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Bridging the gap between large and small scales in astronomical images through simultaneous modeling of point-like and diffuse emission

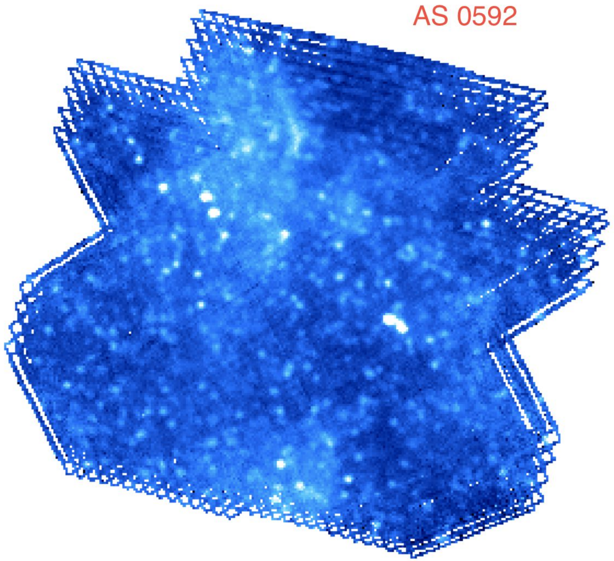
Richard Feder (Caltech), Victoria Butler (RIT), Tansu Daylan (MIT), Stephen Portillo (UW), Jack Sayers (Caltech), Benjamin Vaughan (RIT), Michael Zemcov (RIT)

Introduction

- Millimeter observations are sensitive to a variety of astrophysical/cosmological emission components
- Many analyses are confronted with data where only the joint observed emission is available
  - Measuring point source properties in presence of primary CMB anisotropies
  - In the sub-mm, inference of extragalactic and galactic point sources in the presence of galactic cirrus
  - Galaxy cluster observations are contaminated by all of the above (at different observing frequencies)

Challenges of modeling (out) diffuse emission

- Left uncorrected, diffuse emission can bias source photometry and degrade source detection
- High-pass/derivative filtering techniques attenuate and distort signal of interest
- Depending on the level of diffuse emission, choosing an “optimal” filtering scale can be complicated/ambiguous
- Component separation through spectral information is often not possible



Probabilistic cataloging

- Standard cataloging approaches are ill-equipped to perform accurate point source inference in crowded stellar fields, confusion-limited data
- Probabilistic cataloging (PCAT) is a forward modeling approach to cataloging that alleviates biases in point source photometry by exploring the posterior distribution of all catalogs consistent with an observed image
- Initially proposed in Brewer et *al.* 2013, further developed by Daylan et *al.* 2017a,b; Portillo et *al.* 2017; Feder et *al.* 2019 on various astronomical datasets

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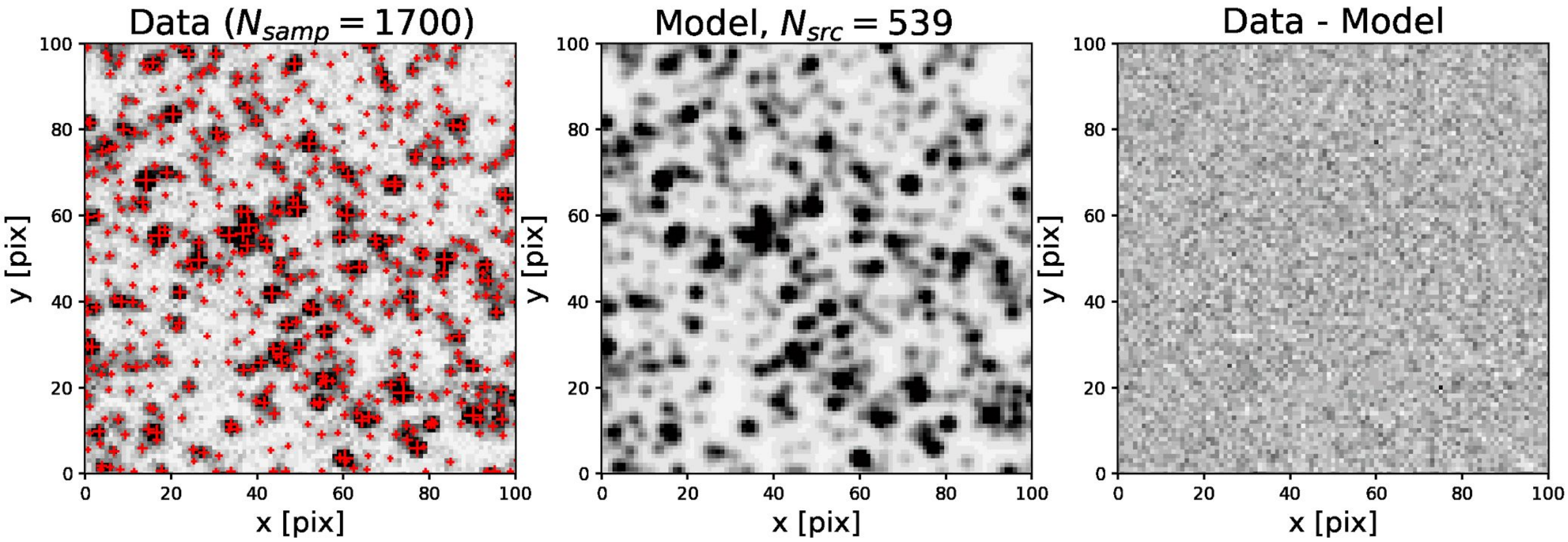
Probabilistic cataloging



PCAT posterior catalog model realizations of Herschel-SPIRE 250μm image cutout of GOODS-N deep field

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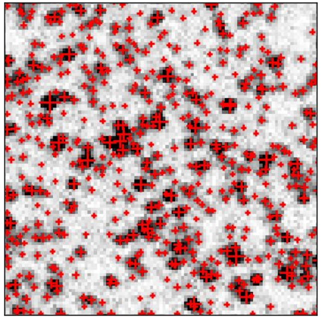
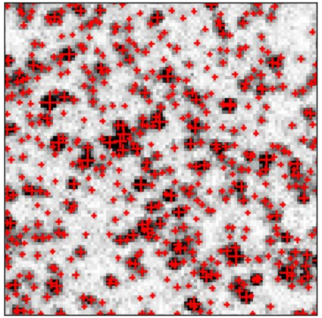
"Catalog Ensemble"

Sample 1

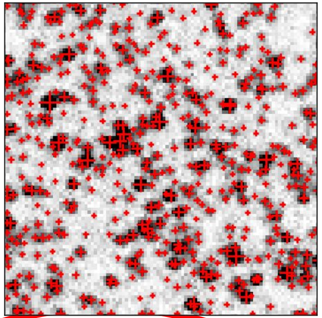


Sample 2

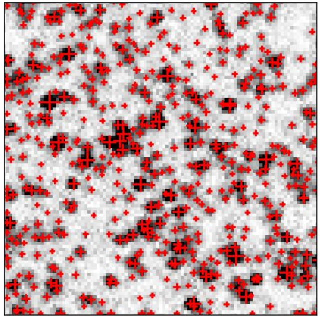


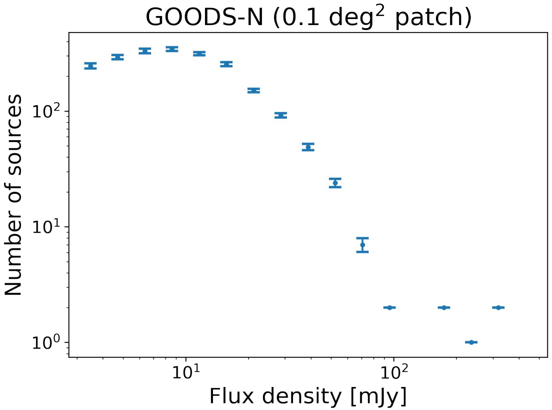
. . . .

