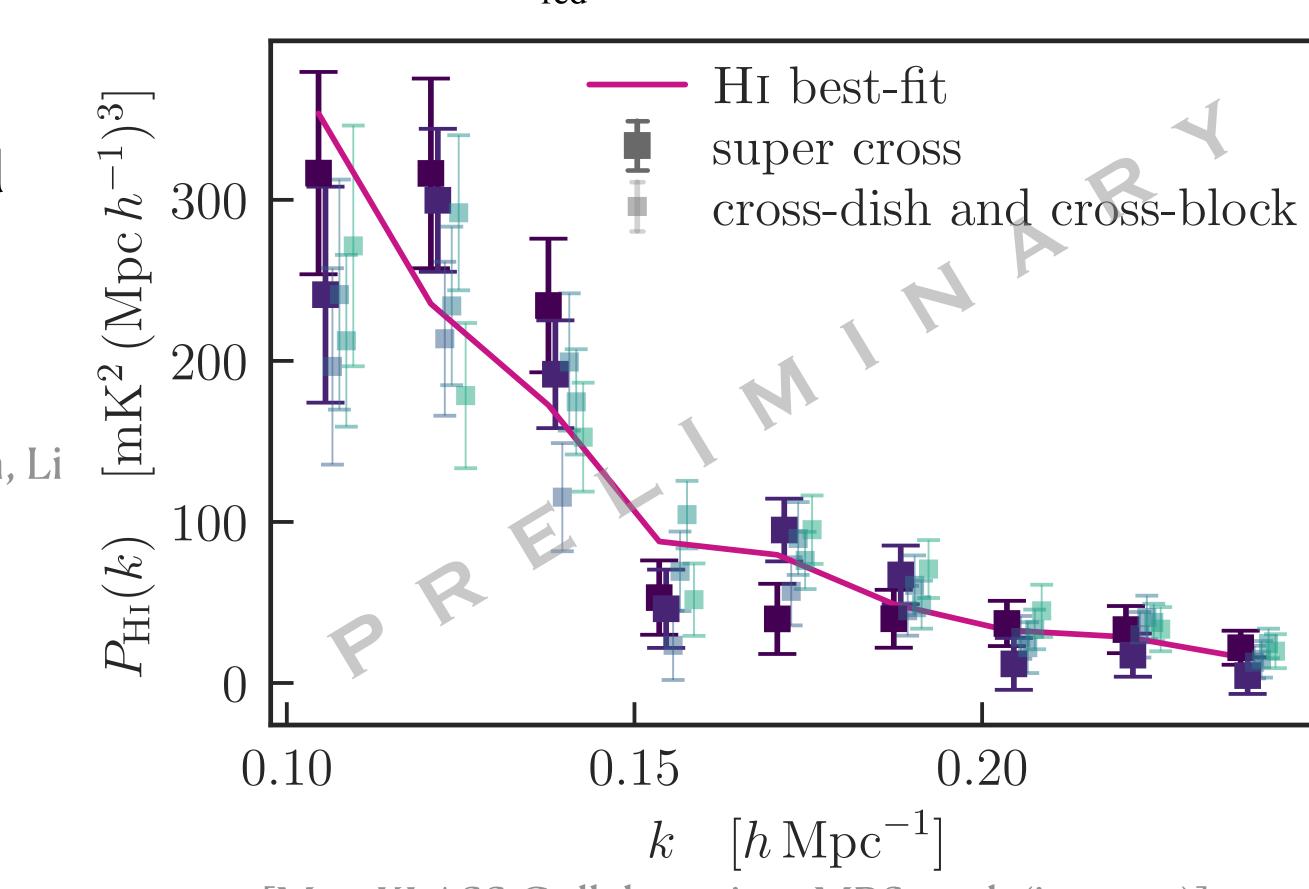
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Focus on the chess-board division

