

Deep Cosmostat Days - 13/02/2026

 Paris, France

“Foreground removal in HI 21 cm intensity mapping under frequency-dependent beam distortions”

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Collaborators: V. Bonjean, J-L. Starck, M. Spinelli, P. Tsakalides



TITAN
ARTIFICIAL INTELLIGENCE
IN ASTROPHYSICS



Signal Processing
Laboratory



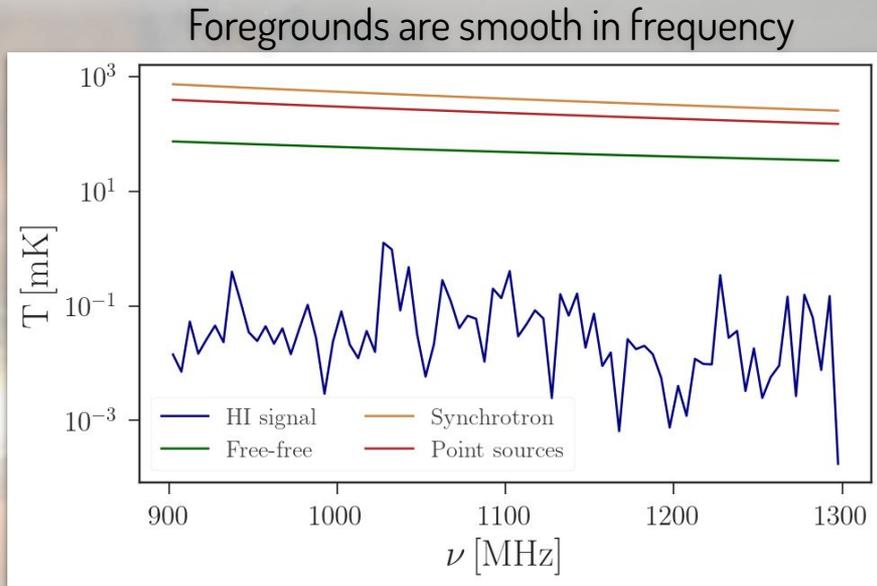
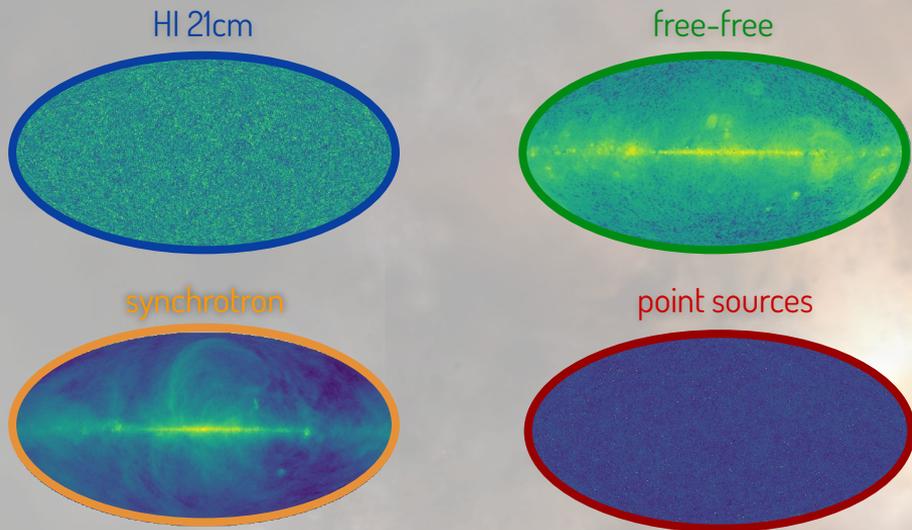
Funded by
the European Union



FORTH
INSTITUTE OF ASTROPHYSICS



Foregrounds of the HI 21 cm signal

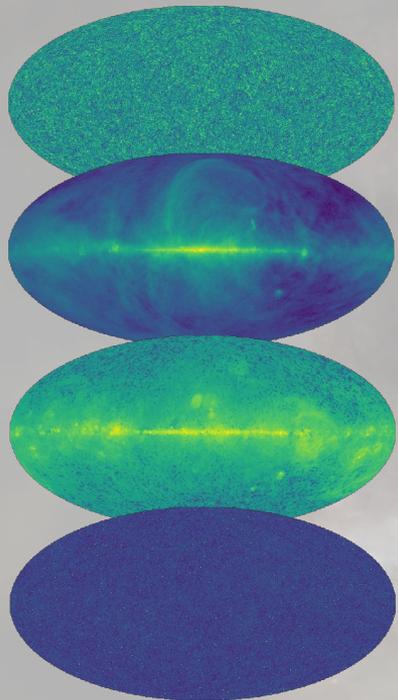


Biggest challenges in extracting HI signal:

