“The Non-Gaussian Universe” workshop - 18/06/2026

📍 Heraklion, Greece

“Foreground removal in HI 21cm intensity mapping”

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FORTH INSTITUTE OF COMPUTER SCIENCE

TITAN ARTIFICIAL INTELLIGENCE IN ASTROPHYSICS

Signal Processing Laboratory

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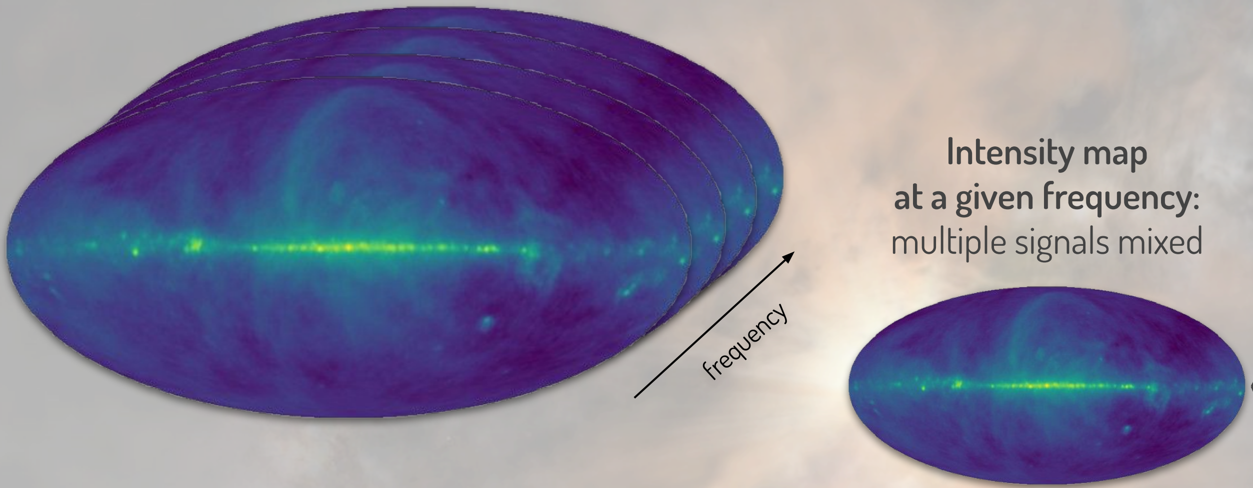
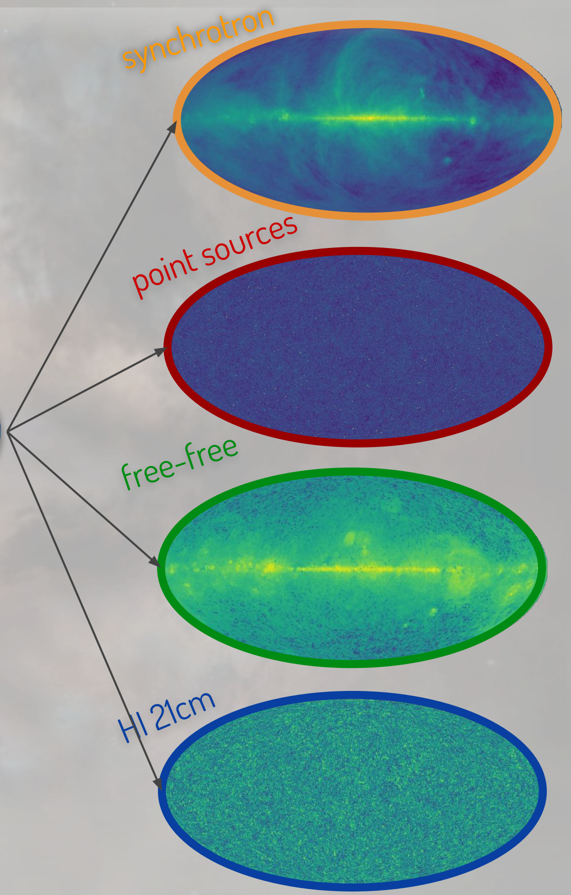
HI 21cm intensity mapping

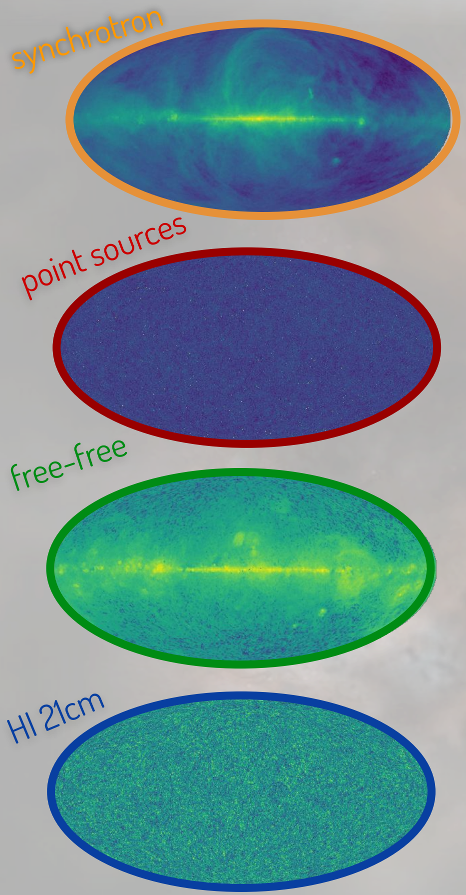


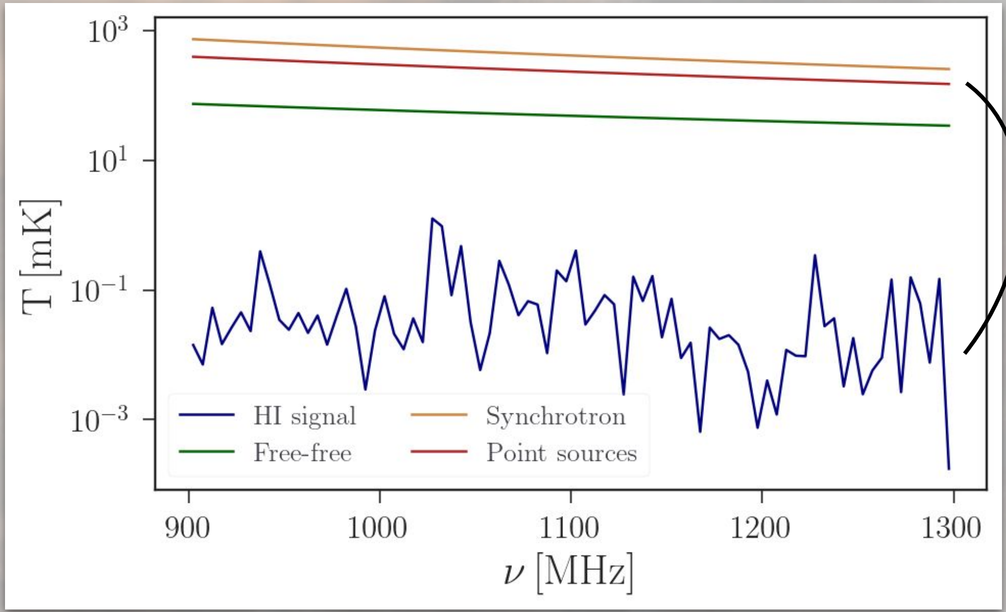


Why <u>intensity mapping</u>?