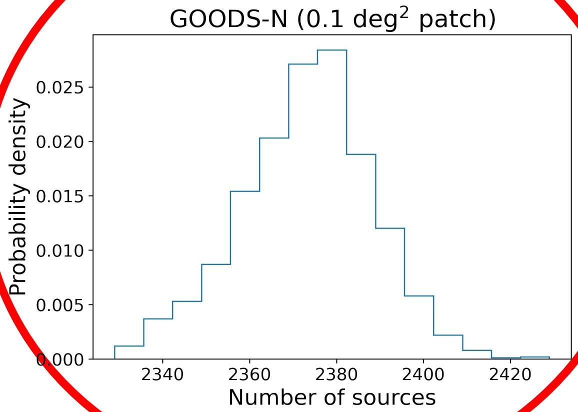
Sample n-1



Sample n







Can statistically *infer* the number of sources in an image!

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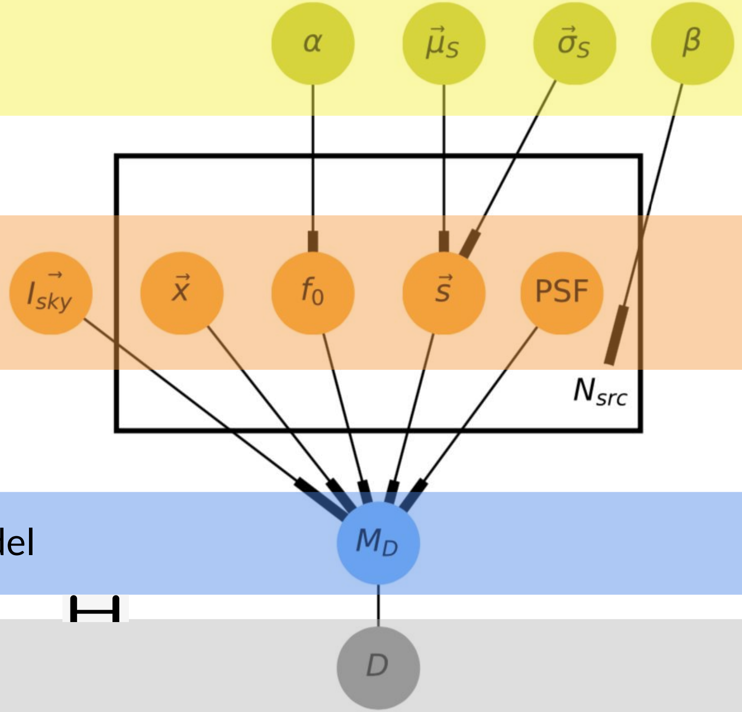
PCAT is a… Bayesian hierarchical model

Hyperparameters for flux distribution, color distribution, number of sources

Parameters for background normalization and collection of point sources

Model image/s generated from catalog + background model

Observed image data



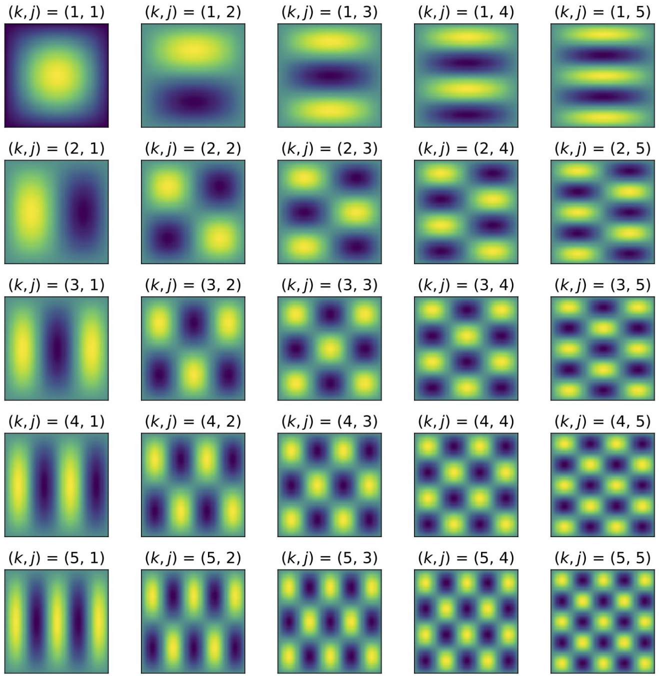
Extending PCAT to model diffuse emission

To model diffuse structured emission, we employ a flexible 2D truncated Fourier series model, where each Fourier component is represented by an image space template. This can be written as:

$$B_{lm} = B_0 + \sum_{k=1}^{N_m} \sum_{j=1}^{N_m} \boldsymbol{\beta}_{kj} \cdot \boldsymbol{\mathcal{F}}_{lm}^{kj}$$

where

$$\boldsymbol{\mathcal{F}}_{lm}^{kj} = \begin{pmatrix} \sin\left(\frac{k\pi l}{W}\right) \sin\left(\frac{j\pi m}{H}\right) \\ \sin\left(\frac{k\pi l}{W}\right) \cos\left(\frac{j\pi m}{H}\right) \\ \cos\left(\frac{k\pi l}{W}\right) \sin\left(\frac{j\pi m}{H}\right) \\ \cos\left(\frac{k\pi l}{W}\right) \cos\left(\frac{j\pi m}{H}\right) \end{pmatrix}$$



