Spatially variant point spread function removal in X-ray observations

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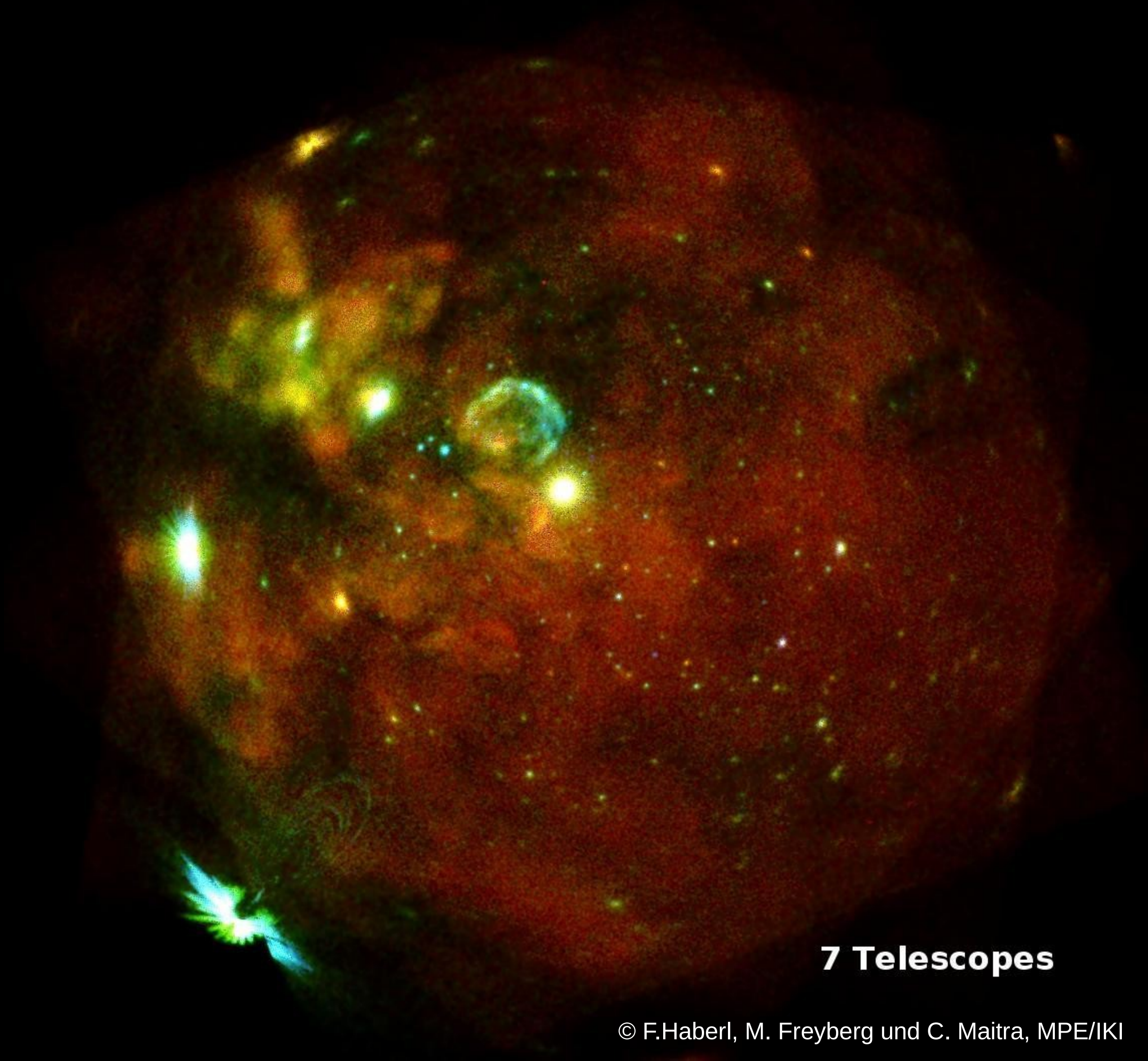
Julia Stadler, Philipp Frank, Philipp Arras,
Torsten Enßlin

1st ErUM-IFT Collaboration Meeting
Garching, Germany
24th November

Motivation



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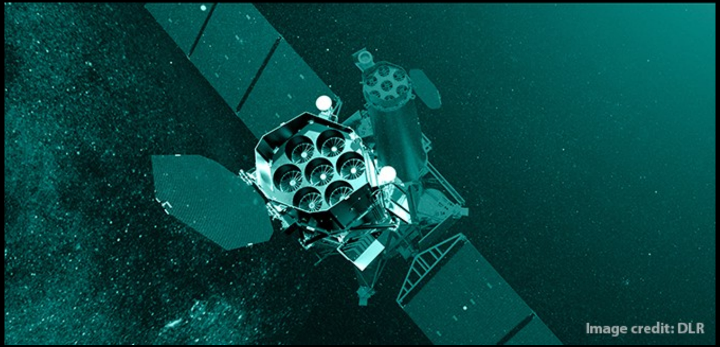
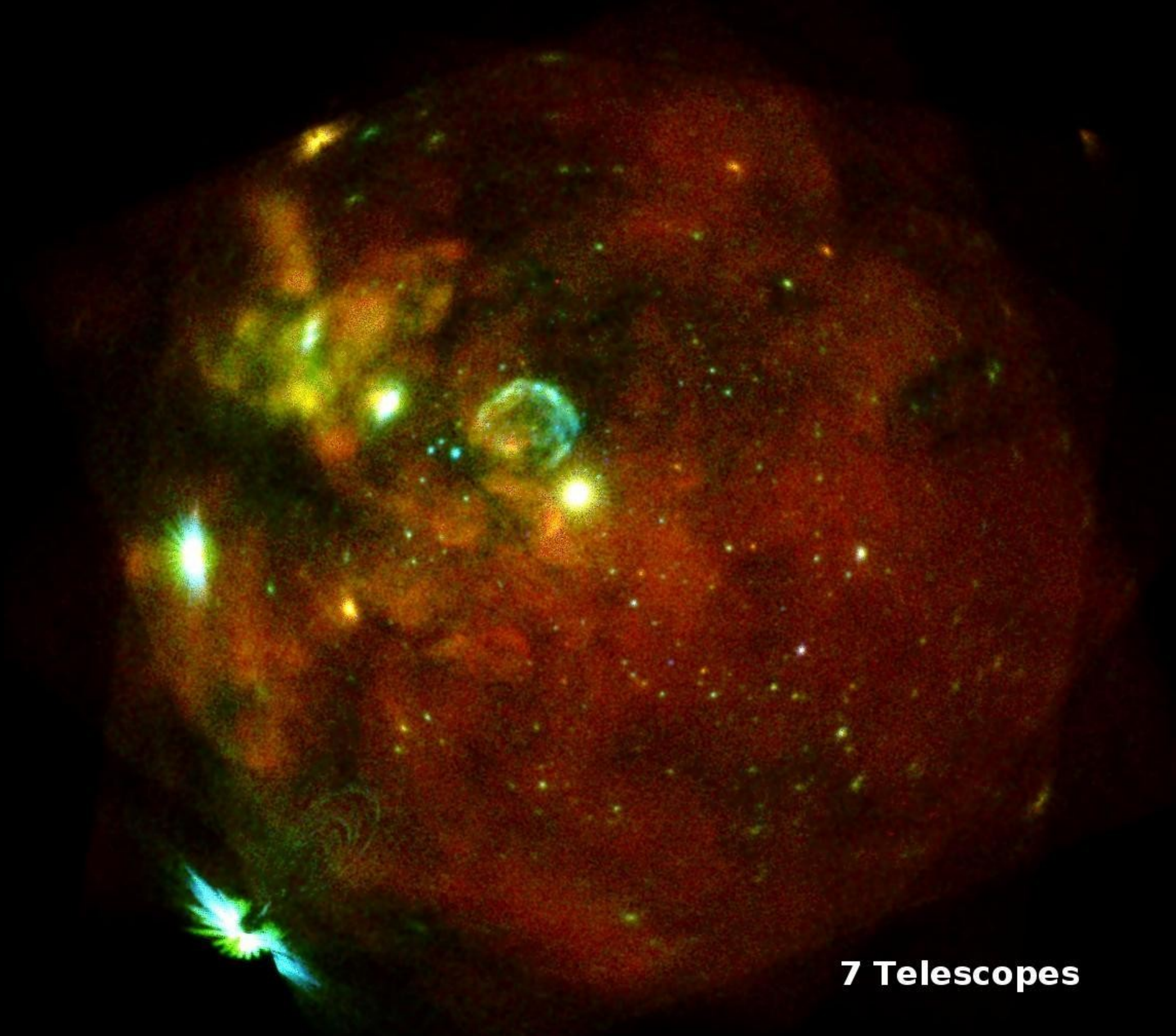


eROSITA – X-ray telescope



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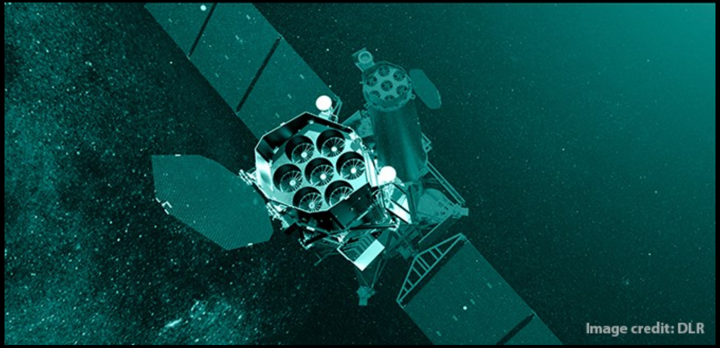

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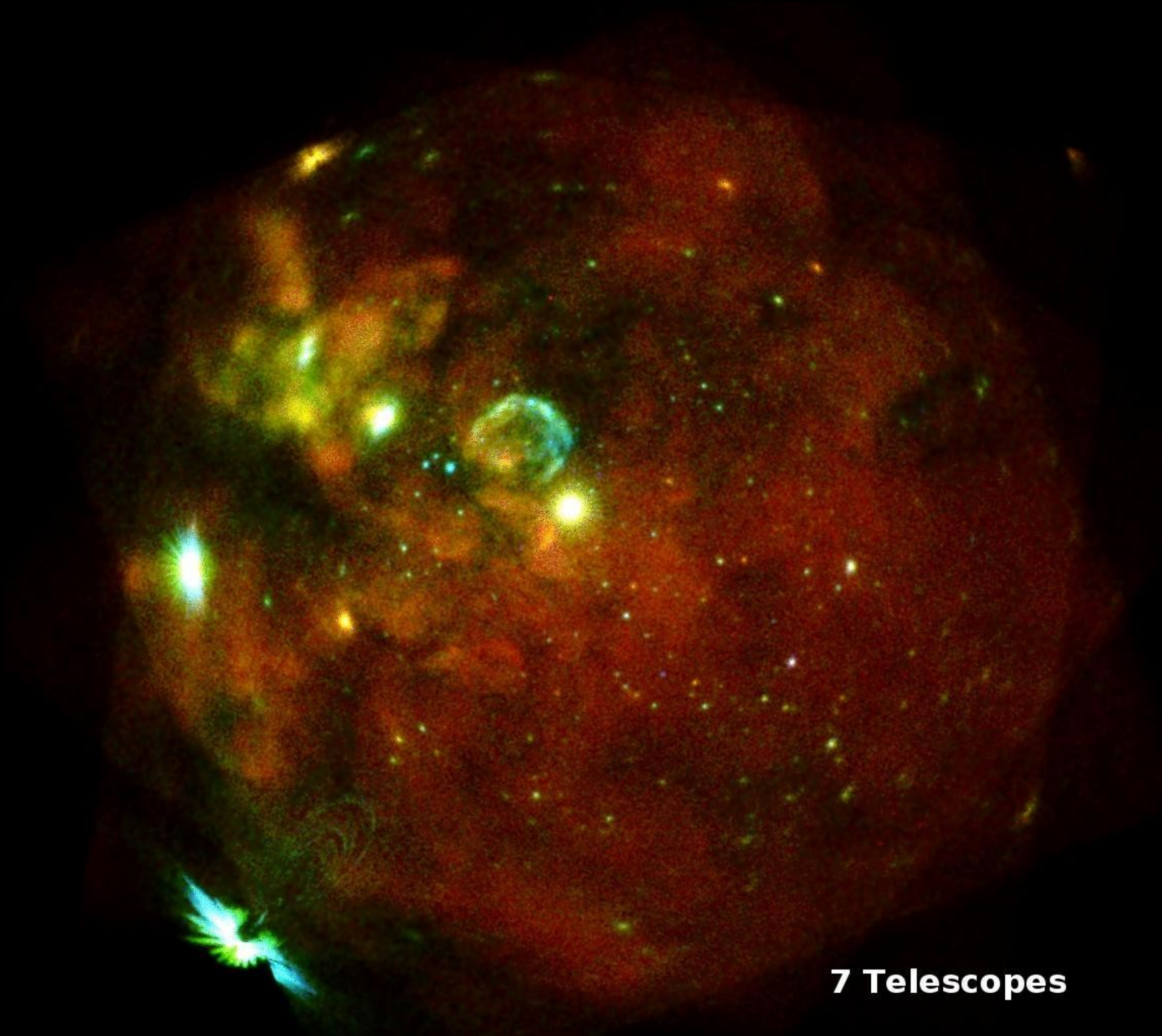
Effects of point spread functions (PSF)

distort X-ray Observations



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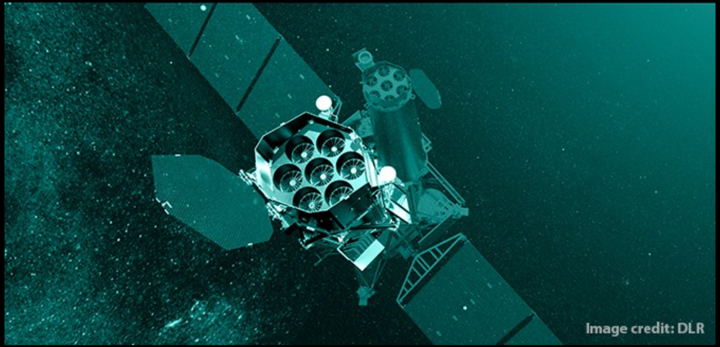

