

Exposing the plural nature of molecular clouds

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IPAG

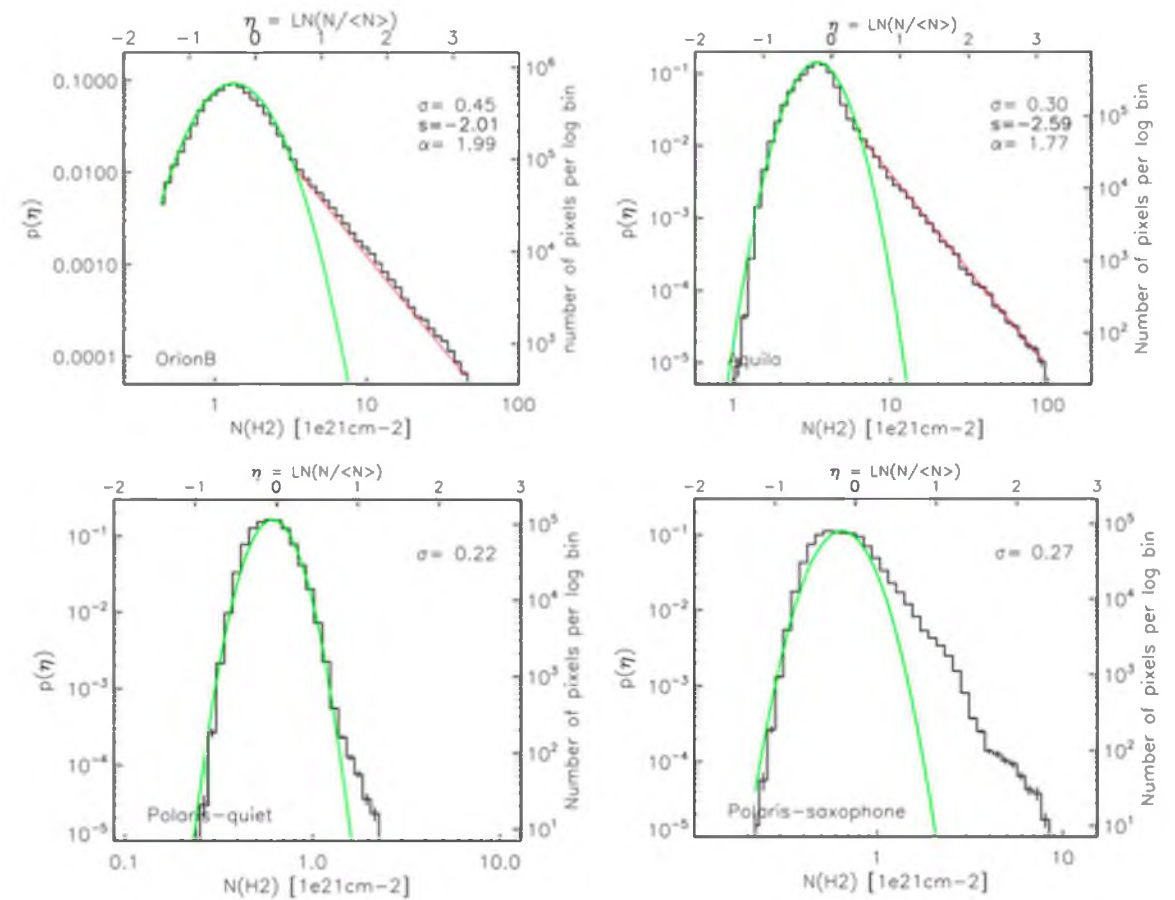
SFM final conference, York
September 18th, 2019



Statistical measurements on molecular clouds

- Probability distribution function (PDF) : the foundation of many modern theories of star formation
 - Because the density distribution of the ISM is very complex, it is dangerous to mix different evolutionary stages over a same region (Hill et al. 2011).
- Power spectrum analysis : one of the best tools to analyse and characterise the turbulence
 - If molecular clouds are dominated by turbulence, the power spectrum should be a complete measure of the density distribution (Green 93, Stutzki et al. 98)

Schneider et al. 2013



Miville-Deschênes et al. 2010

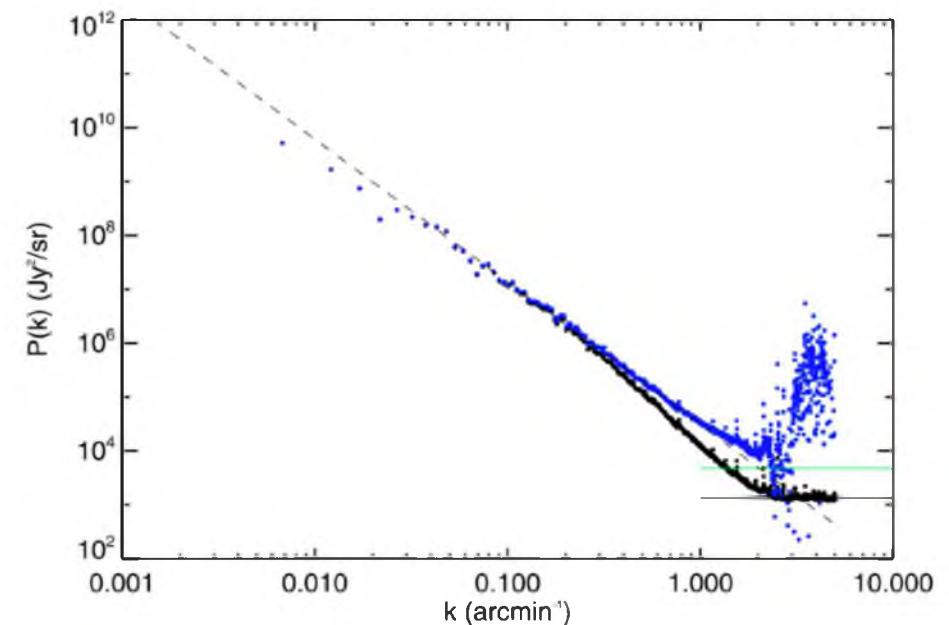


Fig. 3. Power spectrum of the SPIRE 250 μm map of the Polaris flare.

Statistical measurements on molecular clouds

- Power spectrum analysis:
 - Panopoulou et al. 2017 -> search of a characteristic scale in the presence of a characteristic width.
 - Roy et al. 2019 suggest that only filamentary structures with a high area filling factor and/or a high column-density contrast have an impact on the scale-free power spectrum of dust continuum images.

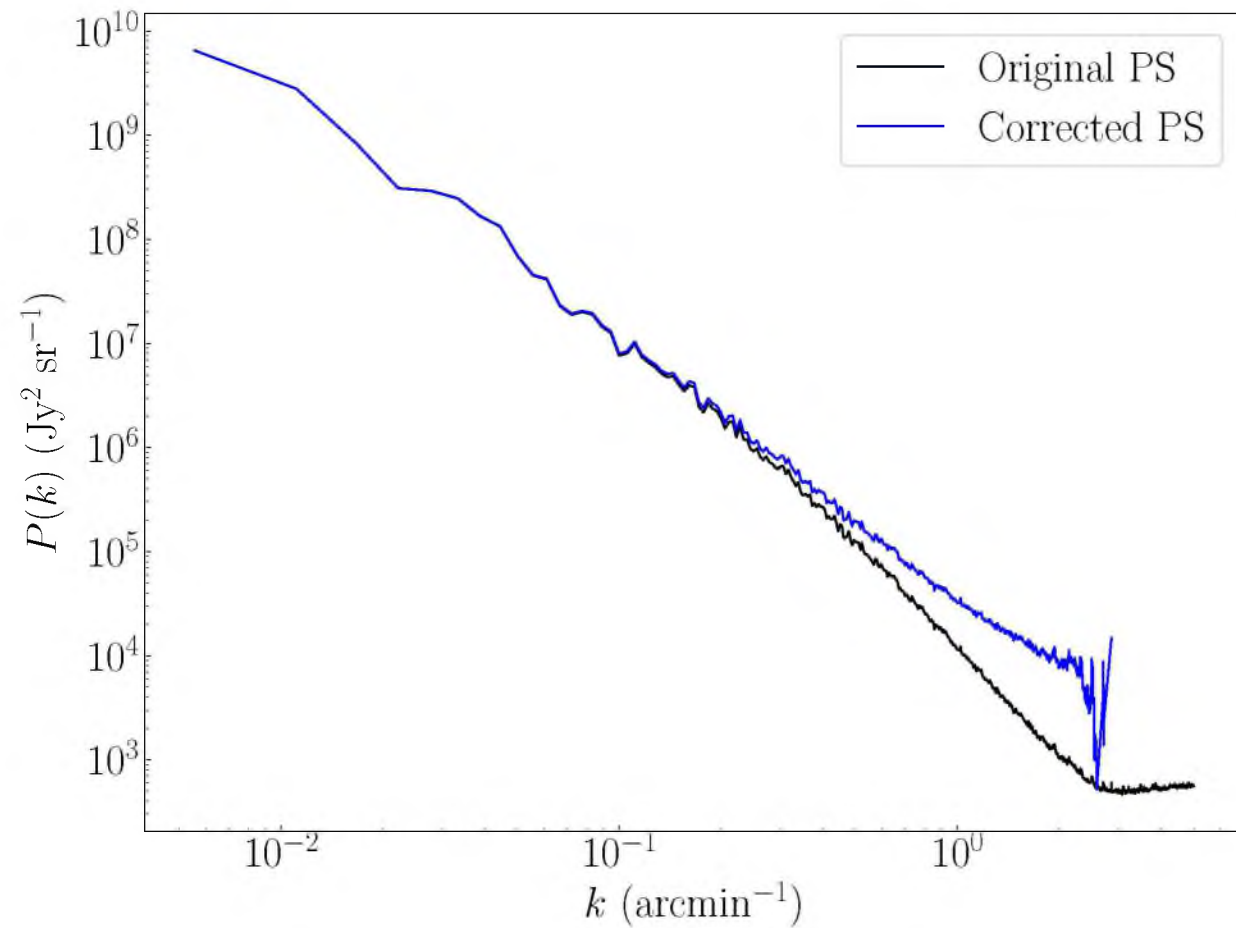


Dust column density
map, Herschel space
observatory

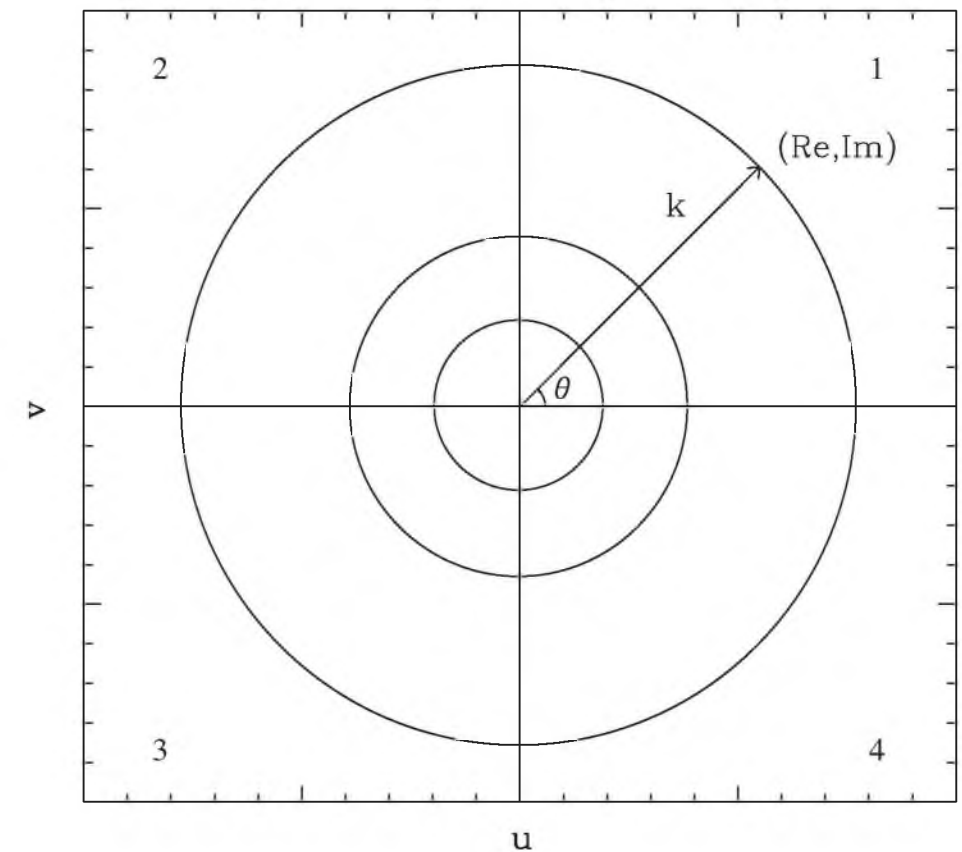
Power spectrum analysis

Power spectrum analysis

GBHS Polaris 250 μm map



Fourier transform



Power

$$P(k) = \langle |A(k)|^2 \rangle_{\theta}$$

Amplitude & Phase

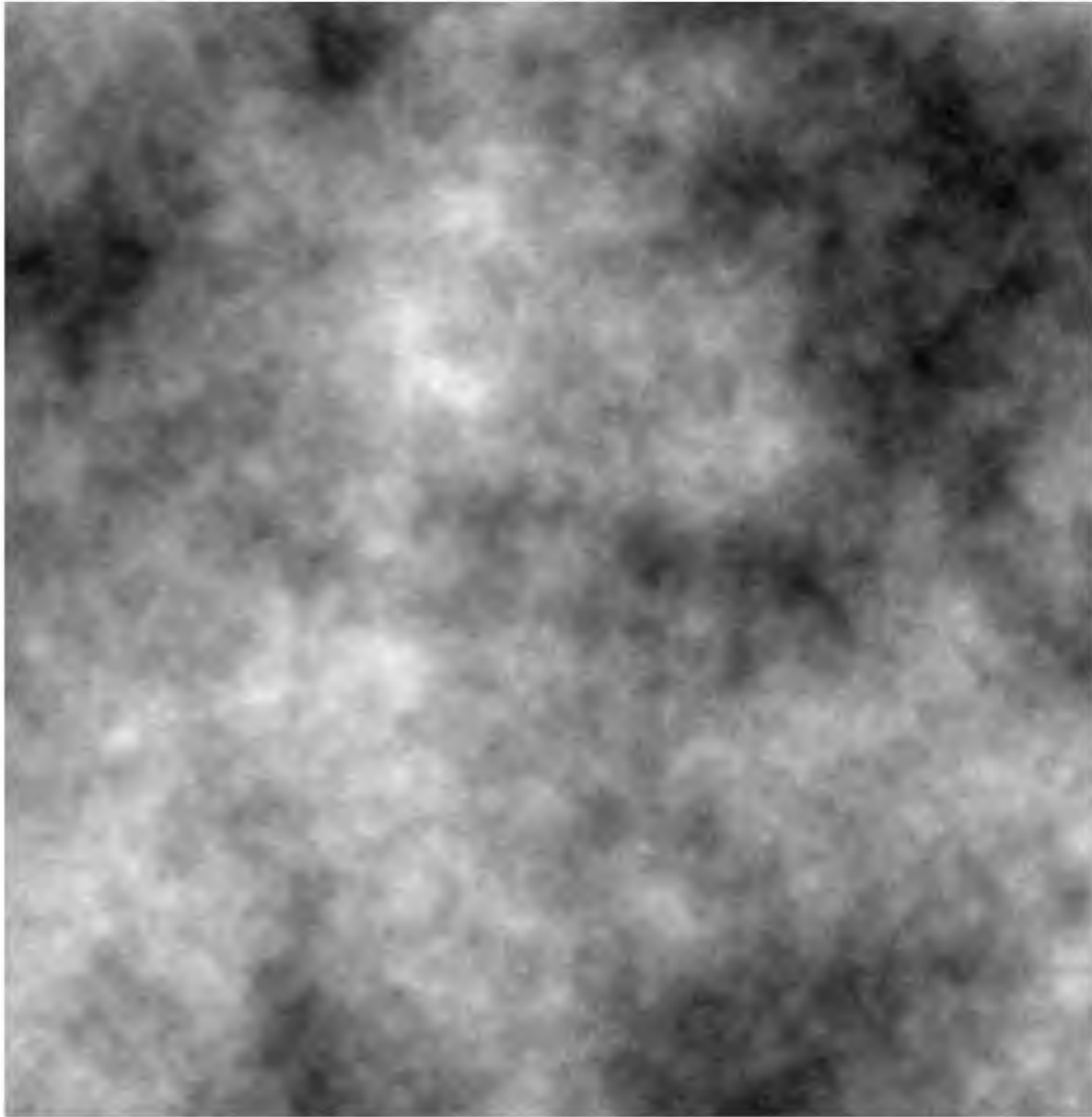
$$A = \sqrt{Re^2 + Im^2}$$
$$\phi = \tan^{-1}(Im/Re)$$