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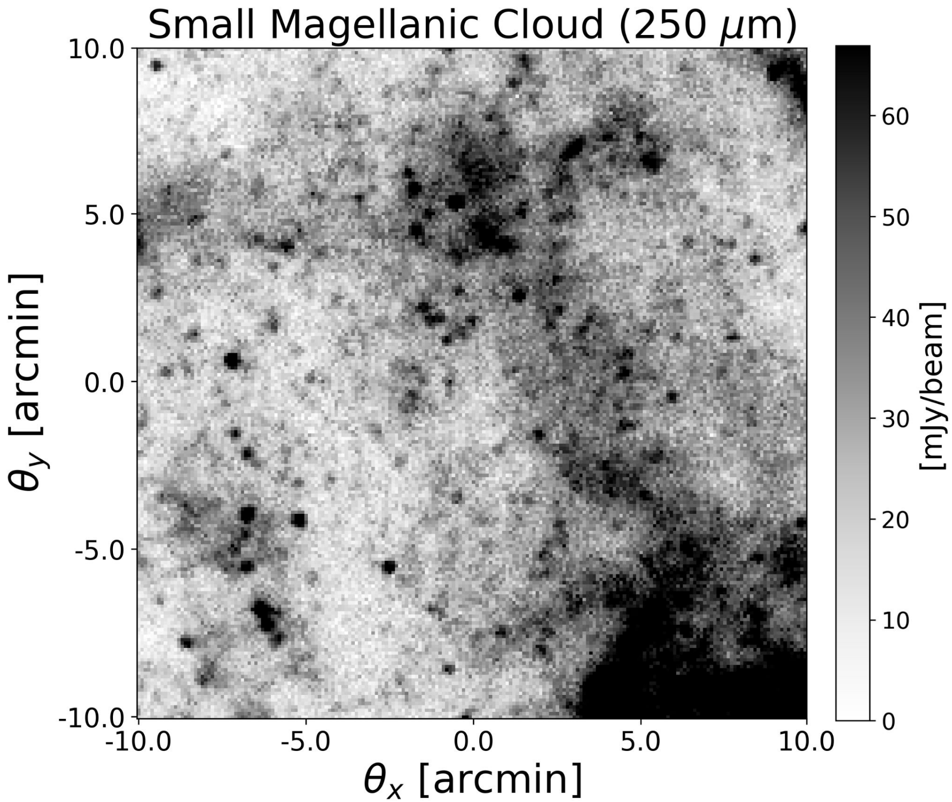
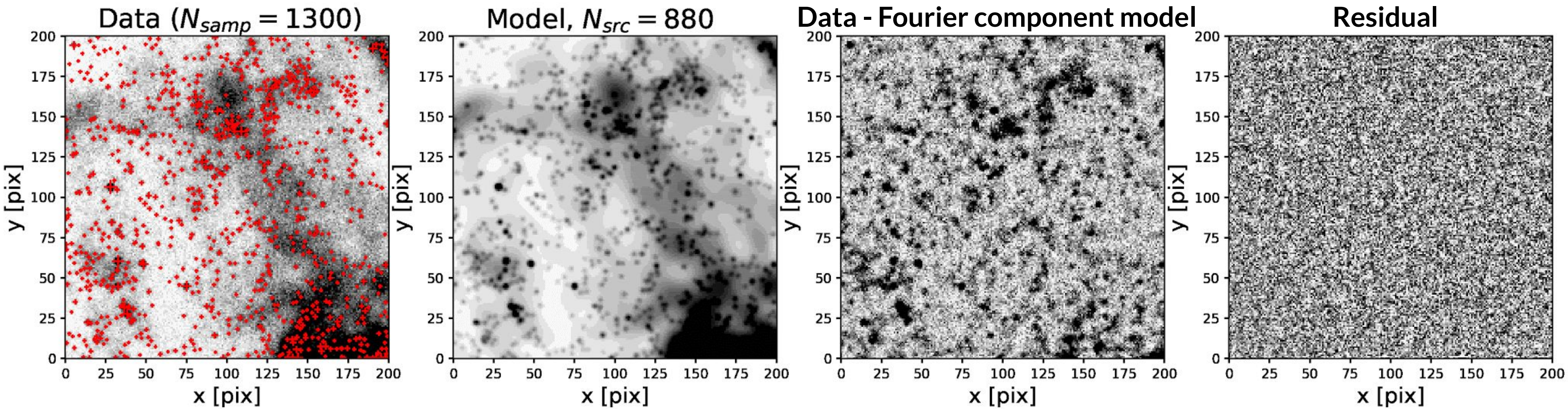


Separating point-like and diffuse emission



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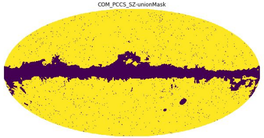
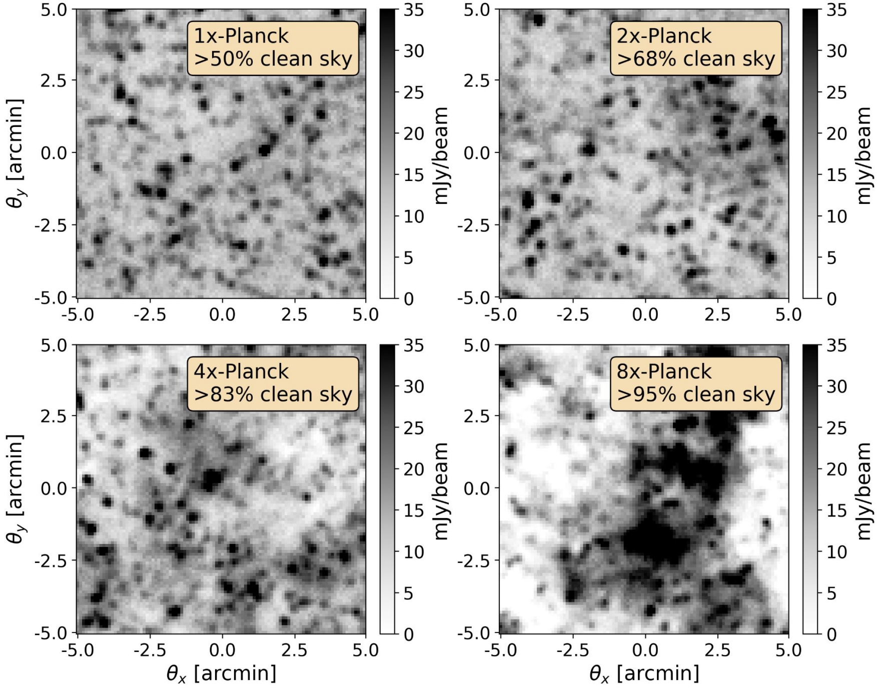
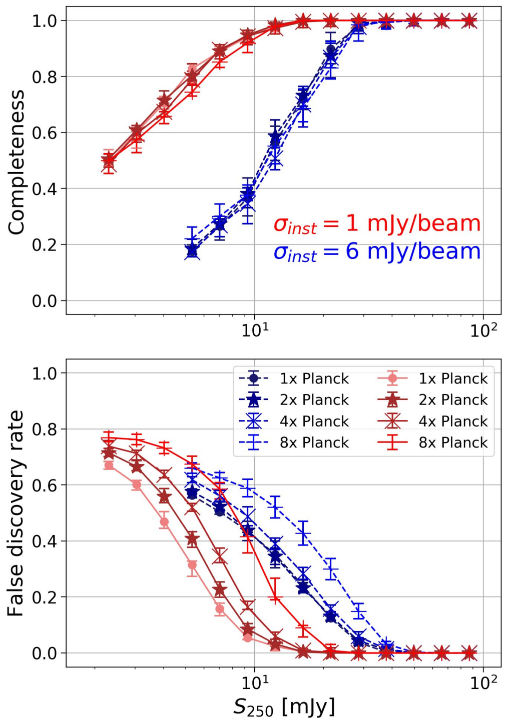