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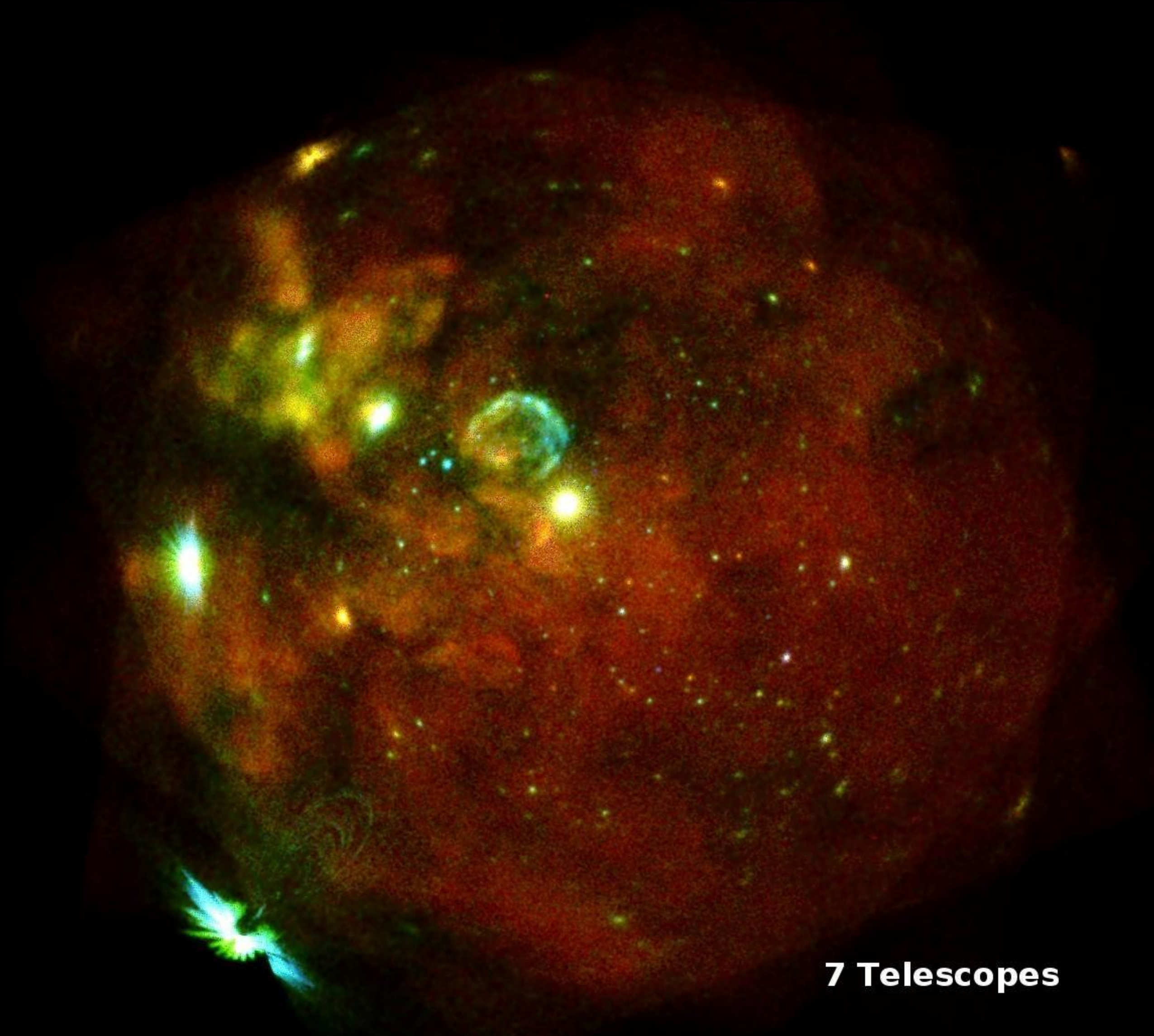

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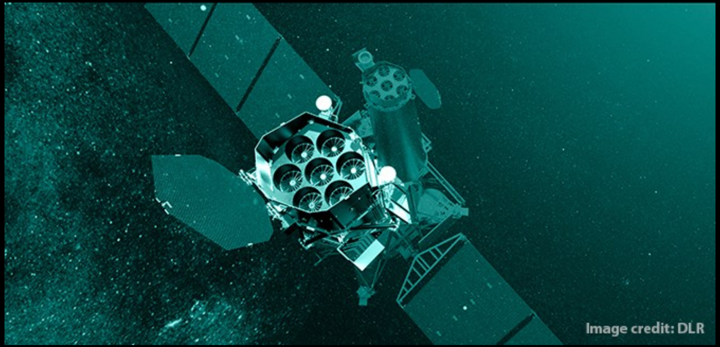

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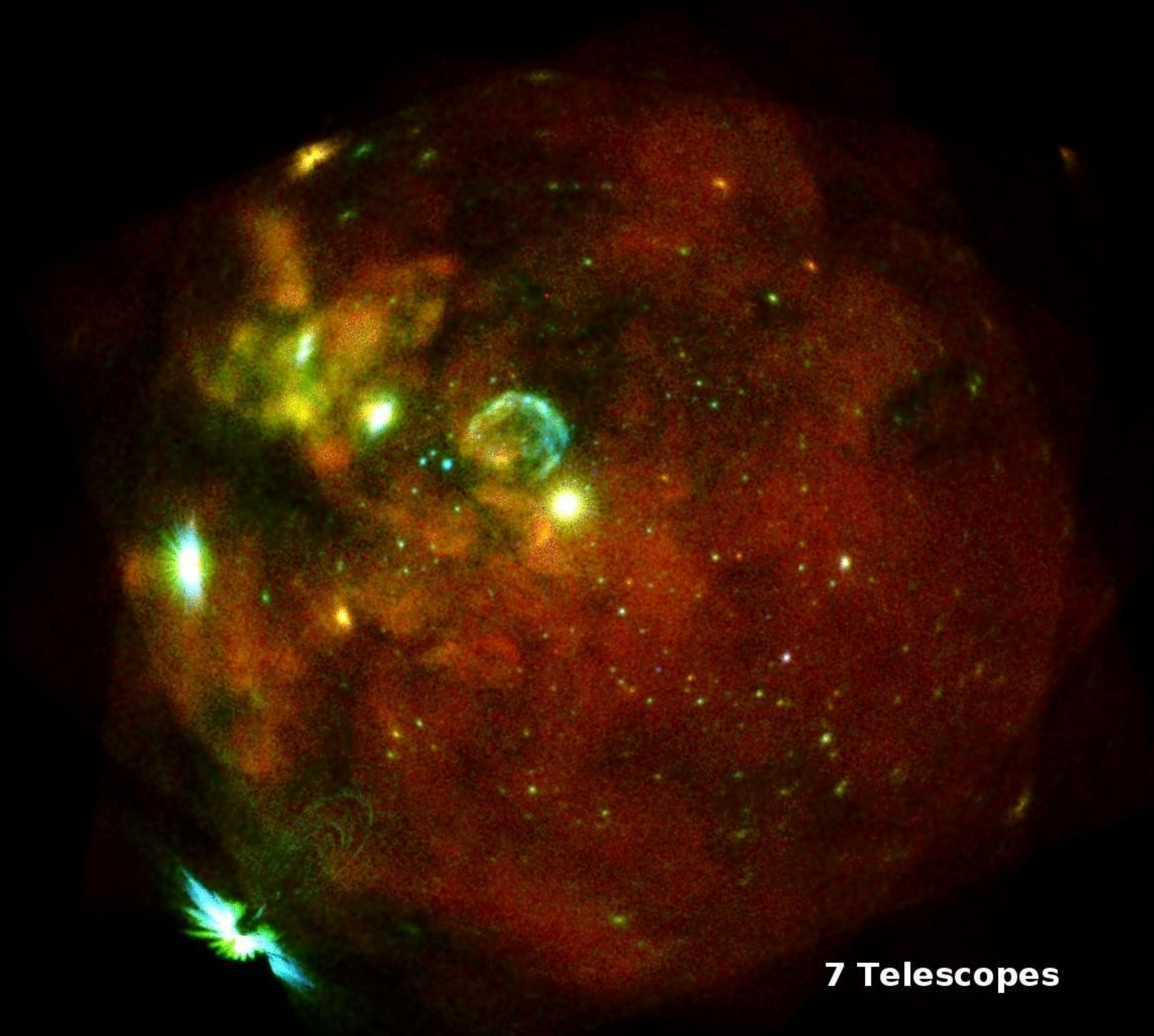
- Spatially **in**variant PSF
- Spatially **variant** PSF
  (off-axis-angle, azimuth and energy)



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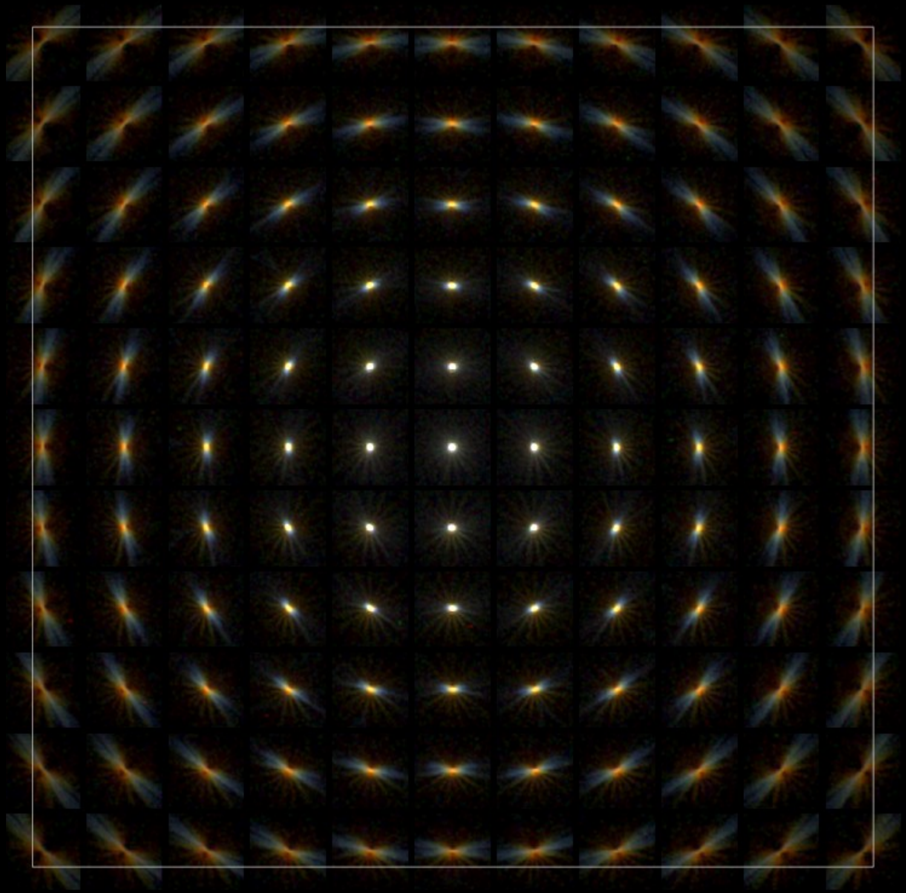
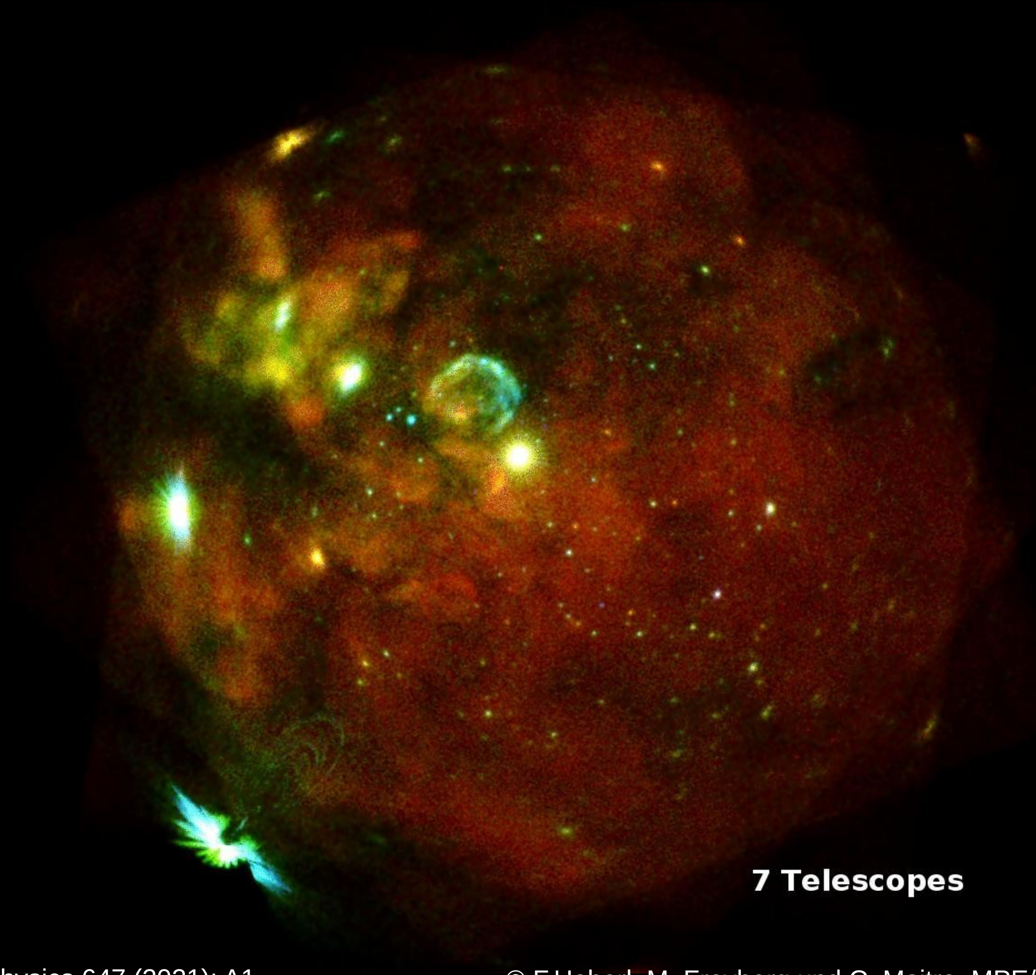
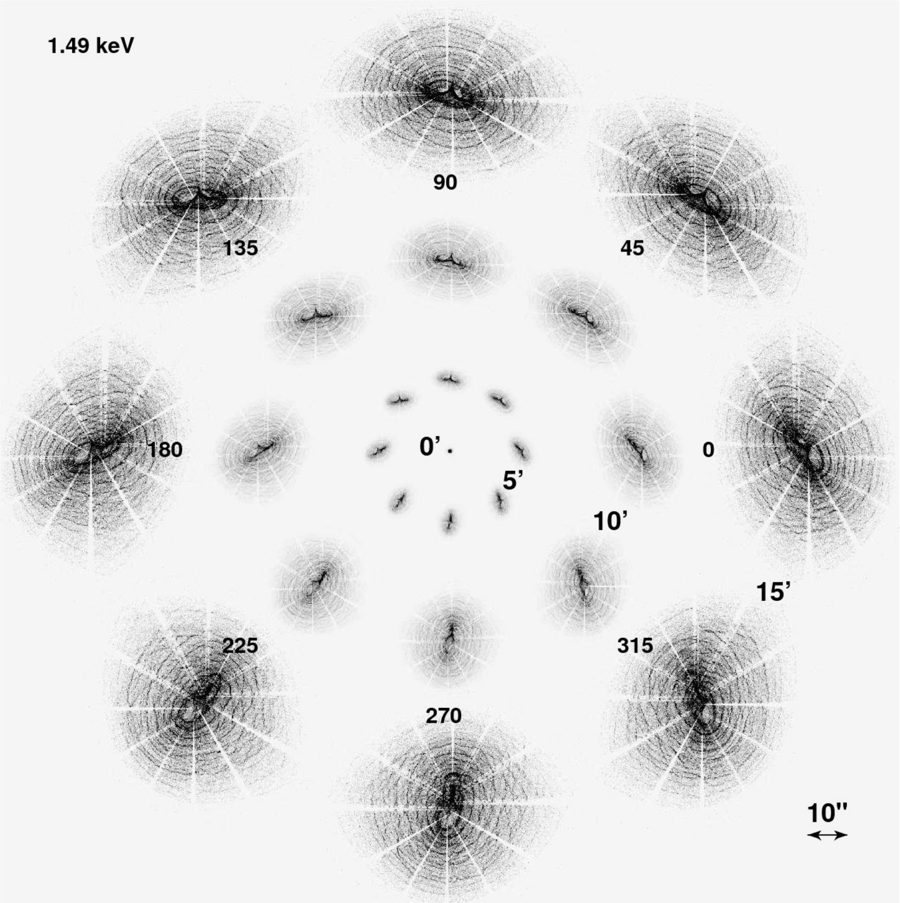
eROSITA PSF