- Foregrounds order of magnitudes brighter than HI
- Telescope beam: frequency-dependent

Foreground removal pipeline

900-1400 MHz



Simulation

Beam convolution

HI-bright sources masked

PCA

FastICA

GMCA

Polinomial Fit

Parametric fit

SDecGMCA

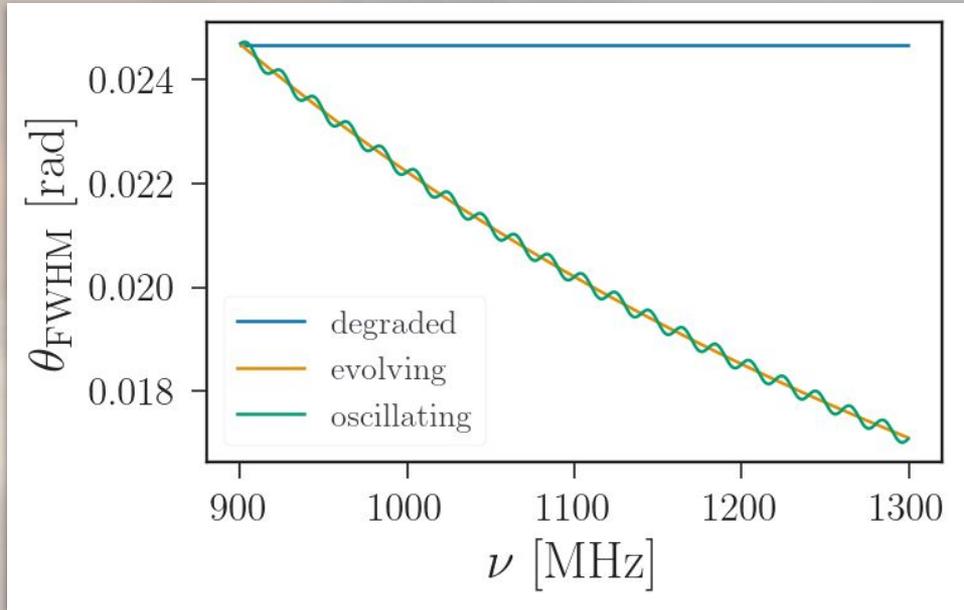
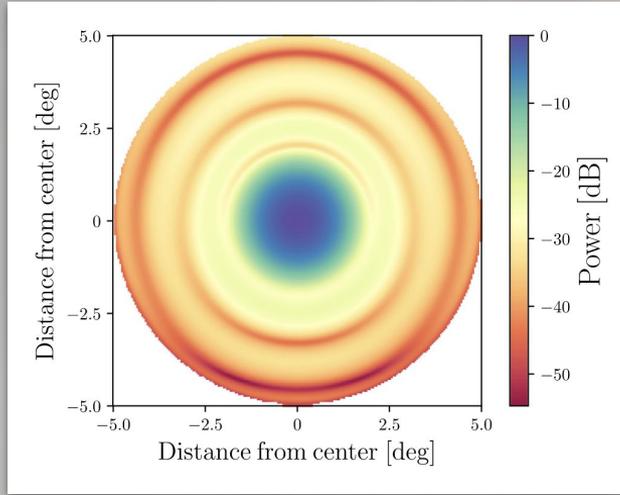
Methods

Radial
(frequency)
power
spectrum
 $P(k_\nu)$

Angular
power
spectrum
 C_ℓ

Validation

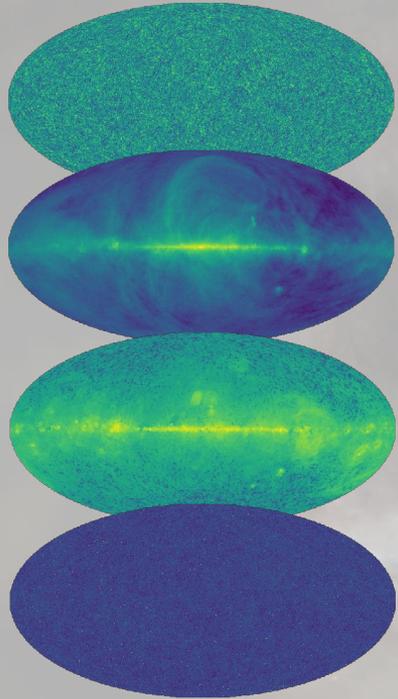
Telescope Beam (e.g., MeerKAT)



$$\theta = \frac{\lambda}{D} \longrightarrow \theta = \frac{\lambda}{D} \times A \sin\left(\frac{2\pi\nu}{T}\right)$$