Separating point-like and diffuse emission



(1x-Planck refers to typical dust level measured in patches within Planck "*COM_PCCS_SZ-unionMask*")



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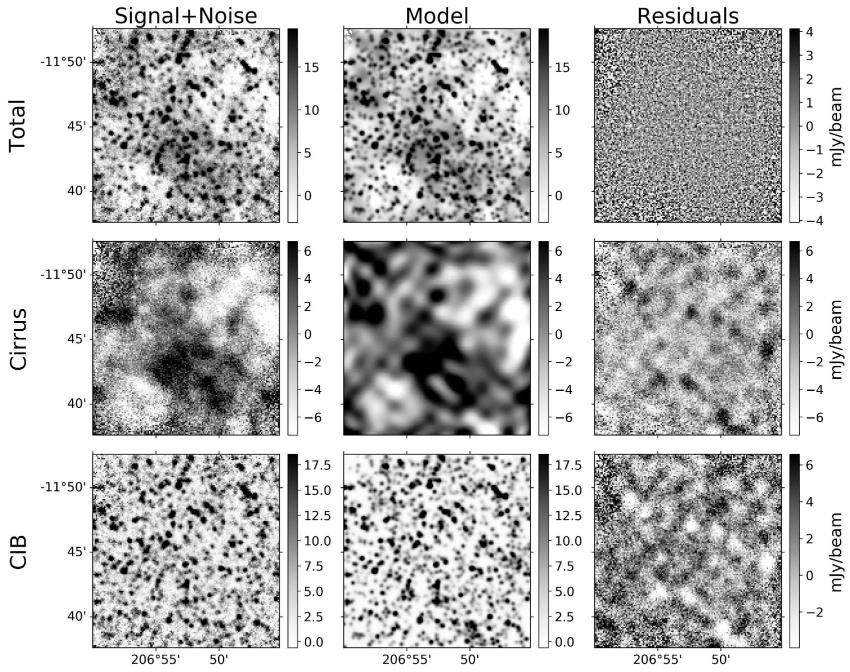
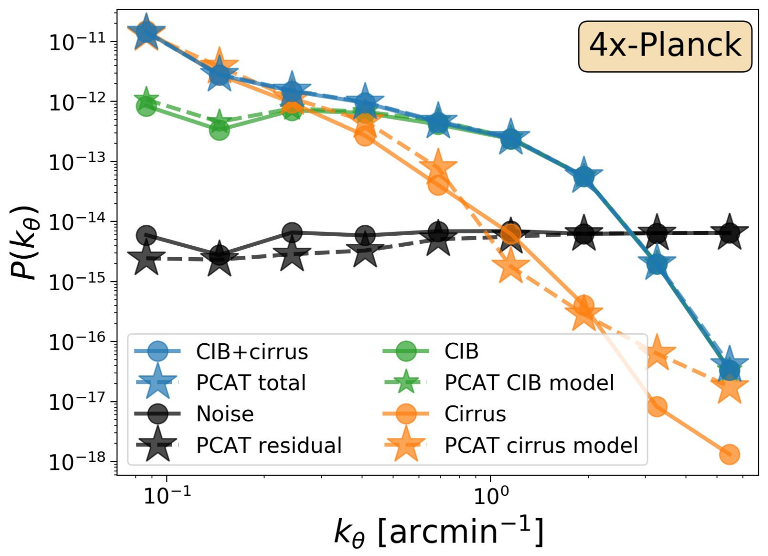
Separating point-like and diffuse emission





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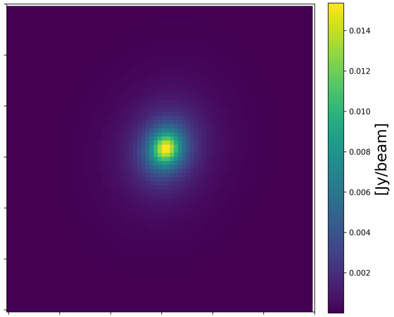
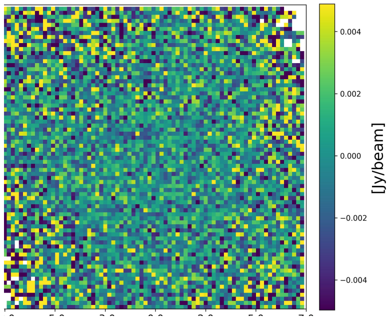
Measuring the tSZ effect using *Herschel*-SPIRE image data

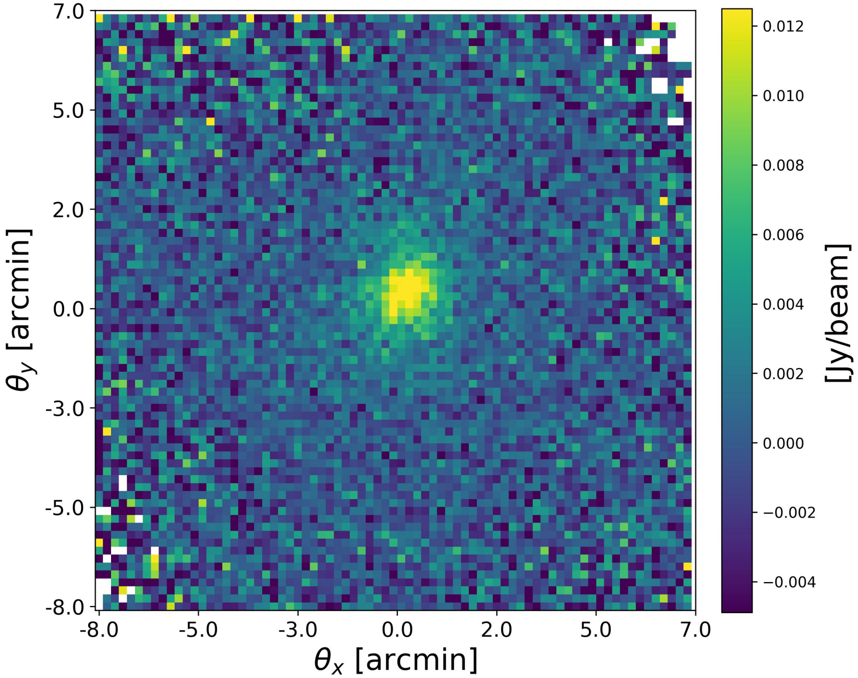
SZ effect



Instrument noise



500 µm



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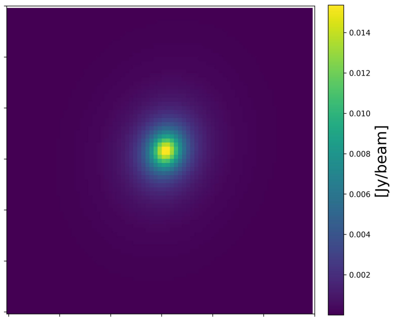
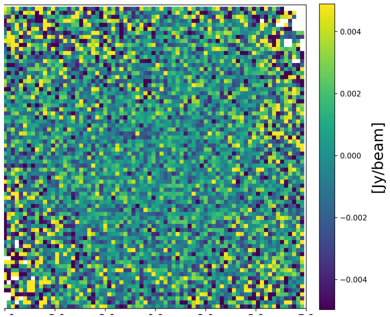
Measuring the tSZ effect using *Herschel*-SPIRE image data