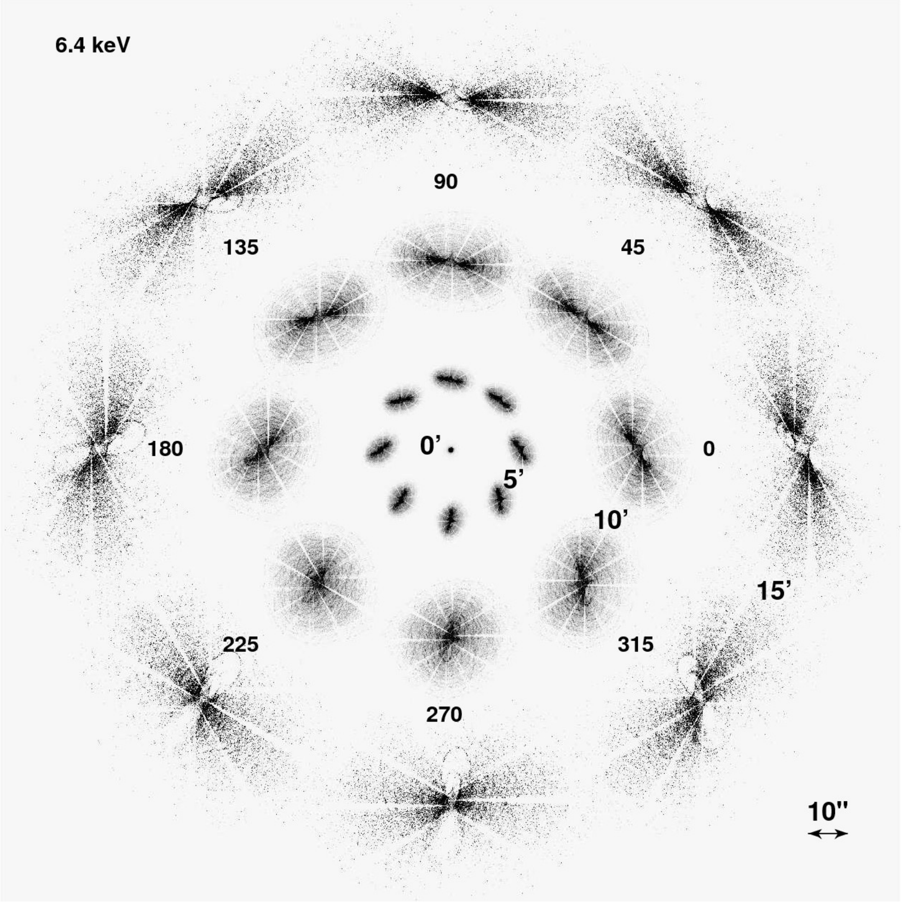




Predehl, Peter, et al. "The eROSITA X-ray telescope on SRG." Astronomy & Astrophysics 647 (2021): A1.

Chandra PSF





https://cxc.harvard.edu/proposer/POG/html/chap4.html

This affects many optical systems.

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Will we have instruments without this effect in the future?

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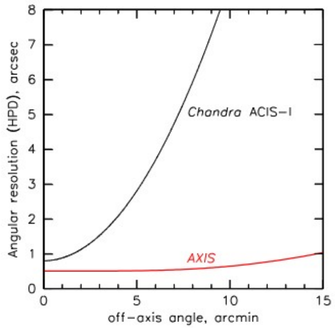
AXIS
Advanced X-ray Imaging Satellite



Mushotzky, Richard F., et al. "The advanced x-ray imaging satellite." arXiv preprint arXiv:1903.04083 (2019).

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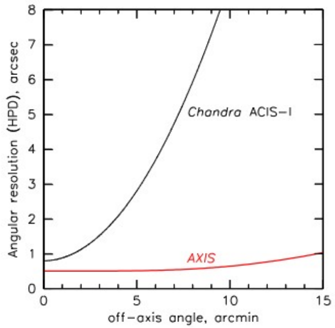

….we don’t want to wait!

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Why is it non-trivial to remove the PSF?

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De-blurring noisy images

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PSF **Representation**

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Information Field Theory
&
Generative Modeling

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Information Field Theory & Generative Models

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- **Geo**metric **V**ariational **I**nference [P. Frank et al. 2021]

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Strategies for spatially variant PSF deblurring:

PSF Representation

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  → Huge memory consumption
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Strategies for spatially variant PSF de-blurring:

- Deconvolution with averaged PSF
- Remove off-axis data

Patched Interpolated Convolution

[Nagy, James G., and Dianne P. O'Leary. "Fast iterative image restoration with a spatially varying PSF." Advanced Signal Processing: Algorithms, Architectures, and Implementations VII. Vol. 3162. SPIE, 1997.]