- Maps large cosmological volumes efficiently
- No need to detect individual galaxies
- Preserves 3D information: angle + frequency/redshift
- Powerful probe of large-scale structure

Foregrounds of the HI 21 cm signal

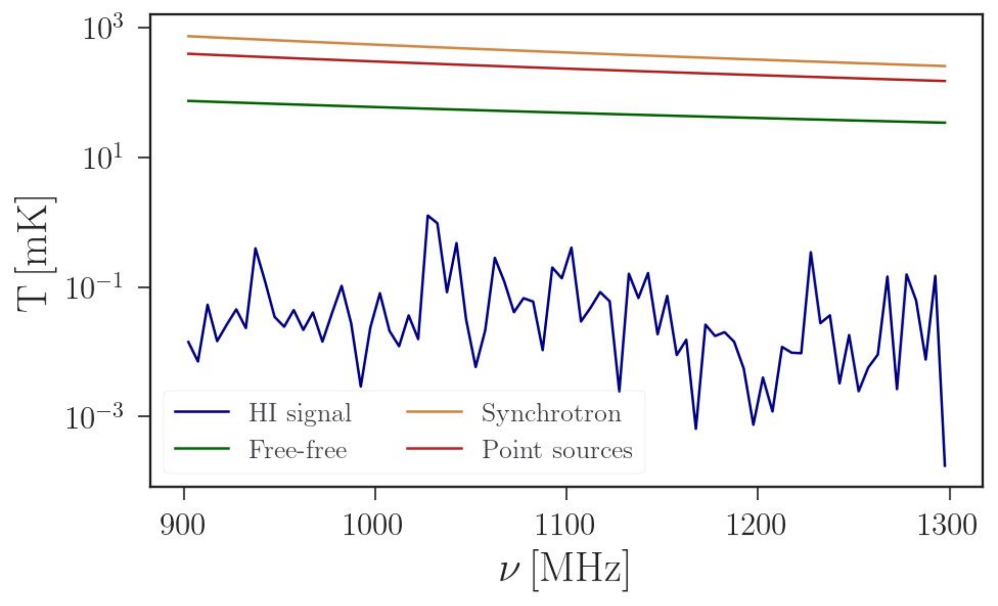




~4 orders of magnitude

Foreground cleaning

What makes foreground cleaning possible?



- Foregrounds are spectrally smooth
- Foregrounds are highly correlated across frequency
- Different components have different spatial morphology / sparsity

Foreground cleaning

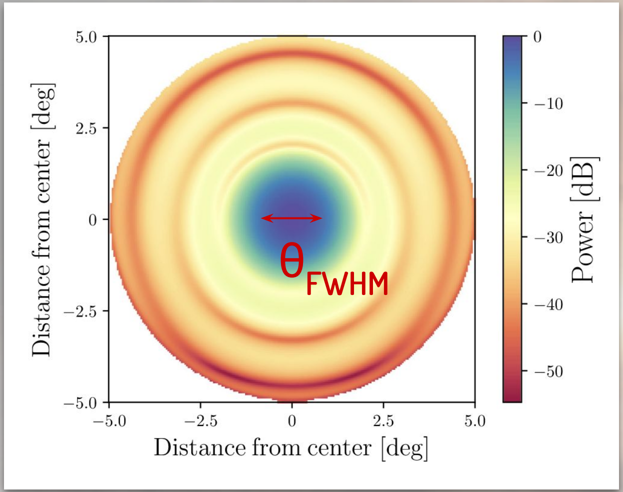
What information do cleaning methods exploit?

- Spectral smoothness → polynomial / parametric fitting
- Low-rank subspace → PCA / ICA
- Sparsity / morphology → GMCA, SDecGMCA, JESSNet
- Known beam model → joint deconvolution + component separation (SDecGMCA, JESSNet)

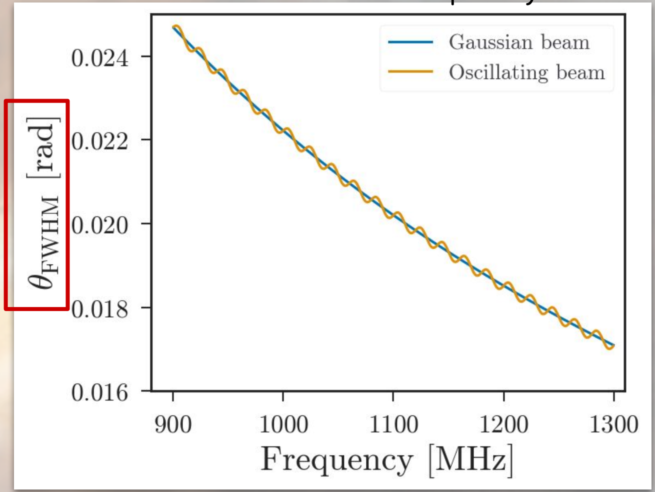
Non smooth frequency evolution of the beam can complicate things further

Chromatic telescope beam

modelled MeerKAT beam behavior



main-lobe width vs frequency

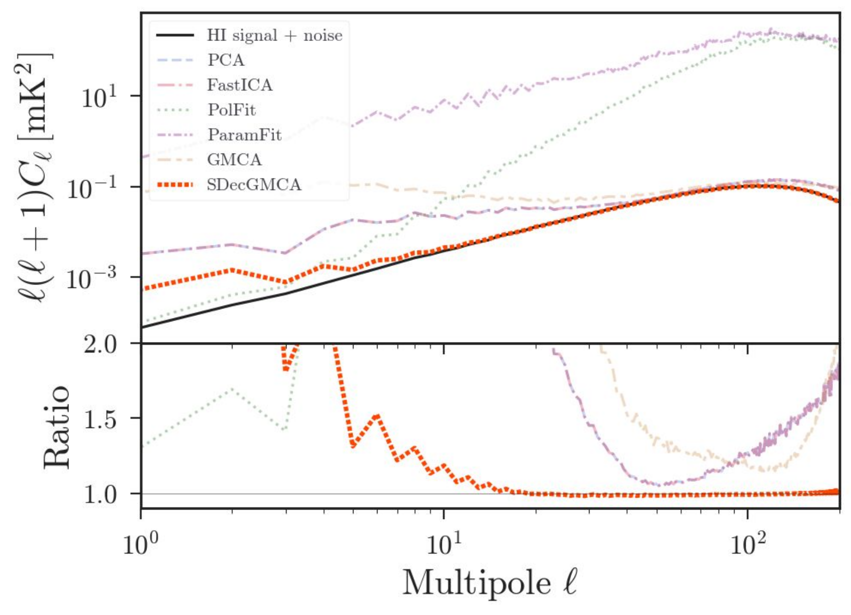


$$\theta_{\mathrm{FWHM}}(\nu) = \frac{\lambda}{D} \longrightarrow \theta_{\mathrm{FWHM}}(\nu) = \frac{\lambda}{D}\left[\sum_{d=0}^{8} a_d\,\nu^d + A\sin\left(\frac{2\pi\nu}{T}\right)\right]$$