Wavenumber

$$k = \sqrt{u^2 + v^2}$$

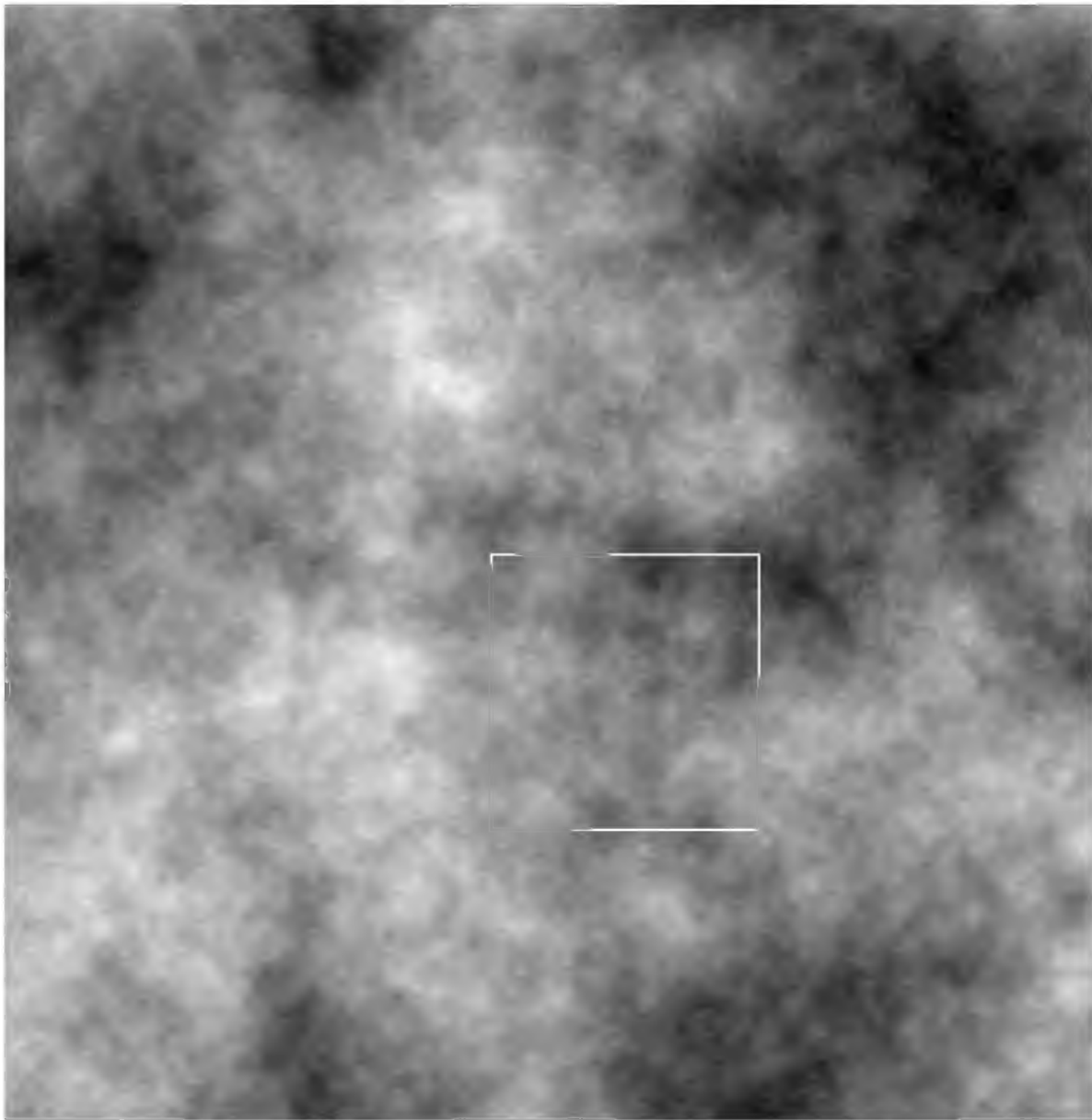
Fractional Brownian motion (fBm)

Self-similar distribution



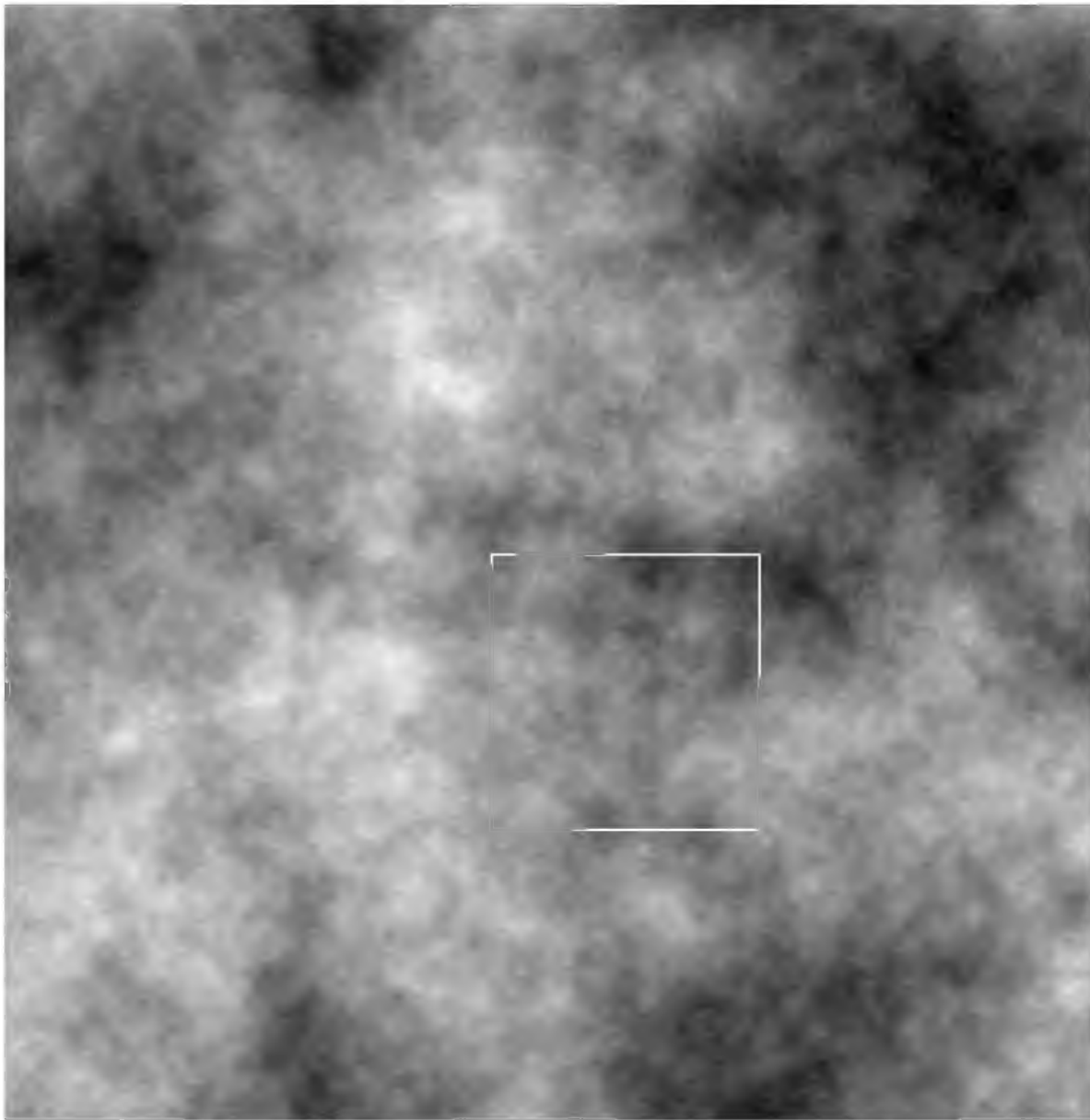
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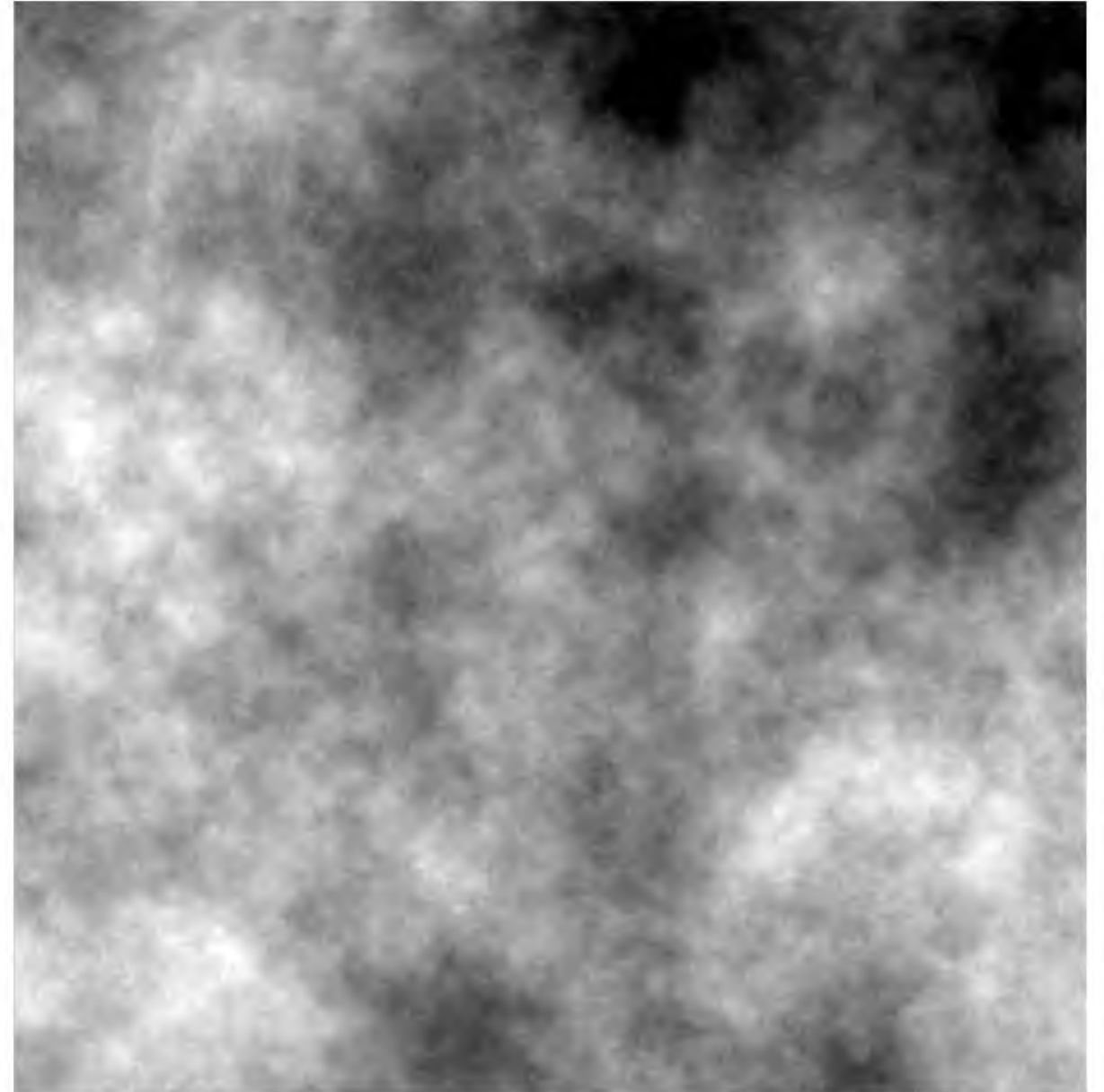
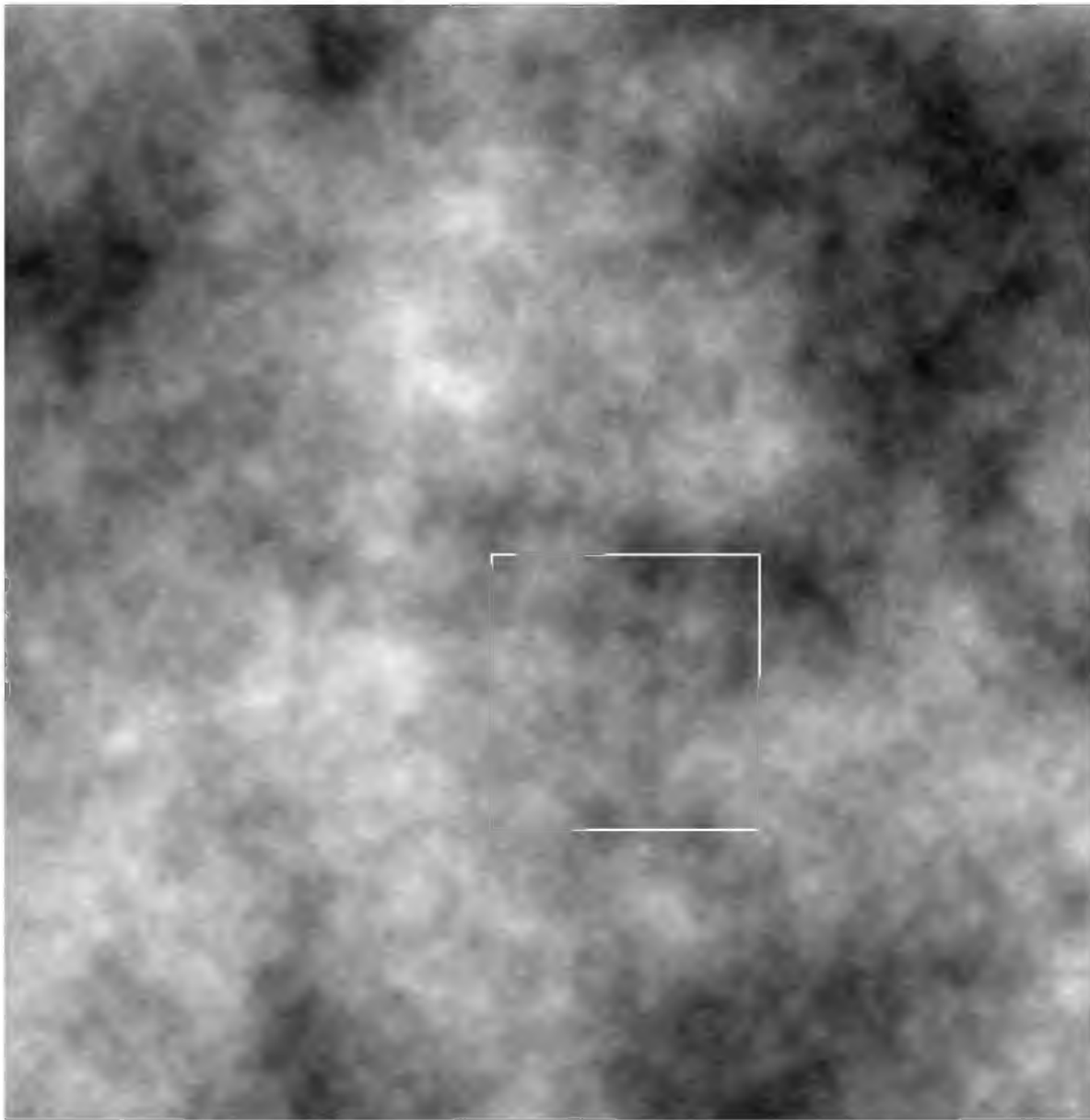
Fractional Brownian motion (fBm)