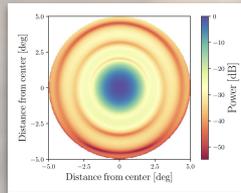
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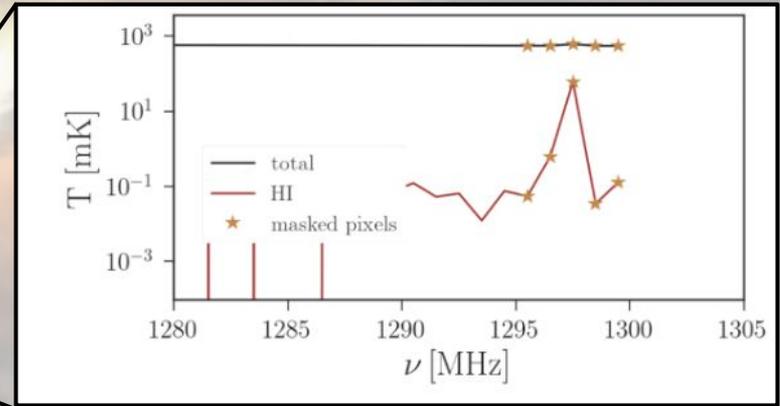
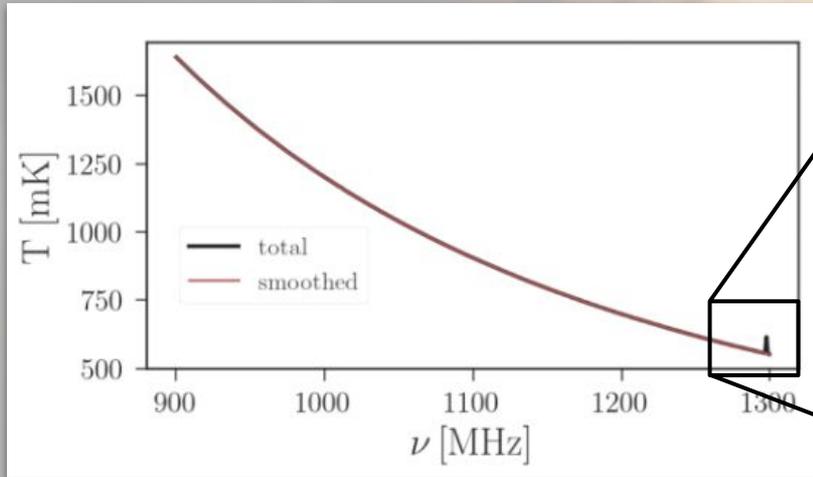
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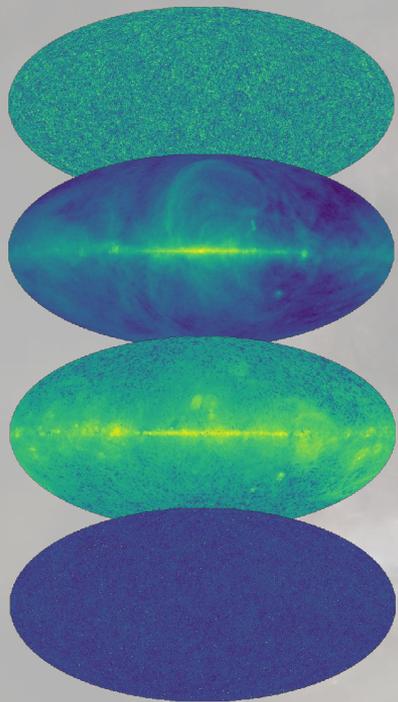
Masking the extremely bright HI sources

- Detecting lines of sight with peaks (extremely bright HI-sources)
- Assigning a the baseline value to this pixel