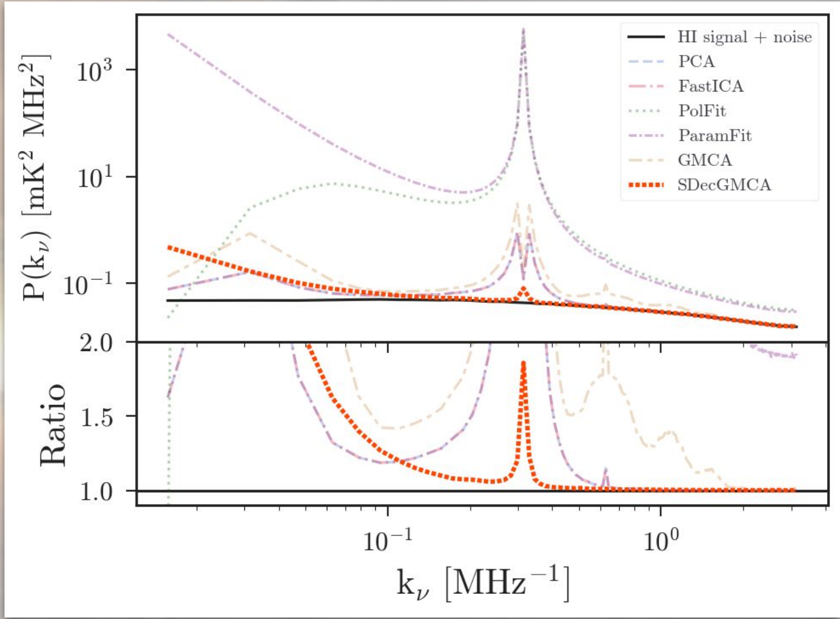
Matshawule et al. (2021)

Need for deconvolution

Angular power spectrum



Frequency power spectrum



➔ The **method** that takes the beam into account has the smallest deviations from the ground truth

➔ Strong indication for a beam-aware foreground cleaning pipeline

Gkogkou et al. (2026)

JESSNet (Joint dEconvolution and Sparse Separation Network)

$$X_\nu = \overbrace{\boxed{(A_\nu S) * H_\nu}}^{\text{foregrounds}} + \overbrace{\boxed{N_\nu}}^{\text{HI+noise}}$$

spherical harmonic space

$$\hat{X}^{\ell m} = \mathrm{diag}(\hat{H}^{\ell})\, A\, \hat{S}^{\ell m} + \hat{N}^{\ell m}$$

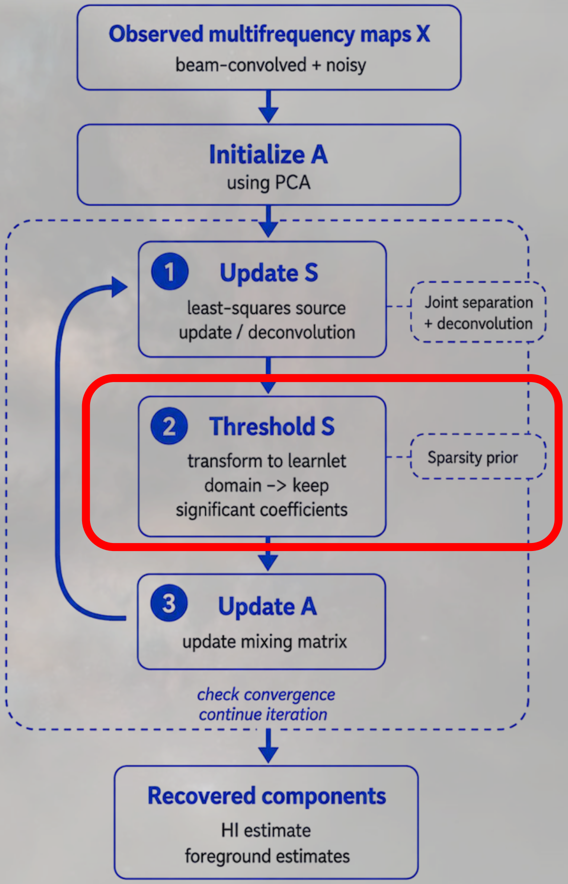
$$\min_{A,\hat{S}} \sum_{\ell m} \left\| \hat{X}^{\ell m} - \mathrm{diag}(\hat{H}^{\ell})\, A \hat{S}^{\ell m} \right\|_2^2 + \lambda\, \mathcal{R}_{\text{sparse}}(S)$$

fit the beam-convolved data **sparsity prior on sources**

$$\boxed{\hat{S}^{\ell m} = \left[A^\top \mathrm{diag}(\hat{H}^{\ell})^2 A + \epsilon_\ell\right]^{-1} A^\top \mathrm{diag}(\hat{H}^{\ell})\, \hat{X}^{\ell m}}$$

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

Tikhonov regularization param



JESSNet (Joint dEconvolution and Sparse Separation Network)

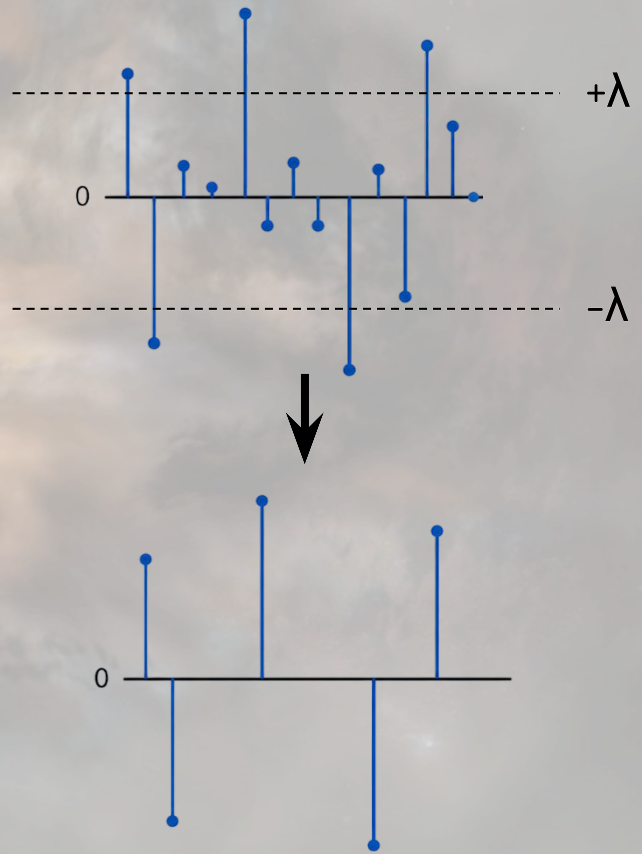
Sparsity and thresholding

Sparse representation

- In the wavelet / learnlet domain, the signal is represented by **a few large coefficients**
- Most coefficients are close to zero
- Noise mainly populates low-amplitude coefficients