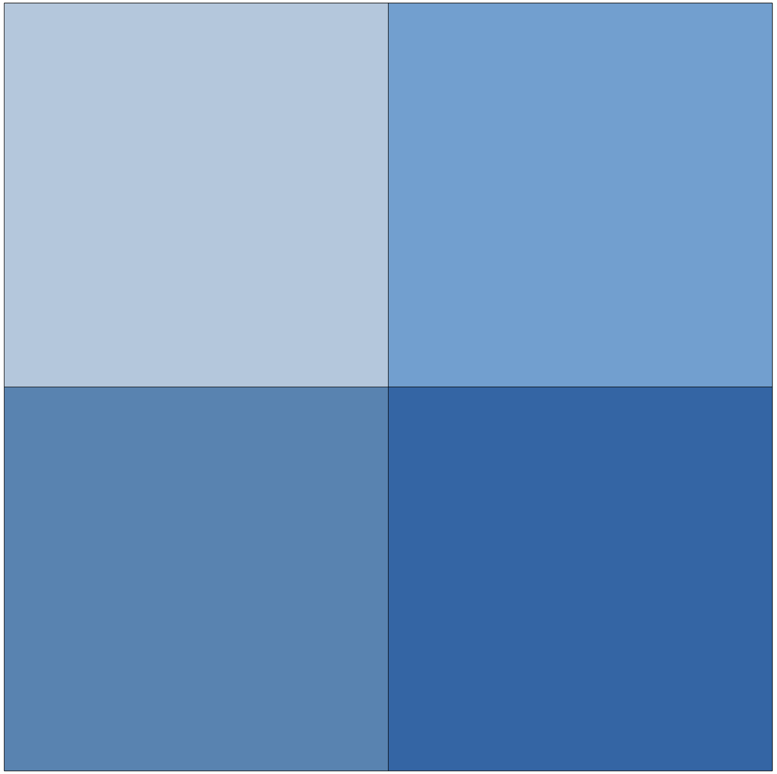
Patched Interpolated Convolution

Image

Patched Interpolated Convolution

Image

Select Patches



Patched Interpolated Convolution

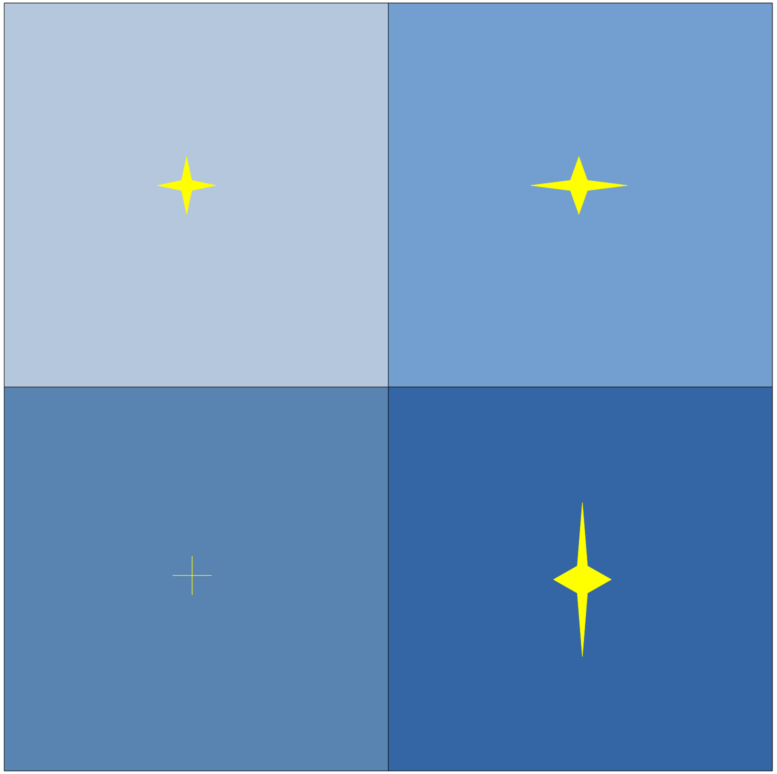
Image

↓

Select Patches

↓

PSF of patch center



Patched Interpolated Convolution

Image

↓

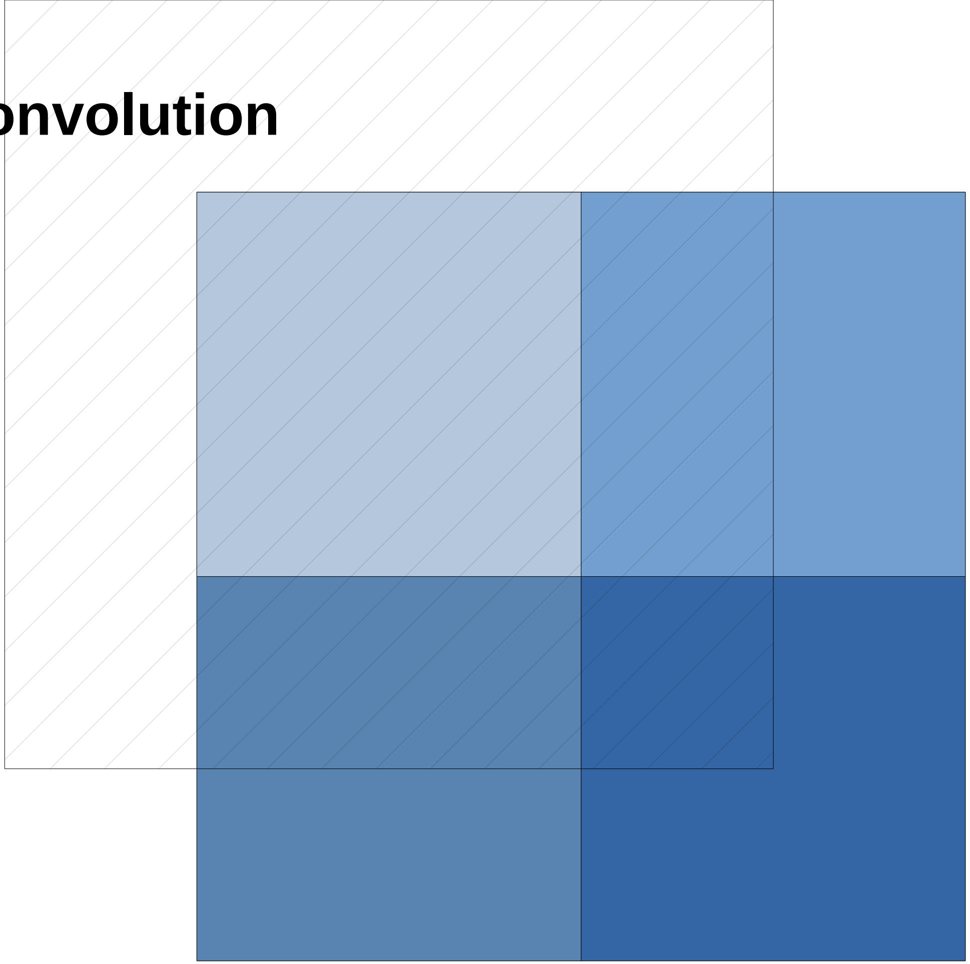
Select Patches

↓

PSF of patch center

↓

Cut out with overlap



Patched Interpolated Convolution

Image

Select Patches

PSF of patch center

Cut out with overlap

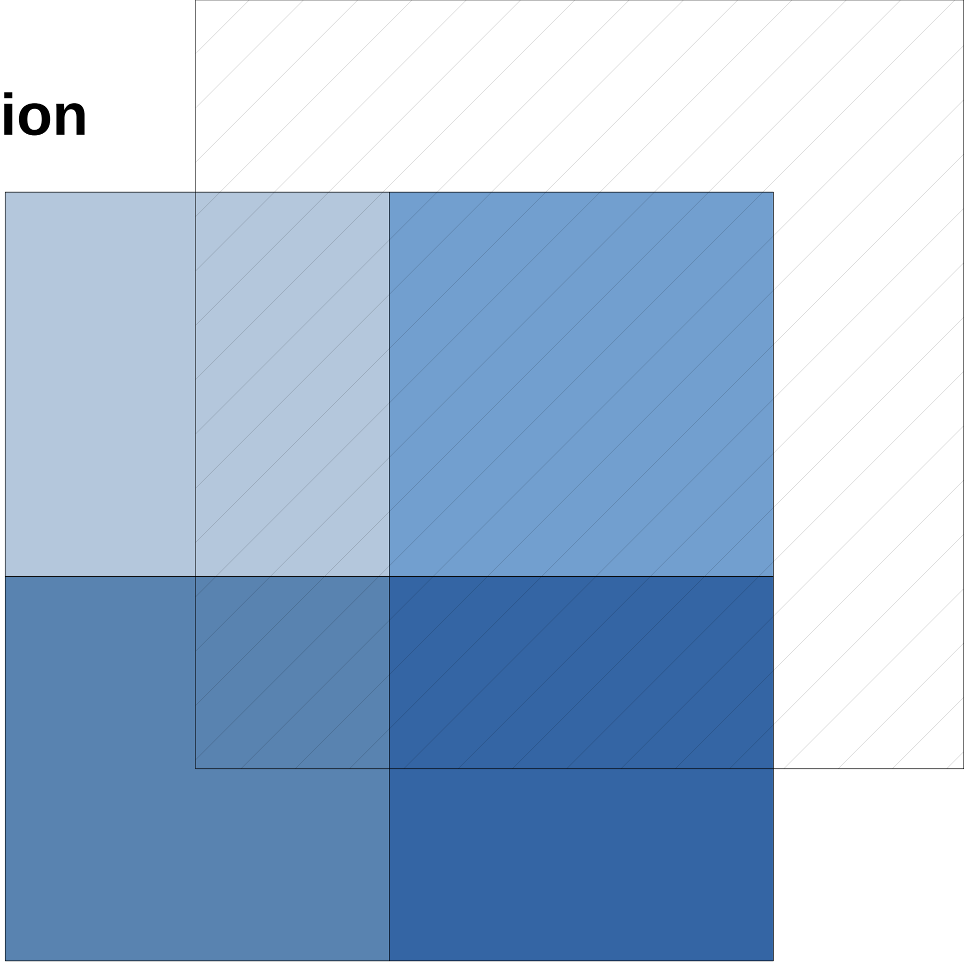


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Image

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Select Patches

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PSF of patch center

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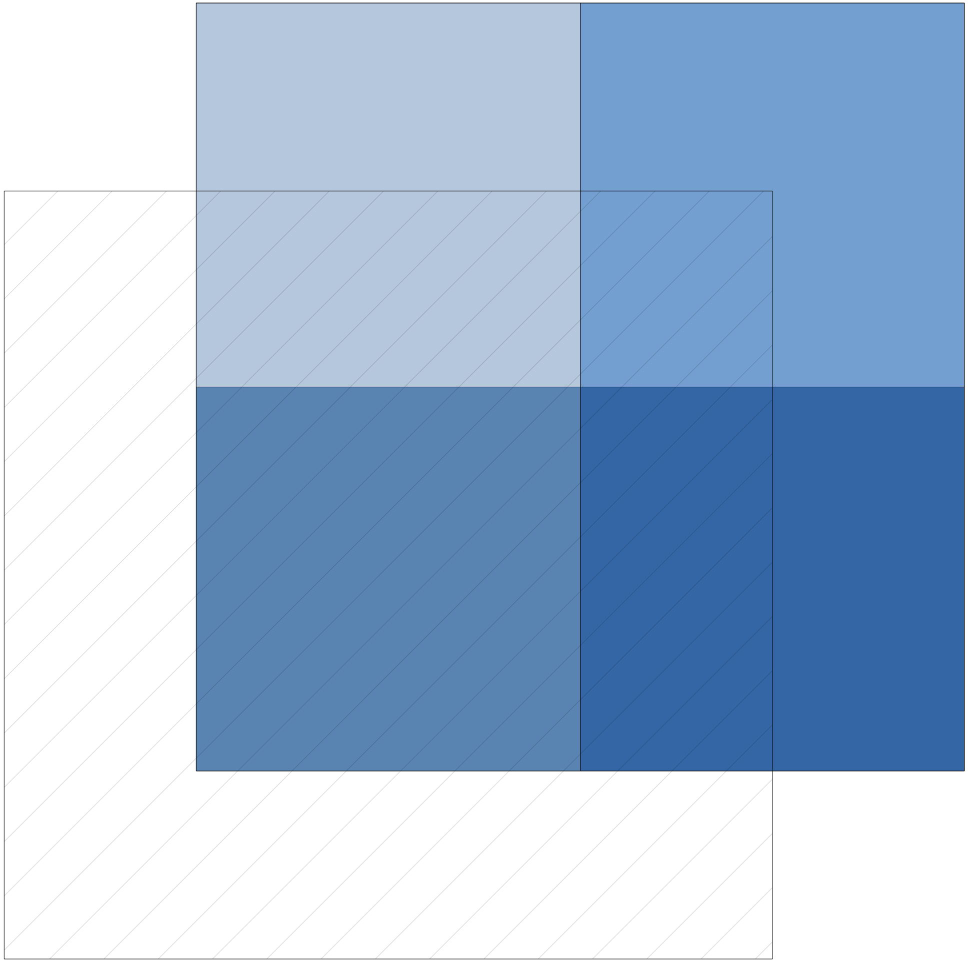

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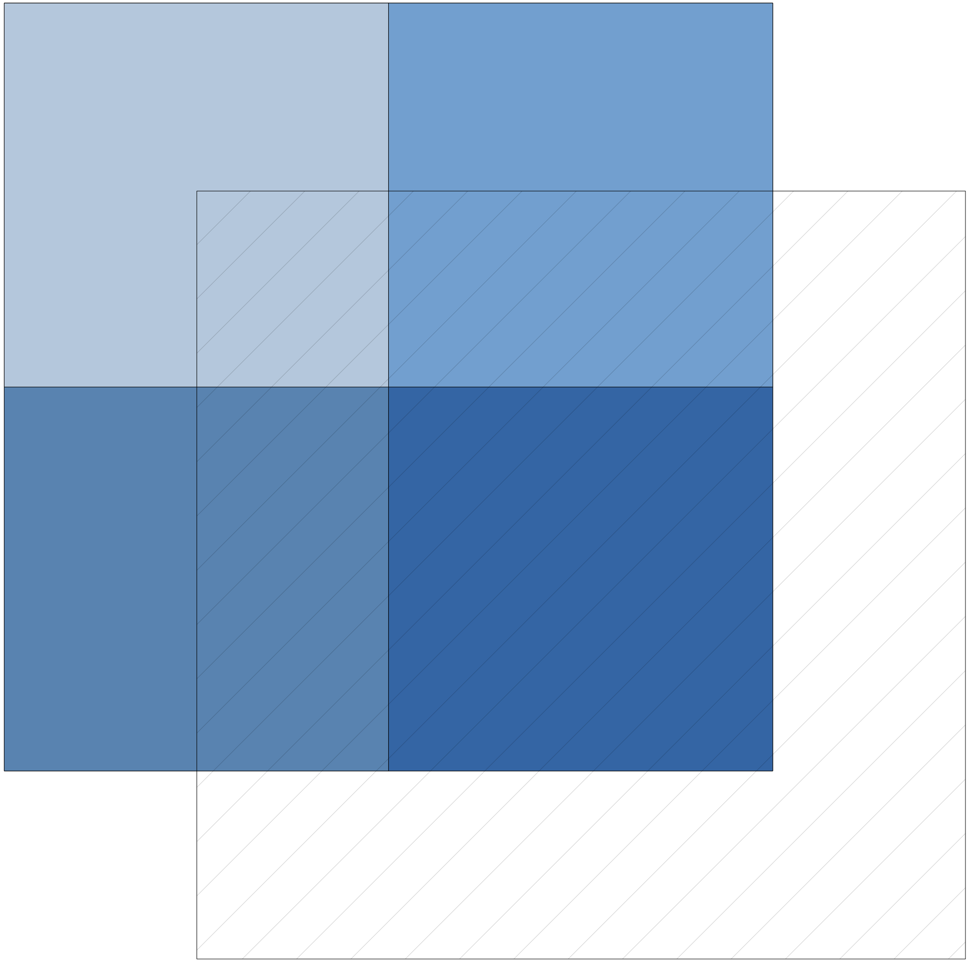
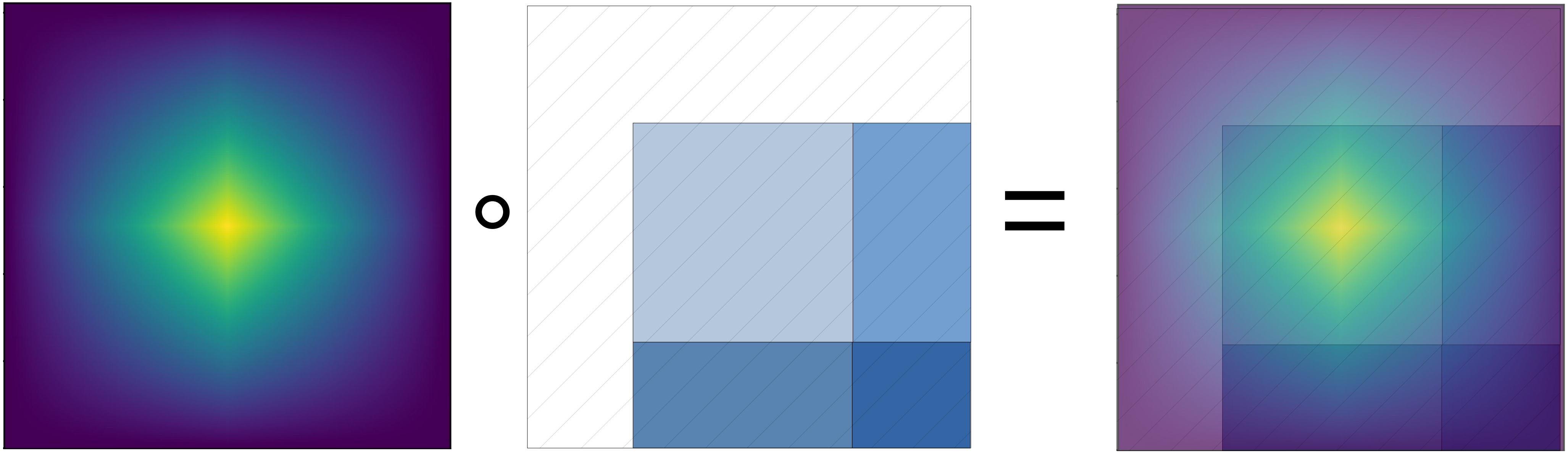


Patched Interpolated Convolution

Weight cut outs bilinearly



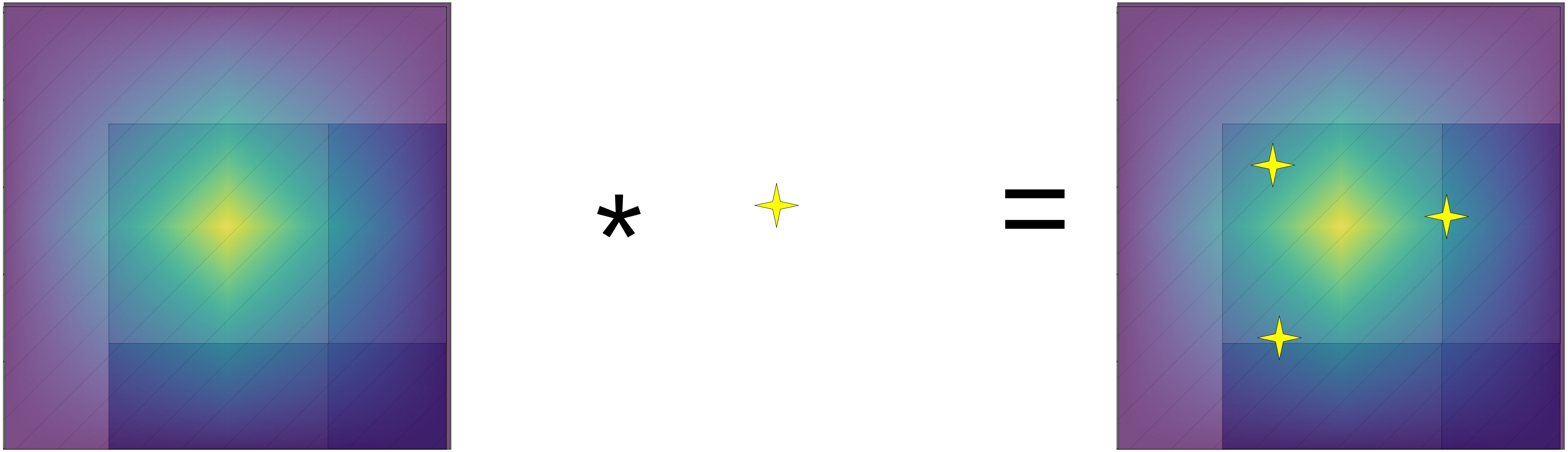
Interpolation weights

Cut out

Weighted cut out

Patched Interpolated Convolution

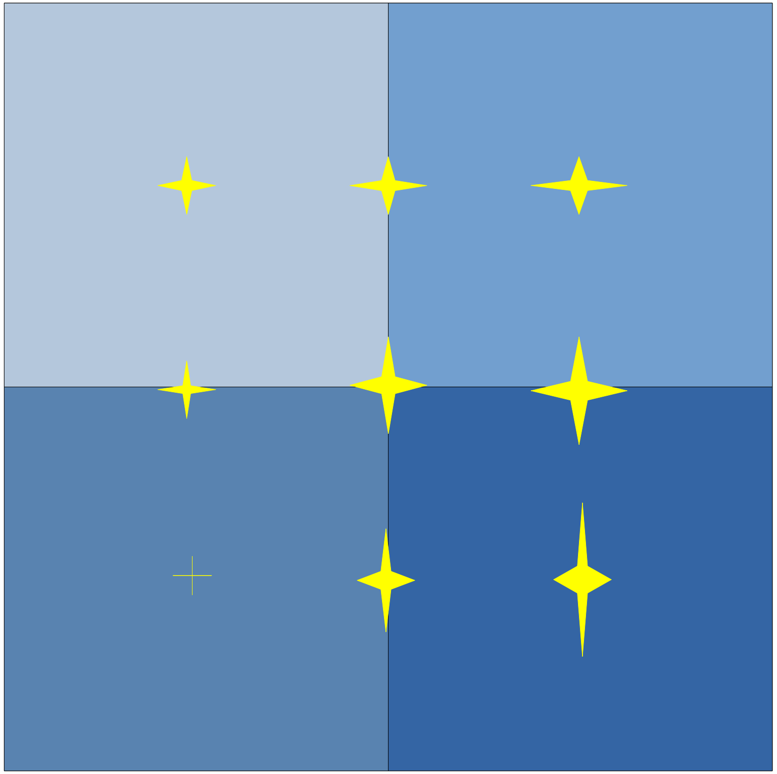
Convolve weighted cut outs with local PSF



Weighted cut out Local PSF Weighted convolved cut out

Patched Interpolated Convolution

Add up the patches...