Foreground removal pipeline

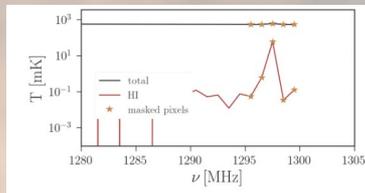
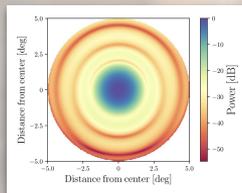
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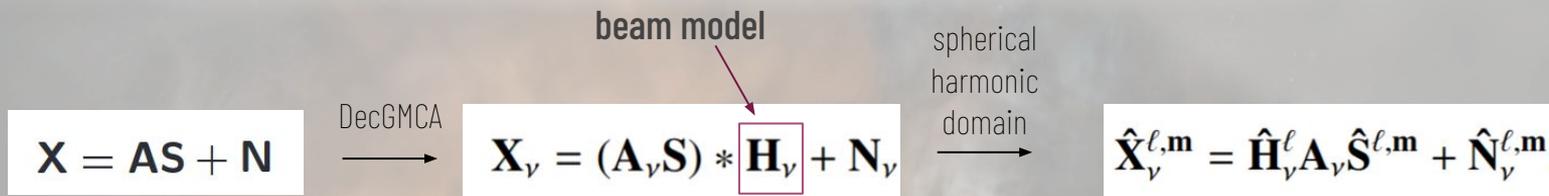
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SDecGMCA: joint component separation and deconvolution on the sphere



$$\min_{\mathbf{A}, \hat{\mathbf{S}}} \|\mathbf{A} \odot (\hat{\mathbf{S}} \mathcal{F}^\dagger \mathbf{\Phi}^\top)\|_1 + \sum_{(\ell,m) \in \mathcal{D}} \|\hat{\mathbf{X}}^{\ell,m} - \text{diag}(\hat{\mathbf{H}}^\ell) \mathbf{A} \hat{\mathbf{S}}^{\ell,m}\|_2^2$$

sarsity
in wavelet space

data fidelity
in SH domain

$$\mathbf{M}[l] = \mathbf{A}^\top \text{diag}(\hat{\mathbf{H}}^l)^2 \mathbf{A}$$

algorithm

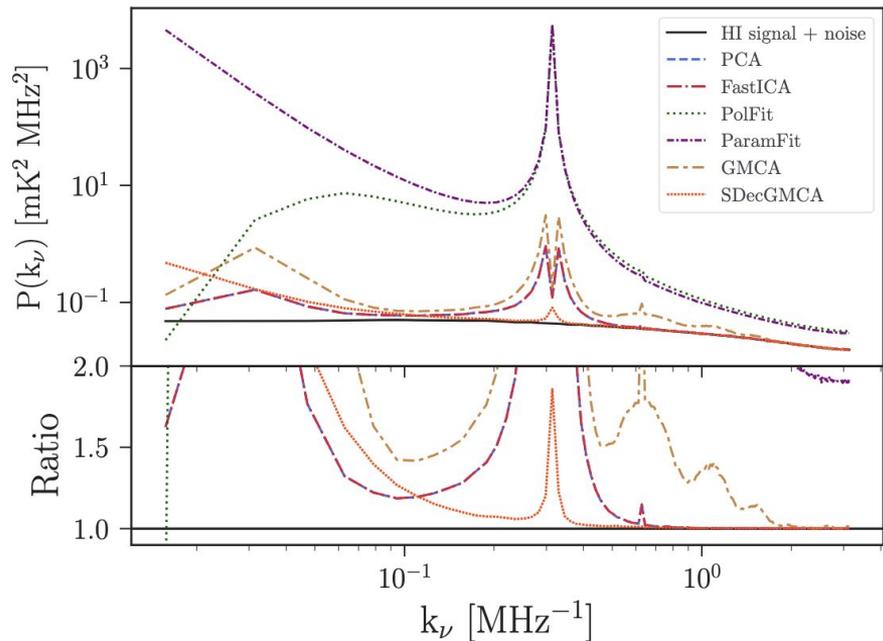
- (i) Update $\hat{\mathbf{S}}$: Solved using a Tikhonov-regularized least-squares solution for each (ℓ, m) , with $\epsilon_{n,l}$ the regularization coefficients
- (ii) Enforce sparsity: After the inverse harmonic transform, $\hat{\mathbf{S}}$ is projected onto the wavelet basis and sparsity is enforced via a soft-thresholding procedure
- (iii) Update \mathbf{A} : The mixing matrix is estimated via least squares over all spherical harmonics

$$\hat{\mathbf{S}}^{\ell,m} \leftarrow \left(\mathbf{M}[l] + \text{diag}(\epsilon_{n,l})_{n \in [1, N_s]} \right)^{-1} \mathbf{A}^\top \text{diag}(\hat{\mathbf{H}}^l) \hat{\mathbf{X}}^{\ell,m}$$