Self-similar distribution

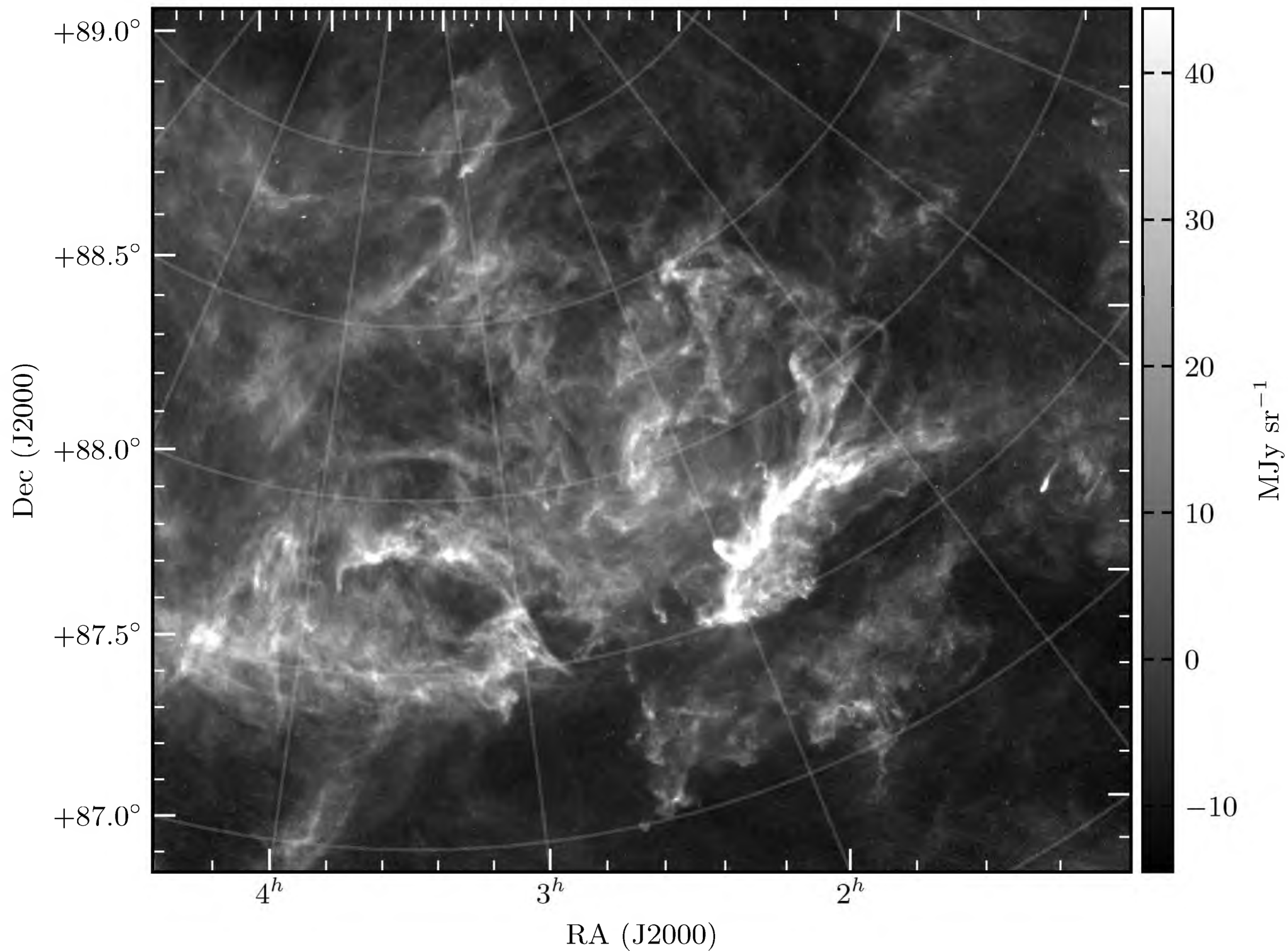


Fractional Brownian motion (fBm)

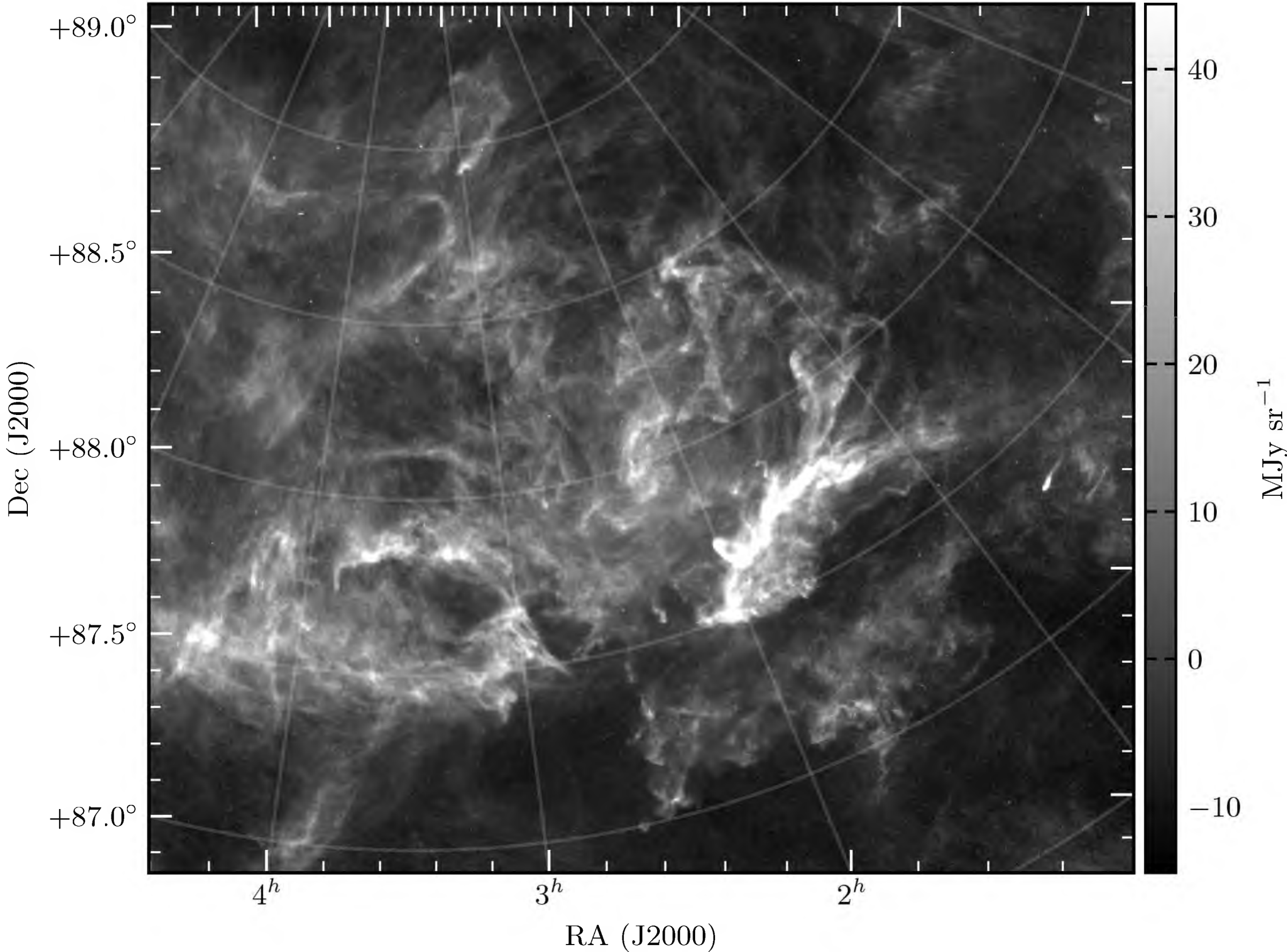
Self-similar distribution



GBHS Polaris 250 μm map



Effect described by Elmegreen et al. 2001 (HI); Miville-Deschênes et al. 2007 (IR)

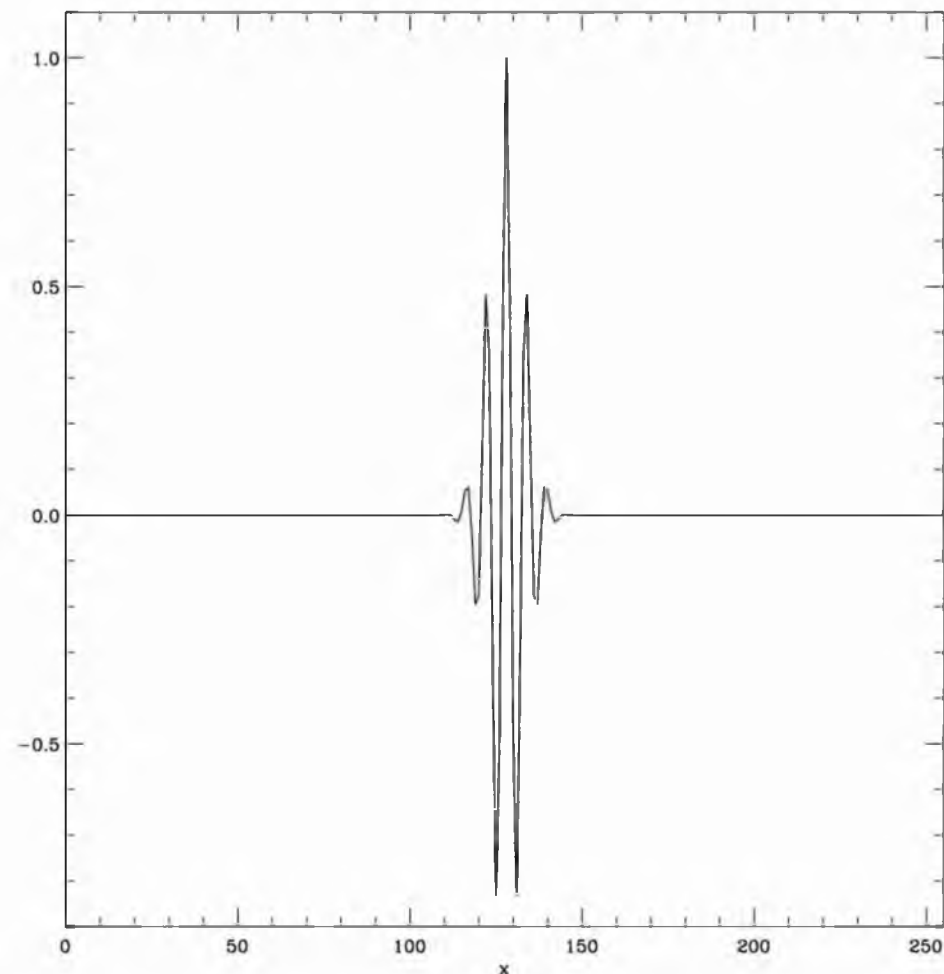


Complex Wavelet transform

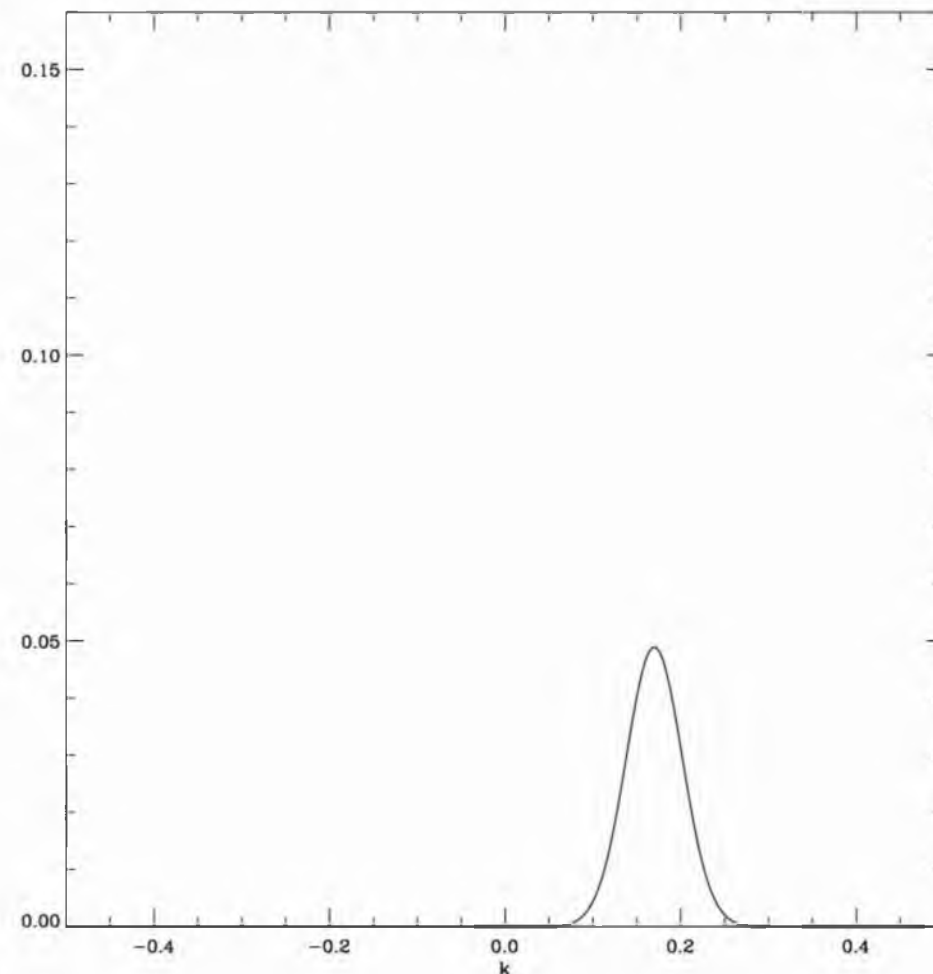
$$\begin{aligned}\psi(\mathbf{x}) &= e^{i\mathbf{k}_0\mathbf{x}} e^{-|\mathbf{x}|^2/2} \\ &= [\cos(\mathbf{k}_0\mathbf{x}) - i \sin(\mathbf{k}_0\mathbf{x})] e^{-|\mathbf{x}|^2/2}\end{aligned}$$

Morlet wavelet

X space (real part)



