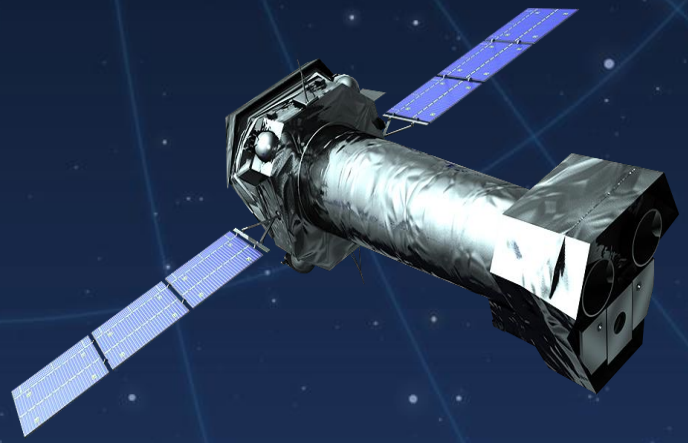
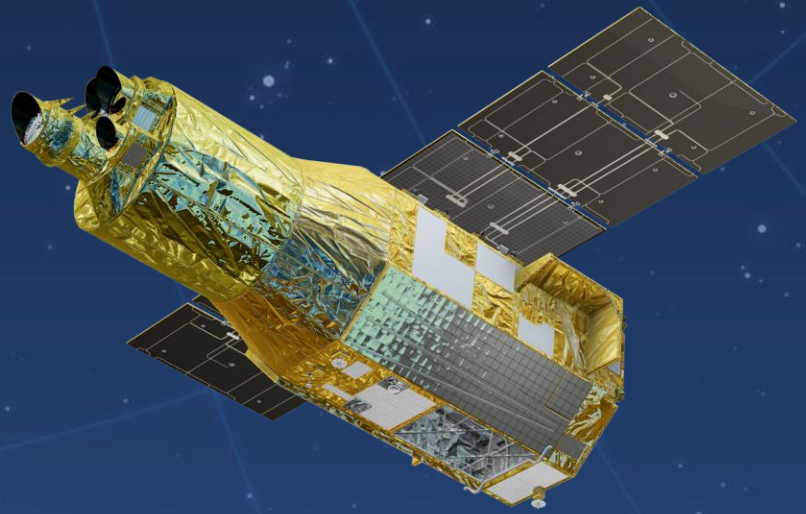




HYPERSPECTRAL FUSION FOR X-RAY ASTROPHYSICS

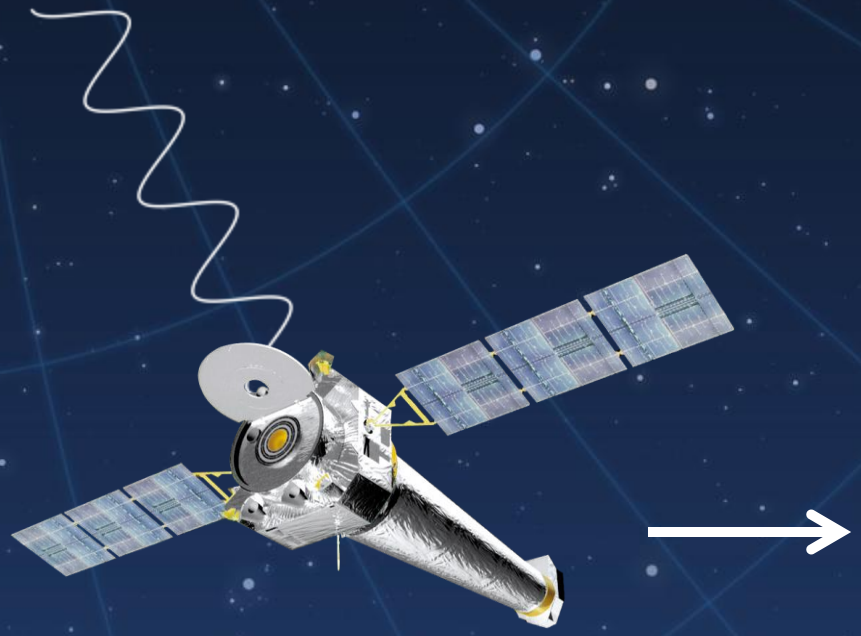
Julia Lascar

Post-Doc at IRAP

Presented work in collaboration with:

Jérôme Bobin & Fabio Acero

X-ray spectro-imager data acquisition

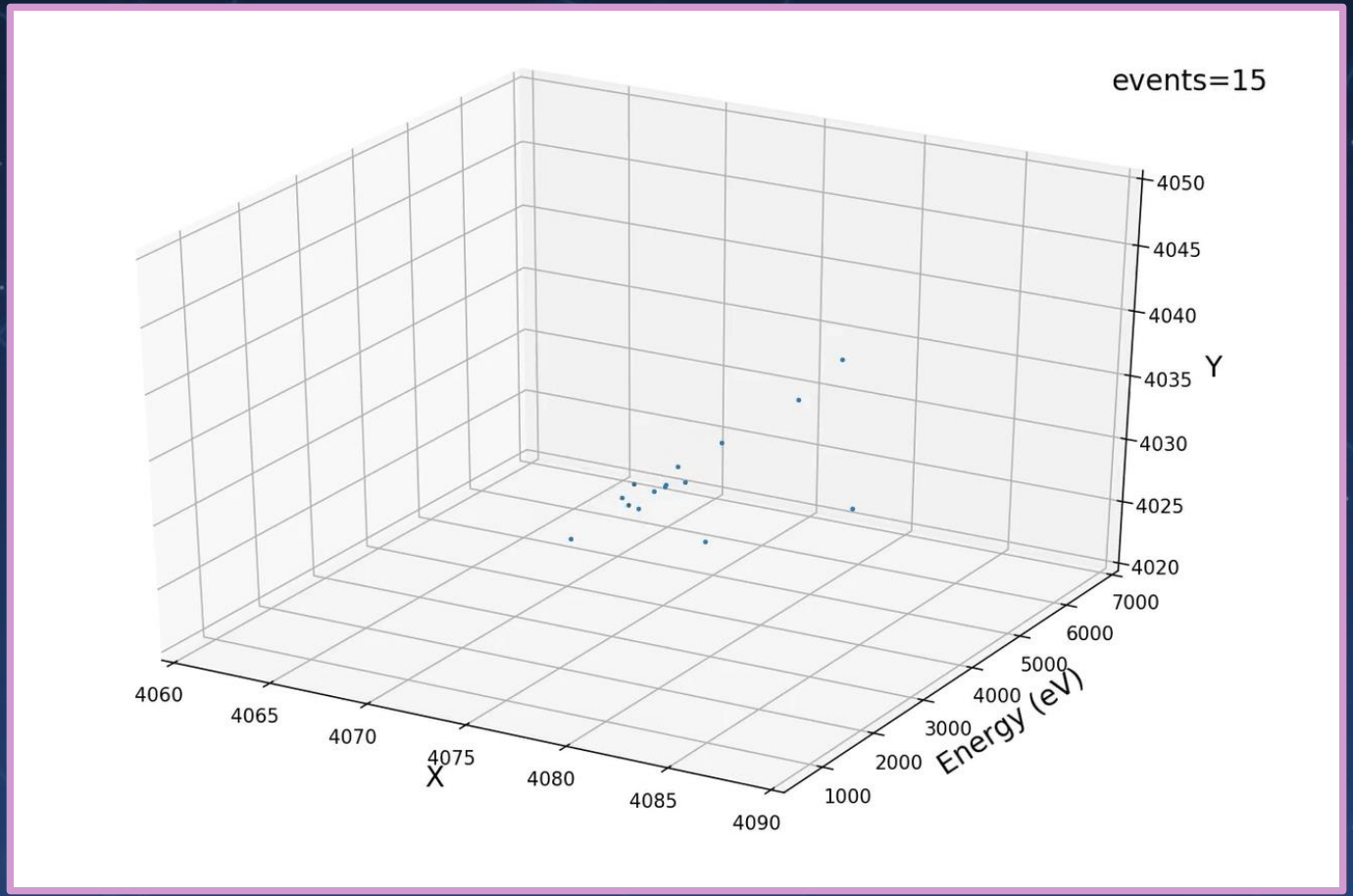


Chandra

Measure each photon one by one:

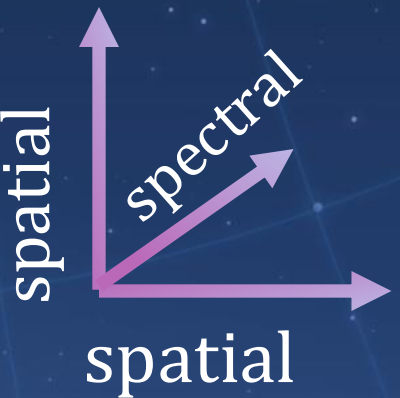
- X, Y, energy (and time)