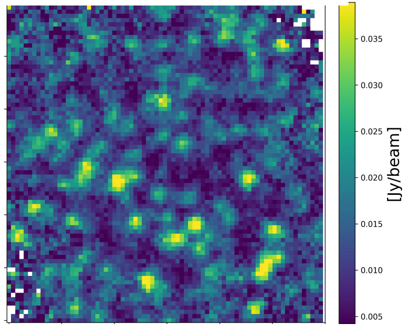
SZ effect



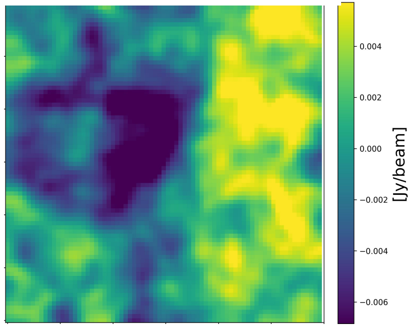
Instrument noise



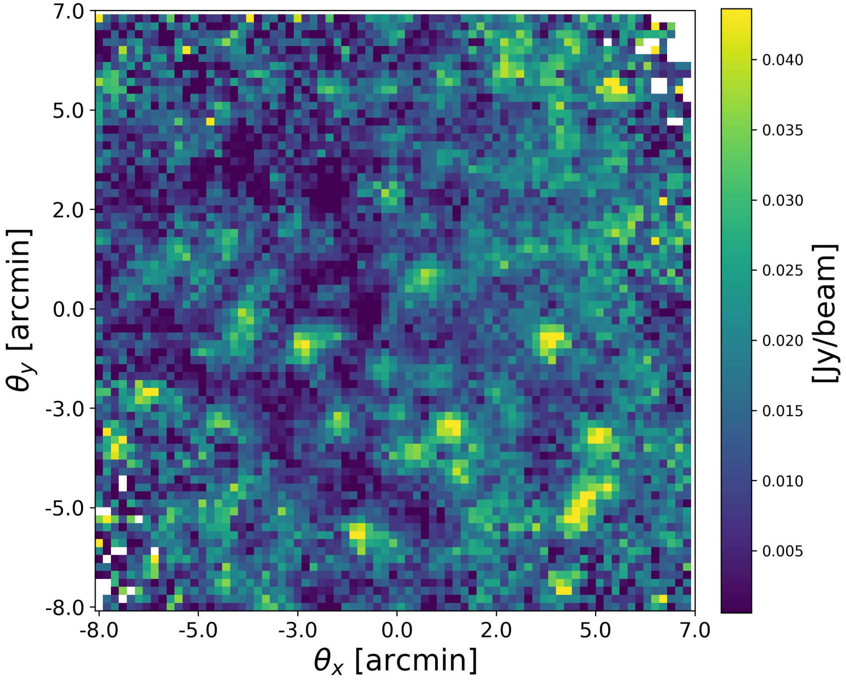
CIB



Cirrus



500 µm



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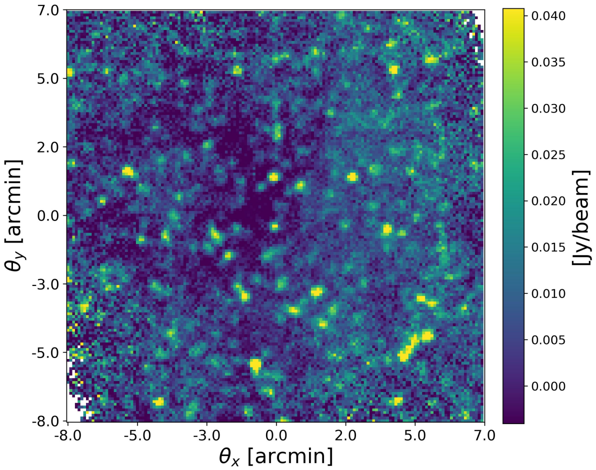
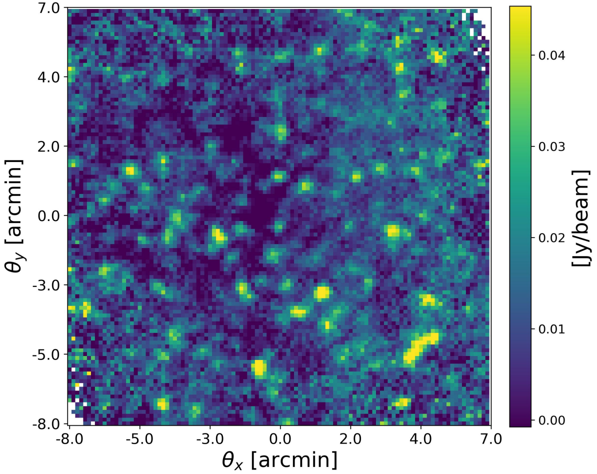
Measuring the tSZ effect using *Herschel*-SPIRE image data

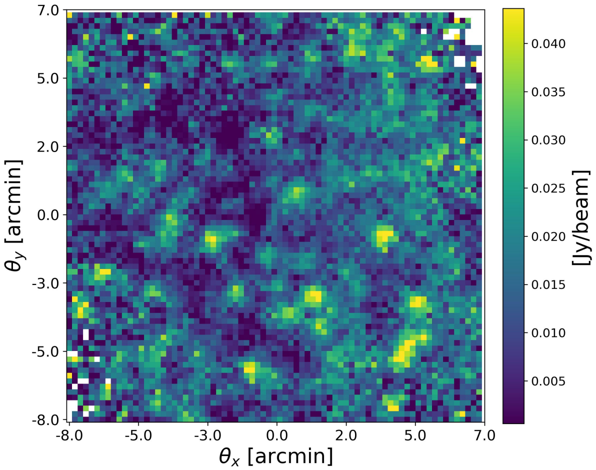
250 μm (18” PSF FWHM)



350 μm (25” PSF FWHM)



500 μm (36” PSF FWHM)



By using SPIRE data from the higher resolution 250 μm passband, the various emission components can be jointly modeled and deblended at longer wavelengths, where the SZ distortion is larger.