Fourier space

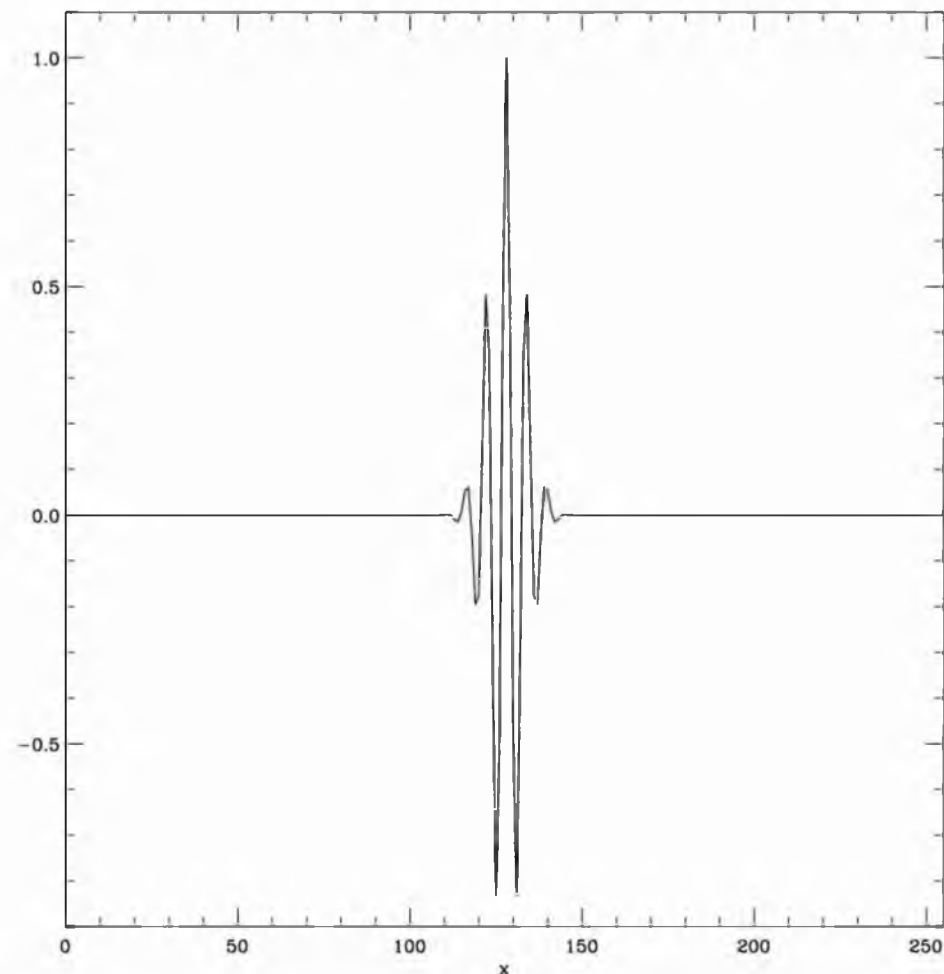


Complex Wavelet transform

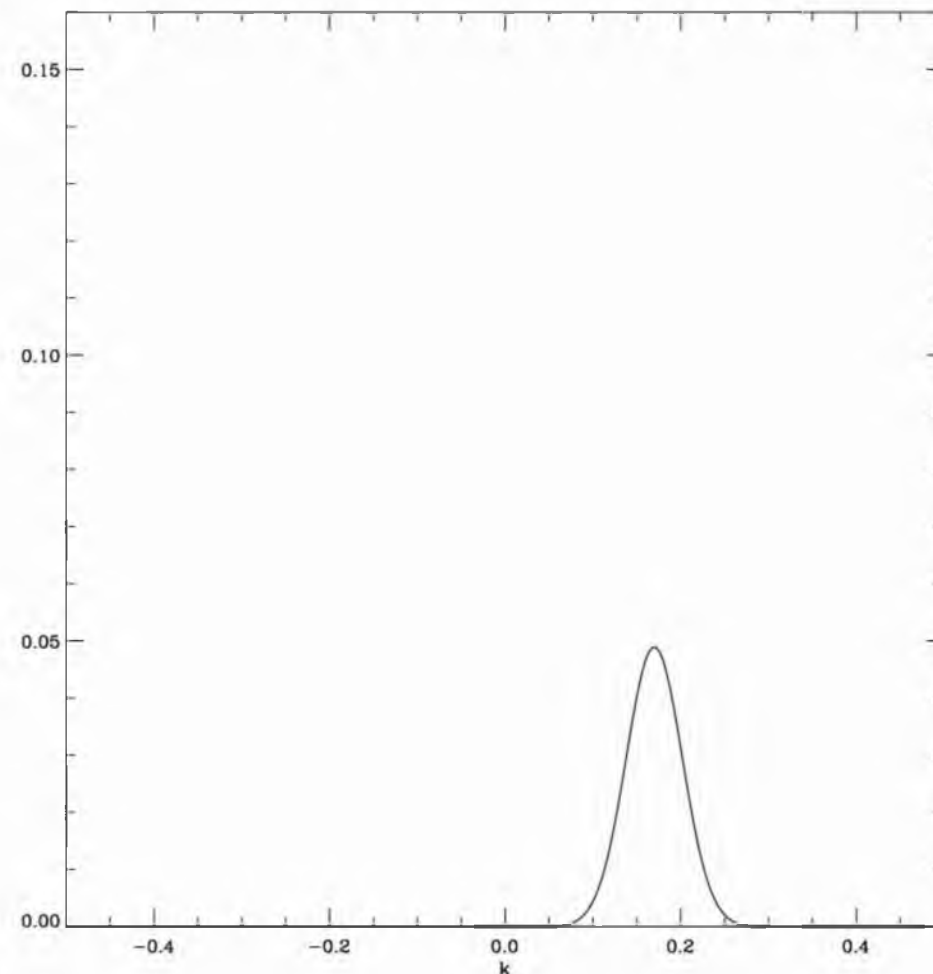
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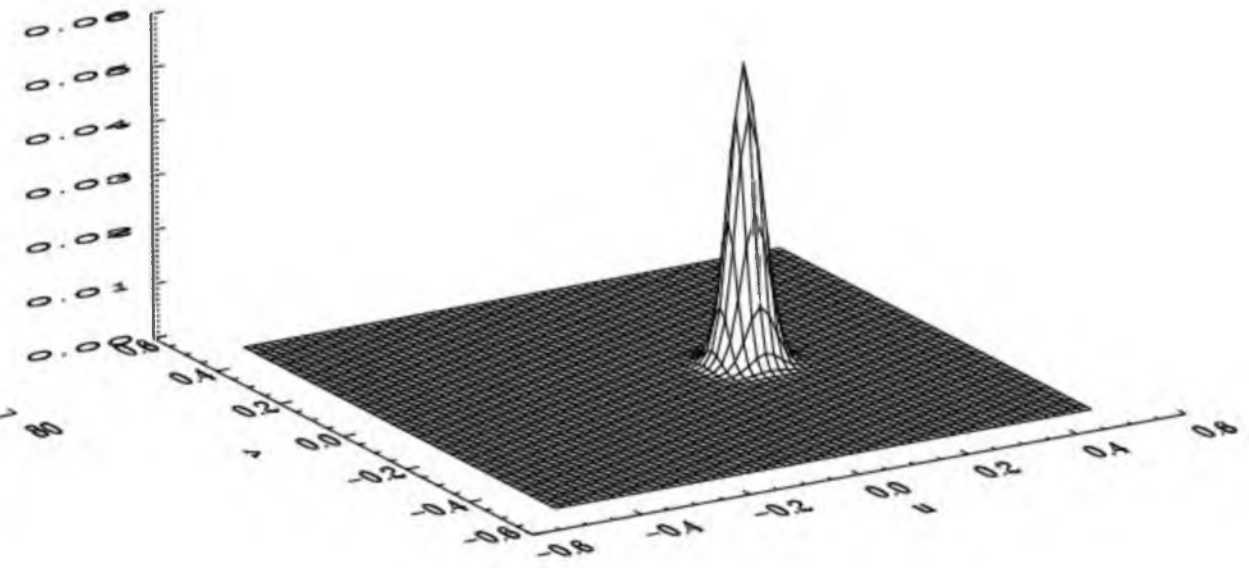
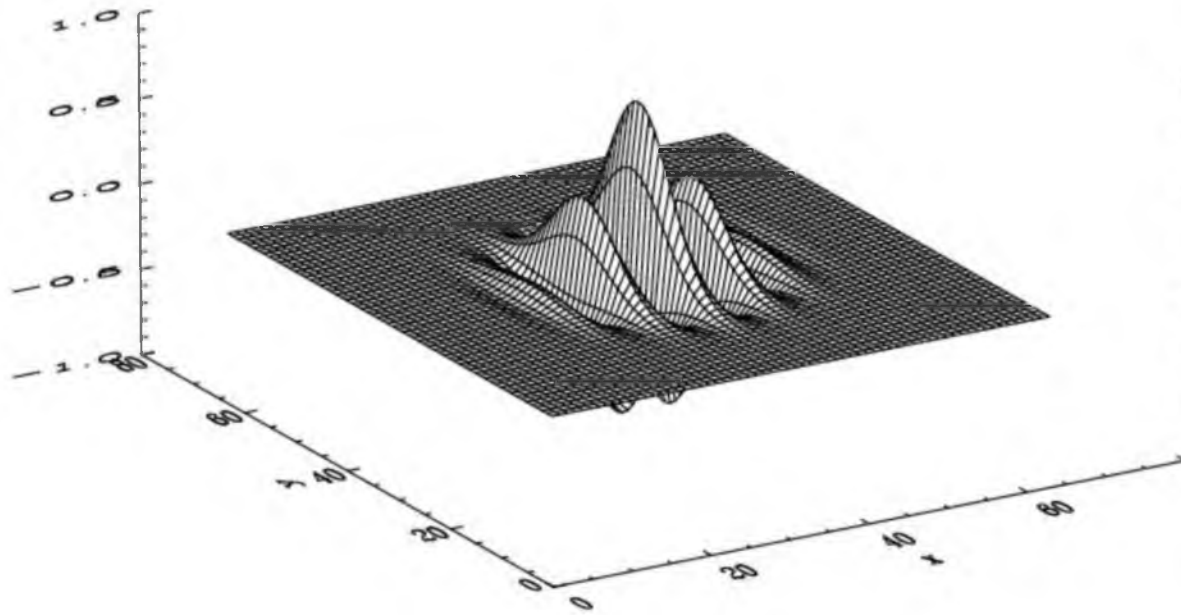
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Morlet wavelet

X space (real part)

Fourier space



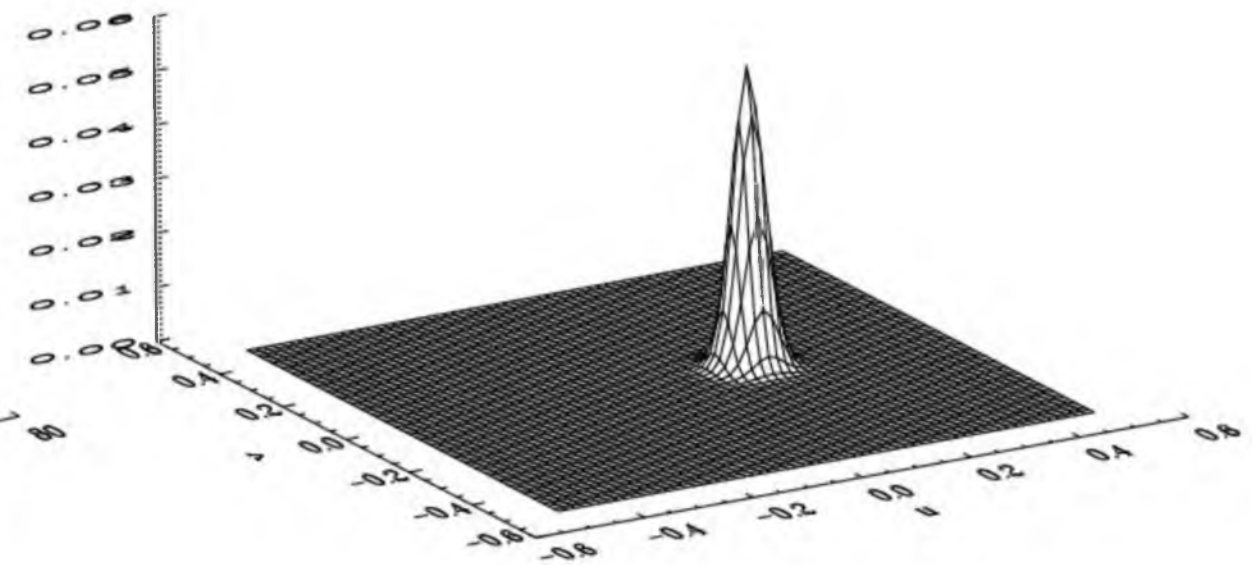
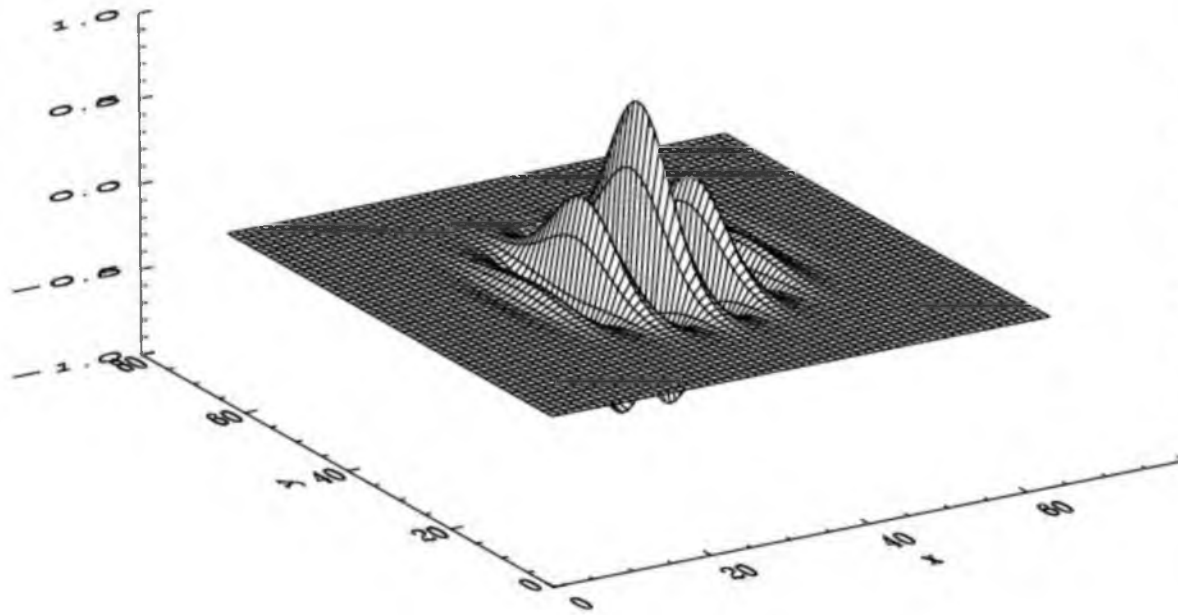
Complex Wavelet transform