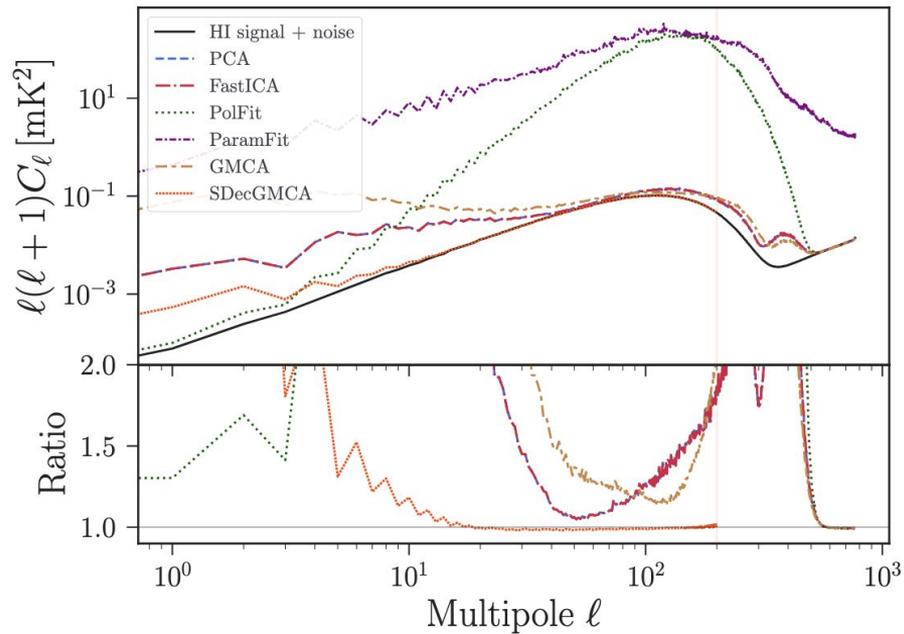
$$\mathbf{A}_v \leftarrow \left(\sum_{(\ell,m) \in \mathcal{D}} \hat{\mathbf{X}}_v^{\ell,m} \hat{\mathbf{H}}_v^\ell \hat{\mathbf{S}}^{\ell,m \dagger} \right) \left(\sum_{(\ell,m) \in \mathcal{D}} \hat{\mathbf{H}}_v^{\ell 2} \hat{\mathbf{S}}^{\ell,m} \hat{\mathbf{S}}^{\ell,m \dagger} \right)^{-1}$$