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Bayesian
De**noising**, De**composition** and De**convolution**
with spatially **variant** PSF

Chandra PSF

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PSFs for patches from Marx [1] simulation, about 1e6 simulated photons, remove 1 photon events

1) Raytracing with MARX: x-ray observatory design, calibration, and support (Davis et al. 2012, SPIE 8443, 84431A)

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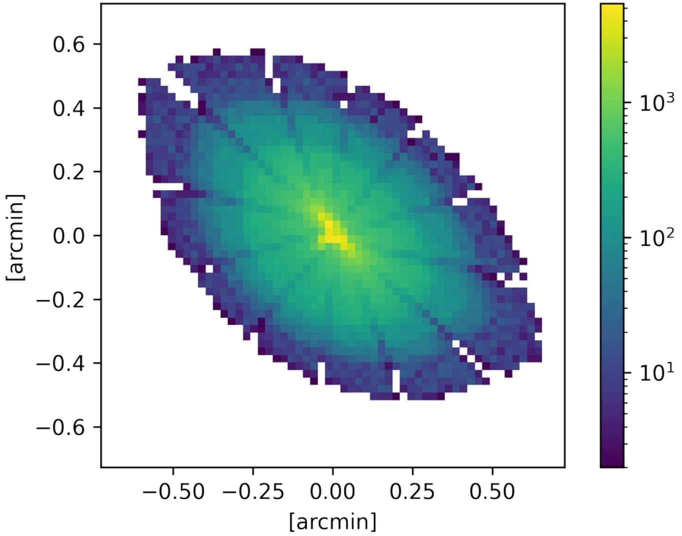

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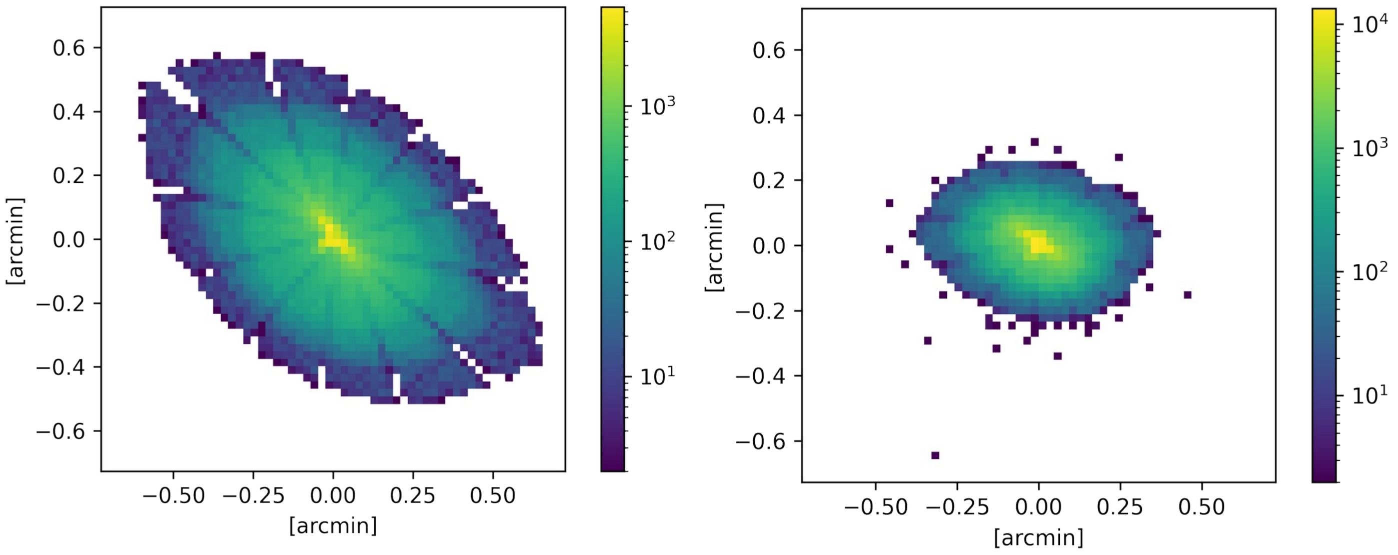

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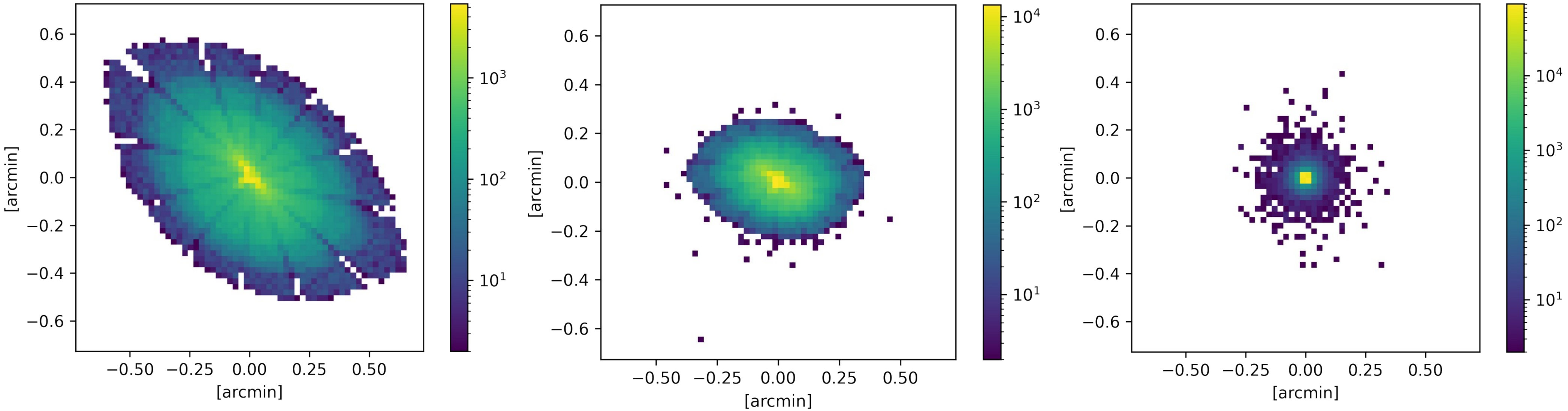

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Application to a synthetic example

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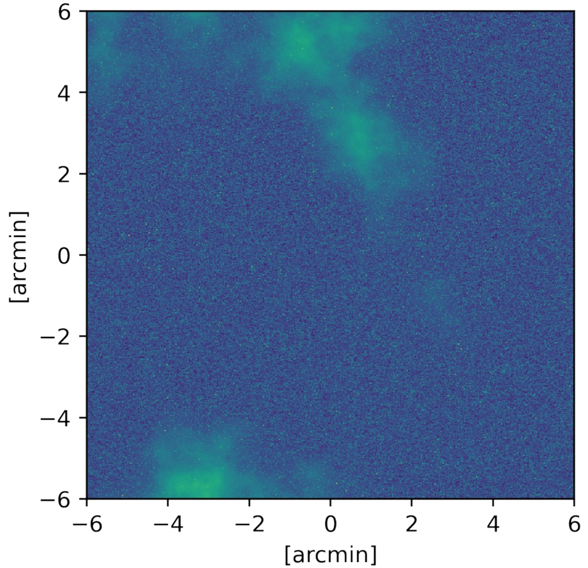
Signal



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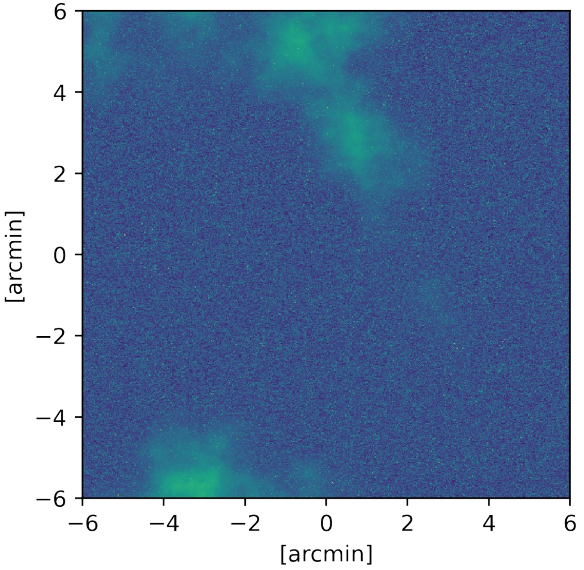

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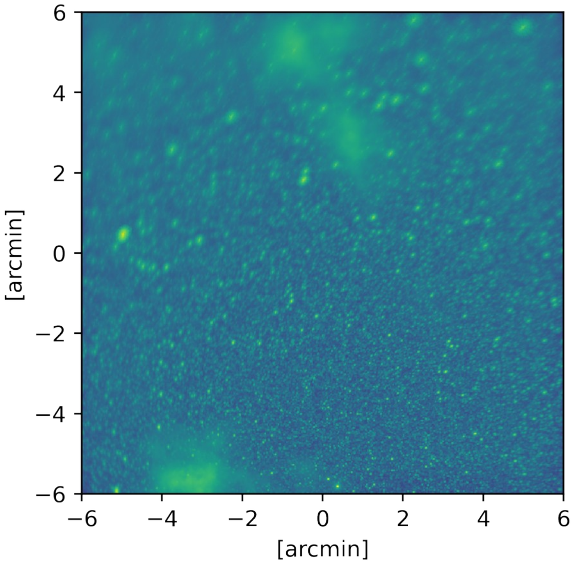

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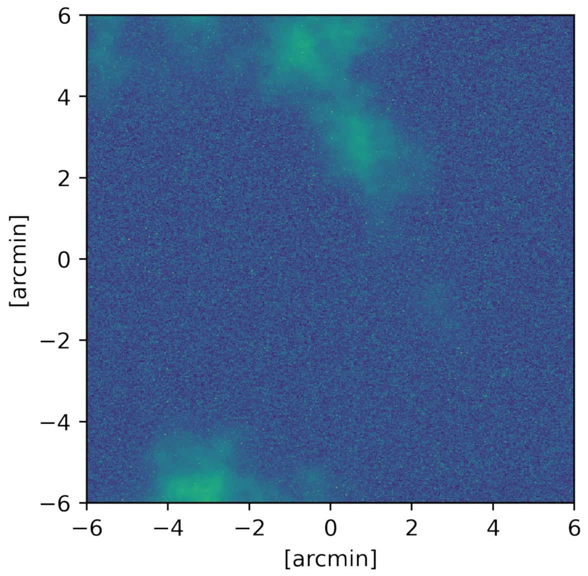

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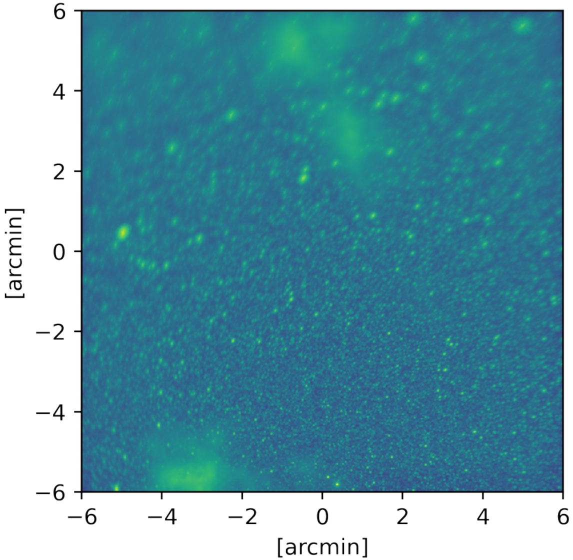

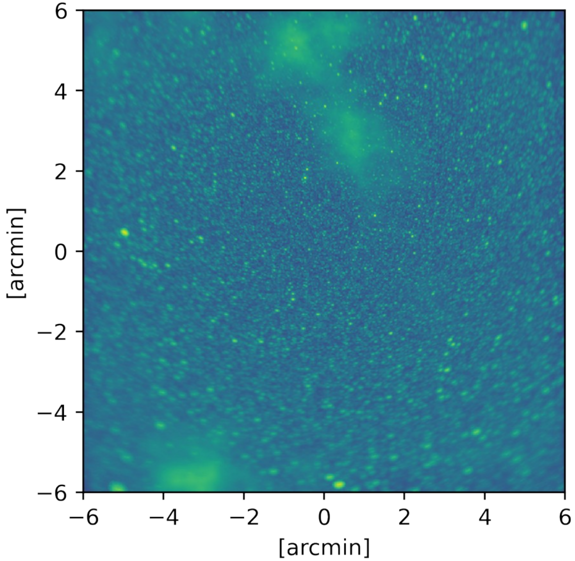

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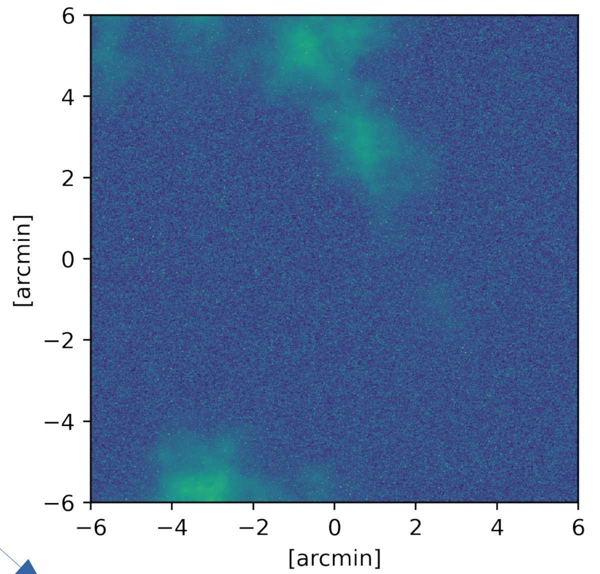

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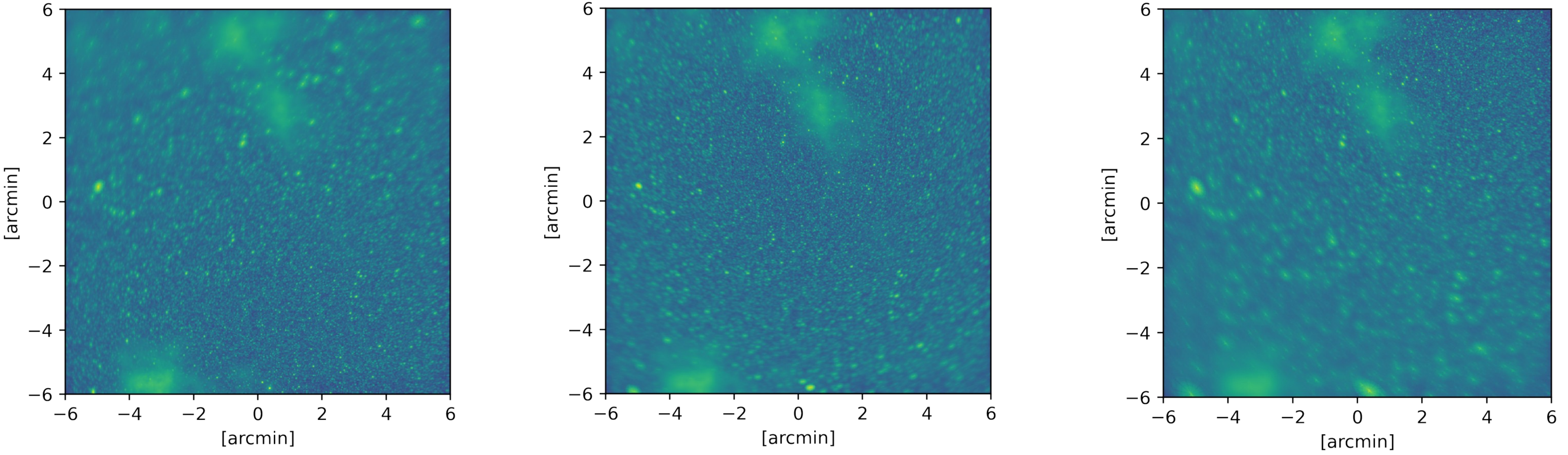
PSF **PSF** **PSF**