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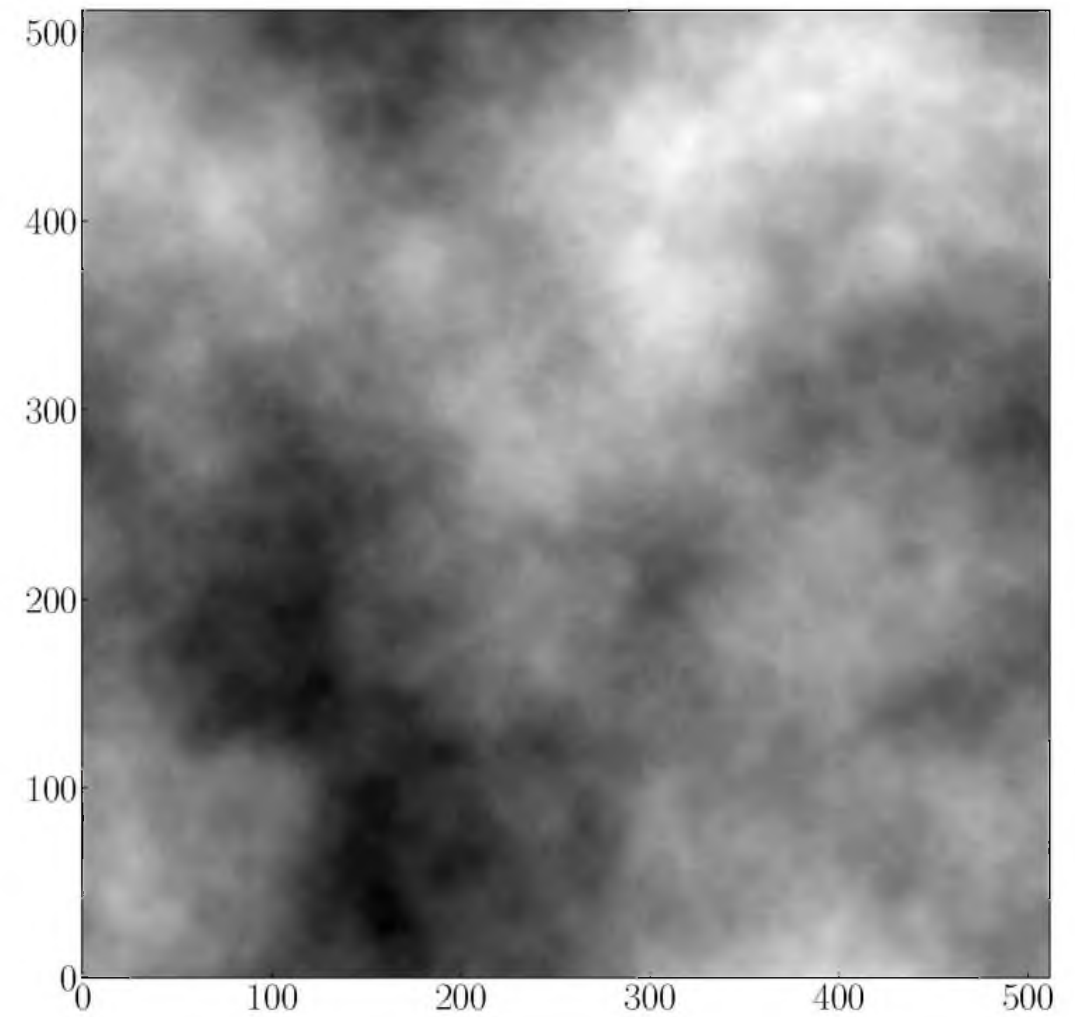
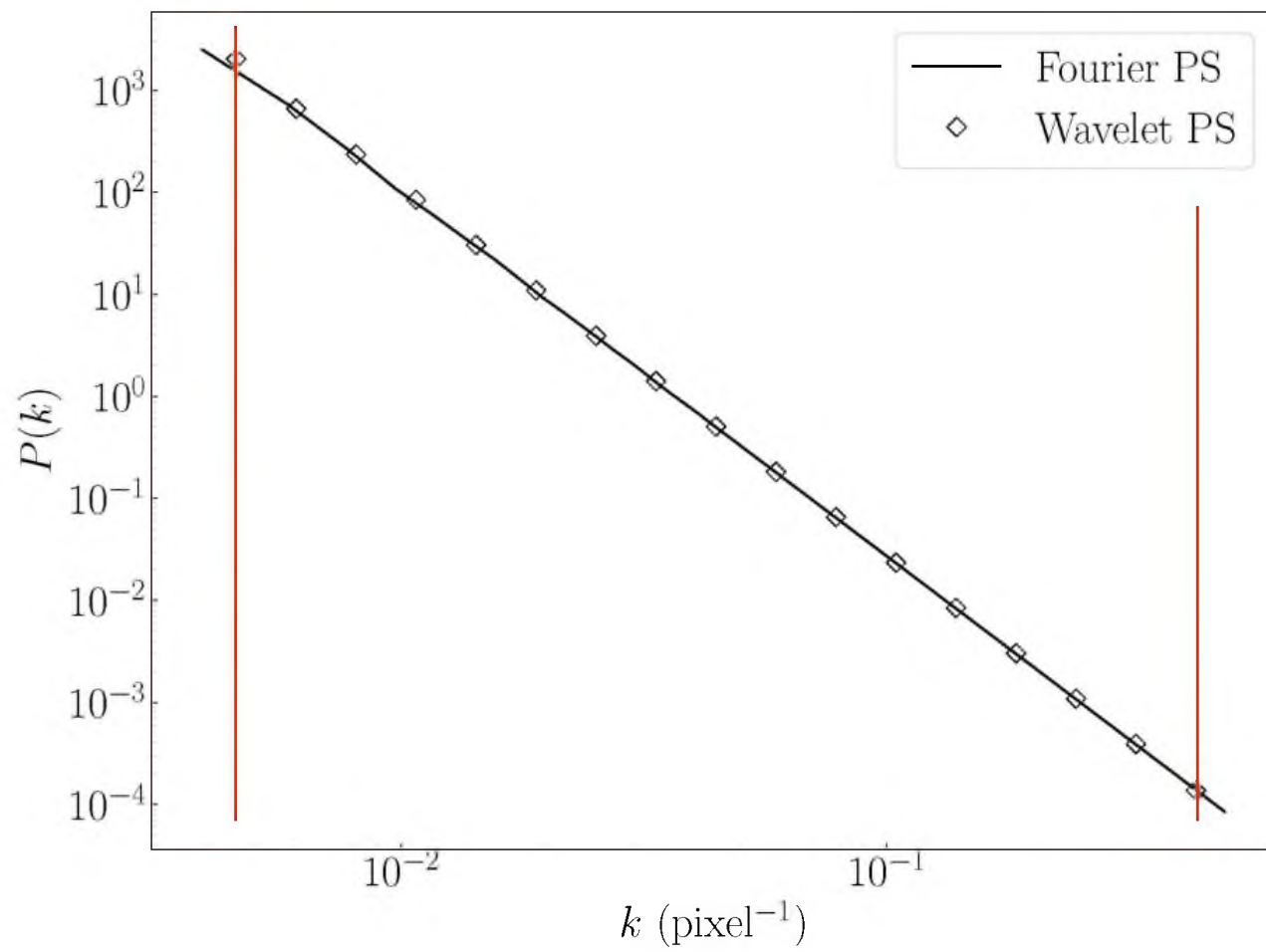
Morlet wavelet

X space (real part)

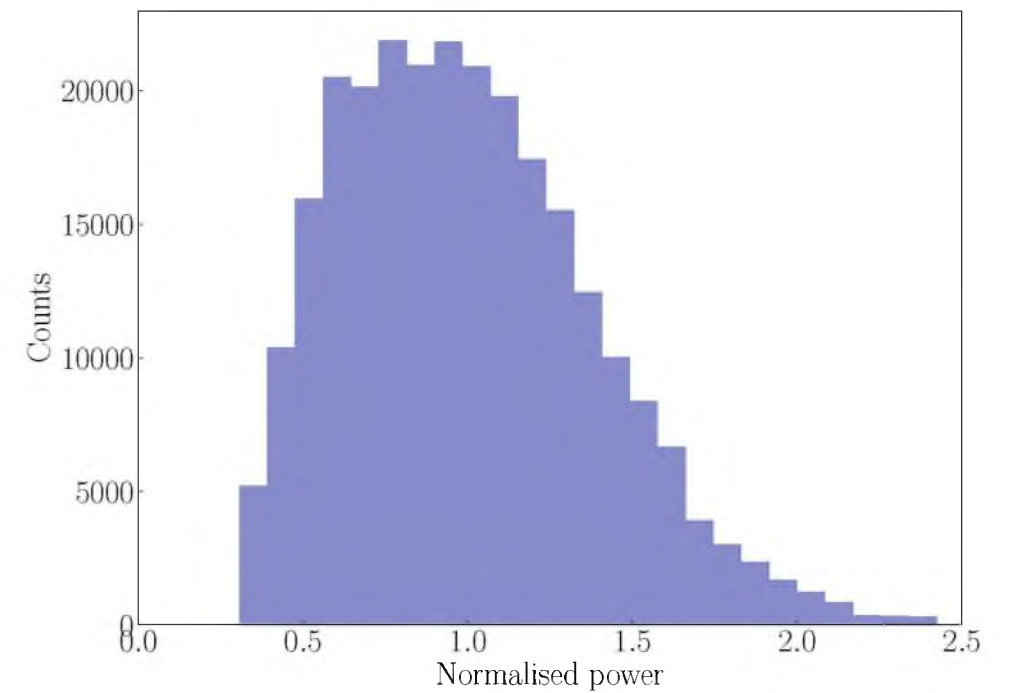
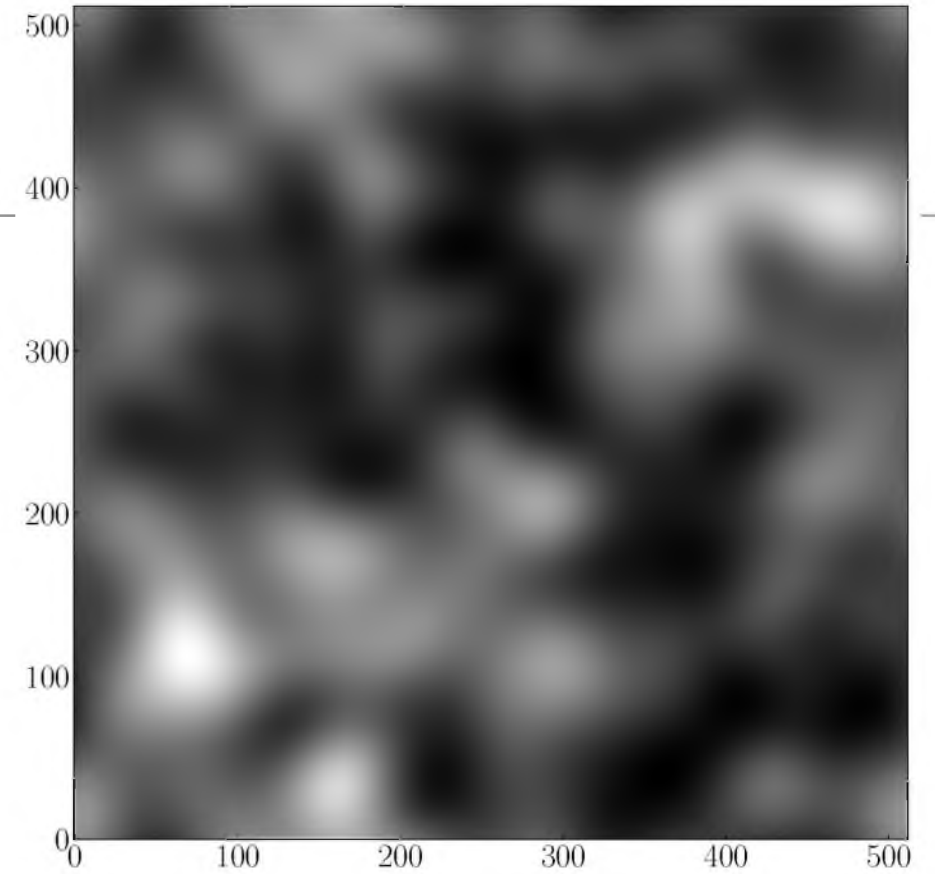
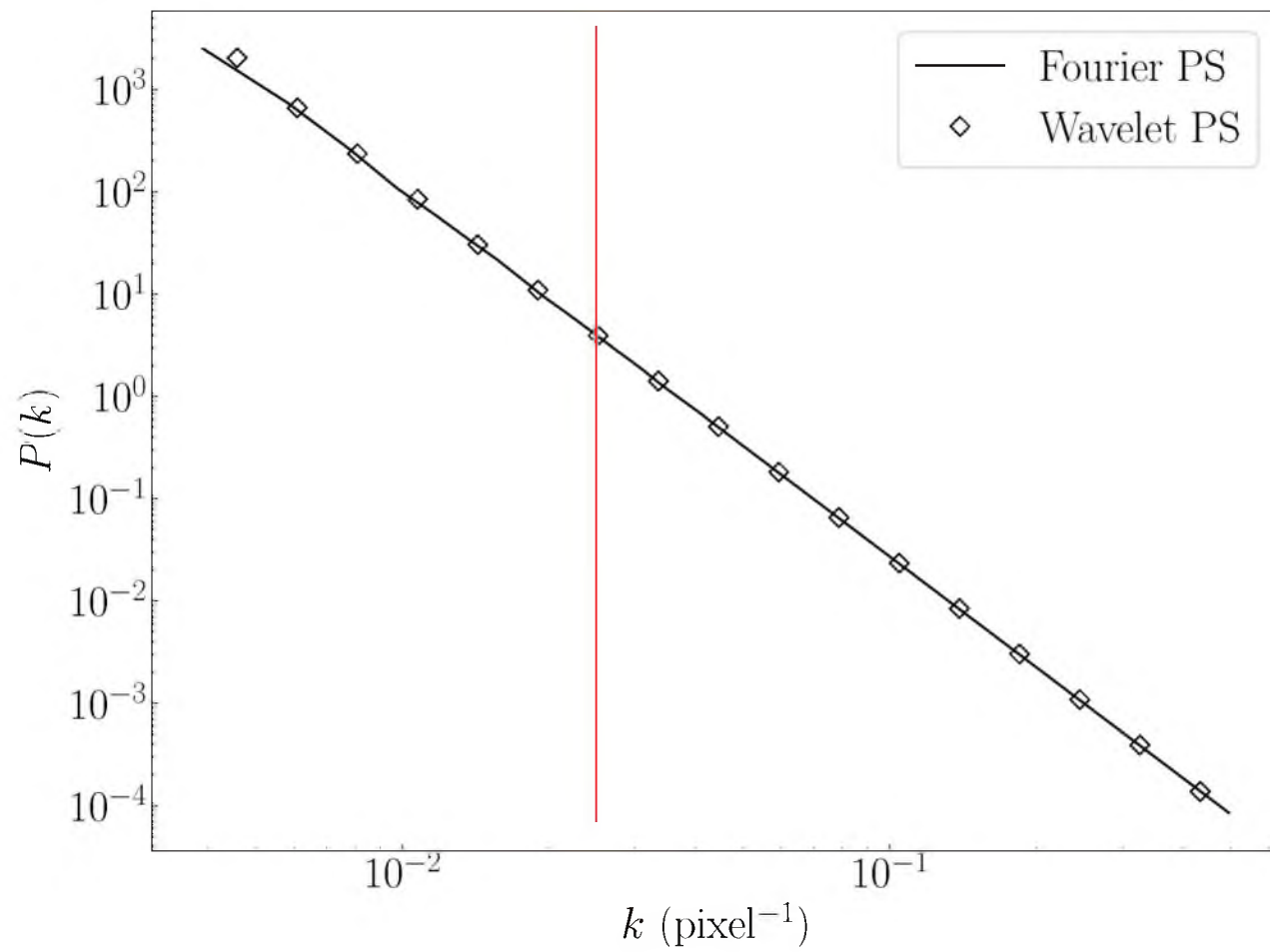
Fourier space