Gaussian oscillating beam

Frequency power spectrum



Angular power spectrum



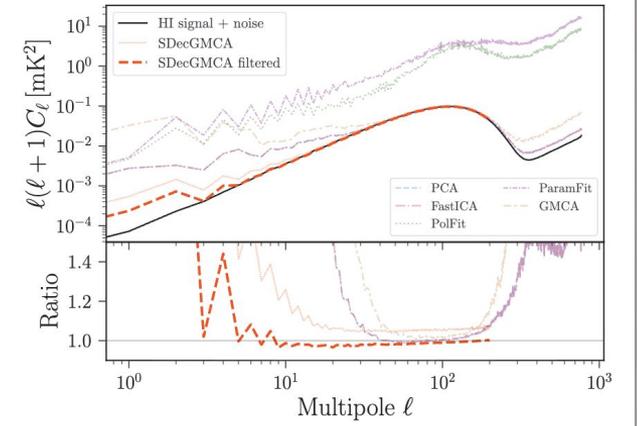
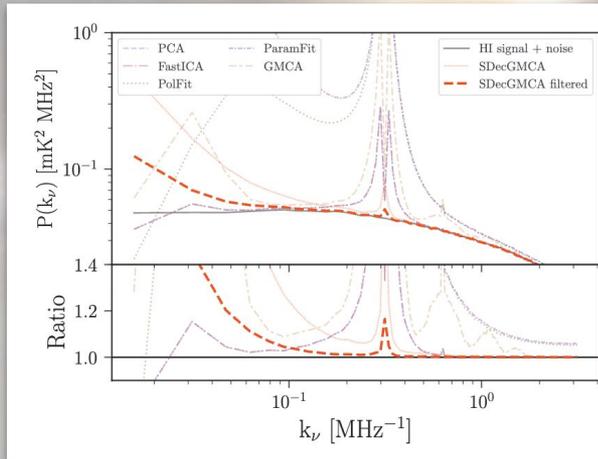
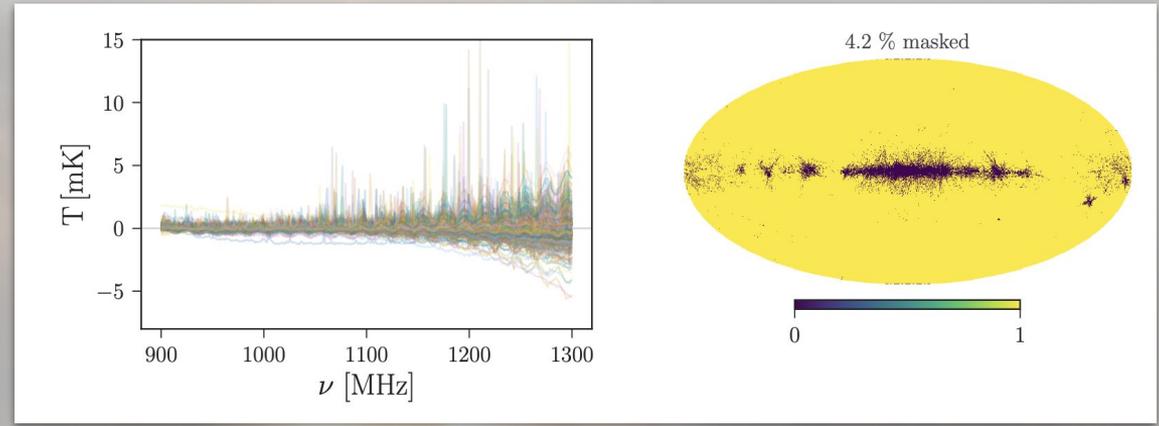
SDecGMCA: limitations

- **Bright Galactic plane**
 - Masked SDecGMCA
 - Applicable to real data (footprint)
- **Sensitive to thresholding hyperparameters**
 - Instead of thresholding in wavelet domain
 - Use learnlets (Bonjean+26)
- **Artificial peak in Cell**
 - SDecGMCA per wavelet scale

Bright Galactic plane

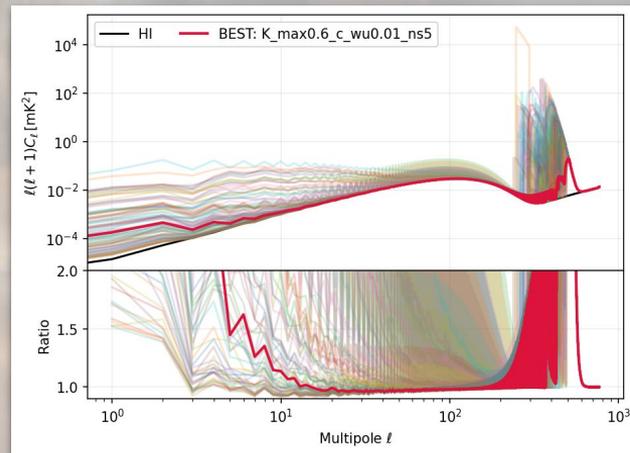
$$|\langle \text{MSE} \rangle - \text{MSE}_{\text{los}}| > \sigma_{\text{MSE}}$$