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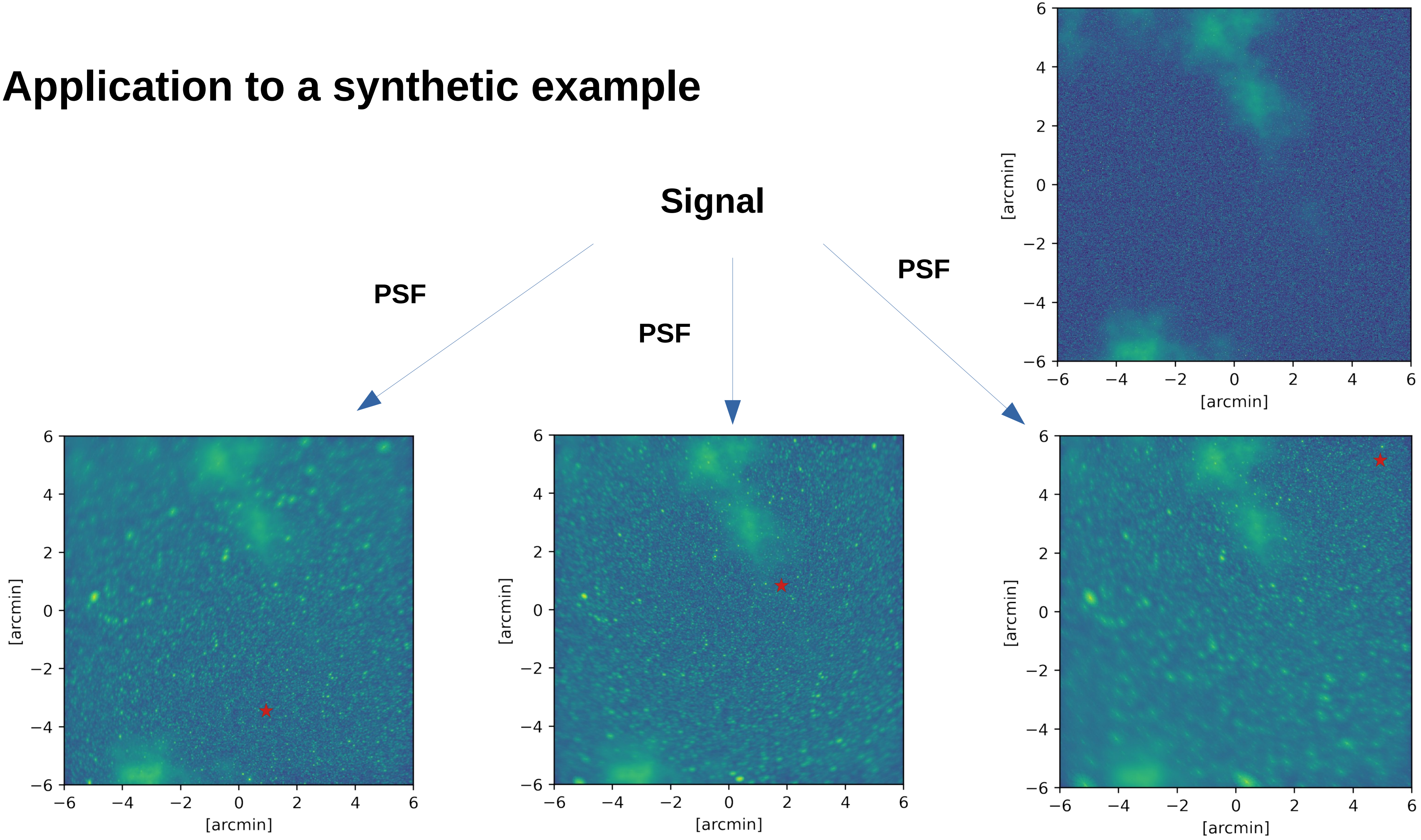

Bayesian Reconstruction of Perseus Cluster

with observation off-axis observation [11713]

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- Energy bins:
  - 0.5 – 1.2 keV
  - 1.2 – 2.9 keV
  - 2.9 - 7 keV

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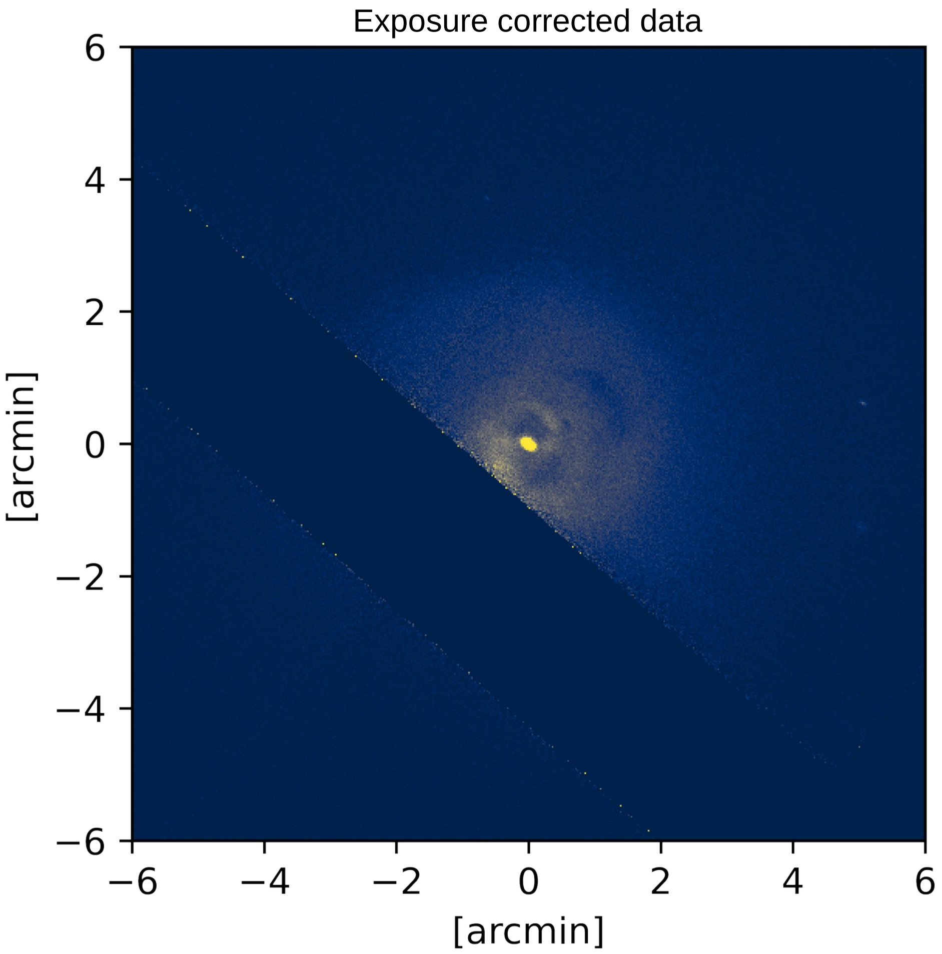
- Generative Model with diffuse & point-source component
- Assuming spatial and spectral correlations

0.5-1.2 keV



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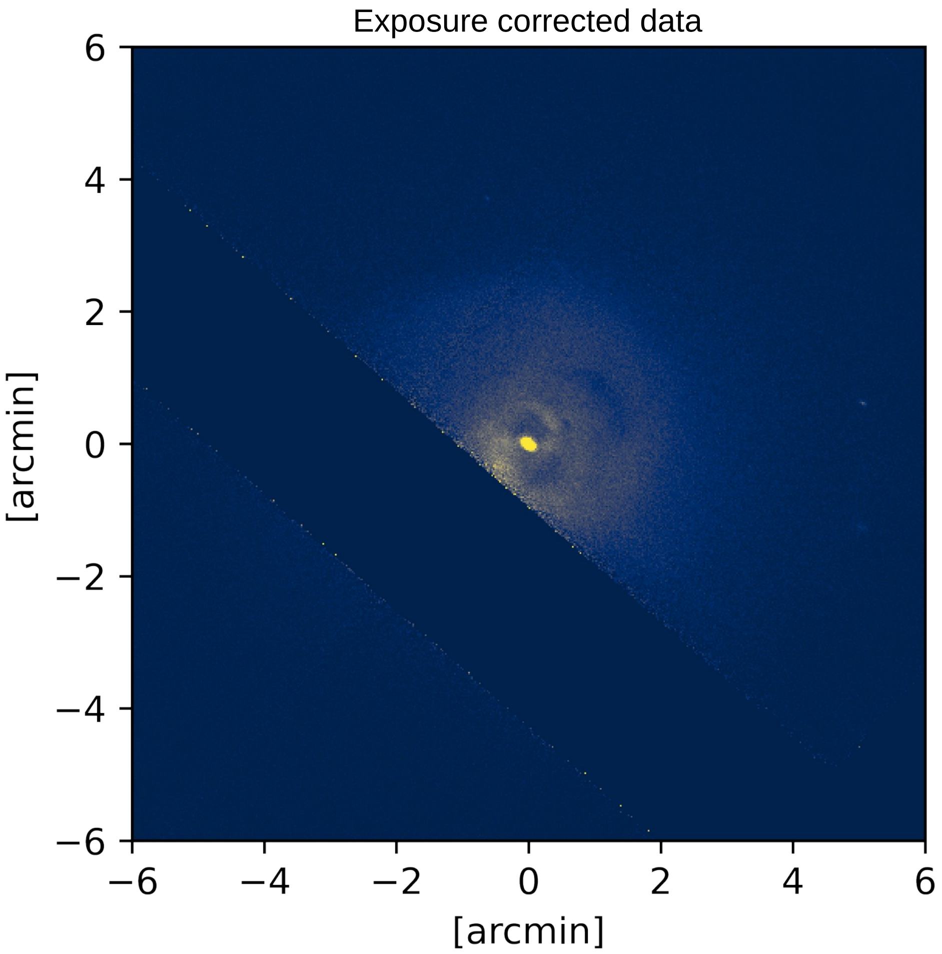
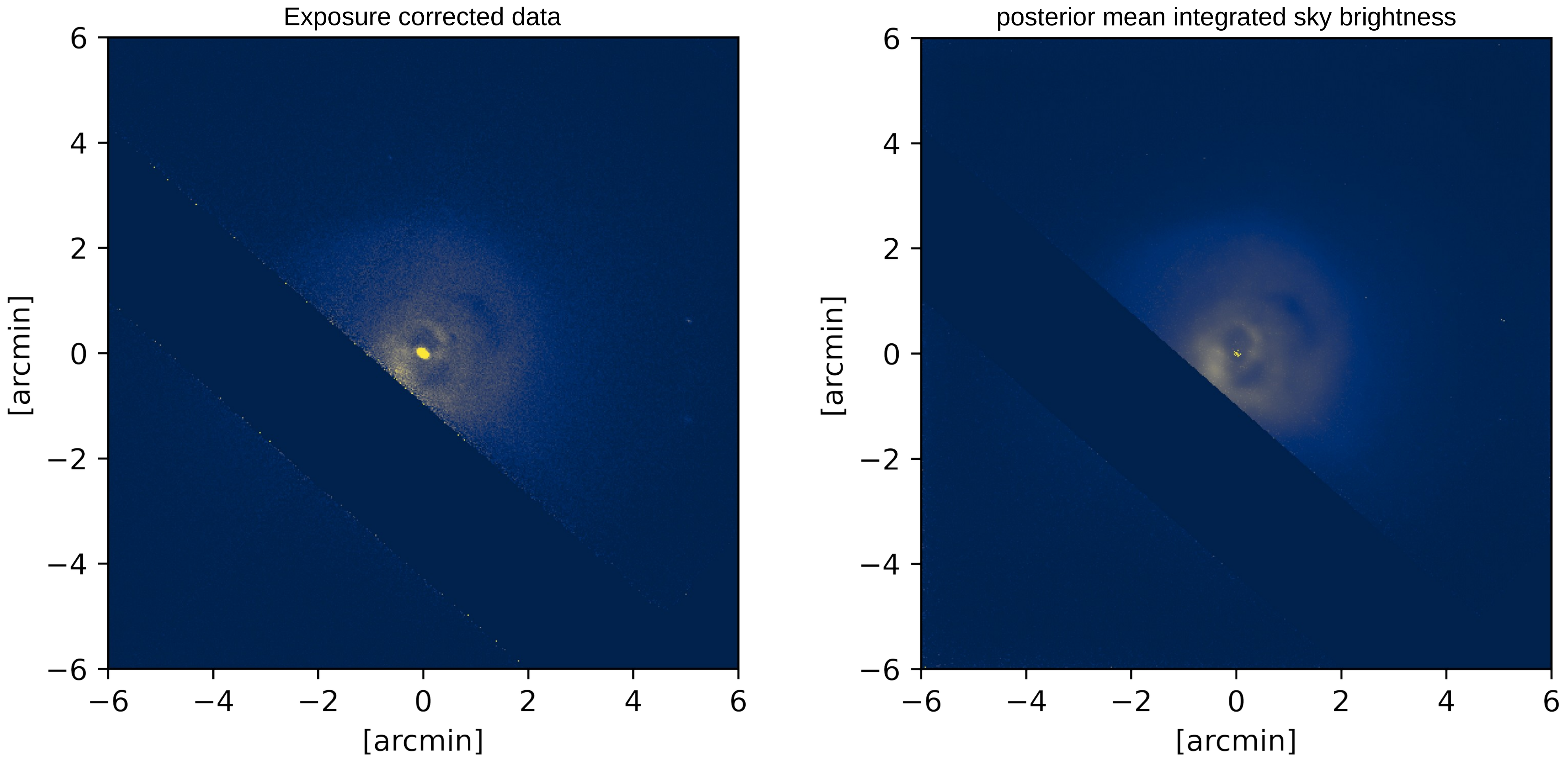

Exposure corrected data
6
4
2
0
−2
−4
−6
[arcmin]
−6
−4
−2
0
2
4
6
[arcmin]