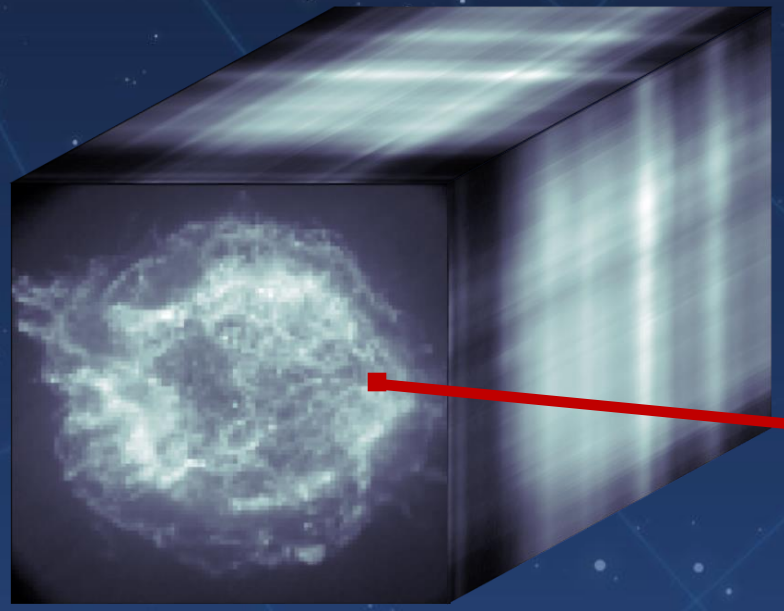
Pulsar B1259 observation

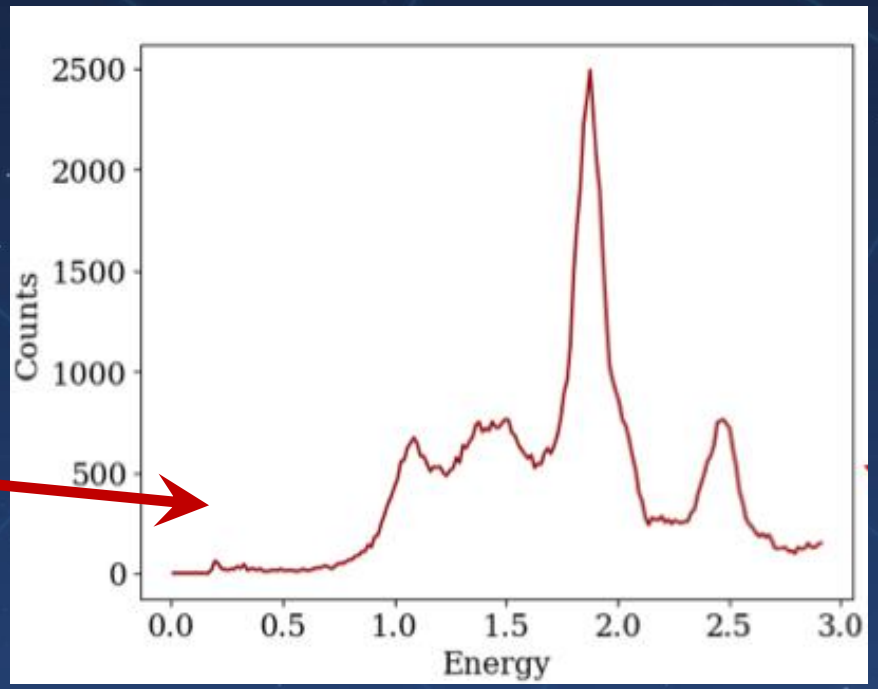


Hyperspectral images

- For each pixel, a spectrum

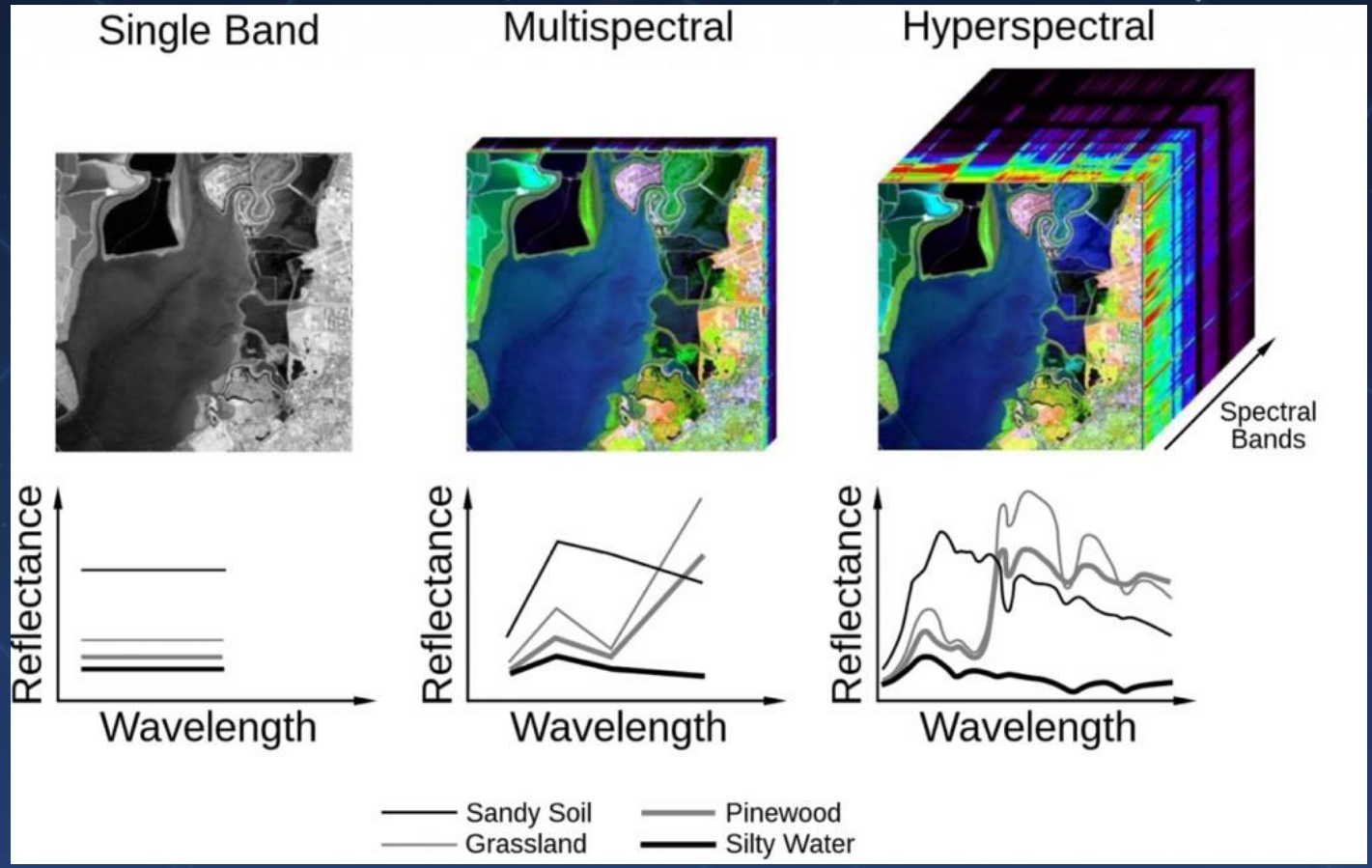






Hyperspectral images

- Rich literature of methods in remote sensing :
  - Source separation GMCA (see talk by L Godinaud), SUSHI (see talk by D Bogensberger)
  - Fusion (this talk)
  - Classification



X-ray telescopes

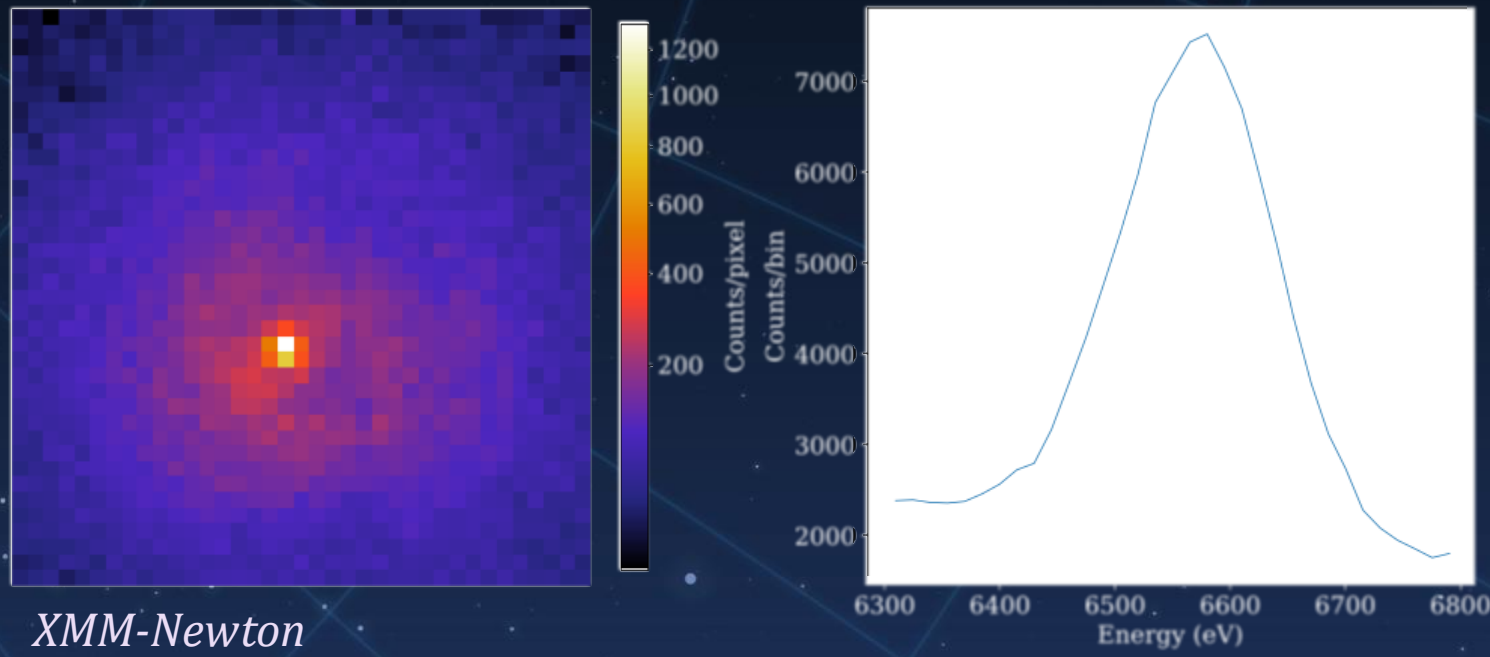
CCD cameras:

Good **spatial** resolution

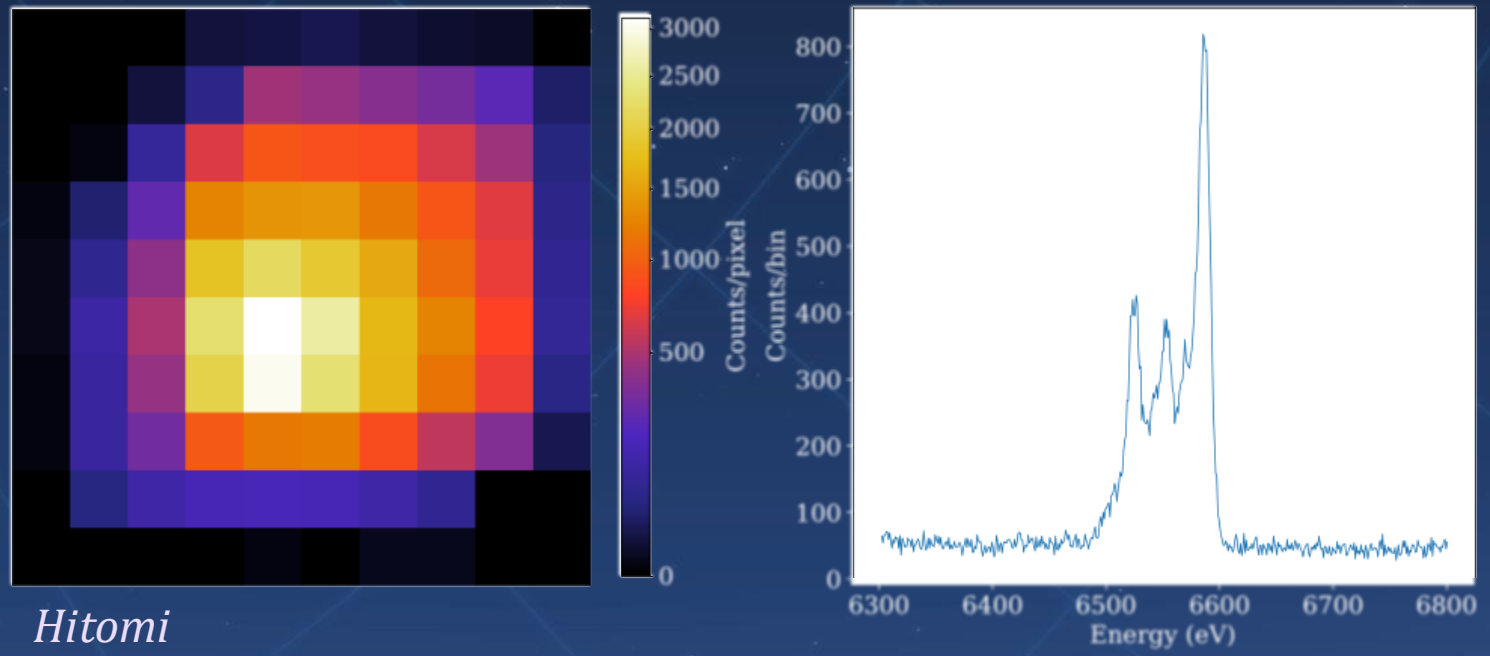
Micro-calorimeters:

Good **spectral** resolution

Perseus galaxy cluster

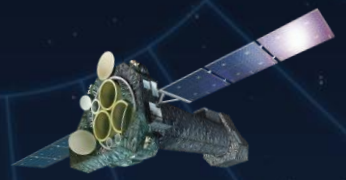


XMM-Newton

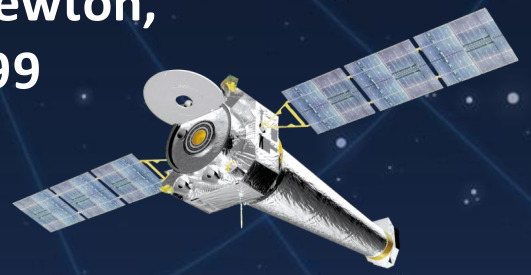


Hitomi

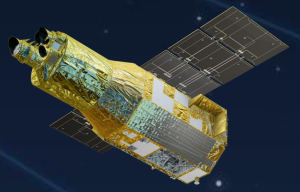
FUSION



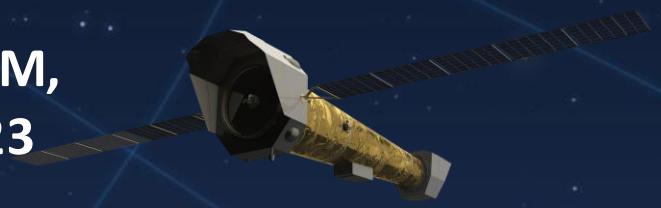
XMM-Newton,
1999



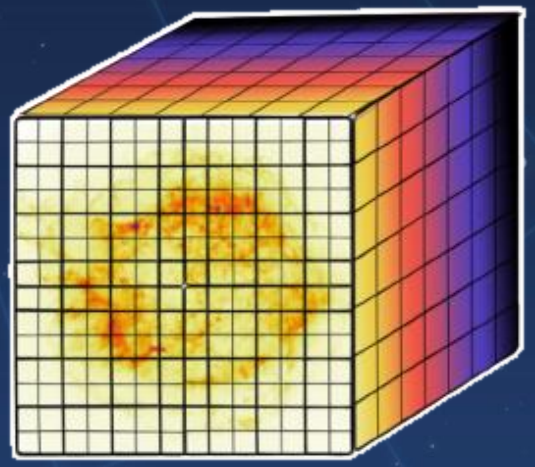
Chandra,
1999



XRISM,
2023

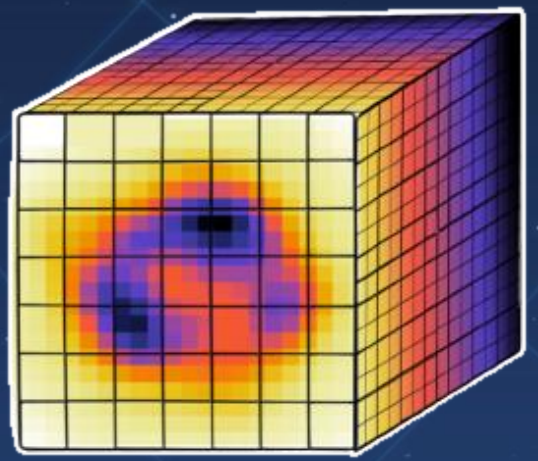


NewAthena-XIFU,
2037

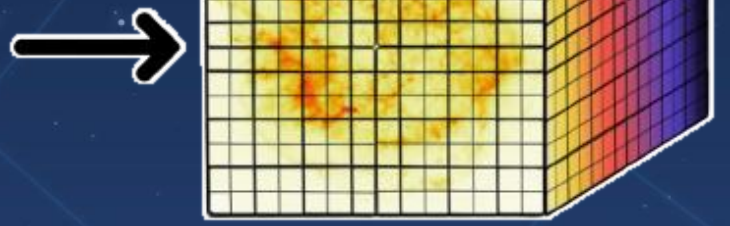


√ Spatial
X Spectral

&



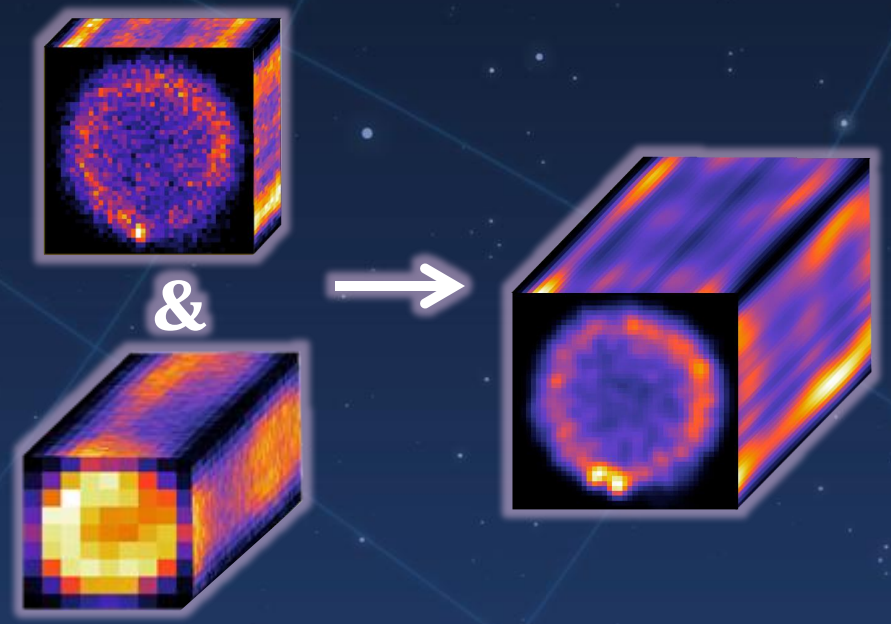
X Spatial
√ Spectral



√ Spatial
√ Spectral

Existing Methods

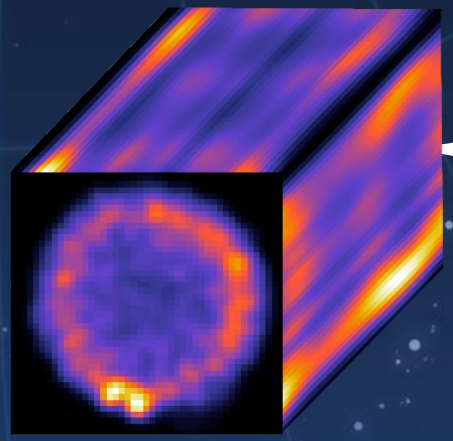
- Rich literature
- Two important elements:
  - **Regularization**
  - **Spectral subspace**
- For the James Webb Space Telescope:
  - Guilloteau et al, 2020 & 2022: PCA spectral subspace
  - Pineau et al, 2024: Deep learning based prior