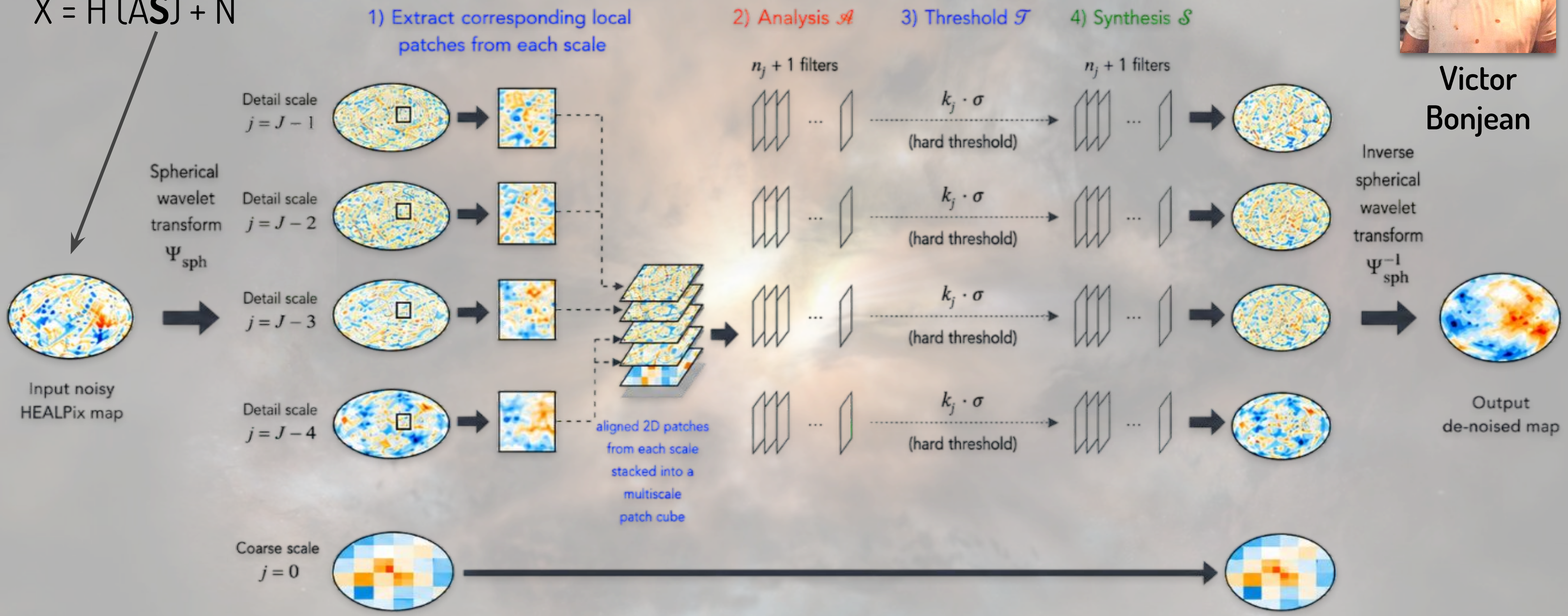
Thresholding

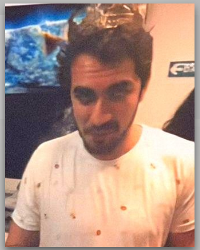
- Keep coefficients with amplitude above a **threshold λ**
- Set small coefficients to zero
- This preserves significant structures and suppresses noise



Learnlets: structure

$X = H(A\mathbf{S}) + N$





Victor Bonjean

Bonjean et al. (2026)
Gkogkou et al. in prep.

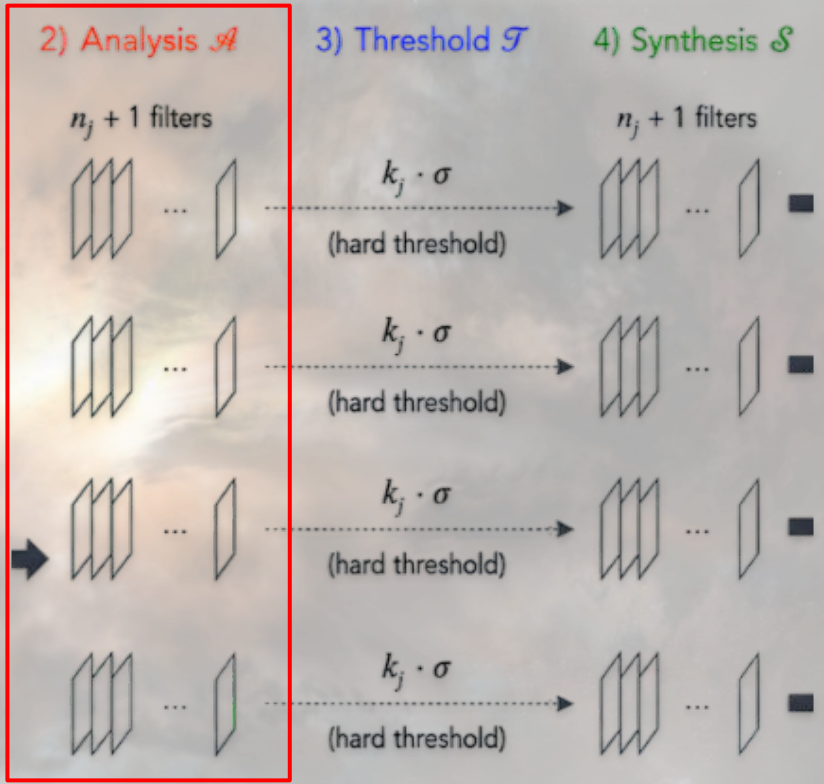
Learnlets: analysis layer

Each detail-scale patch is convolved with a bank of learned filters

The filters are scale- and source-specific

The same filters are applied to all patches from the same scale

The extra (+1) channel is the identity branch for exact reconstruction



Bonjean et al. (2026)
Gkogkou et al. in prep.

Learnlets: thresholding layer

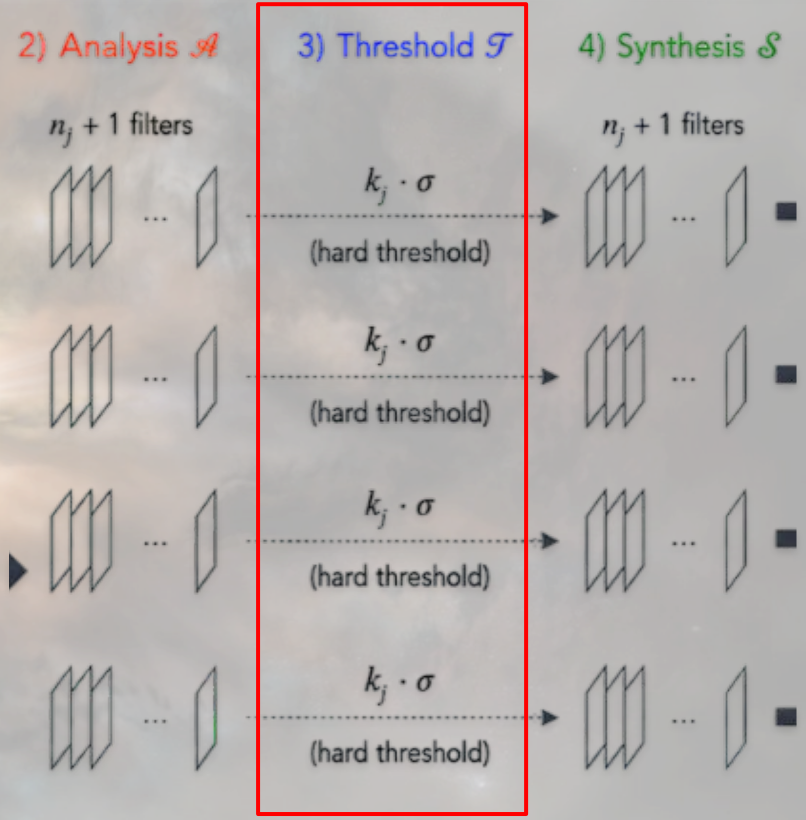
Thresholding promotes sparsity in the learned coefficient domain

Weak coefficients are suppressed

The threshold is computed per source and per scale

k sigma thresholding: $\lambda_{s,j} = k_j \times \sigma_{NMAD}$

k_j comes from the learnlet network through mininet



Bonjean et al. (2026)
Gkogkou et al. in prep.