$\text{HI}_{\text{rec}} - \text{HI}_{\text{true}}$
along each line of sight



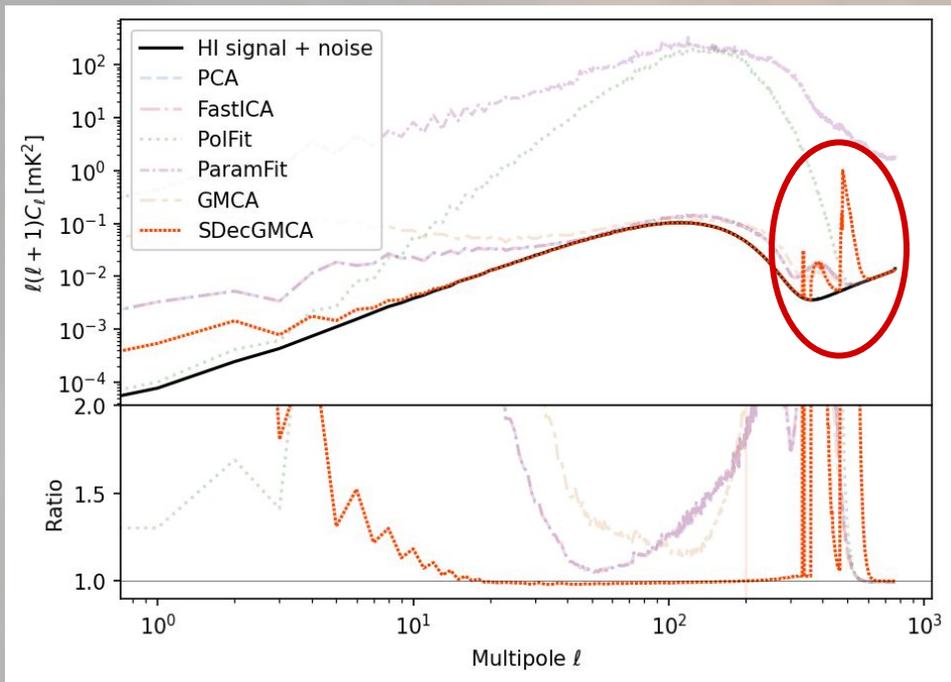
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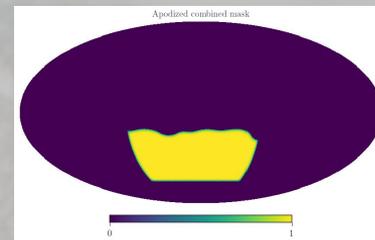
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$$\mathbf{A}_v \leftarrow \left(\sum_{(l,m) \in \mathcal{D}} \hat{\mathbf{X}}_v^{l,m} \hat{\mathbf{H}}_v^{l,m} \hat{\mathbf{S}}^{l,m \dagger} \right) \left(\sum_{(l,m) \in \mathcal{D}} \hat{\mathbf{H}}_v^{l,m} \hat{\mathbf{S}}^{l,m} \hat{\mathbf{S}}^{l,m \dagger} \right)^{-1}$$

SDecGMCA: limitations -> improvements

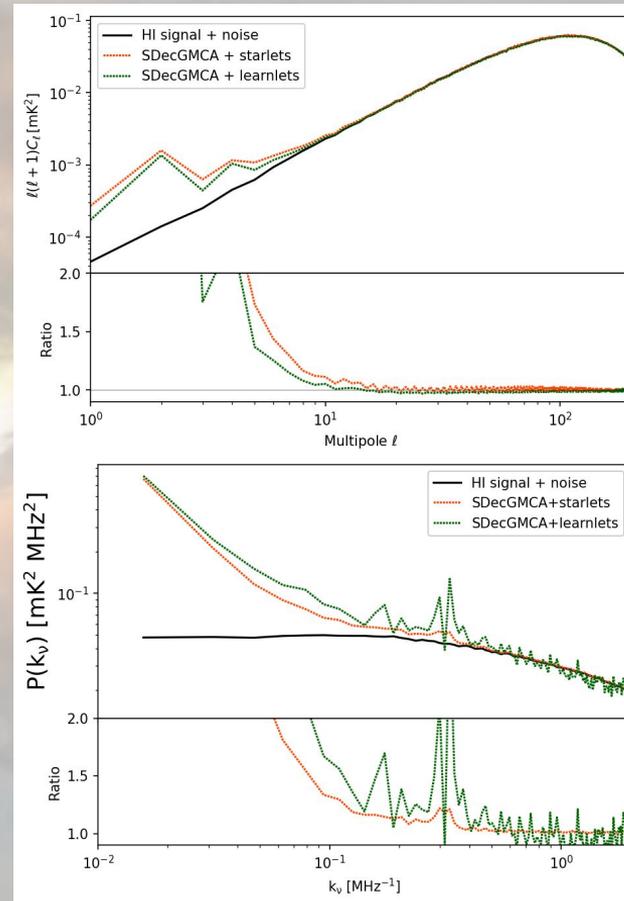
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SDecGMCA: limitations -> improvements