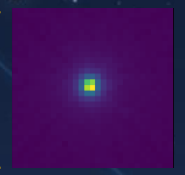
FUSION FORWARD MODEL

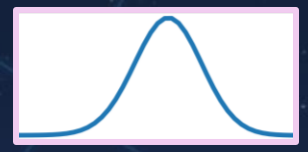
XMM

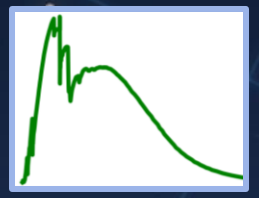
Source
Z



$R_1 \left(\circledast Z \circledast \right) \times$







Spatial 2D
Convolution
Kernel

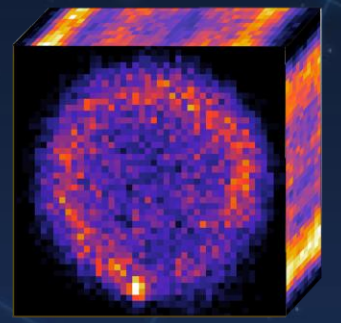
Spectral 1D
Convolution
Kernel

Effective
Area

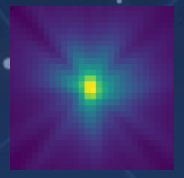
Poisson
Noise

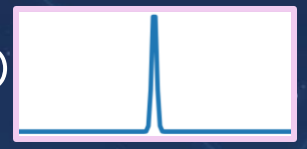
Observed data

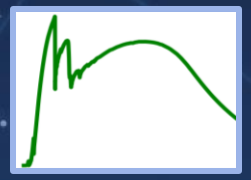
X



$R_2 \left(\circledast Z \circledast \right) \times$



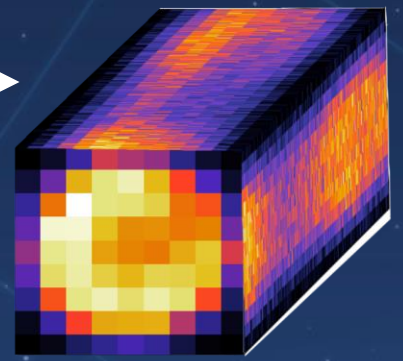


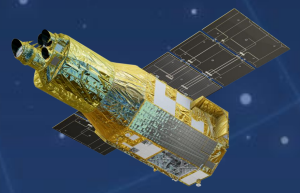


Rebinning
Operators

Poisson
Noise

Y





XRISM

FUSION FORWARD MODEL

Spatial 2D Convolution Kernel

Spectral 1D Convolution Kernel

Effective Area

$$Z_X = \mathbf{R}(PSF_X \circledast Z \circledast RMF_X)\mathbf{EA}$$

→Z, degraded by the response of instrument X

POSING THE INVERSE PROBLEM

$$\min_{Z} \; Cost\left(\boldsymbol{X}_{data} \,|Z_X\right) + Cost\left(\boldsymbol{Y}_{data}|Z_Y\right) + \boldsymbol{\rho\varphi}(Z)$$

DATA FIDELITY

REGULARISATION

Poisson noise:
the cost function is the Poisson log-likelihood

Choice of regularisation is very important

Regularization

- Three methods were implemented and tested:
  - l1 norm of Wavelet 2D-1D coefficients *(space-energy)*
  - Low rank Approximation (using PCA) with Sobolev Regularization

    (inspired by Guilloteau 2020 work on JWST)
  - Low rank Approximation with 2D Wavelet Regularization

HI-FReD: Hyperspectral Image Fusion via Regularized Deconvolution

- Proximal gradient descent
- coded with Jax

Calculate FFT of convolution kernels

***while** stopping criterion is not reached:*

> ***for** each instrument x:*
>
> **Calculate** gradient part that depends on x

Gradient descent update on Z

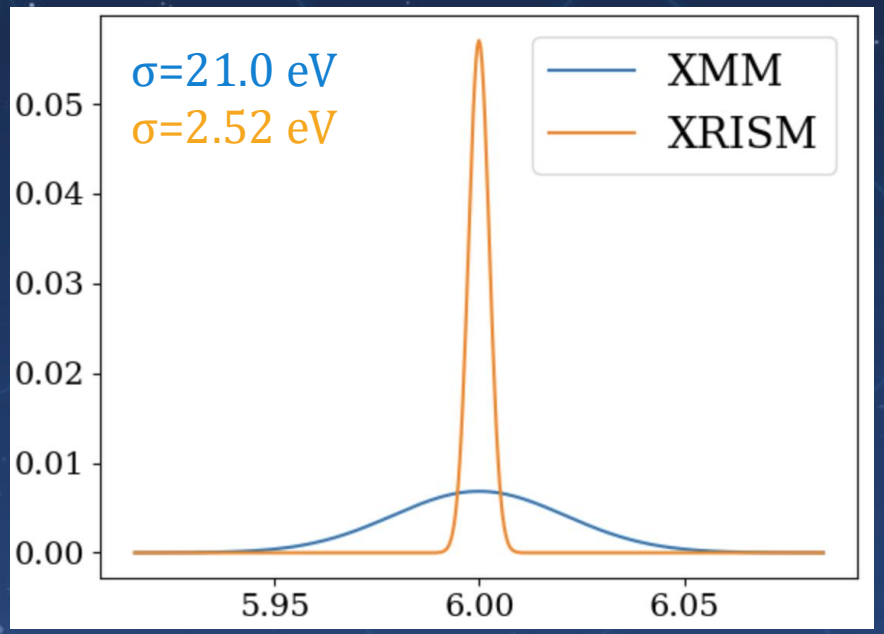
Proximal operator to regularize Z

Results

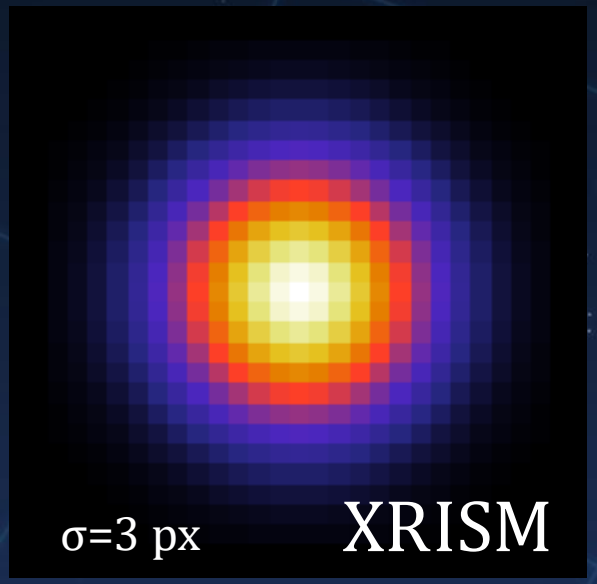
Toy model

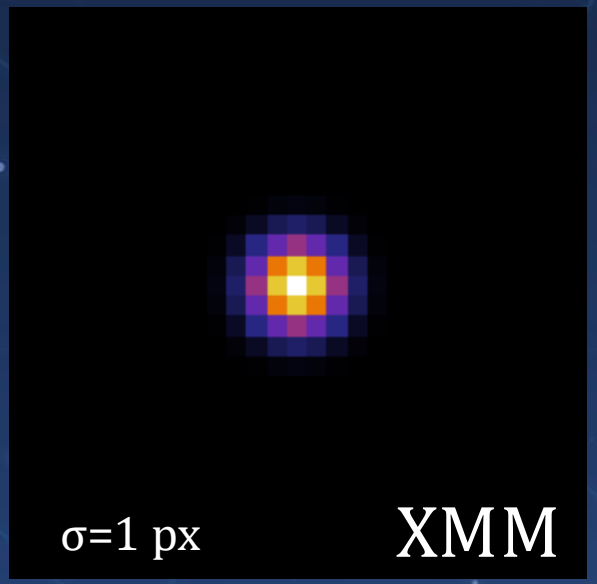
- Hydro simulation of SNR (Orlando 2016)
- XMM and XRISM mock data
- Method was tested on toy-models of varying complexity