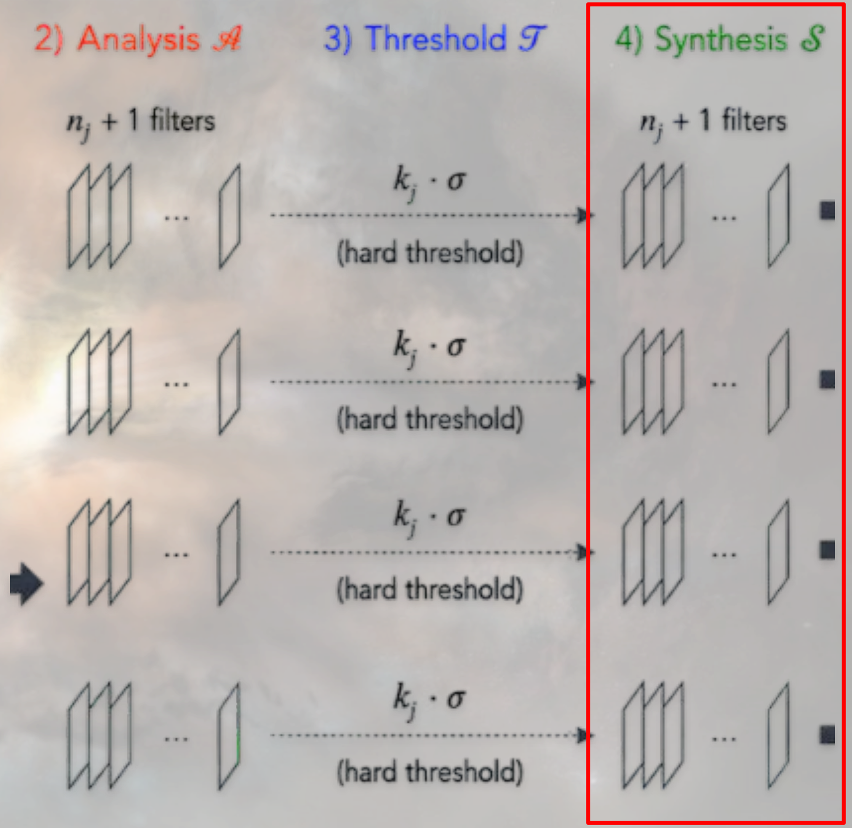
Learnlets: synthesis layer

Converts sparse learned coefficients back into an image-like patch

Uses learned synthesis filters, different from the analysis filters

For each scale and each source

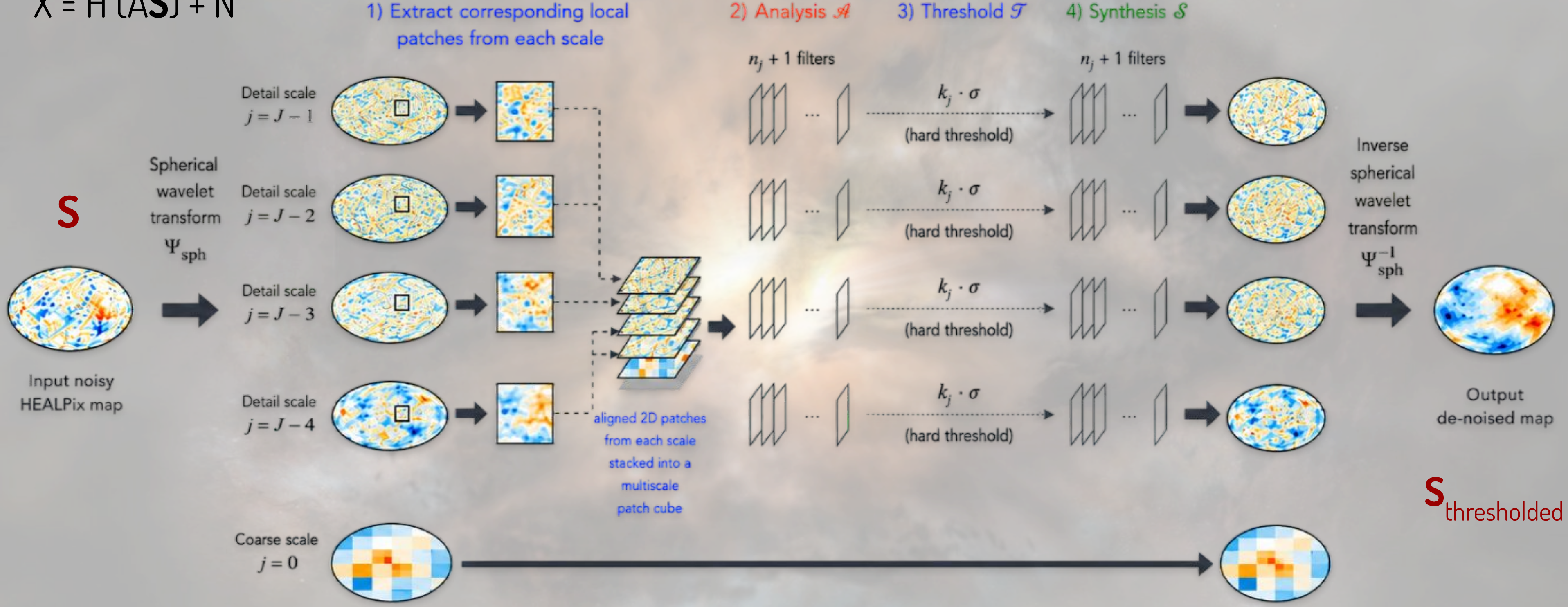
The detail-scale outputs are combined with the preserved coarse scale



Bonjean et al. (2026)
Gkogkou et al. in prep.

Learnlets: structure

$X = H(A\mathbf{S}) + N$

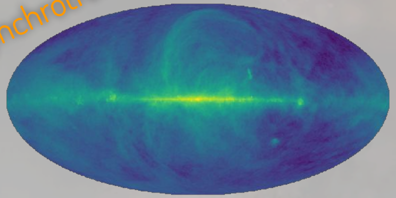


Bonjean et al. (2026)
Gkogkou et al. in prep.

Learnlets: training

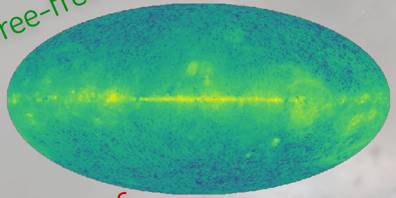
Frequency range: 1000-1100 MHz
Varying spectral indices

synchrotron



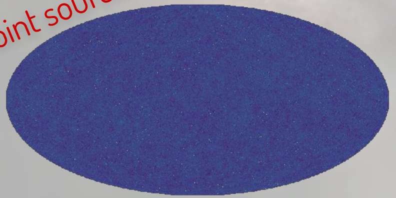
$$T_{\rm sy}(\nu, p) = T_s(p)\left(\frac{\nu}{\nu_0}\right)^{\beta_{\rm sy}(p)}$$

free-free



$$T_{\rm ff}(\nu, p) = T_{\rm ff}(p)\left(\frac{\nu}{\nu_0}\right)^{\beta_{\rm ff}}$$

point sources



$$T_{\rm ps}(\nu, p) = T_{\rm ps}(1.4\,\mathrm{GHz}, p)\left(\frac{\nu}{\nu_0}\right)^{\beta_{\rm ps}(p)}$$

What is learned?