Measuring the tSZ effect using *Herschel*-SPIRE image data

$$\lambda^b_{lm} = \sum_{n=1}^{N_{src}} S^b_n \mathcal{P}^b(l - x^b_n, m - y^b_n) + A^b_{SZ} I^b_{SZ}(l, m) + B^b_{lm}.$$

Model of image data in pixel (l, m) in band b	Sum over point sources	Contribution of SZ template	Cirrus dust model

Data likelihood:

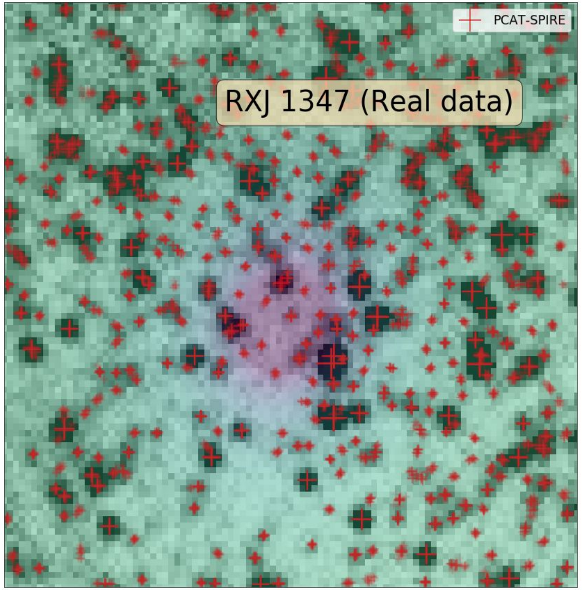
$$\log \mathcal{L} \approx \sum_{b=1}^{B} \sum_{l=1}^{W} \sum_{m=1}^{H} - \frac{(k^b_{lm} - \lambda^b_{lm})^2}{2\sigma^b_{lm}}$$

Model priors:

$$\{\pi(f_0), \pi(\boldsymbol{s}), \pi(x, y), \pi(N_{src})\}$$
$$\pi(\mathbf{B}(\nu_b))$$

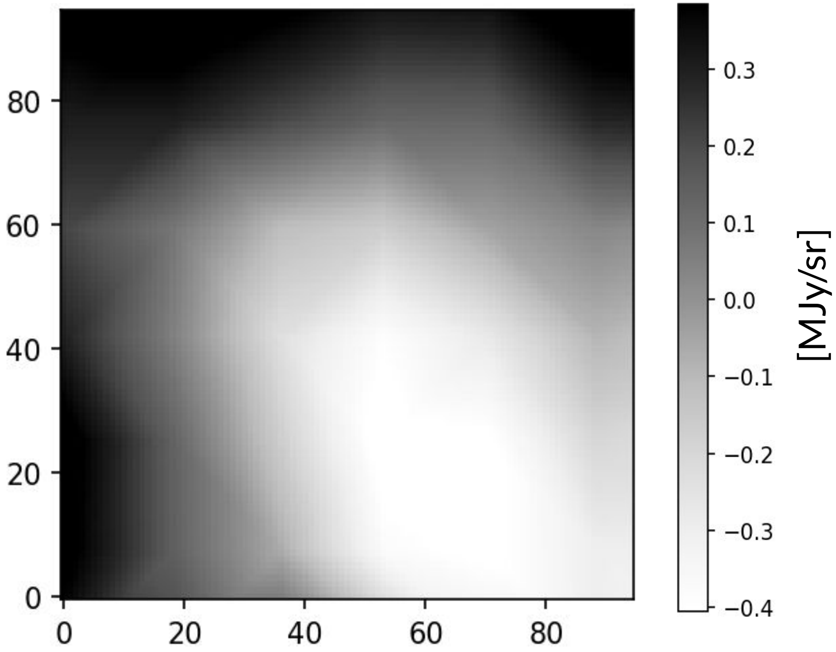
Cirrus contamination in RX J1347.5-1145

Median Nsrc = 470



Purple region indicates location of SZ signal, for visualization only

Best fit Planck cirrus model



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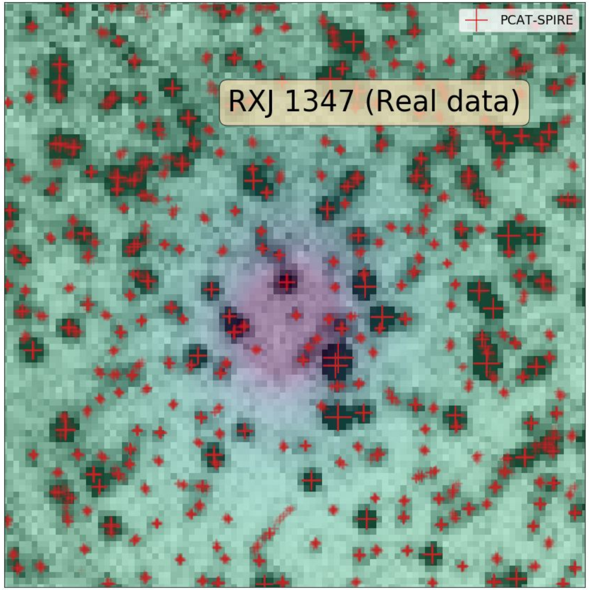
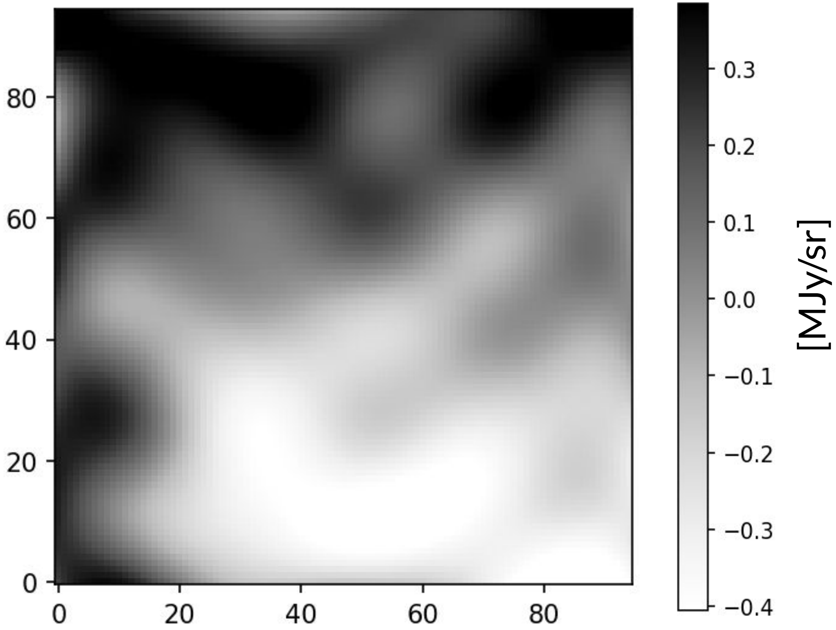
Cirrus contamination in RX J1347.5-1145

Median Nsrc = 385



Purple region indicates location of SZ signal, for visualization only

Best fit Fourier cirrus model (6th order)