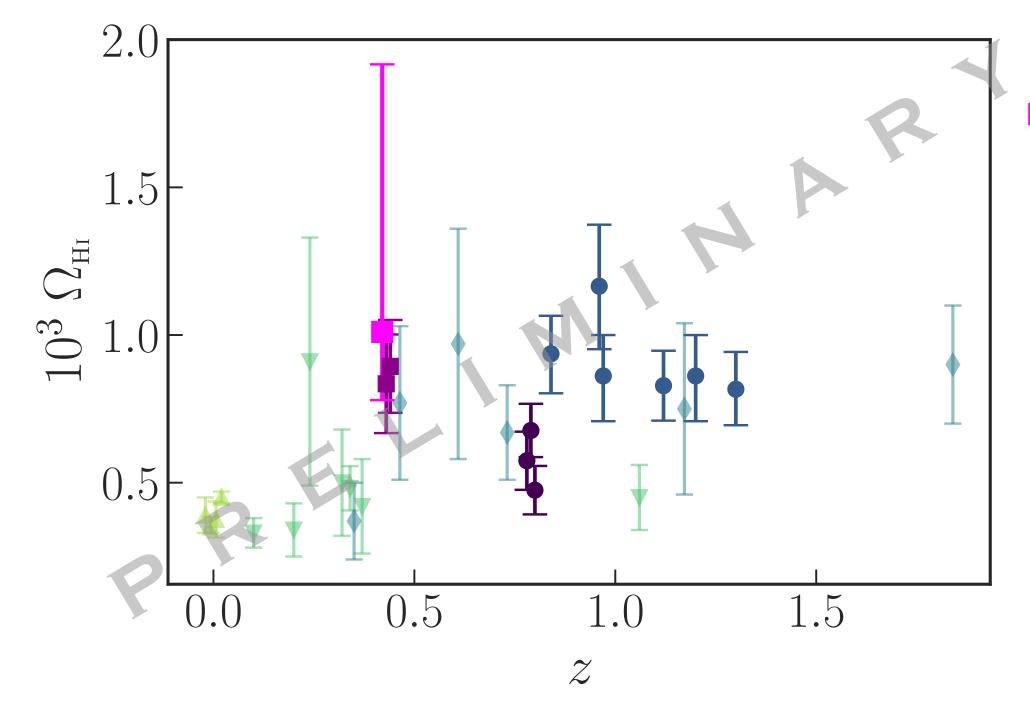
$$\chi^2_{\rm red} \sim 1.00$$

SNR ∼ 10.1

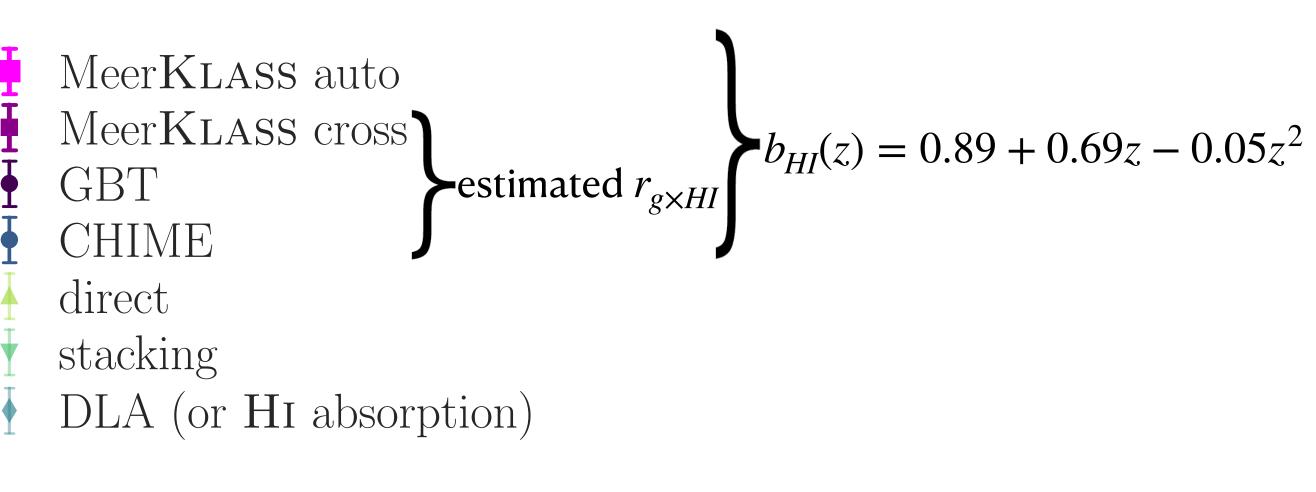


## MeerKLASS in the HI landscape

- A comparison with other measurements of the abundance of Hi
  - Other intensity mapping measurements (but in cross correlation with galaxies)  $\rightarrow \Omega_{\rm HI} \, b_{\rm HI} \, r_{g imes {
    m HI}}$
  - Direct measurements  $\rightarrow \Omega_{\rm HI}$
  - Staking measurements  $\to \Omega_{\rm HI}$



- Damped Lyman- $\alpha$  measurements  $\to \Omega_{\rm HI}$
- Hi absorption measurements  $\to \Omega_{\rm HI}$



#### 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 HI 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 HI signal independently on external data sets [MeerKLASS Collaboration: MBS et al. (in prep.)]