A_j: analysis filters (n_j)

S_j: synthesis filters (n_j)

k_j: scale-dependent threshold multipliers (J-1)

Training target

Noisy multiscale patch cube → clean multiscale patch cube

Purpose

Learn a foreground-adapted denoising / sparse representation

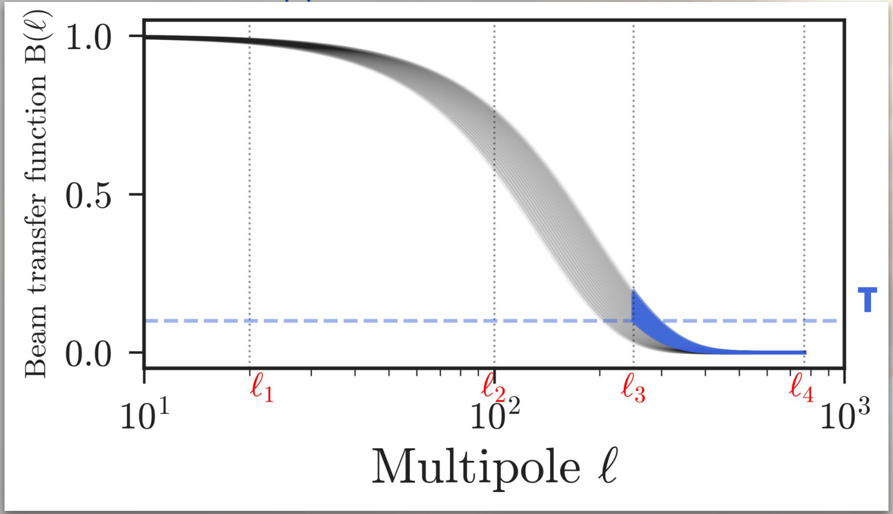
Per scale JESSNet

Windowed data

$$\widehat{X}^{(j)}_{\nu,\ell m} = W_j(\ell)\,\widehat{X}_{\nu,\ell m}$$

ℓ bin: exclude channels with severe beam suppression

$$B_{\nu_b}(\ell_b) \geq \tau$$



HI reconstruction in each ℓ bin & recombination

hard binning

$$\widehat{\mathrm{HI}}_{\ell m} = \begin{cases} \widehat{\mathrm{HI}}^{(1)}_{\ell m}, & \ell < \ell_1 \\ \widehat{\mathrm{HI}}^{(2)}_{\ell m}, & \ell_1 \leq \ell < \ell_2 \\ \vdots & \\ \widehat{\mathrm{HI}}^{(N_b)}_{\ell m}, & \ell \geq \ell_{\mathrm{last}} \end{cases}$$

any other binning

$$\widehat{\mathrm{HI}}_{\ell m} = \frac{\sum_j W_j(\ell)\,\widehat{\mathrm{HI}}^{(j)}_{\ell m}}{\sum_j W_j(\ell)}$$

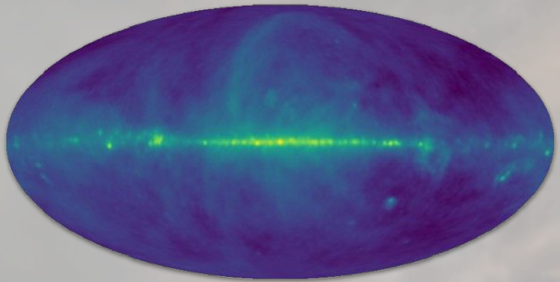
From spherical harmonics back to pixel space

$$\mathrm{HI}(\hat{\mathbf{n}}) = \sum_{\ell m} \widehat{\mathrm{HI}}_{\ell m}\, Y_{\ell m}(\hat{\mathbf{n}})$$

JESSNet: masked

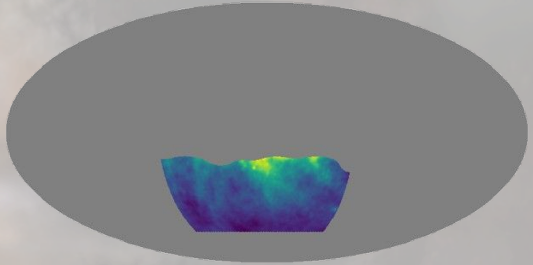
Full sky

$$X_\nu = (A_\nu S) * H_\nu + N_\nu$$

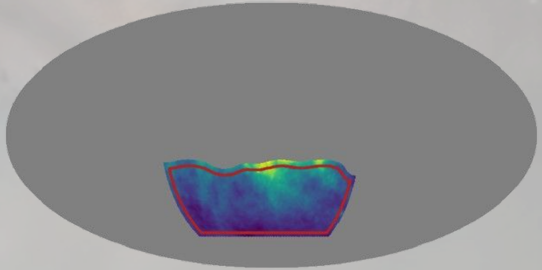


masked region

$$X_\nu^{\text{mask}} = M\left[(A_\nu S) * H_\nu\right] + M N_\nu$$



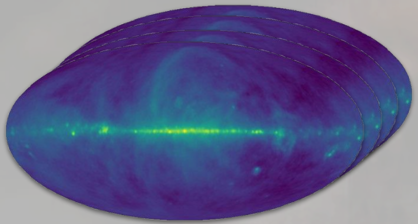
$$X_\nu^{\text{mask}} \simeq (A_\nu M S) * H_\nu + M N_\nu$$