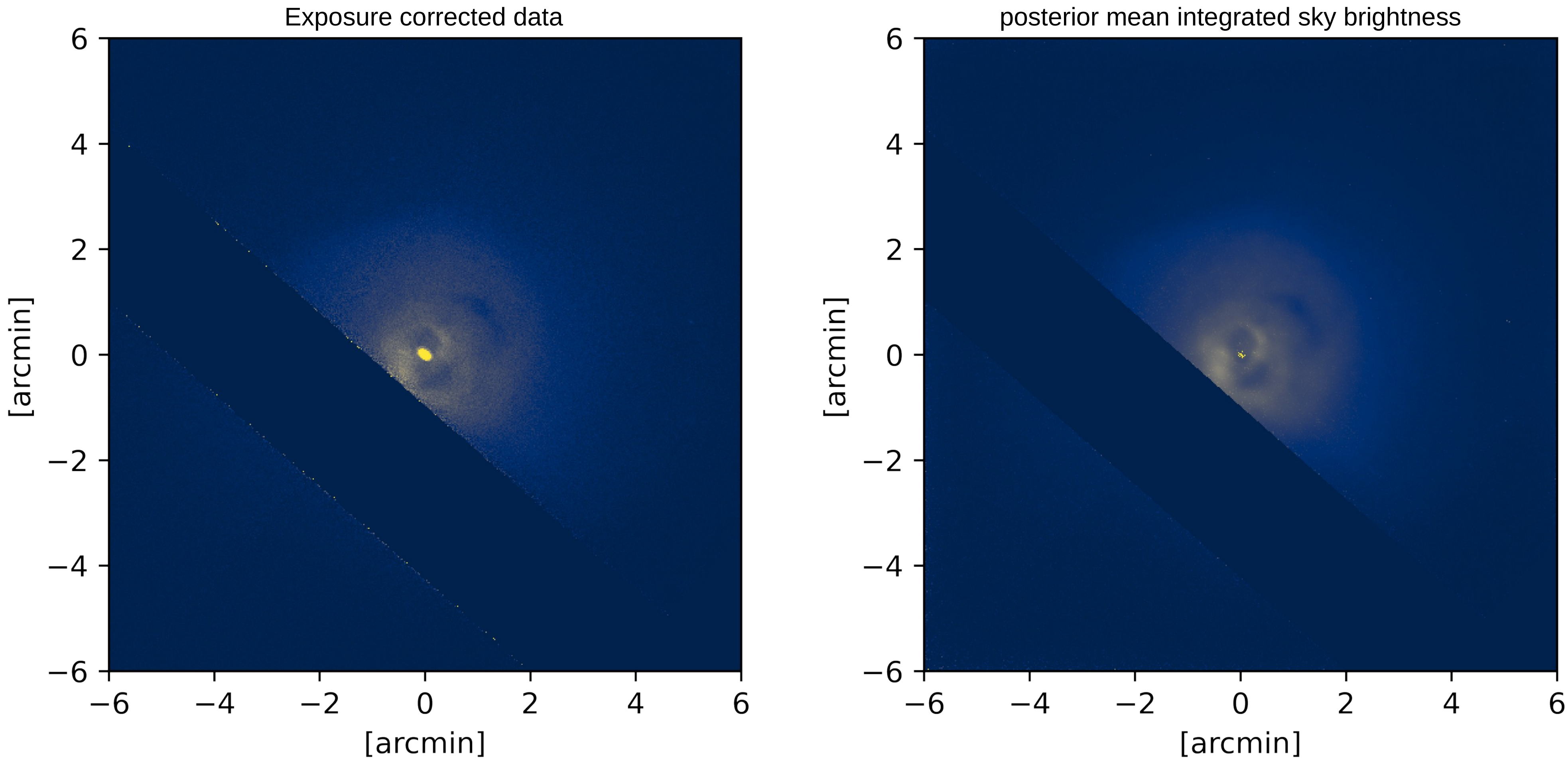

MAGIC
BUTTON

0.5-1.2 keV



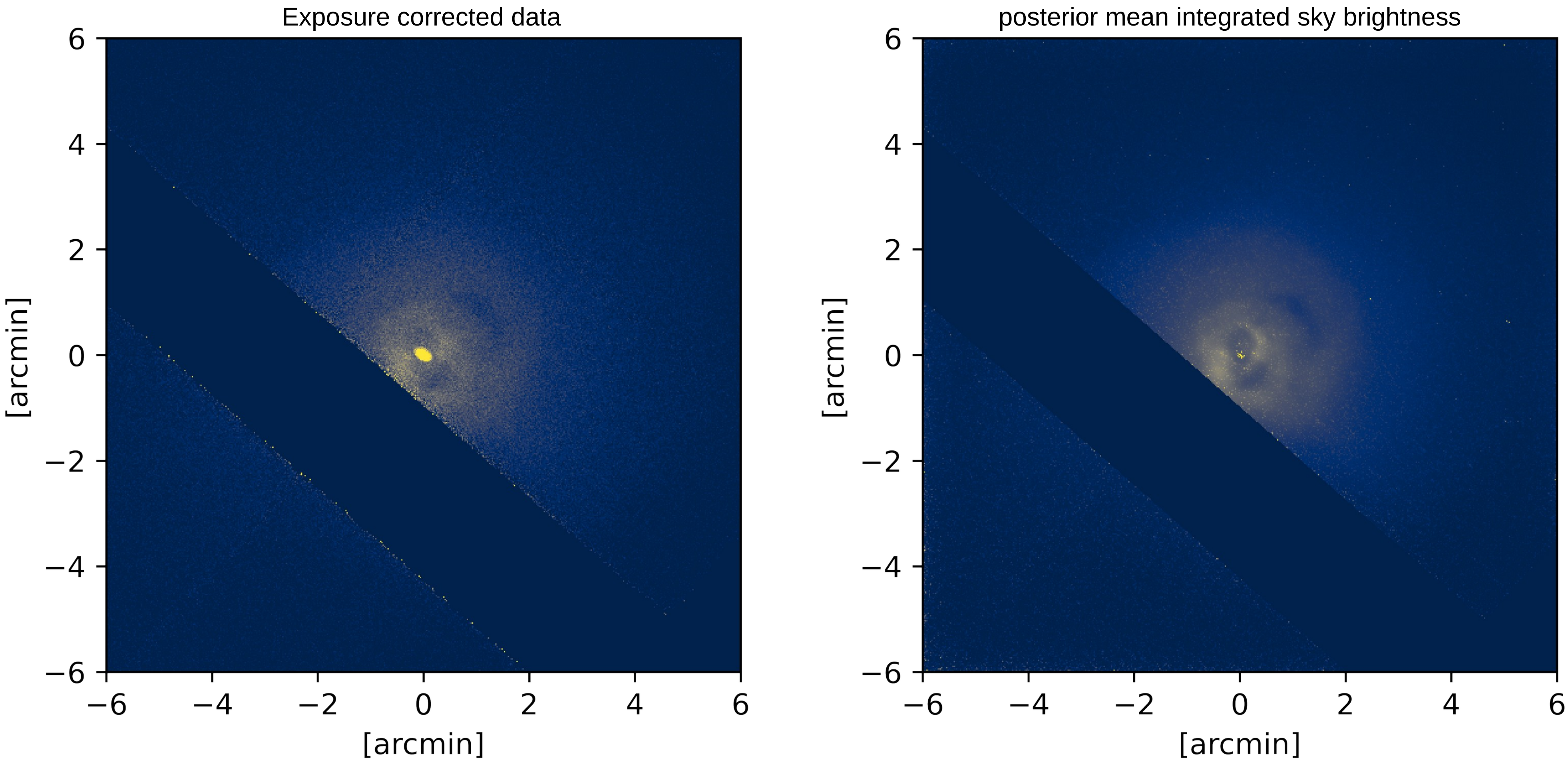
Exposure corrected data
posterior mean integrated sky brightness
[arcmin]
[arcmin]
[arcmin]
[arcmin]
6
4
2
0
−2
−4
−6

1.2 keV – 2.9 keV



Exposure corrected data
posterior mean integrated sky brightness
[arcmin]
[arcmin]
[arcmin]
[arcmin]
6
4
2
0
−2
−4
−6

2.9 – 7 keV



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[arcmin]
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−4
−2
0
2
4
6

More data? No Problem!

Observations: 11713-11716, 3209, 4289, 4948, 4952

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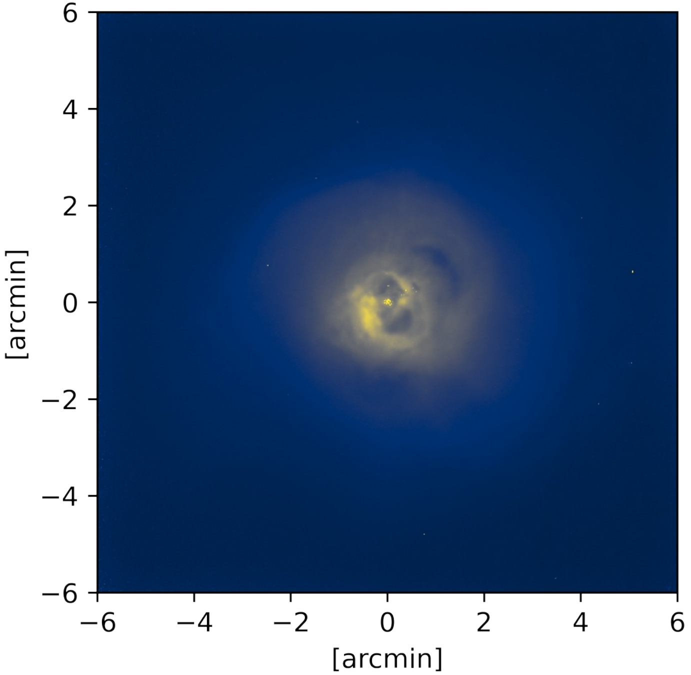
Observations: 11713-11716, 3209, 4289, 4948, 4952

X-ray emission



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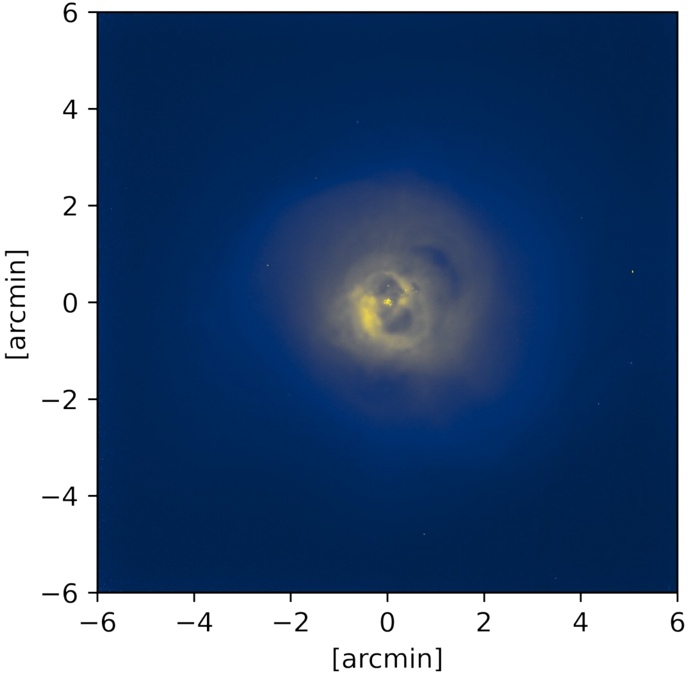
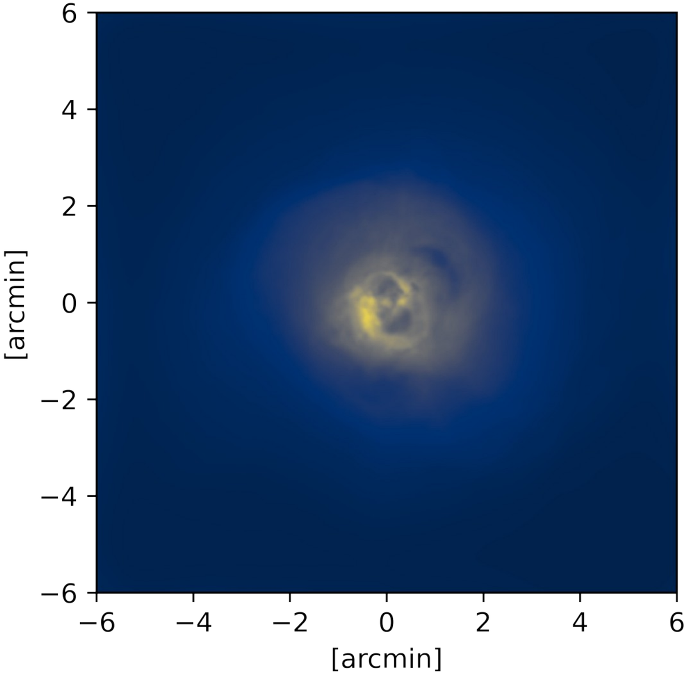
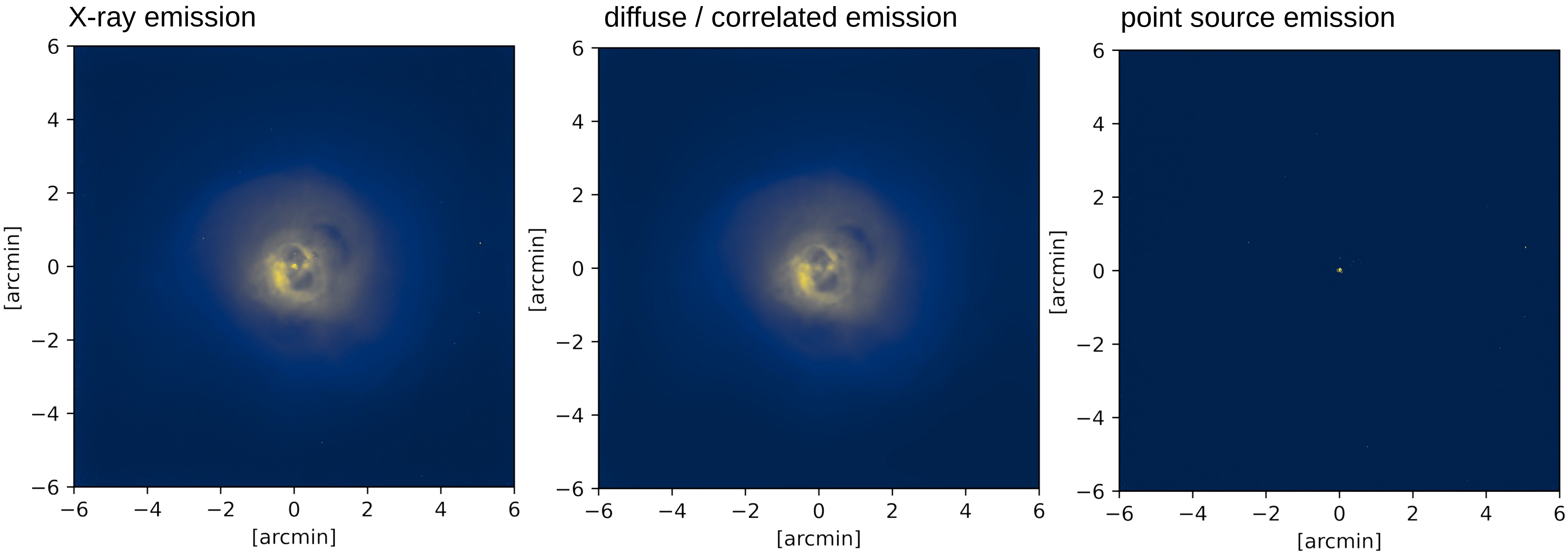


diffuse / correlated emission

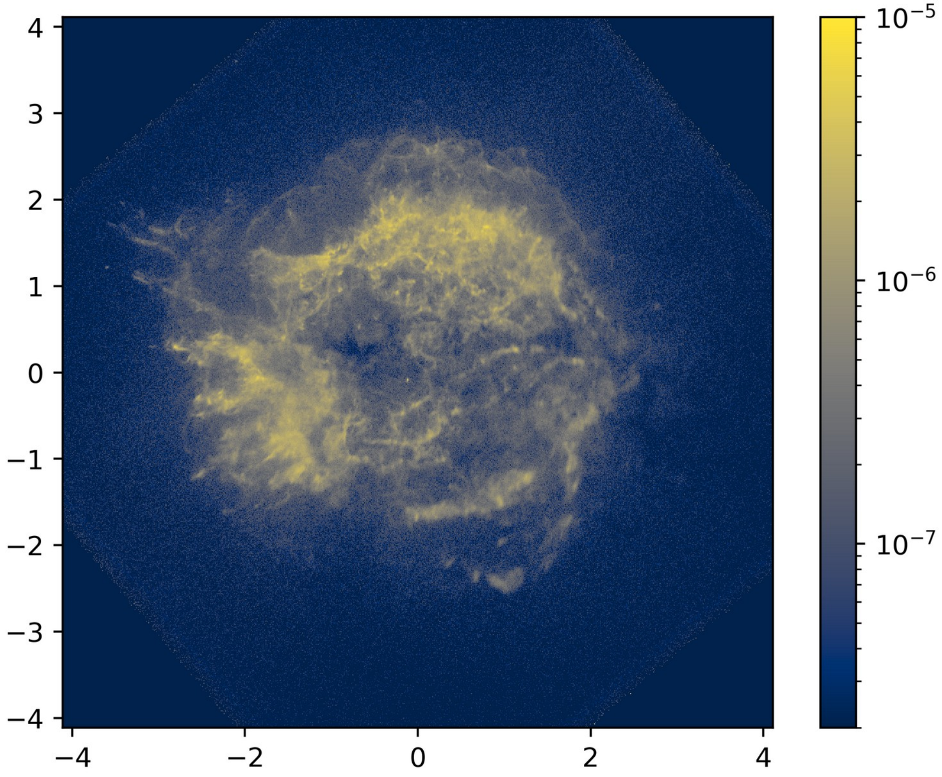


More data? No Problem!