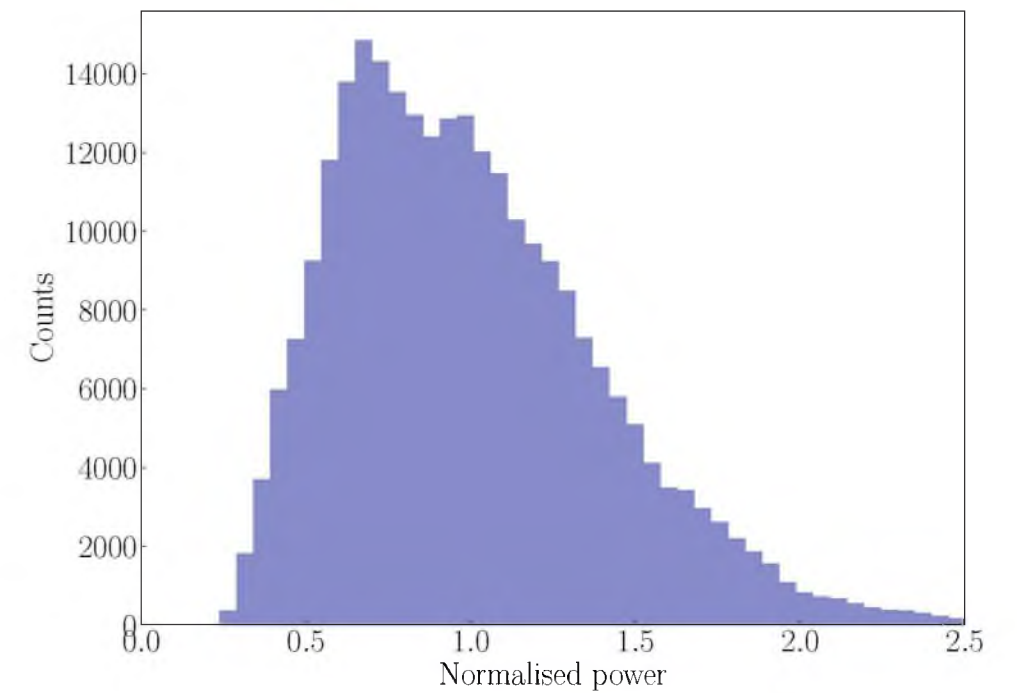
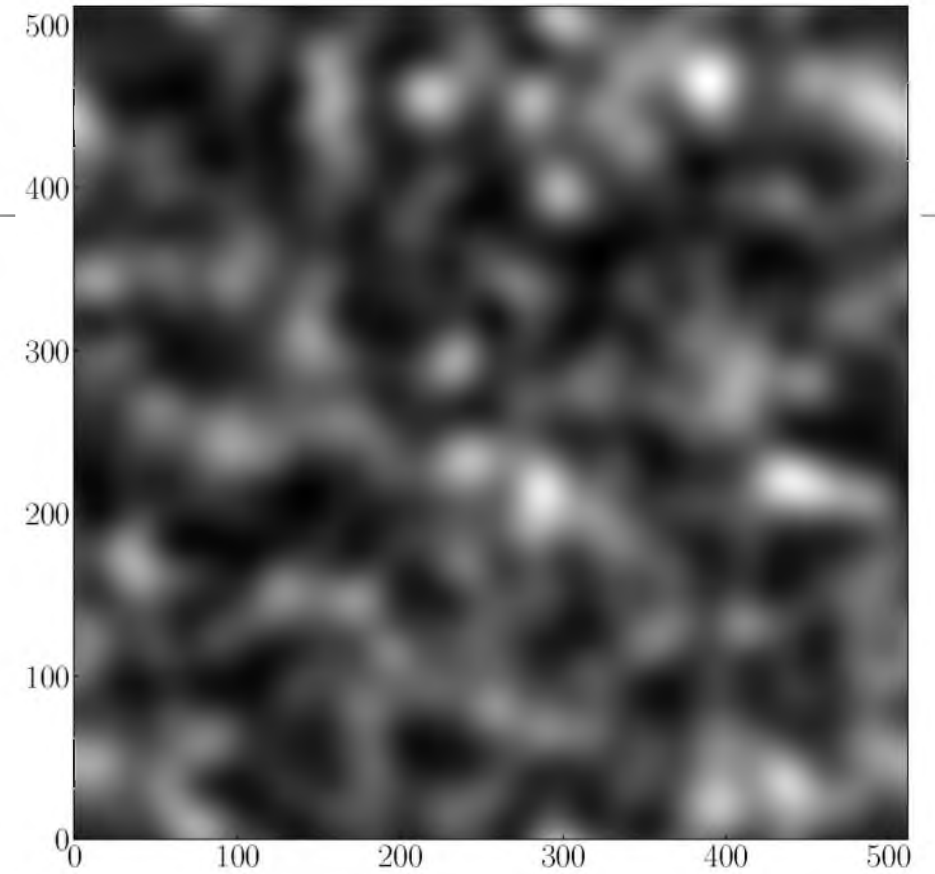
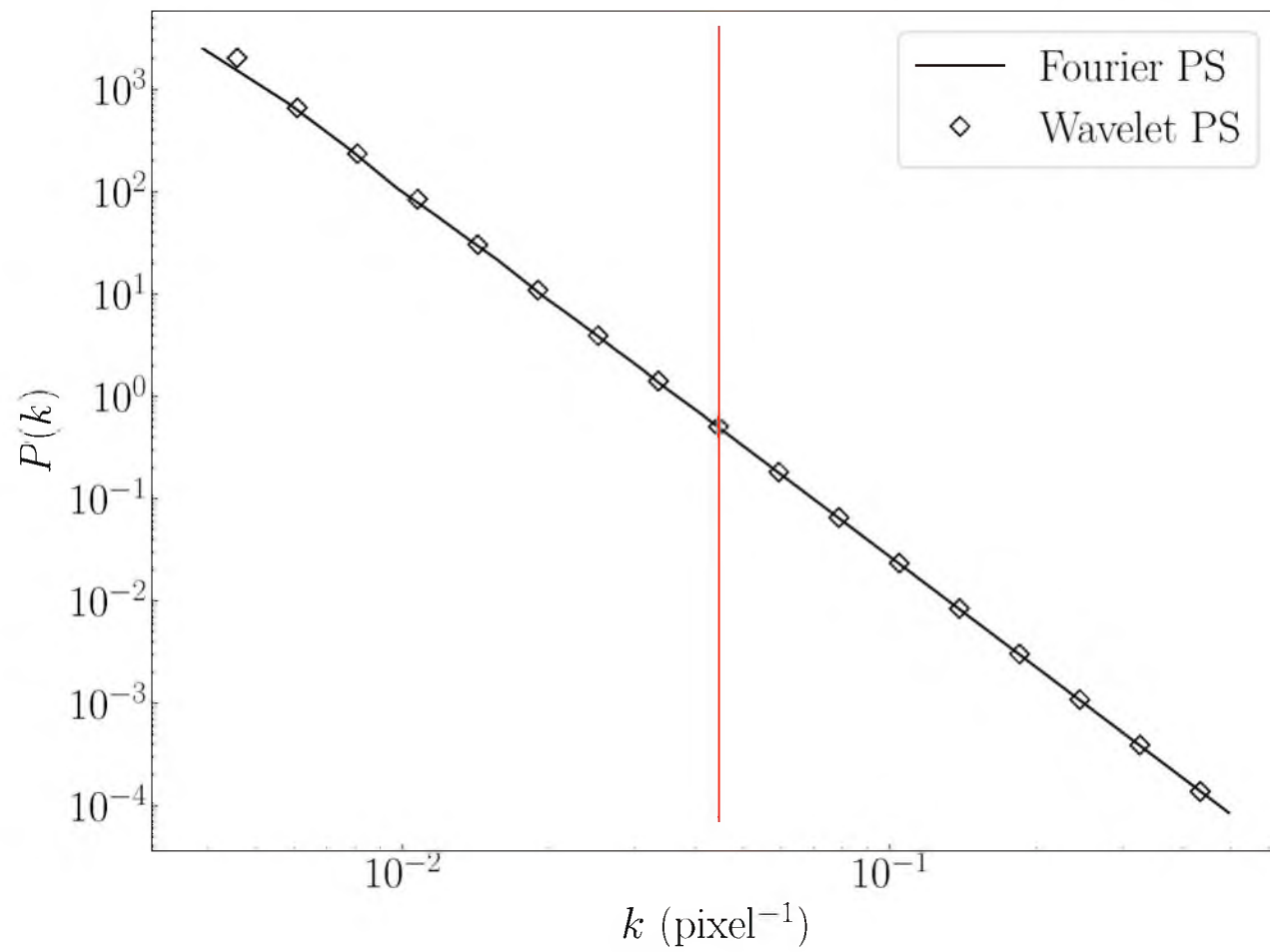
Self-similar distribution



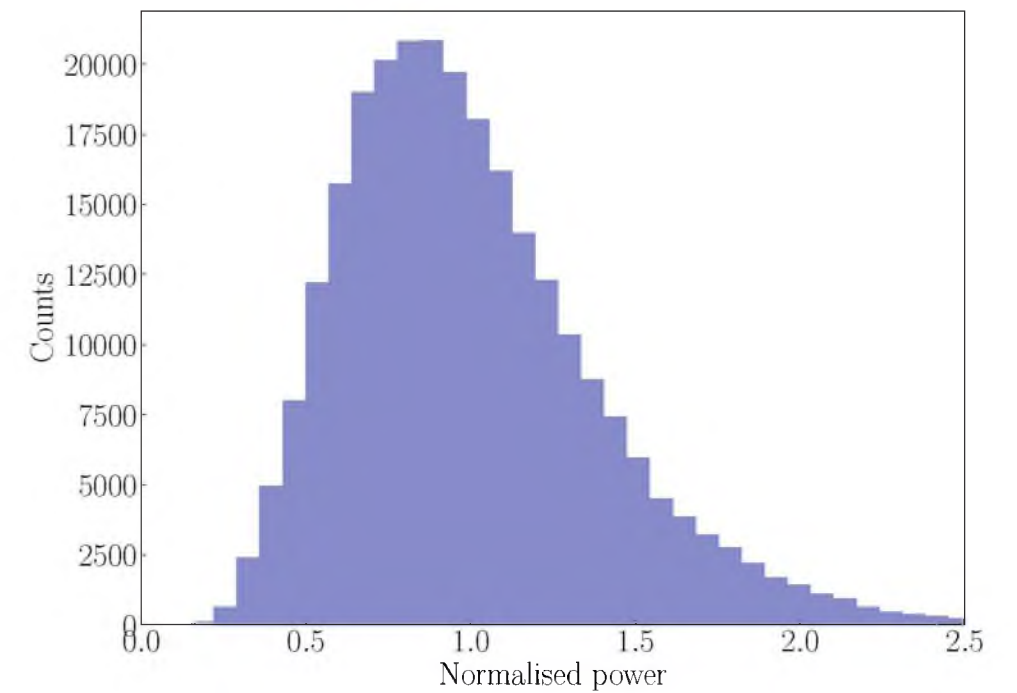
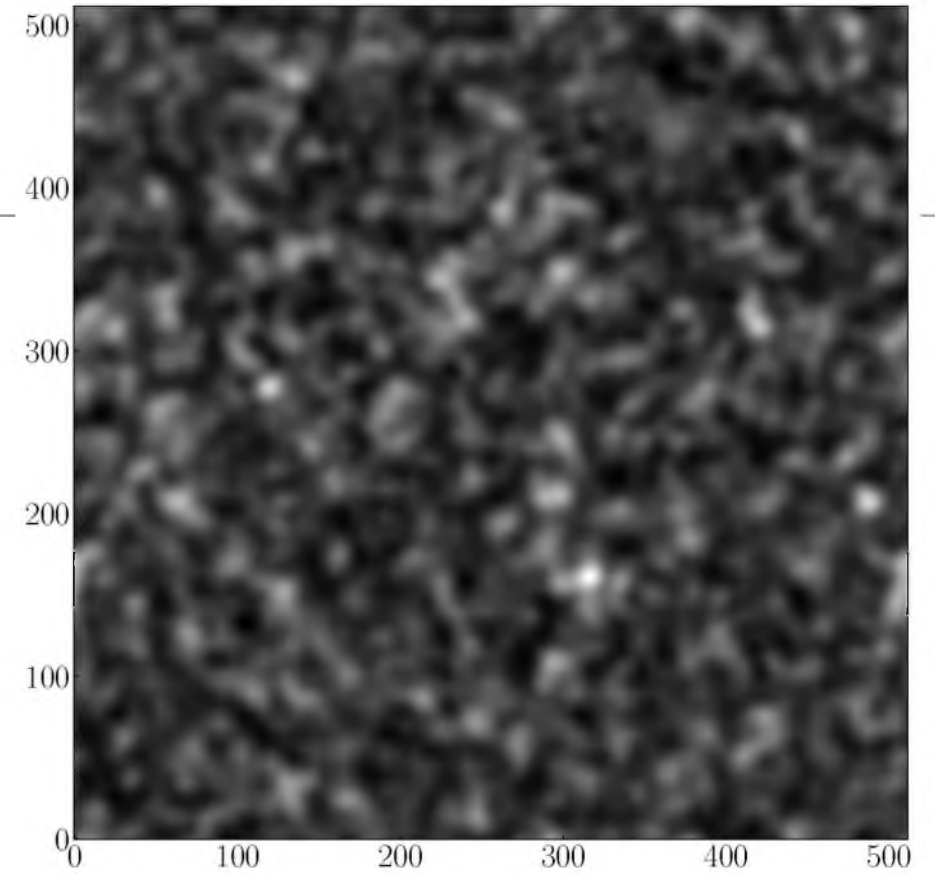
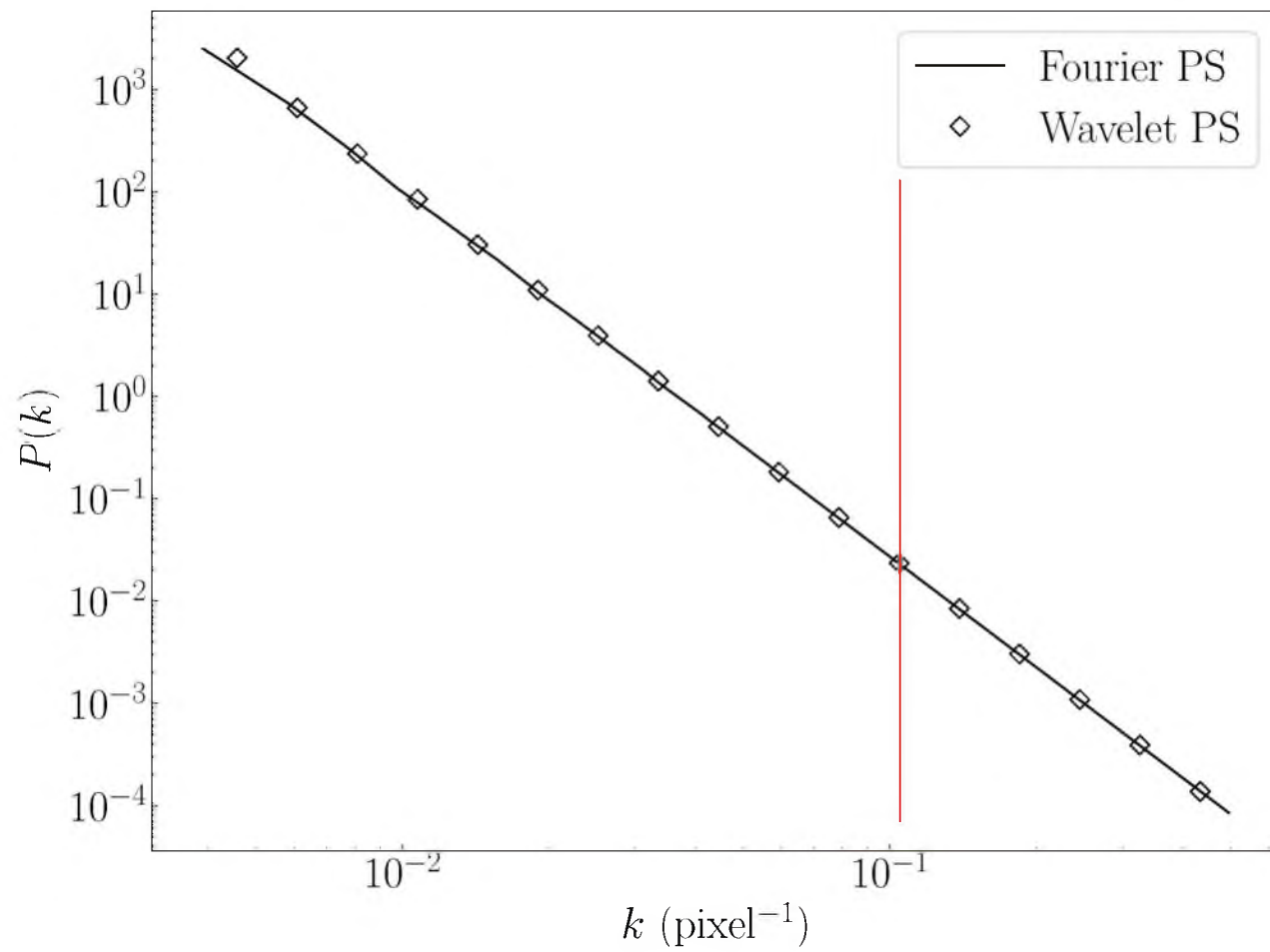
Self-similar distribution