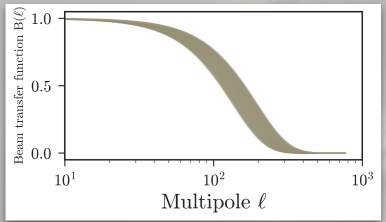
JESSNet: summary

INPUT

Observations (cube)
Full sky / survey footprint



Input the telescope beam



Choose the ℓ binning

Joint **deconvolution** & component separation with JESSNet

Estimating **A** and **S**
Thresholding S with **learnlets**

Apply it **per ℓ scale**

OUTPUT

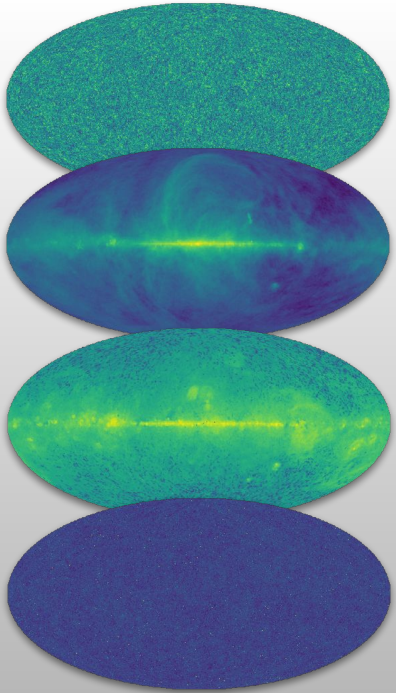
Estimated foregrounds

Residuals = obs - estimated foregrounds

HI+noise = residuals

Foreground cleaning pipeline

Simulate the data



* Beam

Pre-processing

Masking the HI-bright sources

Apply the methods

PCA
FastICA
GMCA
Polinomial Fit
Parametric fit
JESSNet

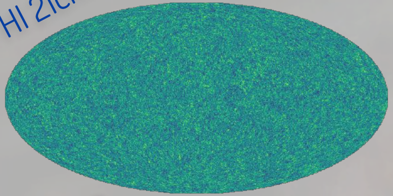
Validation

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

Angular power spectrum **C_ℓ**

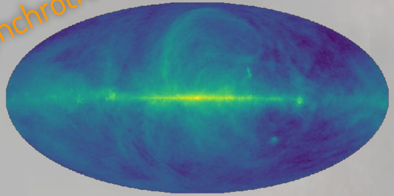
Simulating the data

HI 21cm



Cosmological simulations
CoLoRe

synchrotron



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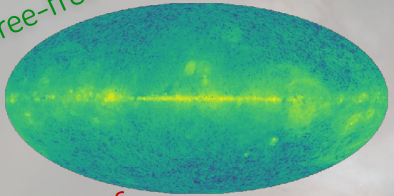

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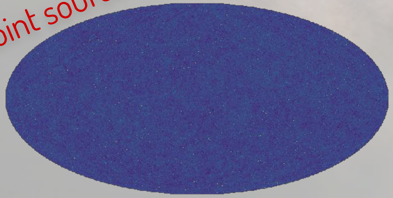

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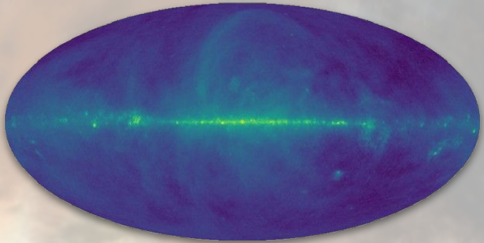
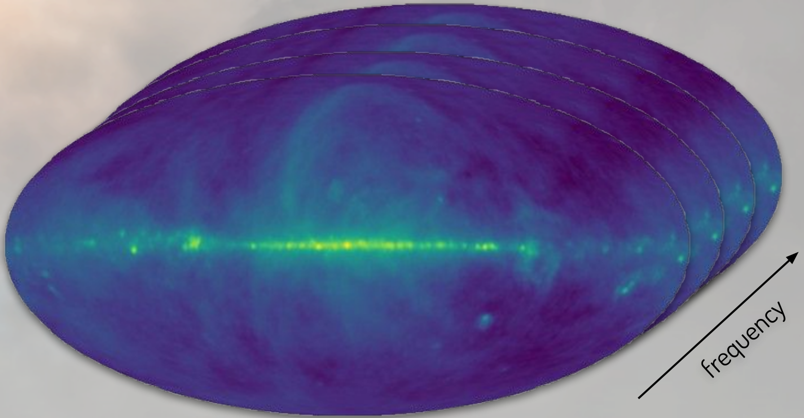
+



* telescope beam

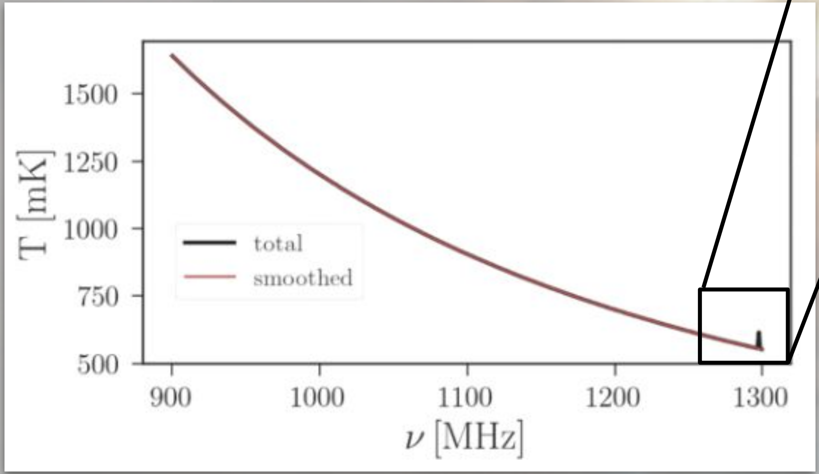
+ instrumental noise

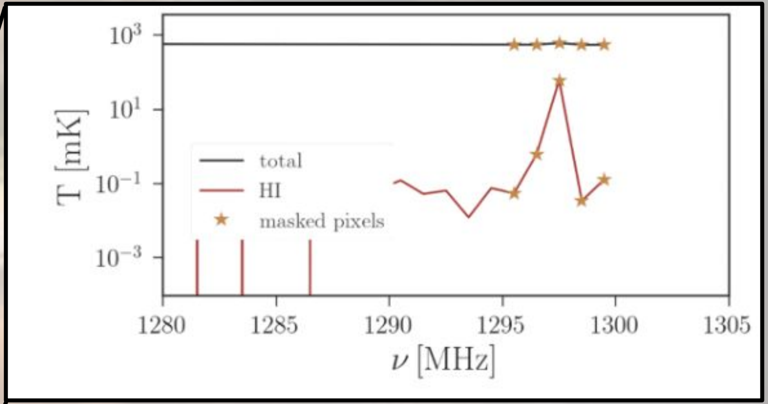
=



Pre-processing

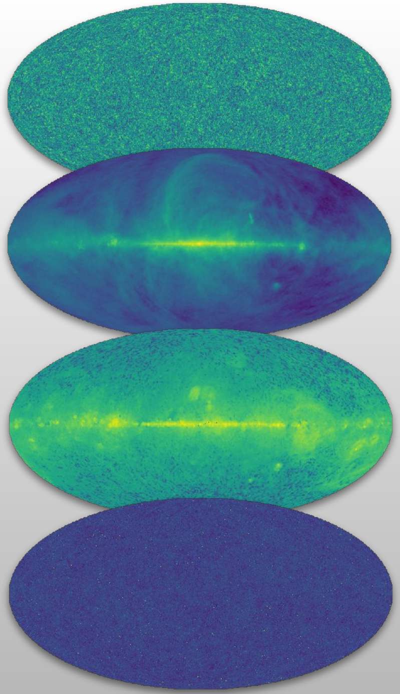
- Detecting lines of sight with peaks (extremely bright HI-sources)
- Assigning the baseline value to this pixel