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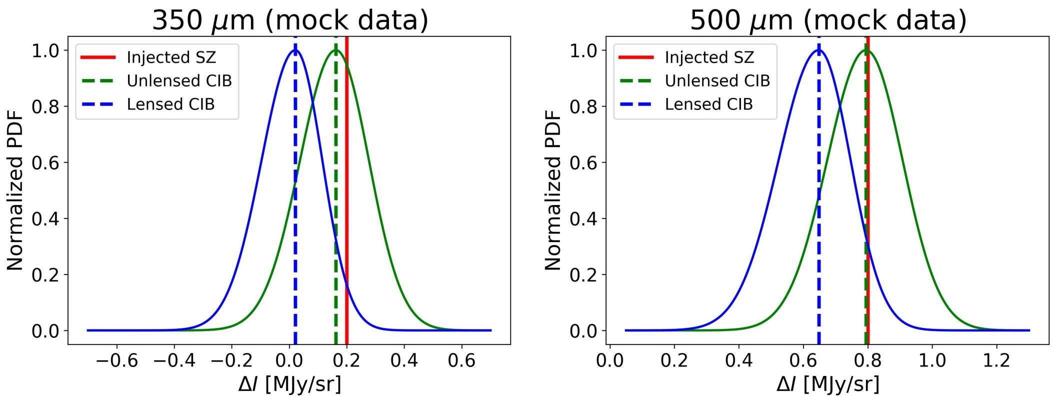
Recovery of the tSZ effect from *Herschel*-SPIRE clusters

- CIB model from Bethermin et *al.* 2013 used to generate set of mock SPIRE observations
- When testing on unlensed realizations of the CIB, our pipeline yields unbiased estimates of the SZ effect
- Strong gravitational lensing leads to an overall surface brightness deficit near the cluster center, biases SZ template estimation (addressed in Butler+Feder et *al.* 2021, in prep.)



Aggregate posteriors from 100 mock CIB realizations

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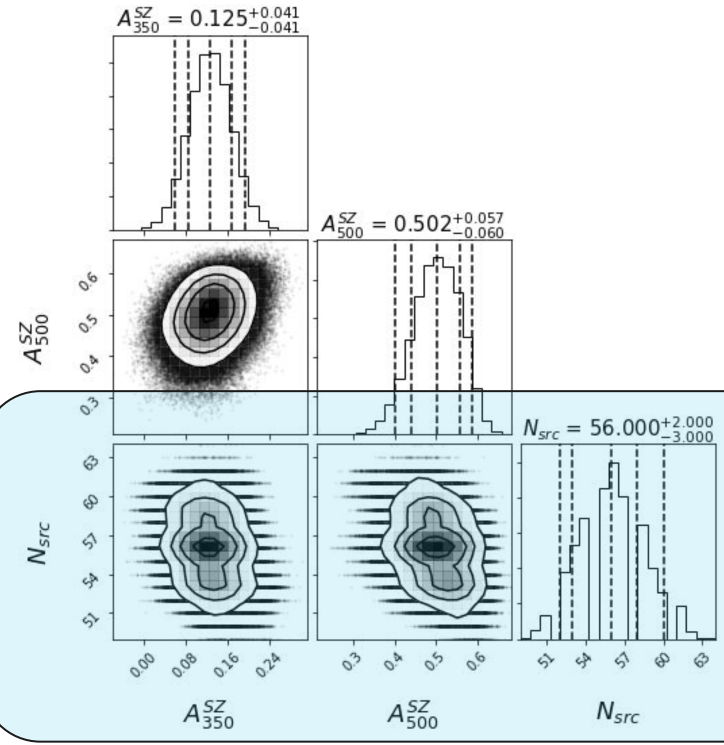
Recovery of the tSZ effect from *Herschel*-SPIRE clusters

Figure made with *corner.py*



PRELIMINARY RXJ 1347.5-1145 (uncorrected for lensing bias)

We quantify the uncertainty due to a CIB model where the number of sources is unknown *a priori* !

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Conclusion

- The incorporation of a flexible Fourier component model to PCAT shows promise for analyzing clusters and cataloging fields with moderate amounts of dust contamination, or removal of point sources from a foreground/background of interest (see Feder et *al* 2021, in prep.)
- PCAT's Bayesian forward modeling framework naturally accommodates more detailed SZ emission models
- While cirrus dust is the diffuse emission source considered in this work, PCAT-*DE* may be applied to other situations, e.g., residual atmospheric fluctuations from ground-based observations
- Current implementation can be found at https://github.com/RichardFeder/multiband_pcat. Tutorials/examples coming soon!

Thank you!

Extra slides

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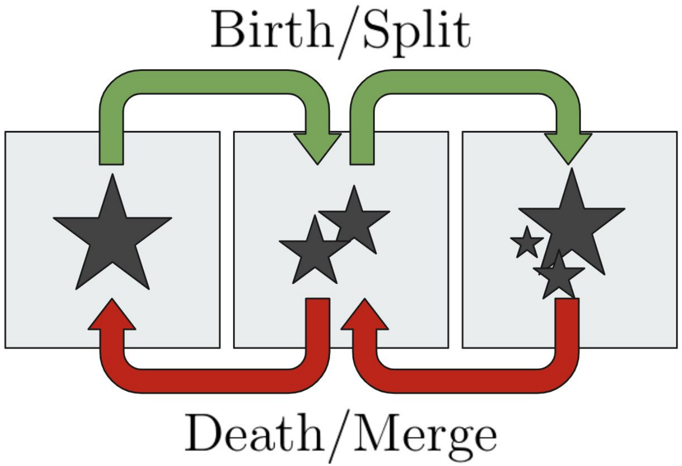
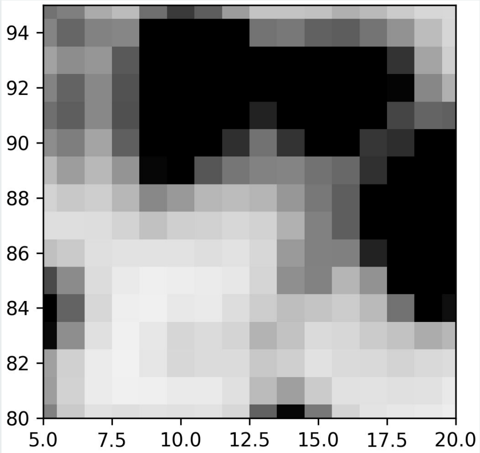
PCAT is a… transdimensional sampler



to explore

“Catalog space”

$$\mathcal{C} = \bigcup_{N=N_{min}}^{N_{max}} \mathcal{C}_N = \bigcup_{N=N_{min}}^{N_{max}} X_N \times Y_N \times \mathcal{F}_N \times \ldots$$



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Modified Proposal Steps/Acceptance Ratios

Source flux prior decomposition:

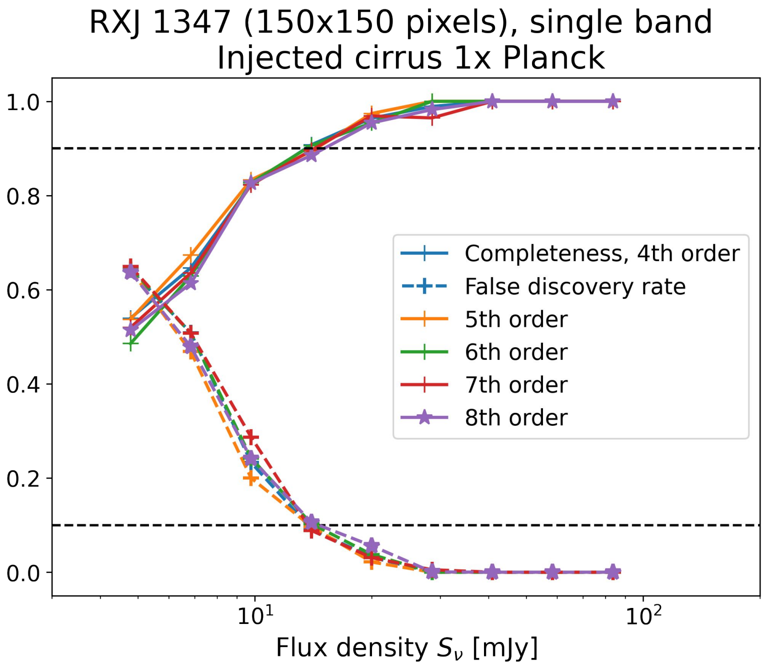
$$\pi(\vec{f}) = \pi(f_1) \times \prod_{i=2}^{k} \pi(s_i)$$

Merge/Split Acceptance Factor

$$\alpha_{split} = \frac{2\pi k^2}{A} \frac{\pi_1(f_1)\pi_2(f_1)}{\pi_0(f_1)q(F_1)} \prod_i \frac{\pi_1(s_i)\pi_2(s_i)}{\pi_2(s_i)q(F_i)} \mathcal{J}$$

$$\mathcal{J} = \prod_{i=1}^{n} \frac{2.5}{\log(10)} \frac{1}{F_i(1-F_i)}$$

Completeness/false discovery rate vs. F.C. order



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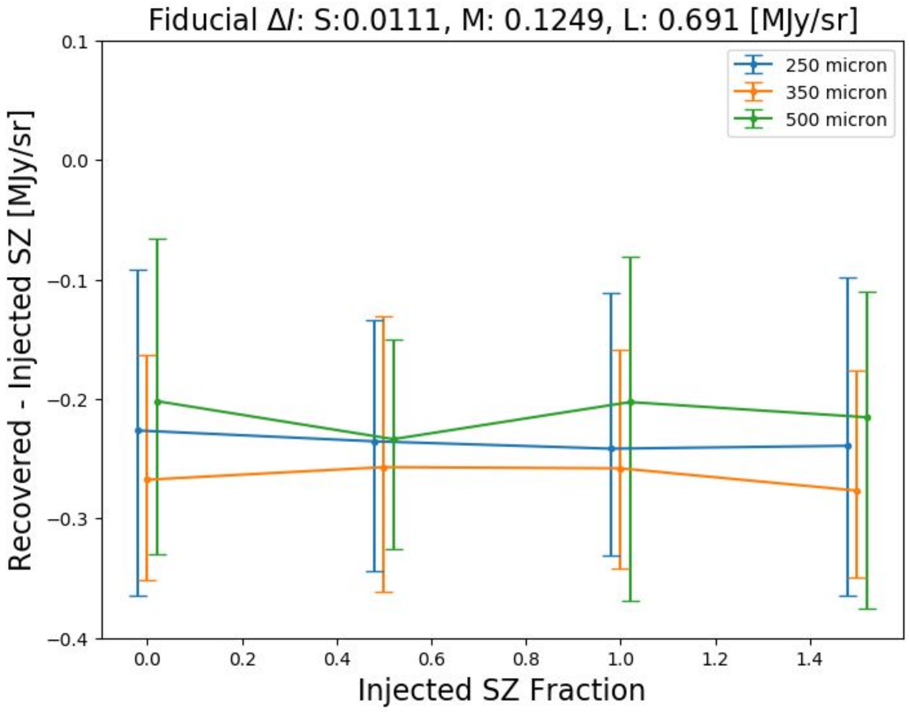
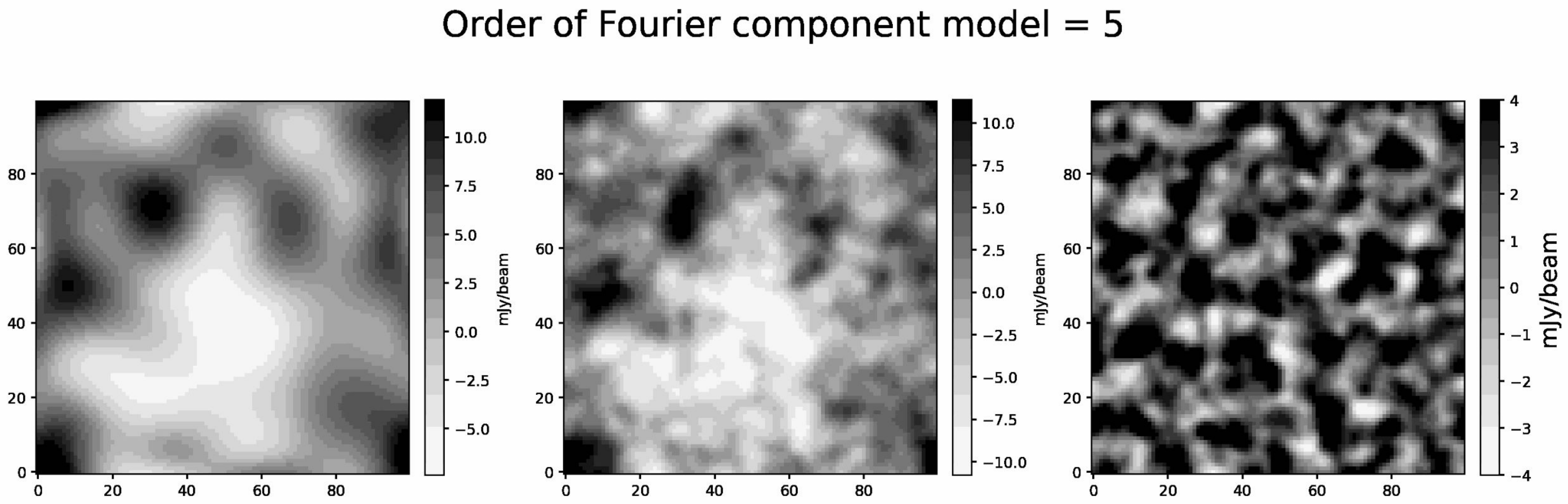
Dependence of lensing bias on injected SZ signal



Diffuse background data, Fourier component model



Diffuse background data, Fourier component + point source model

Order of Fourier component model = 5