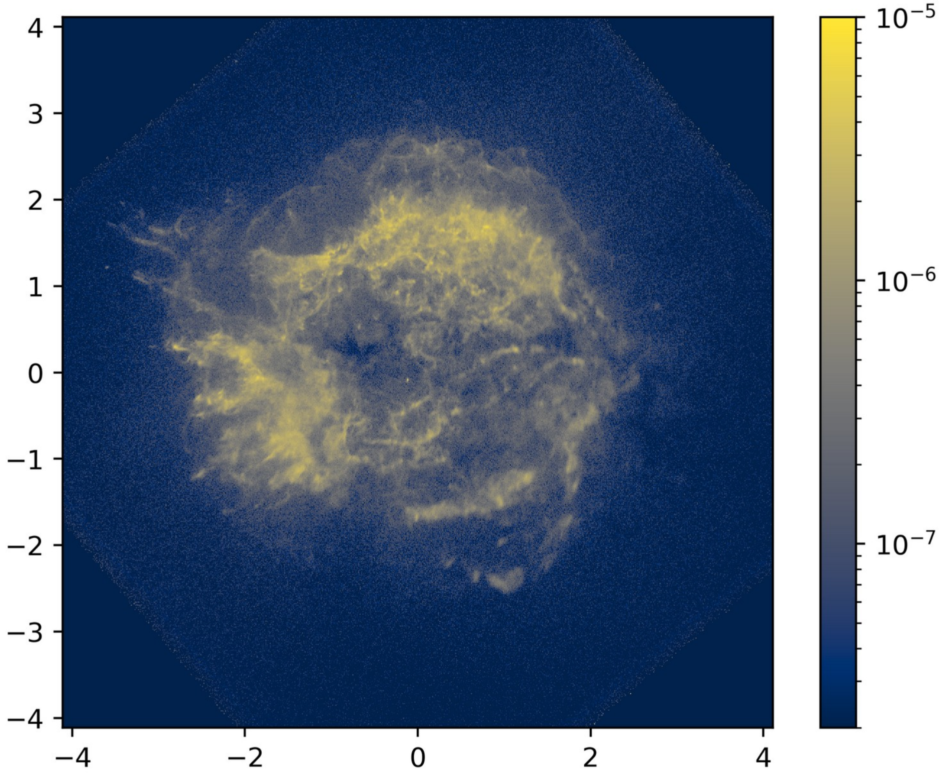
Observations: 11713-11716, 3209, 4289, 4948, 4952

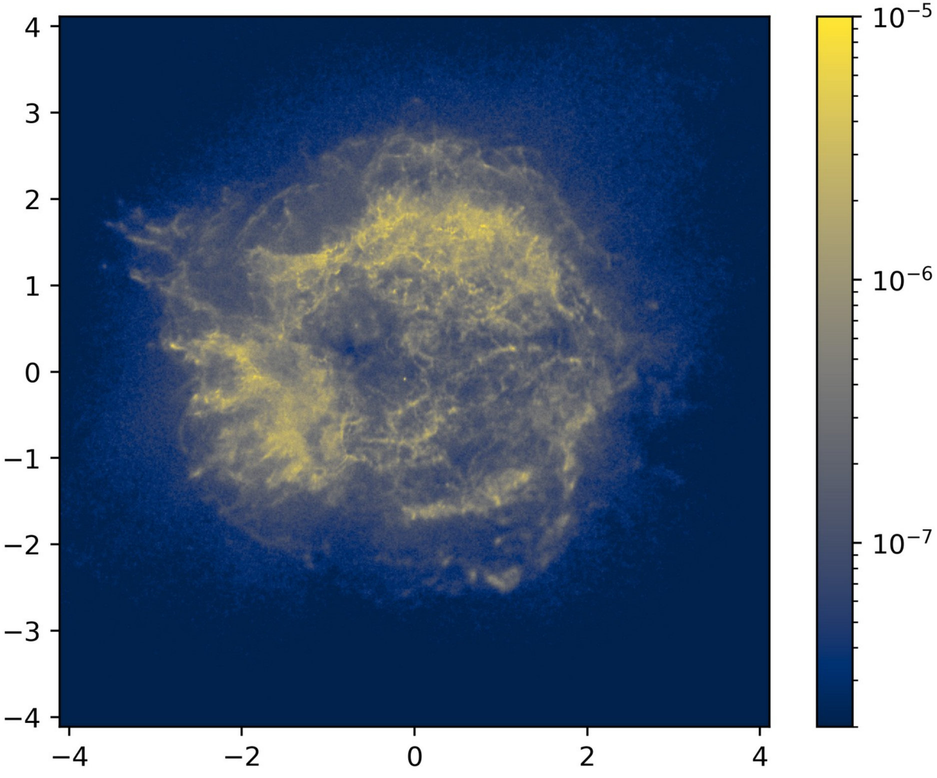


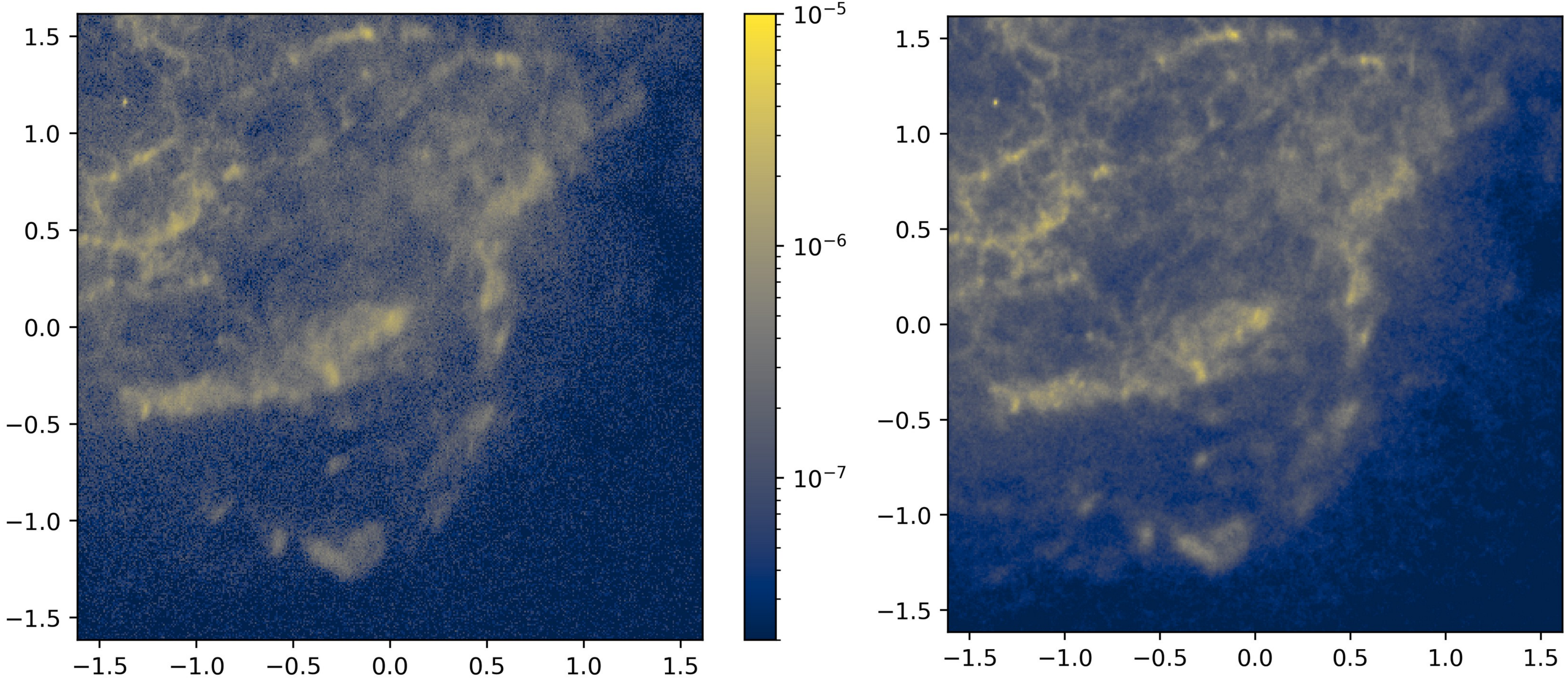
Preliminary new results (CasA):



Preliminary new results (CasA):



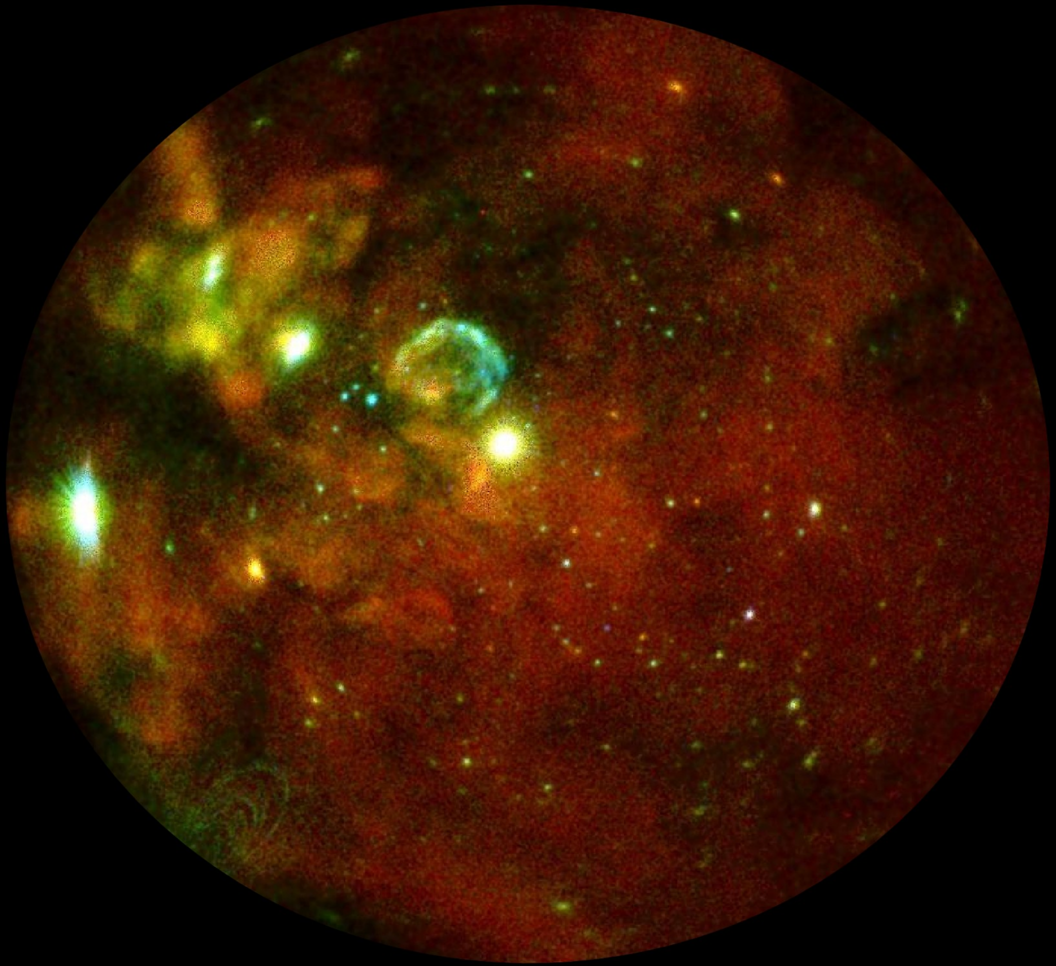




1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
10^{-5}
10^{-6}
10^{-7}

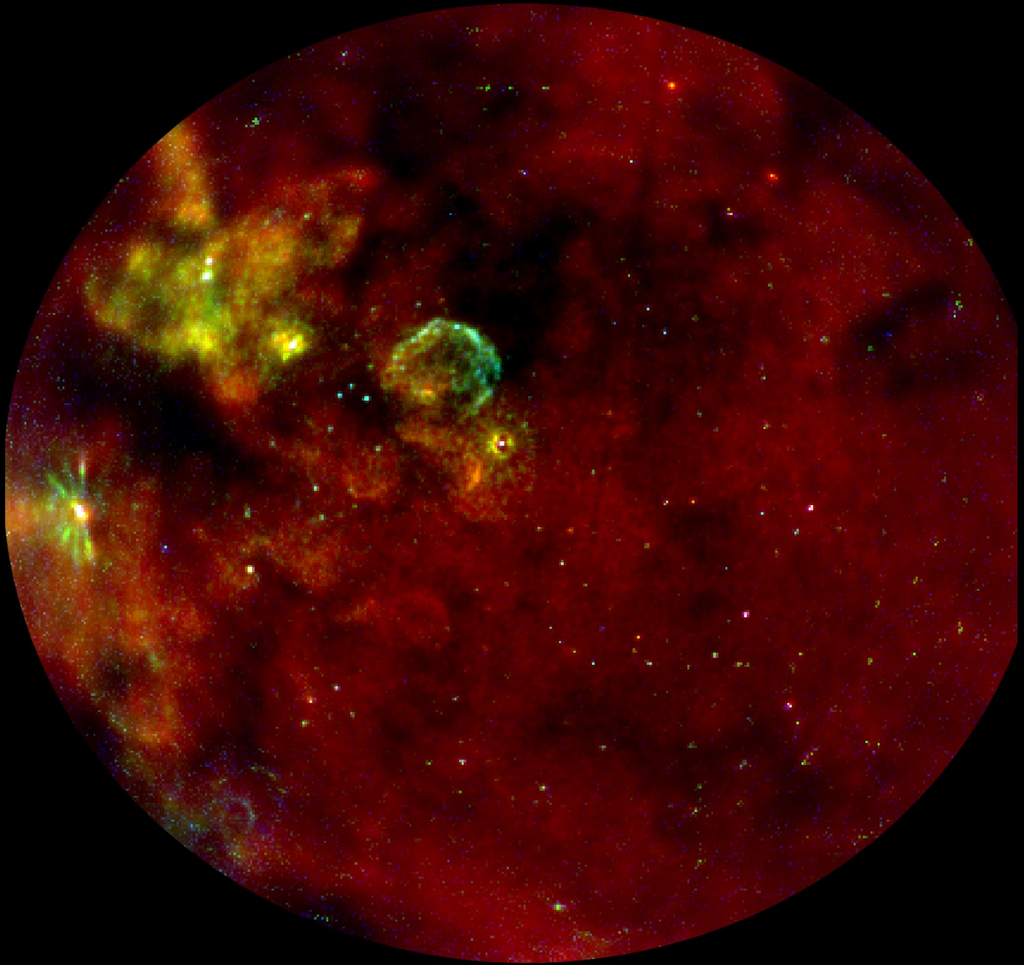
eROSITA

LMC 1987A



eROSITA

LMC 1987A



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Future:

- Search for even faster and more precise representations
- Infer PSF and other detector effects (pileup etc.) from redundancy in data

You want to know more about PSF Representation, IFT or NIFTy?

Get in contact direct or via mail:

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