Spectral responses



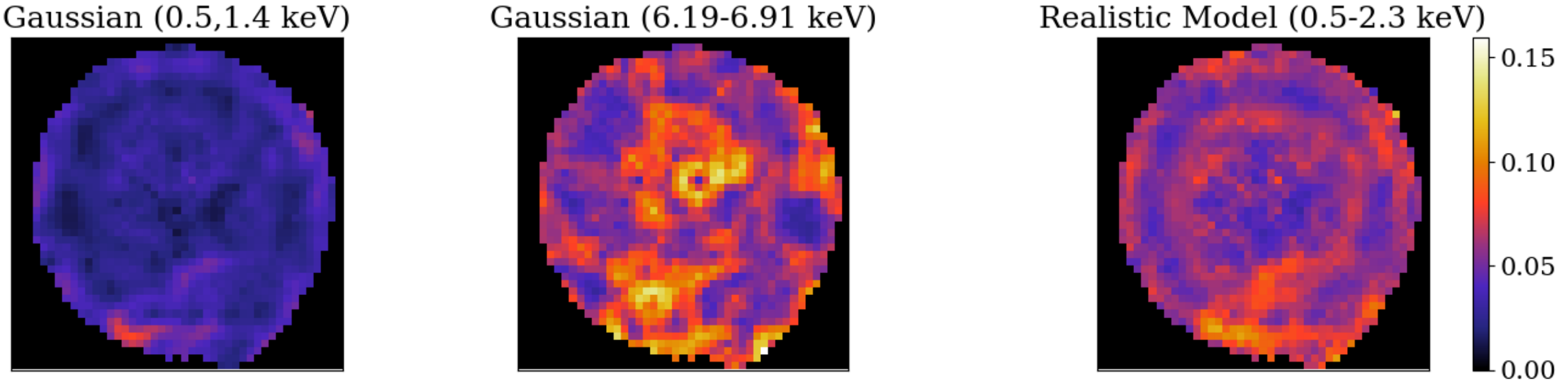
Gaussian Spatial responses





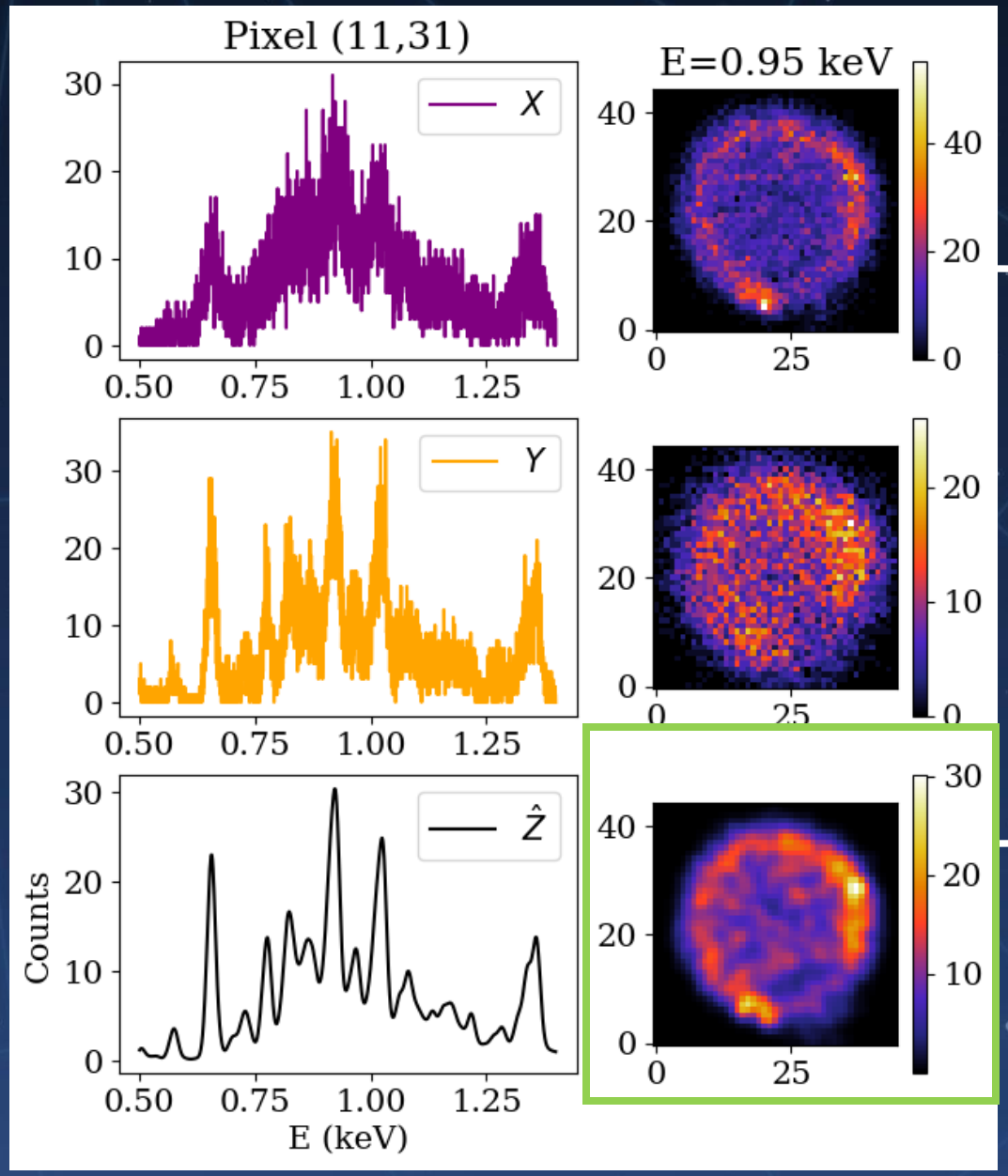
Spectral Variability at different ranges

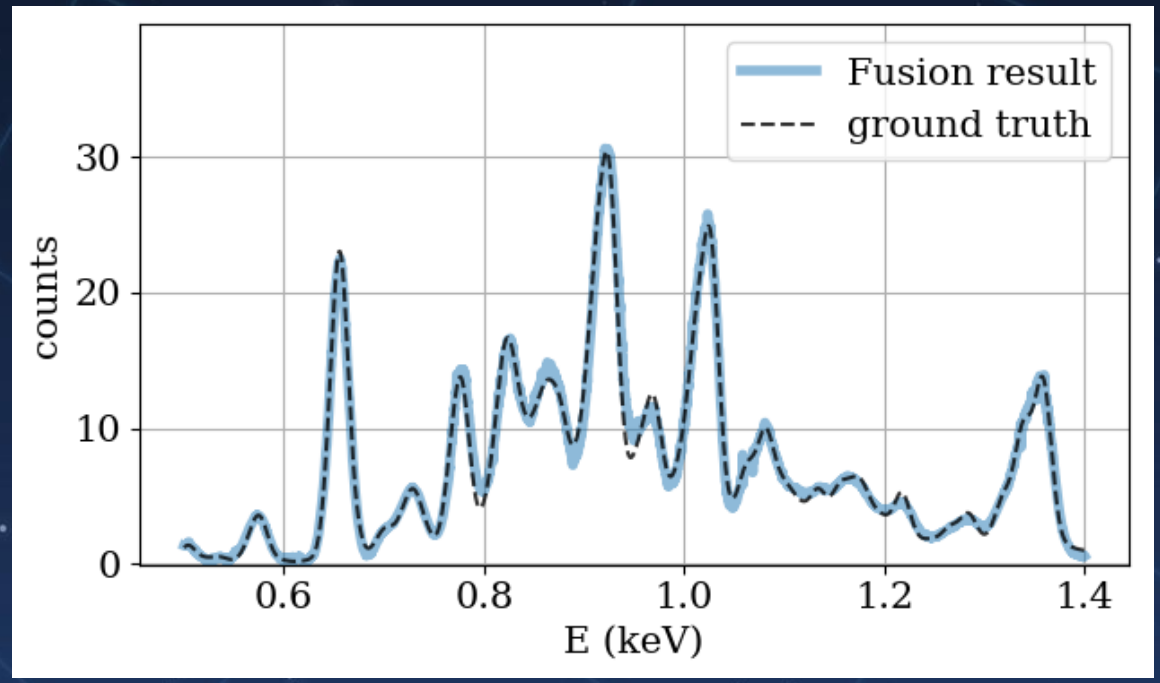
Mean Angular Distance between neighbouring pixels

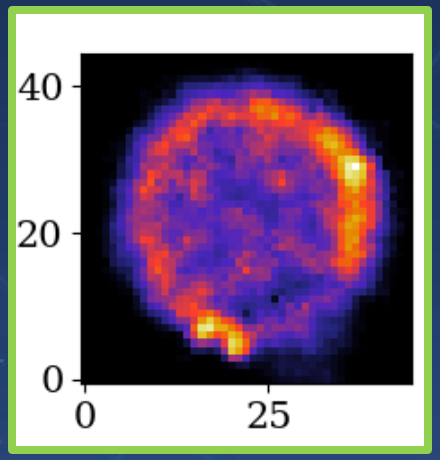


$$\theta(Z_k) = \sum_{Z_{k'} \in \mathcal{N}} \arccos\left(\frac{< Z_k, Z_{k'} >}{\sqrt{(||Z_k||_2^2 * ||Z_{k'}||_2^2)}}\right) / \mathrm{card}(\mathcal{N}),$$