Foreground cleaning pipeline

Simulate the data



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Parametric fit
JESSNet

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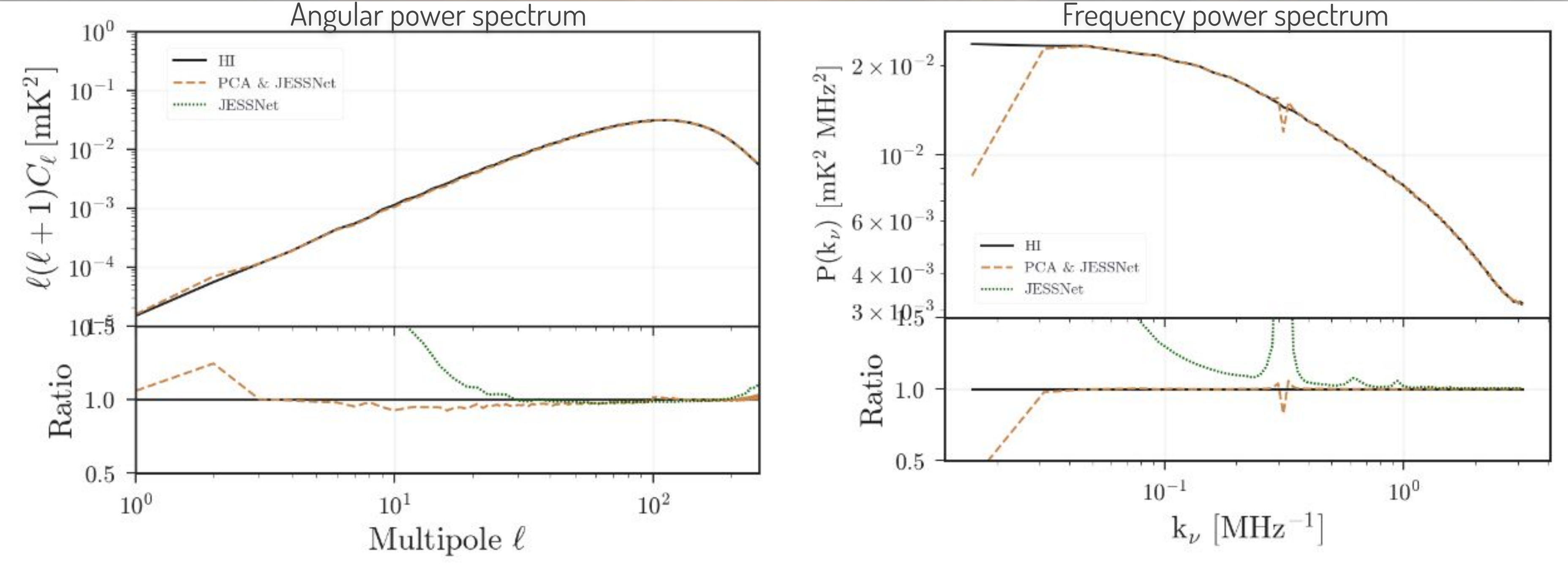
Radial (frequency) power spectrum $\mathbf{P(k_\nu)}$

Angular power spectrum $\mathbf{C_\ell}$

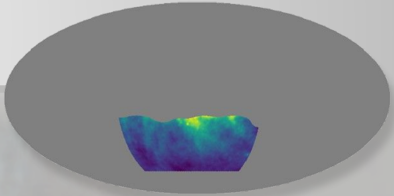
Results on full sky

All scales VS. per-scale cleaning



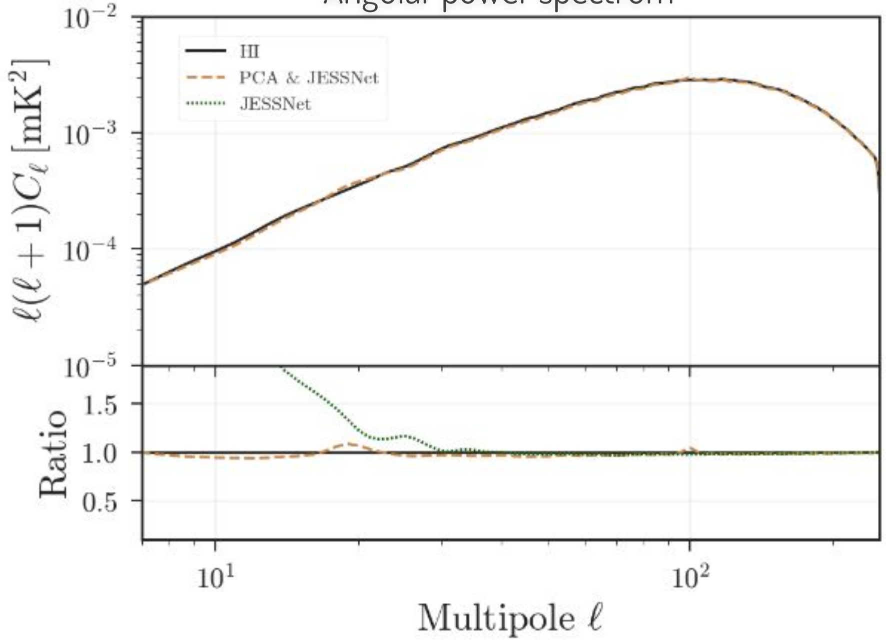
Gkogkou et al. in prep.

Results on a footprint

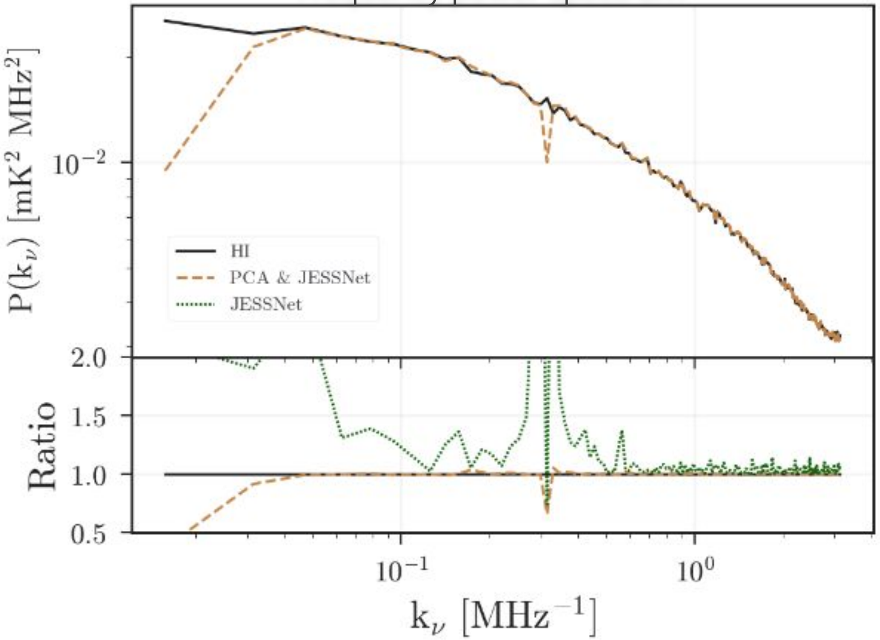


All scales VS. per-scale cleaning

Angular power spectrum



Frequency power spectrum



Gkogkou et al. in prep.

Summary & Conclusions

- **Foreground removal is a central challenge for HI intensity mapping**
- **A non-smooth beam evolution imprints artificial spectral structure on foregrounds**
  They imprint artificial frequency structure on otherwise smooth foregrounds
- **This motivates joint deconvolution and component separation**
  The beam should be included directly in the cleaning model
- **`JESSNet`** provides a beam-aware sparse separation framework
  - Joint beam deconvolution + component separation
  - Learnlet-based sparse regularization
  - Applicable to partial-sky / survey-footprint data
  - Per-scale cleaning improves flexibility and recovery
  - **Per-scale `JESSNet` gives better HI recovery in both full-sky and footprint**