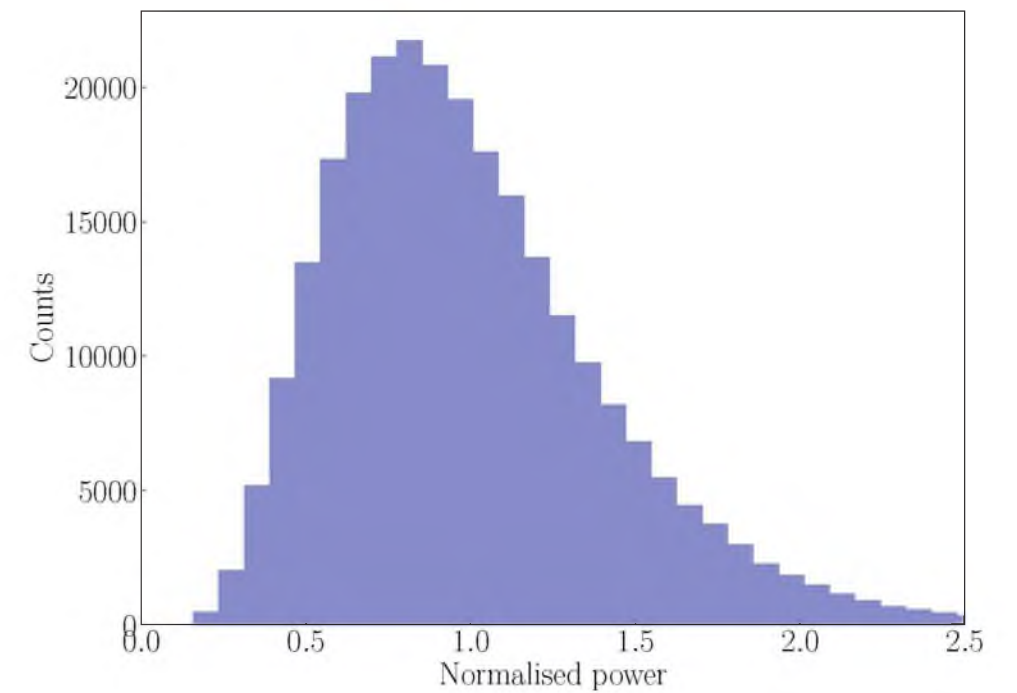
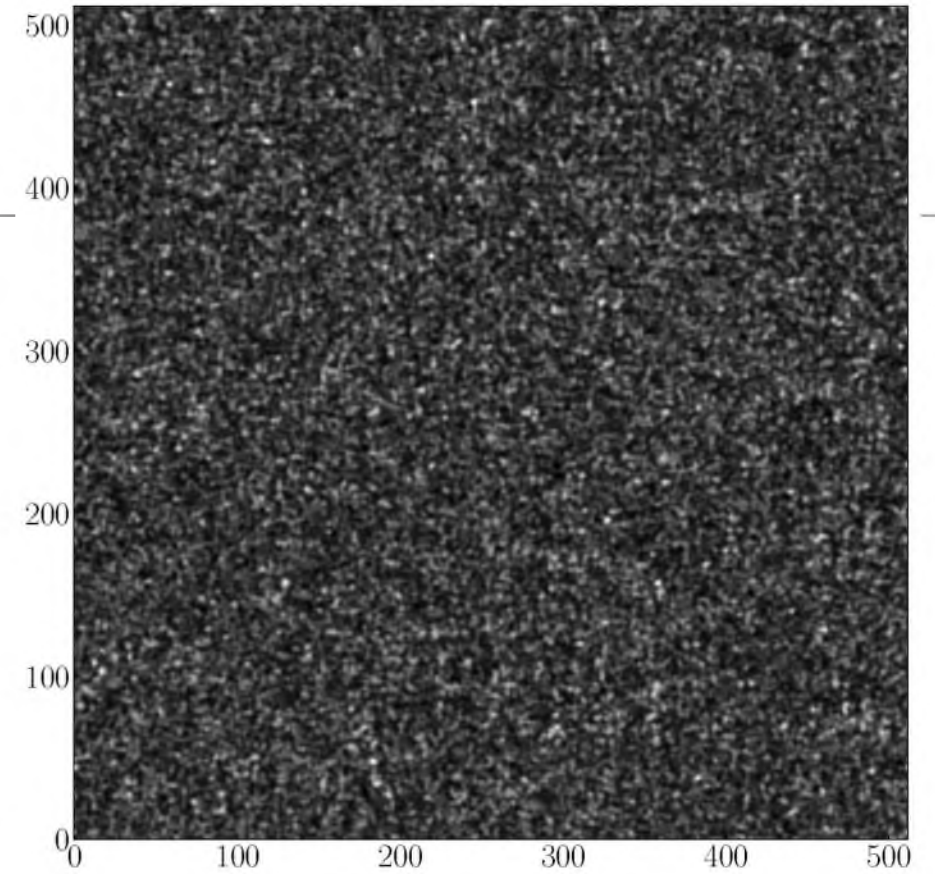
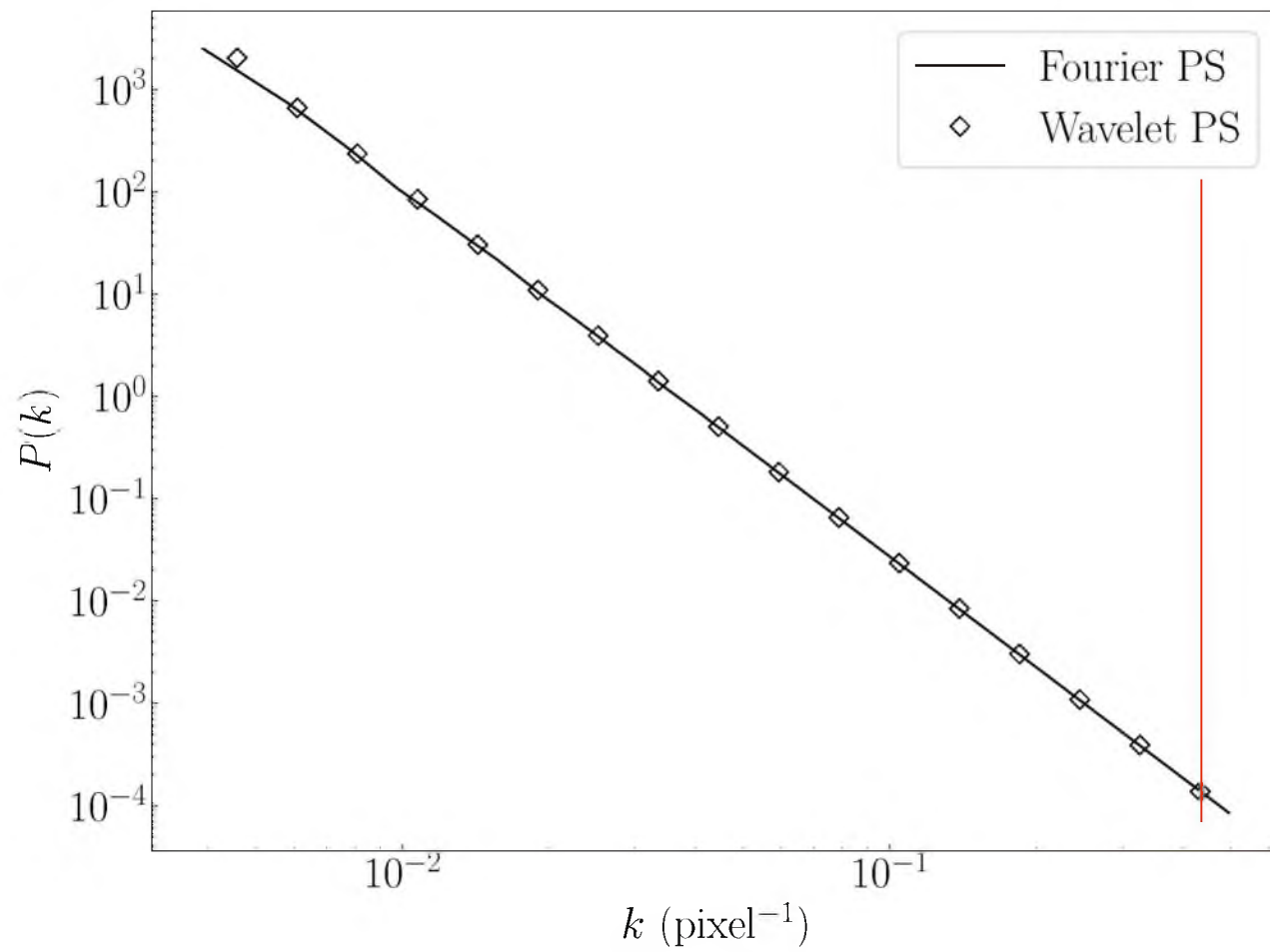
Self-similar distribution



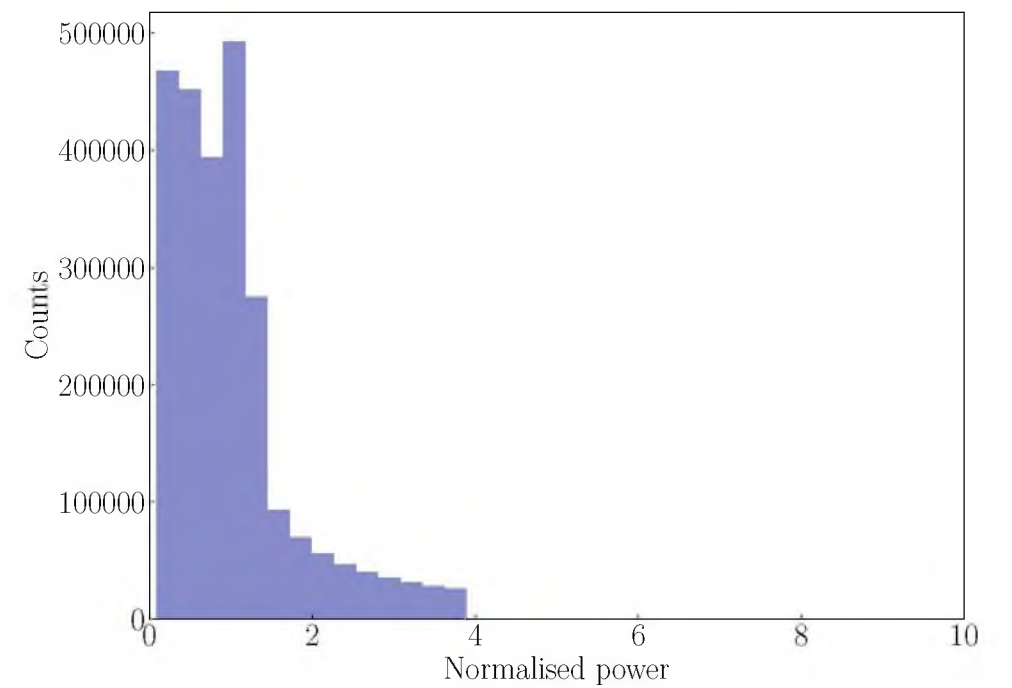
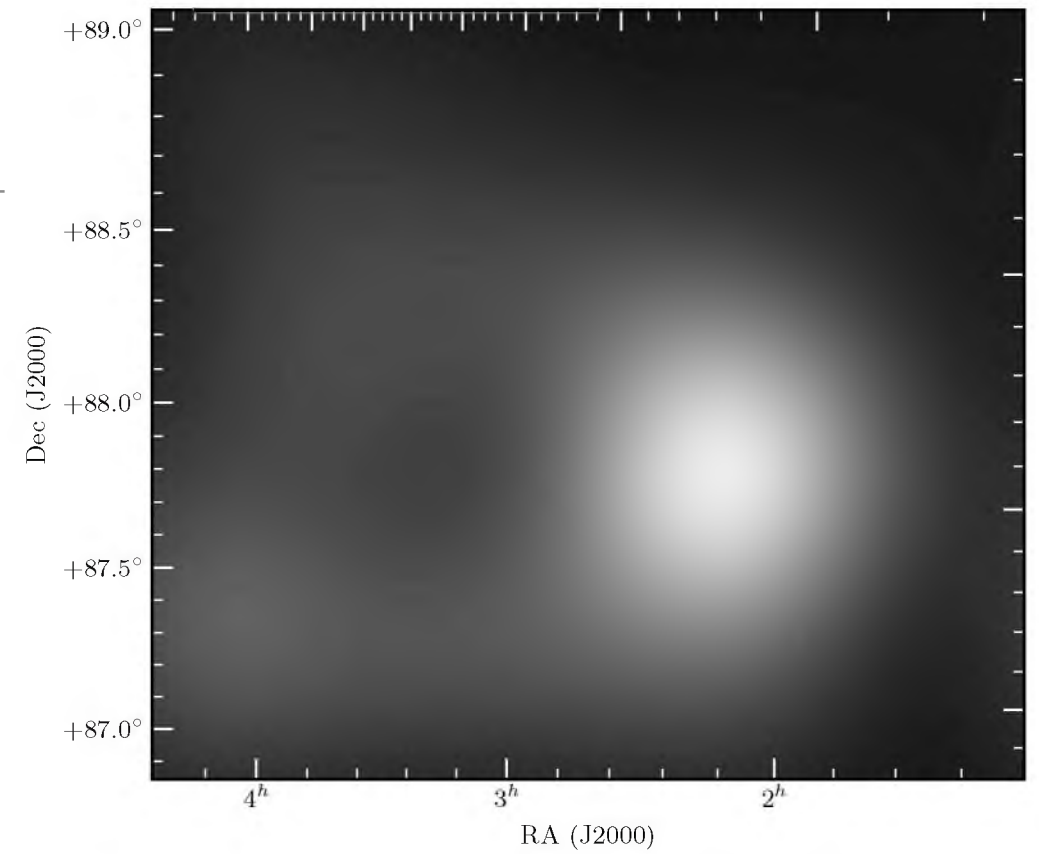
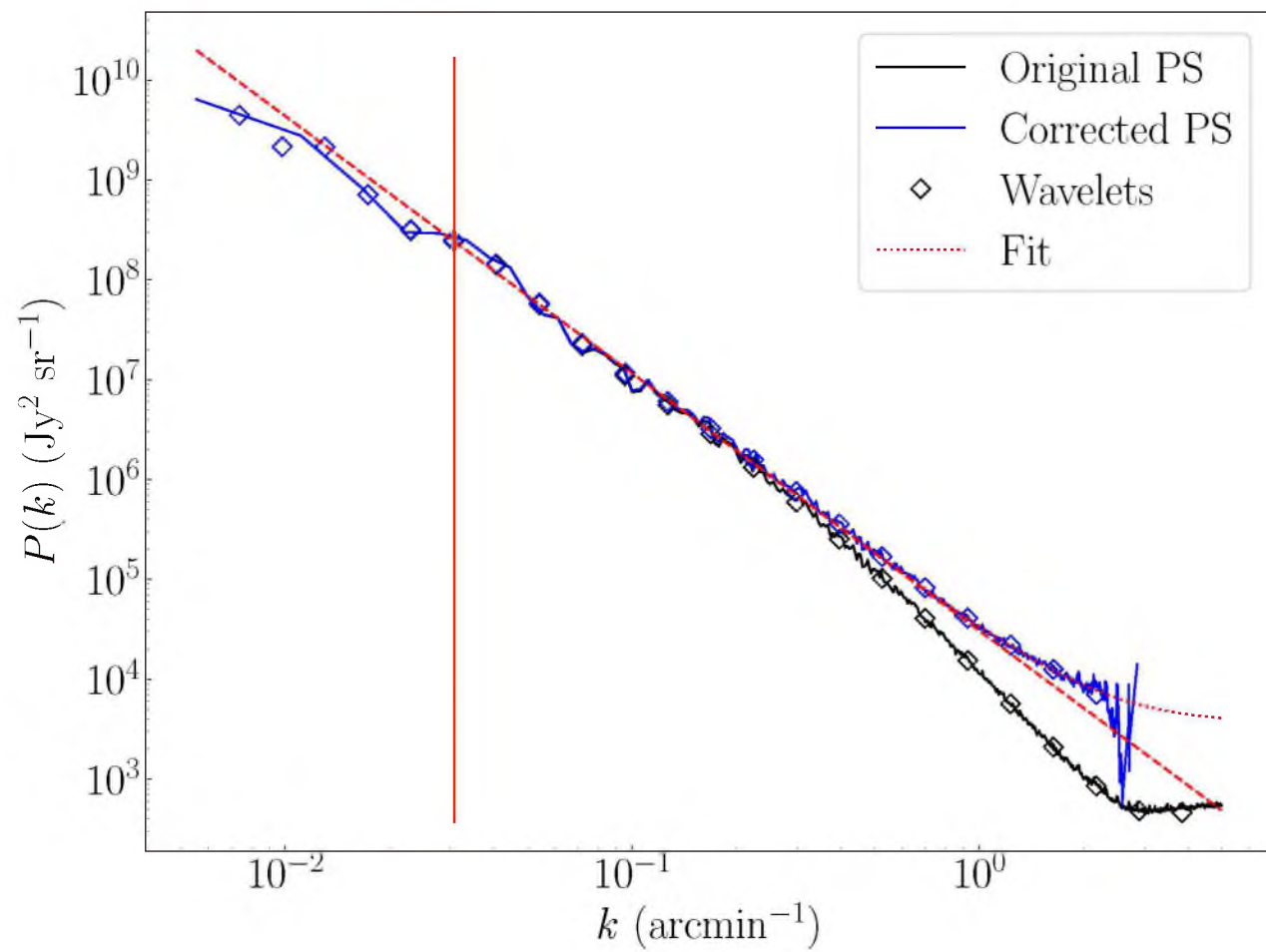
Self-similar distribution