RESULT: Gaussian



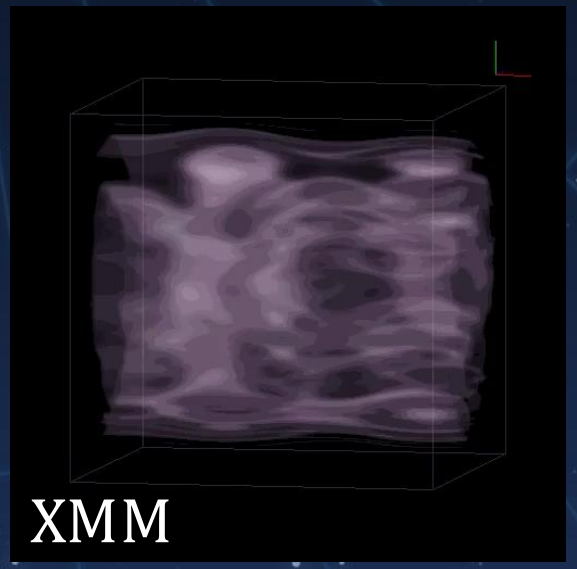


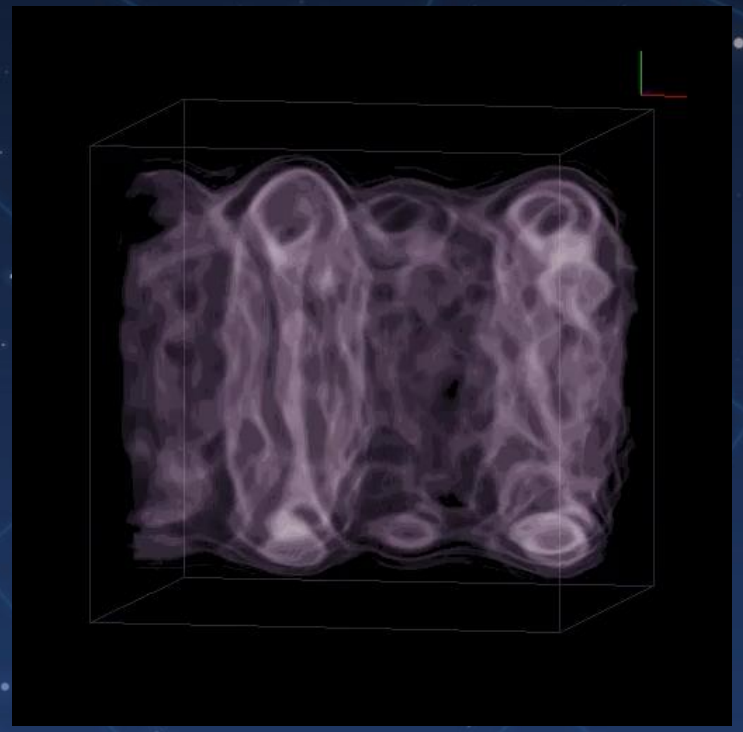


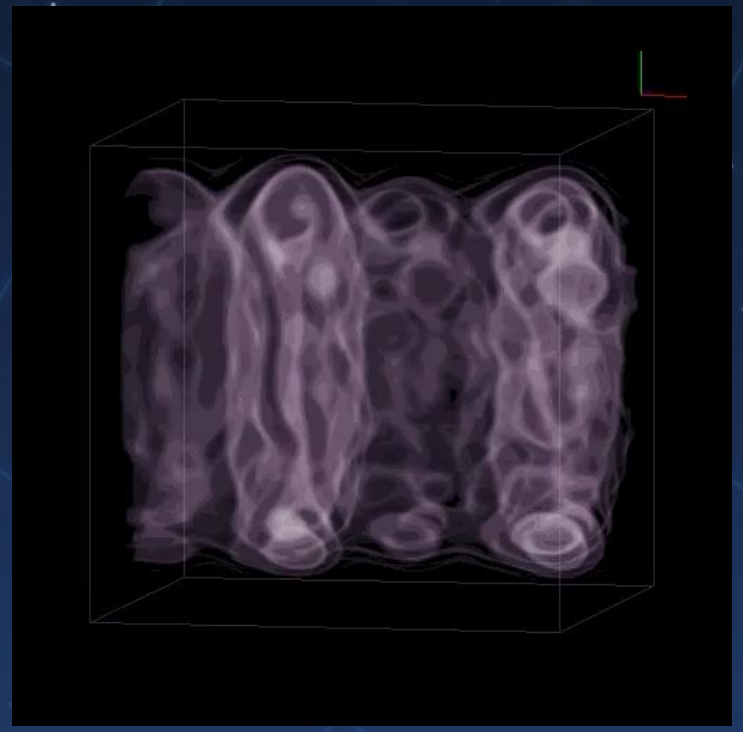
INPUT

RESULT

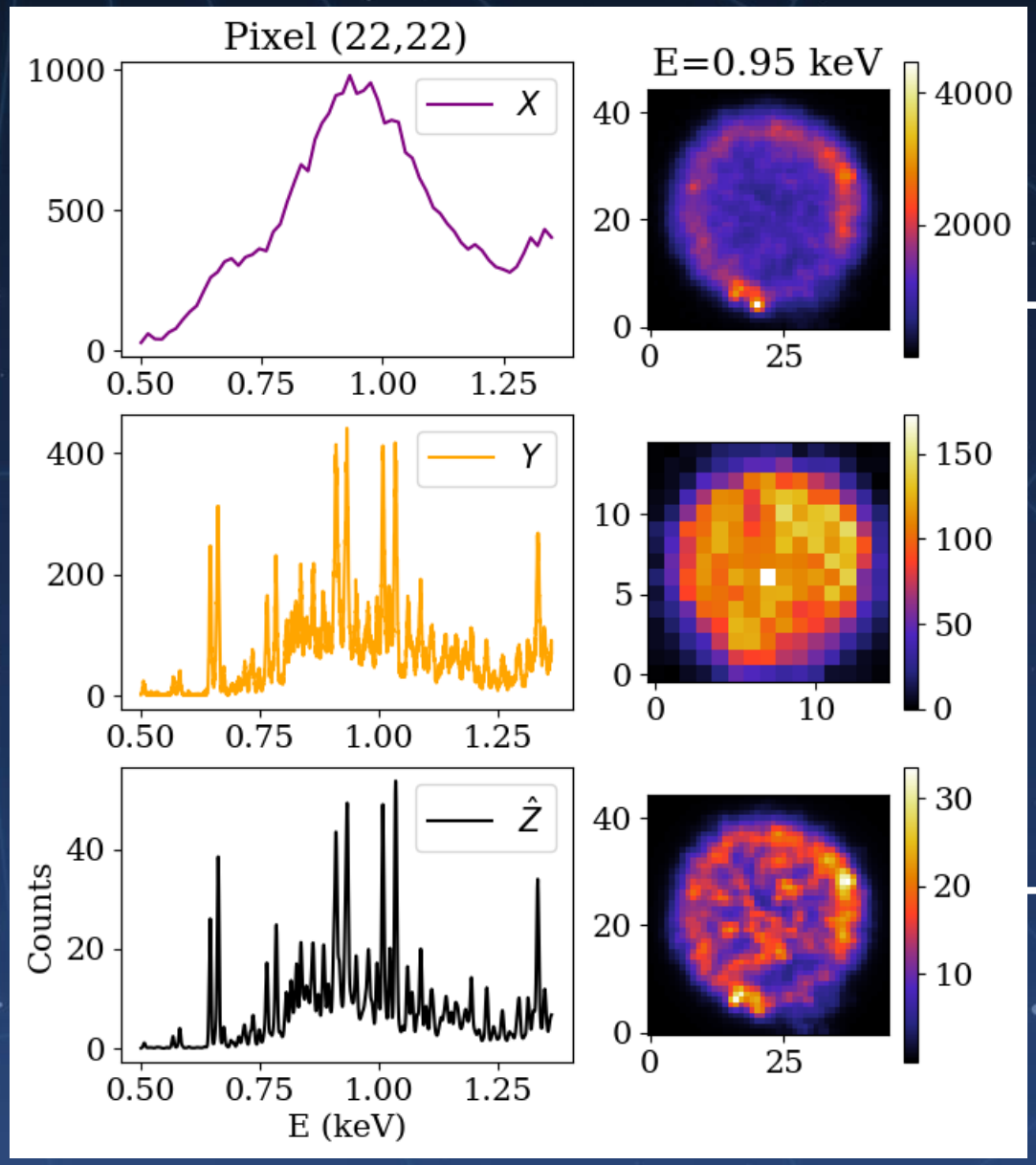
GROUND TRUTH

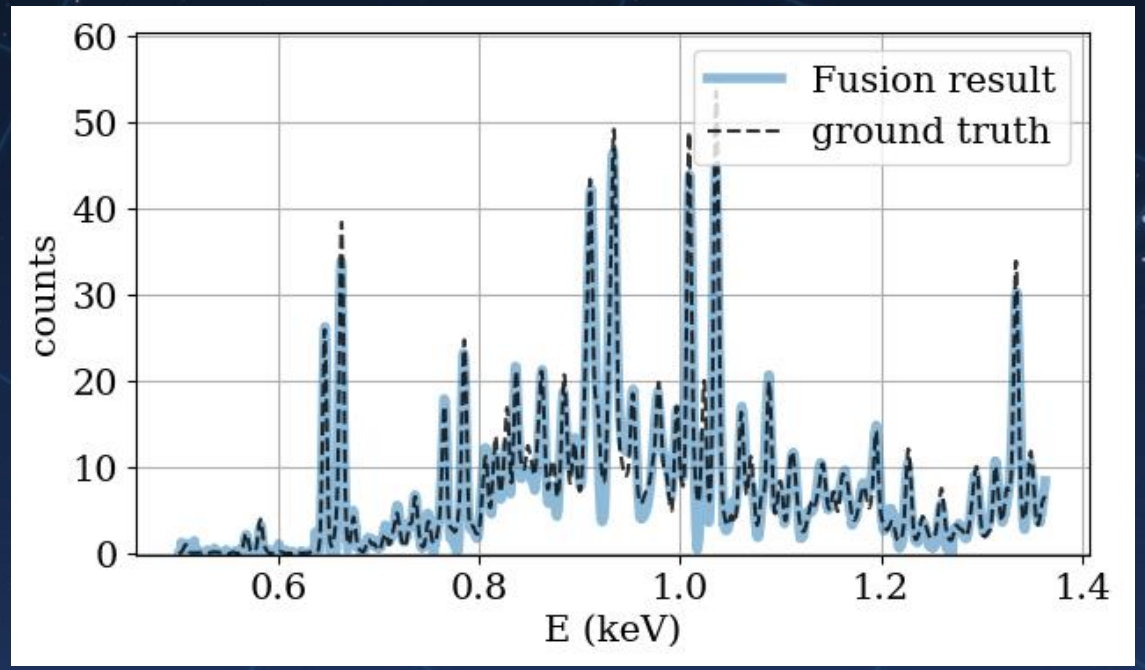


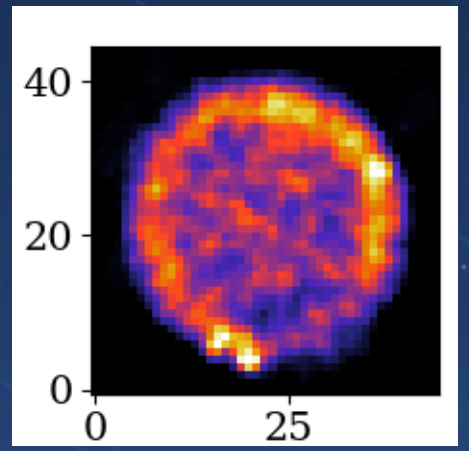




RESULT: Realistic



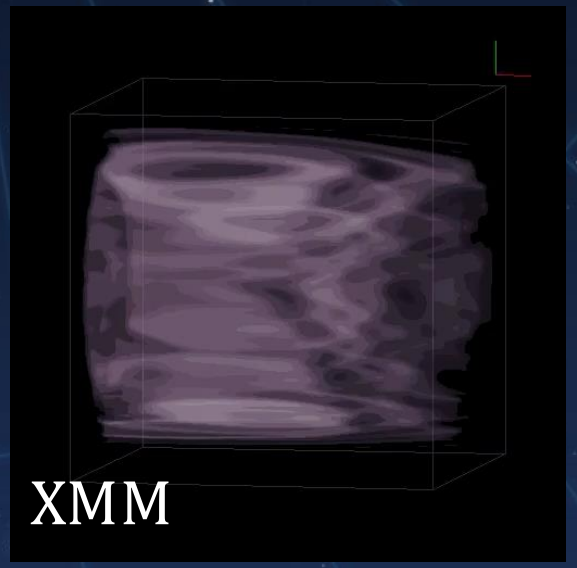


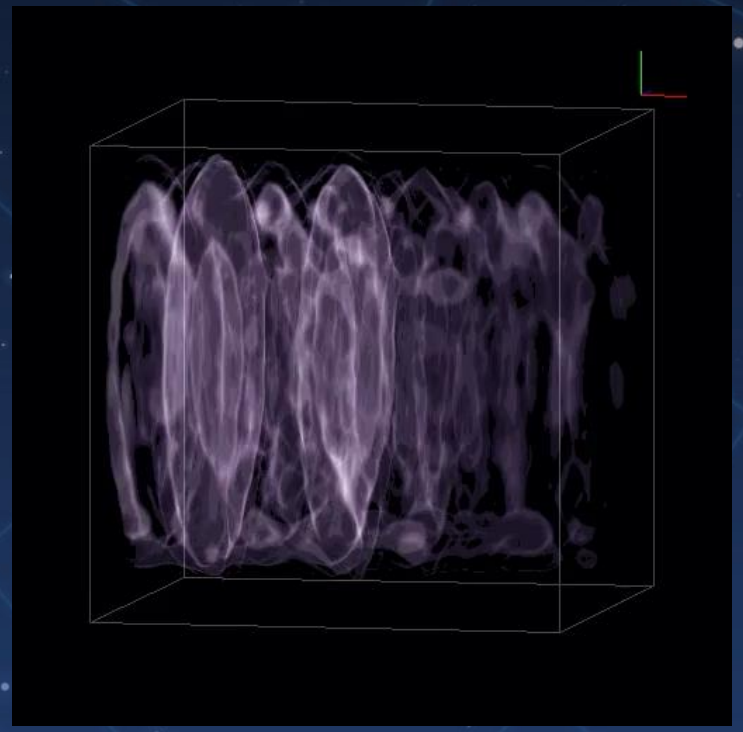


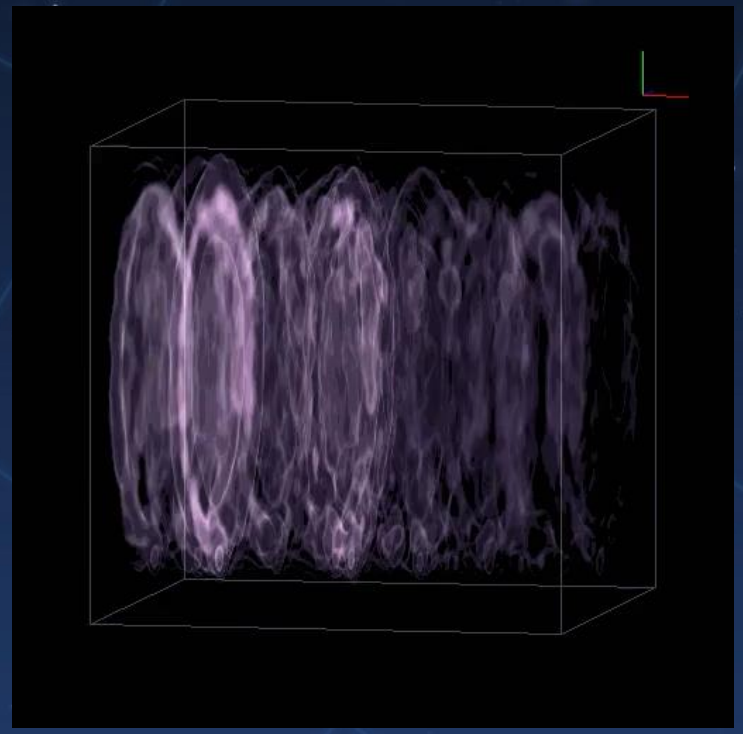
Input

RESULT

GROUND TRUTH

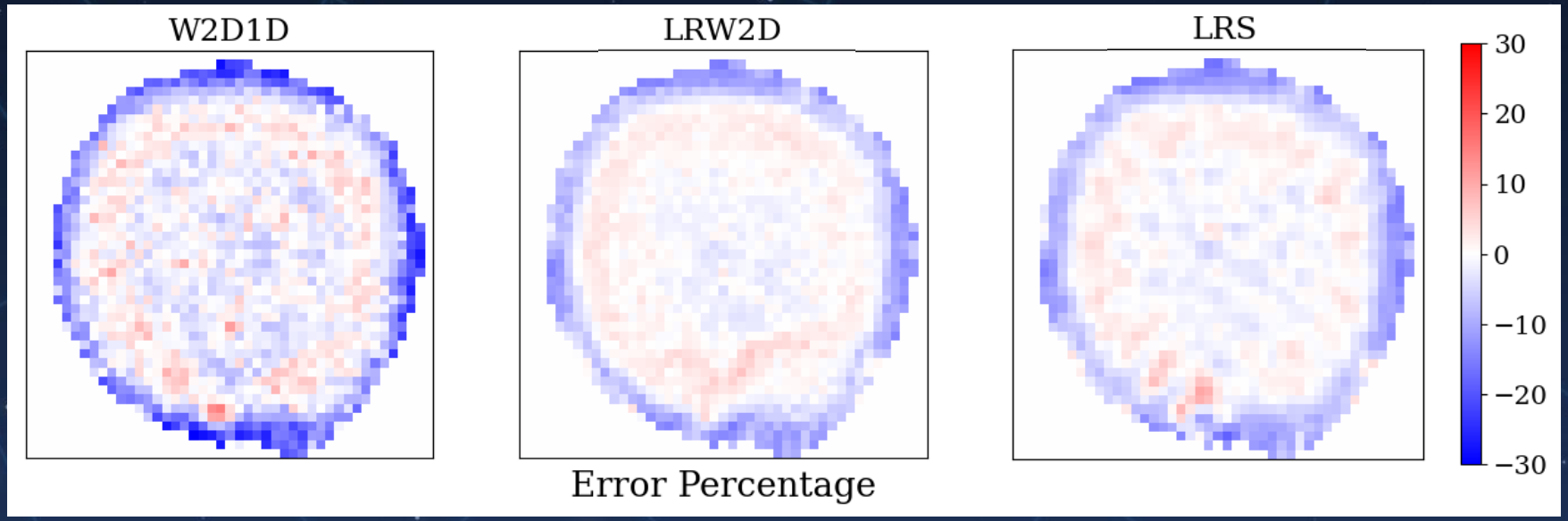