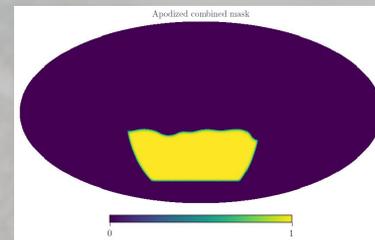
algorithm

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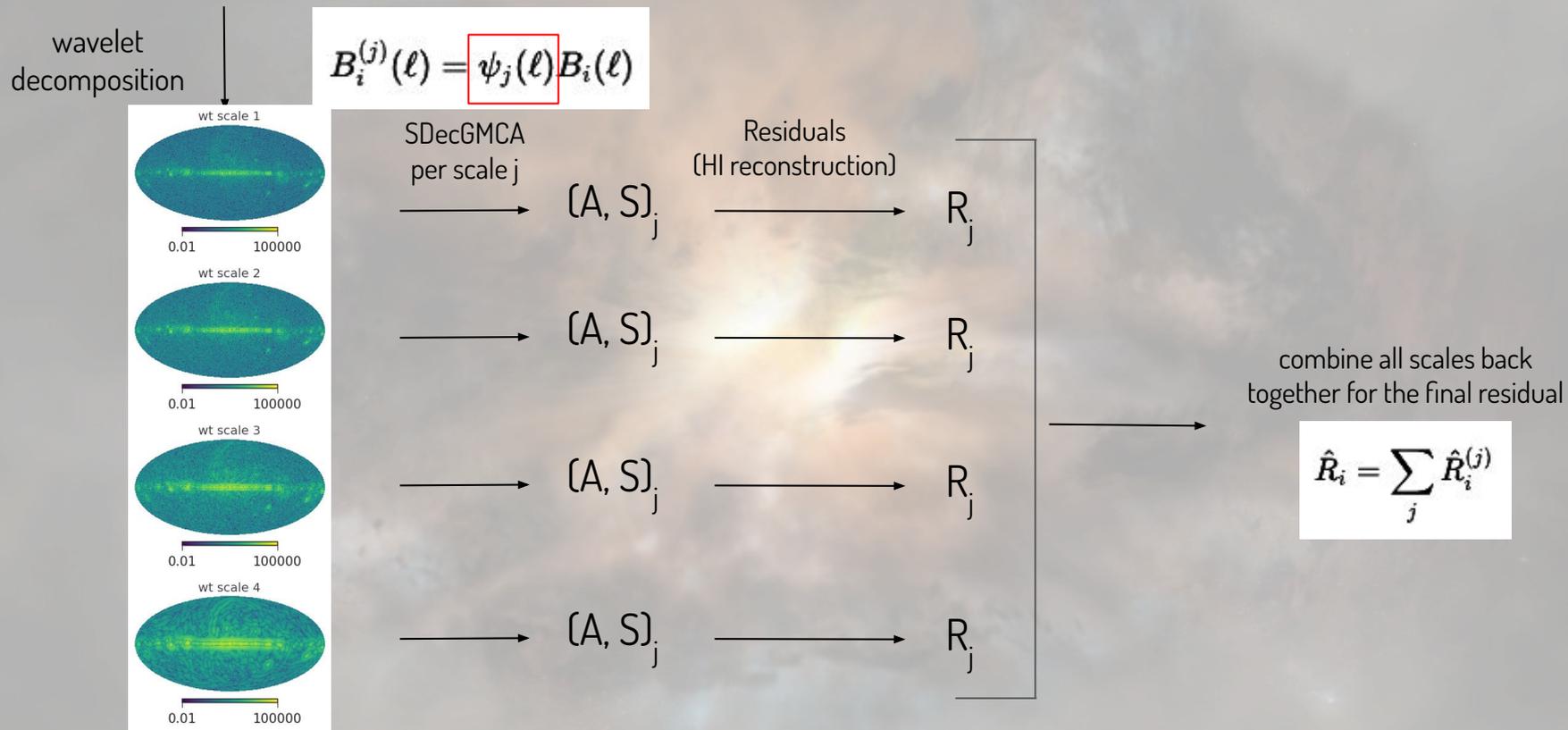


SDecGMCA: limitations -> improvements

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SDecGMCA: limitations -> improvements



Summary & Conclusions

- SDecGMCA works the best in the realistic beam scenario on full sky
- Improvements that will lead to the application of the method on real data
 - Run the method in a footprint (masked version)
 - Using trained learnlets instead of starlets
- Artificial peak mitigation -> SDecGMCA per scale (?)