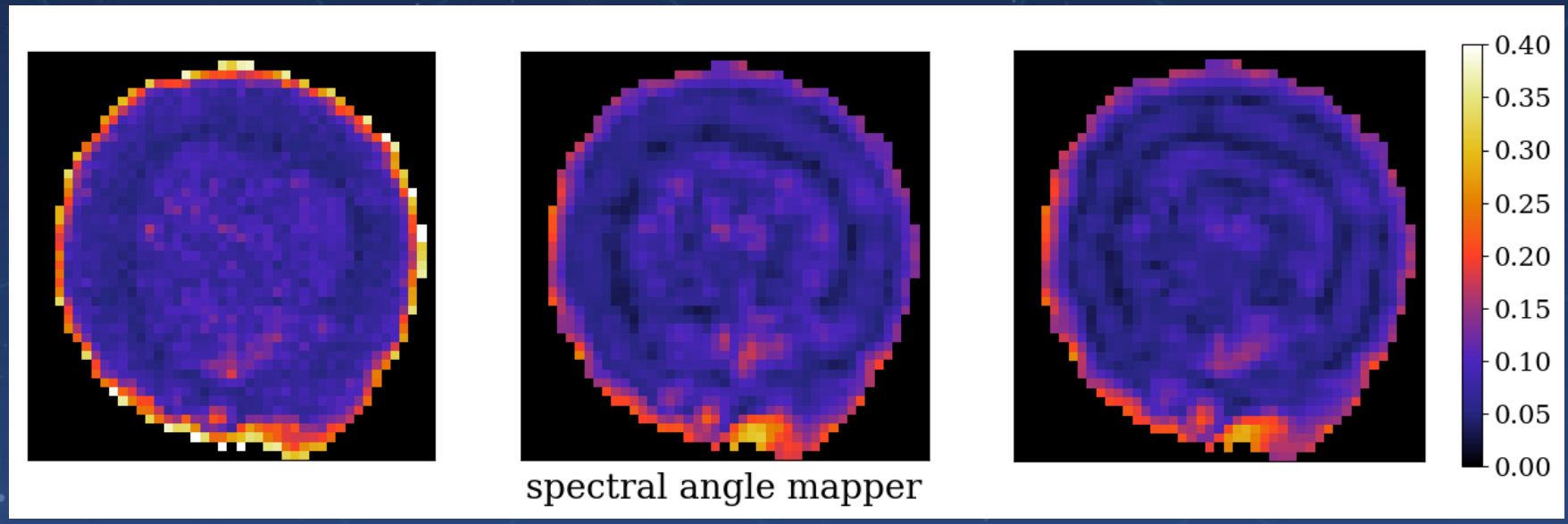




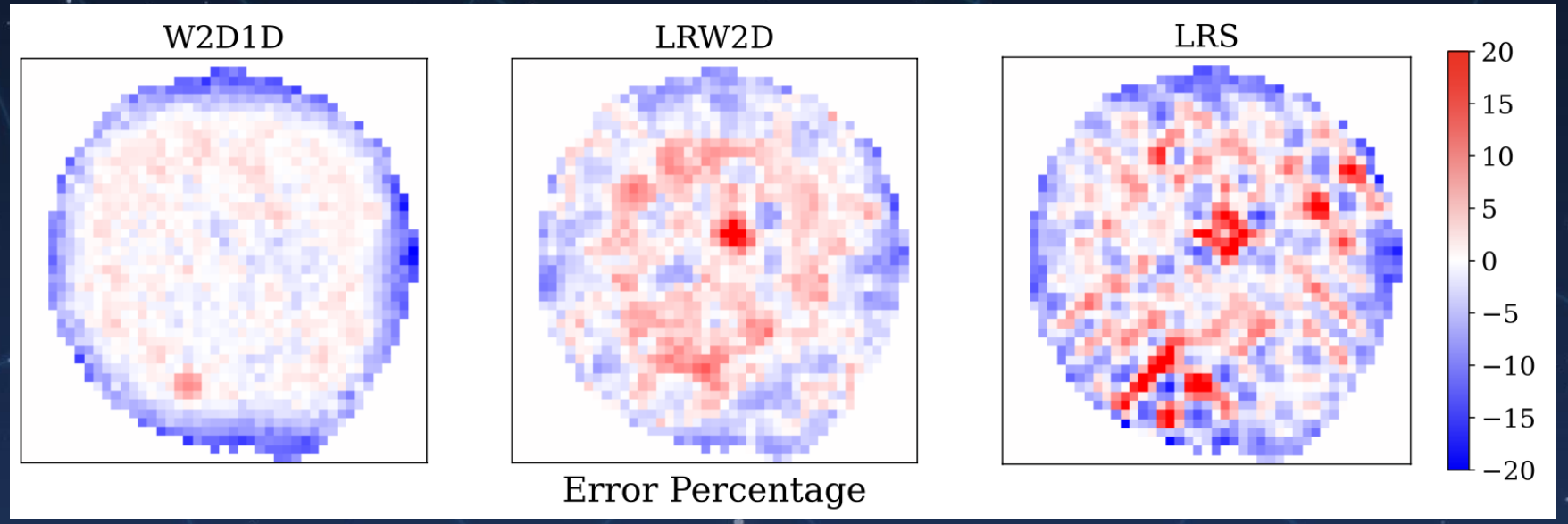
REALISTIC MODEL

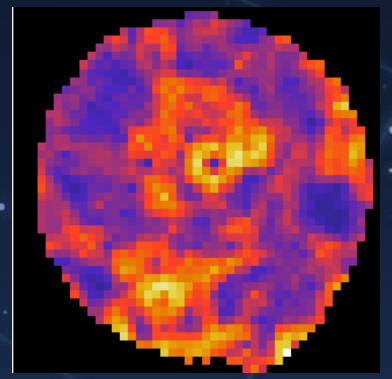
Between 0.5-1.4 keV (low spectral variation)



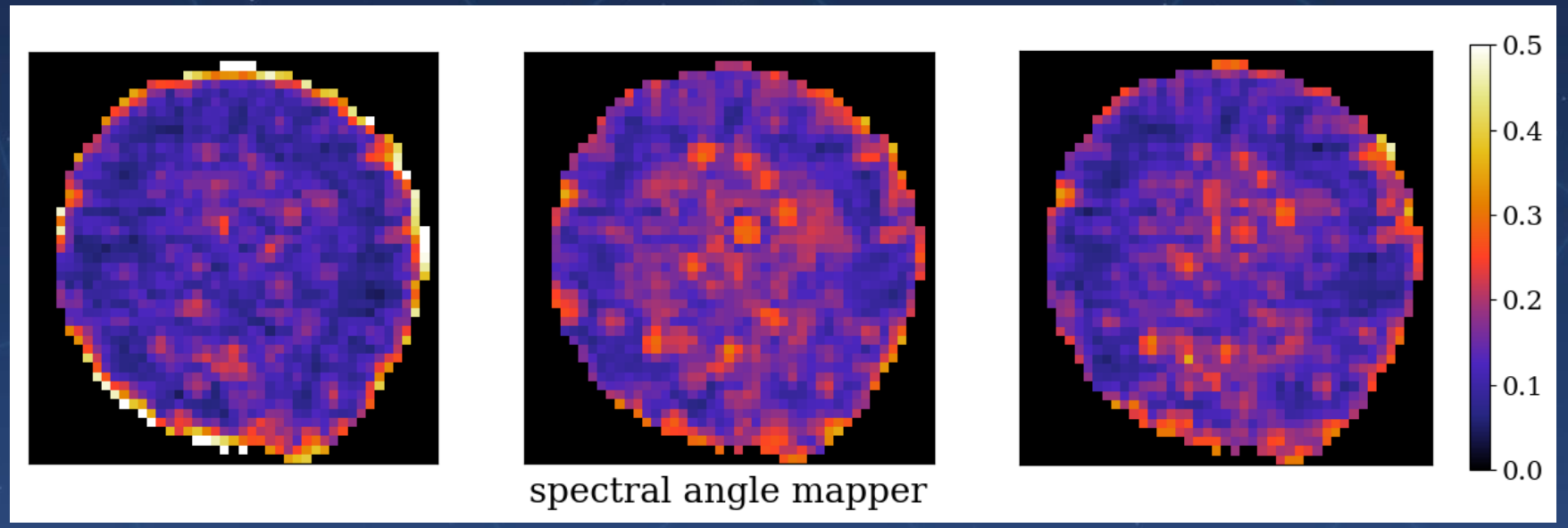


Between 6.2-6.9 keV (high spectral variation)





Mean angular distance between neighbouring pixels



Perspectives

- **Including spectral modelling**
  - ML Surrogate model
  - Use a non-ML based model (jaxspec, Dupourqué 2024)
  - Tackle the problem differently (more task-oriented)
- **More realistic hyperspectral fusion**
  - Include varying spectral and spatial blur
  - Realistic rebinning / alligning data
  - Objective: Applying on real XRISM data
- **Test other spatial regularisations**
  - Plug and play denoisers for example

Thank you!

- Publications in Astronomy & Astrophysics:
  - Lascar, Bobin, Acero 2025

- github.com/JMLascar

  /HIFReD_Fusion — hyperspectral fusion

  /Jax_Convolution — jax-compiled convolution toolbox (including non-stationary)