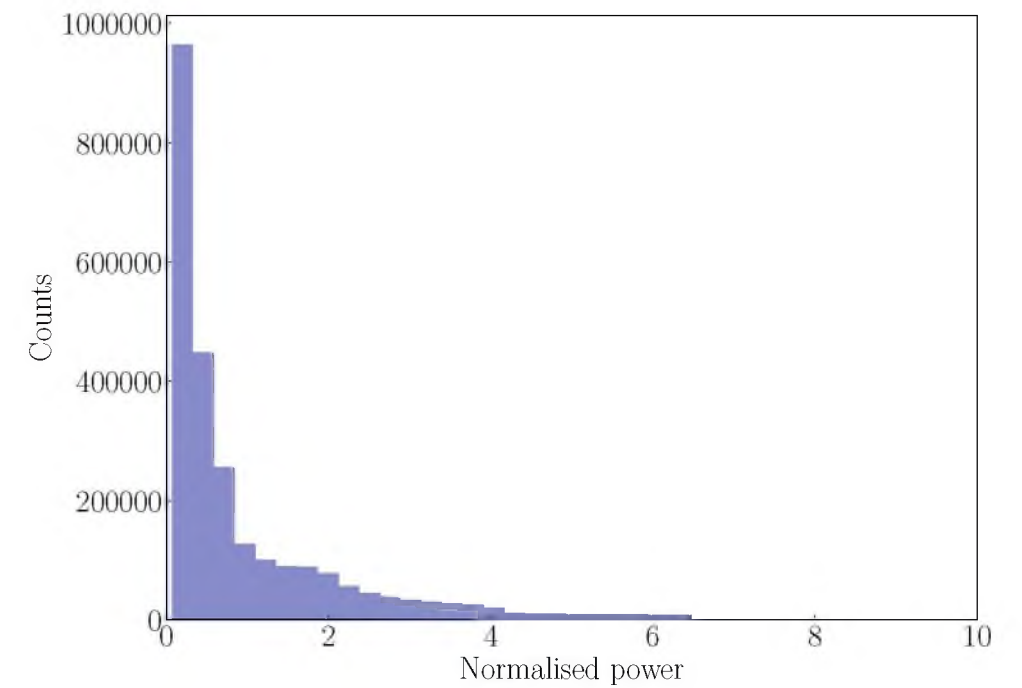
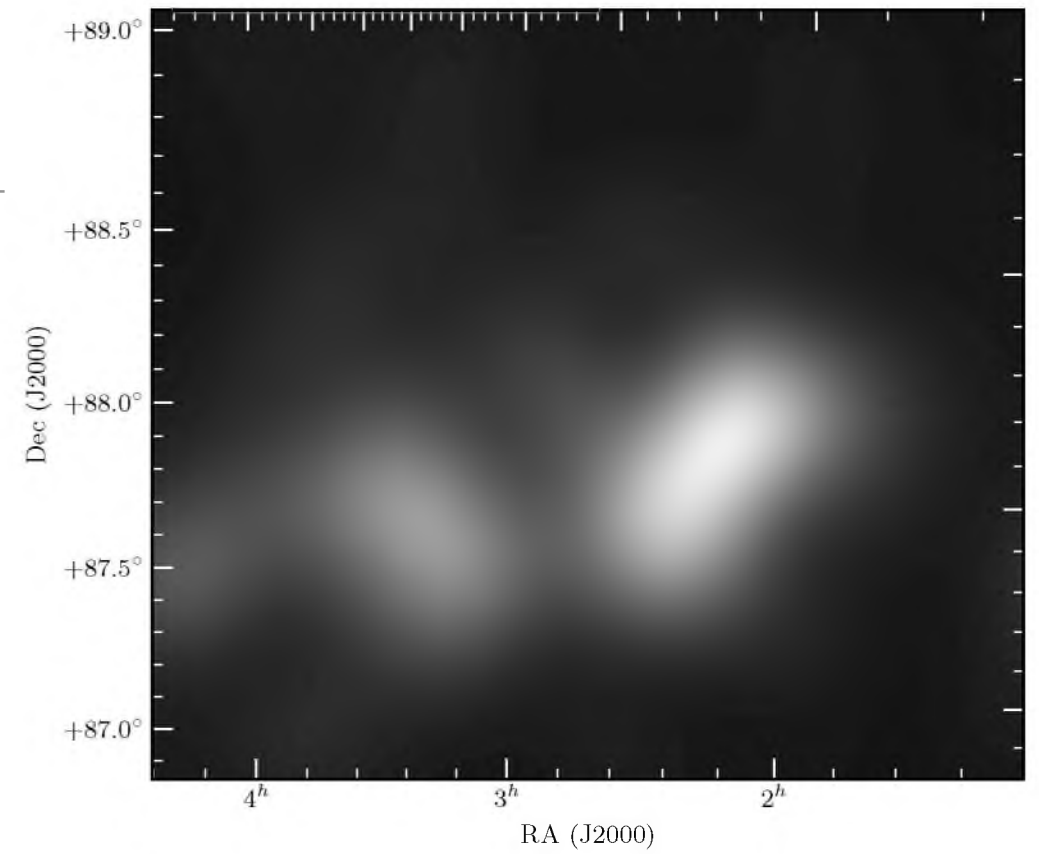
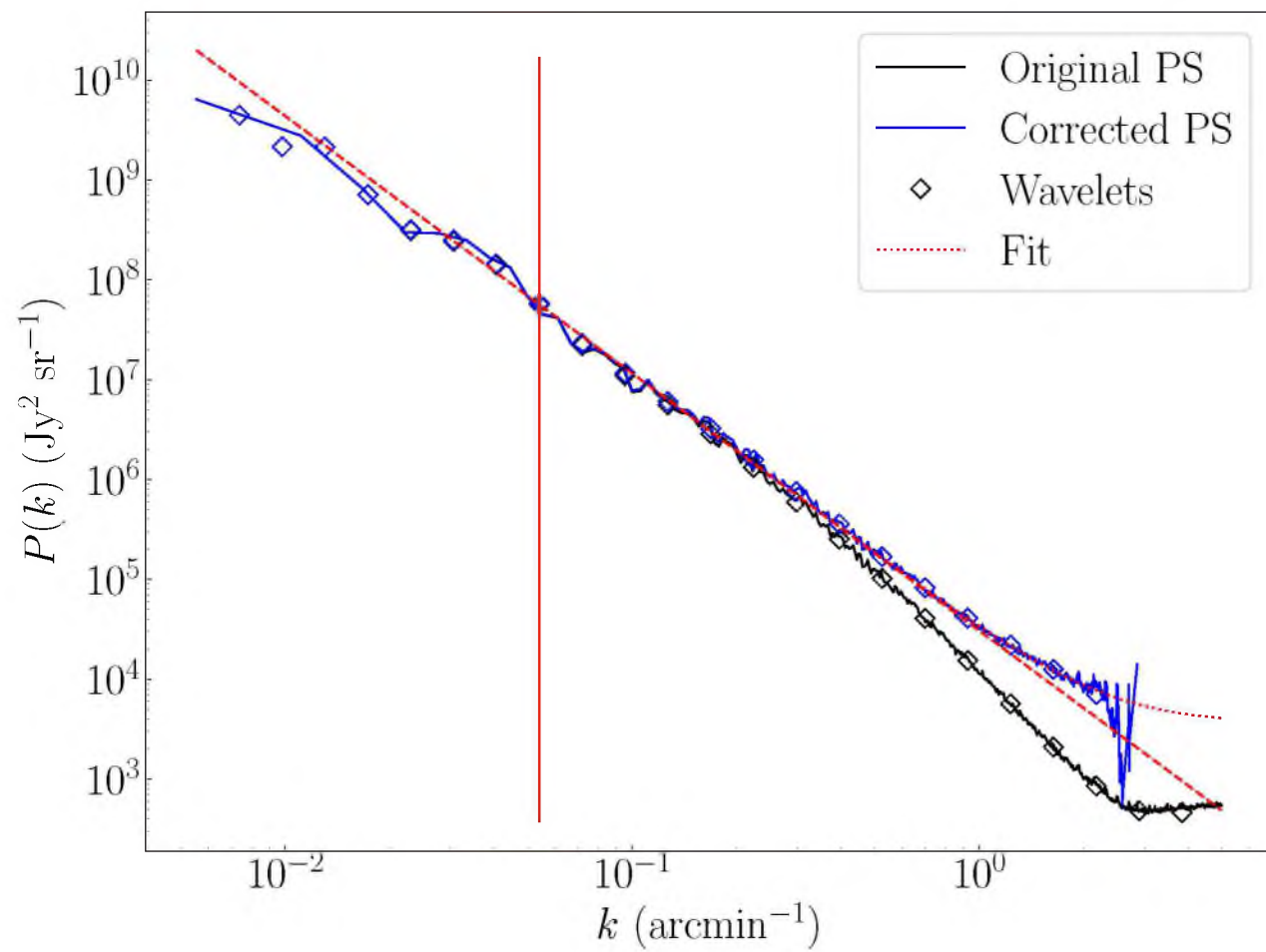
Self-similar distribution



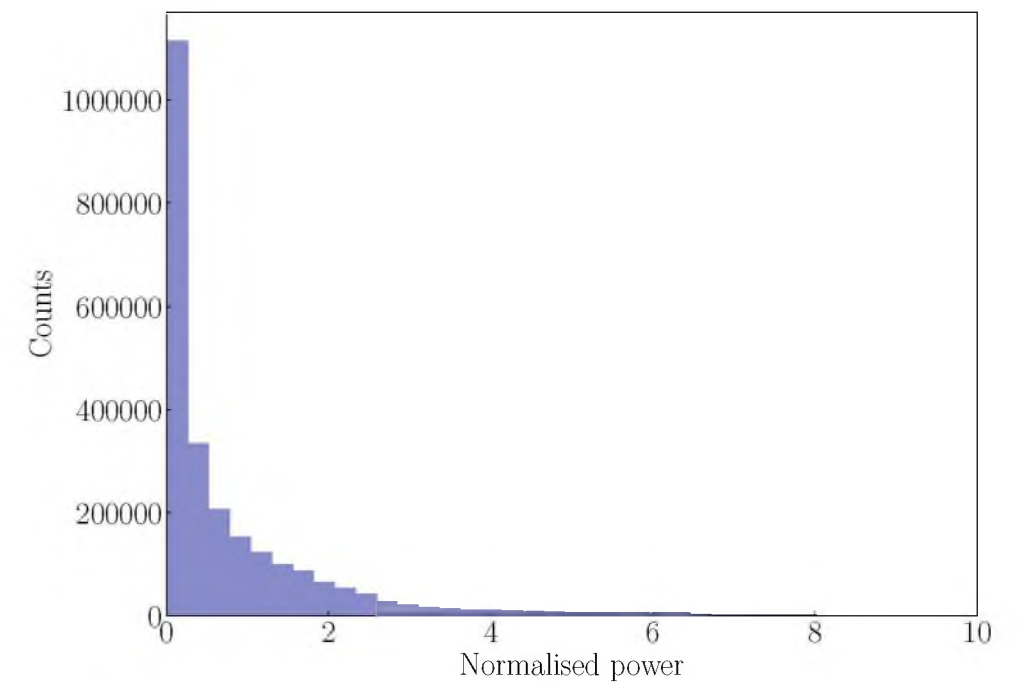
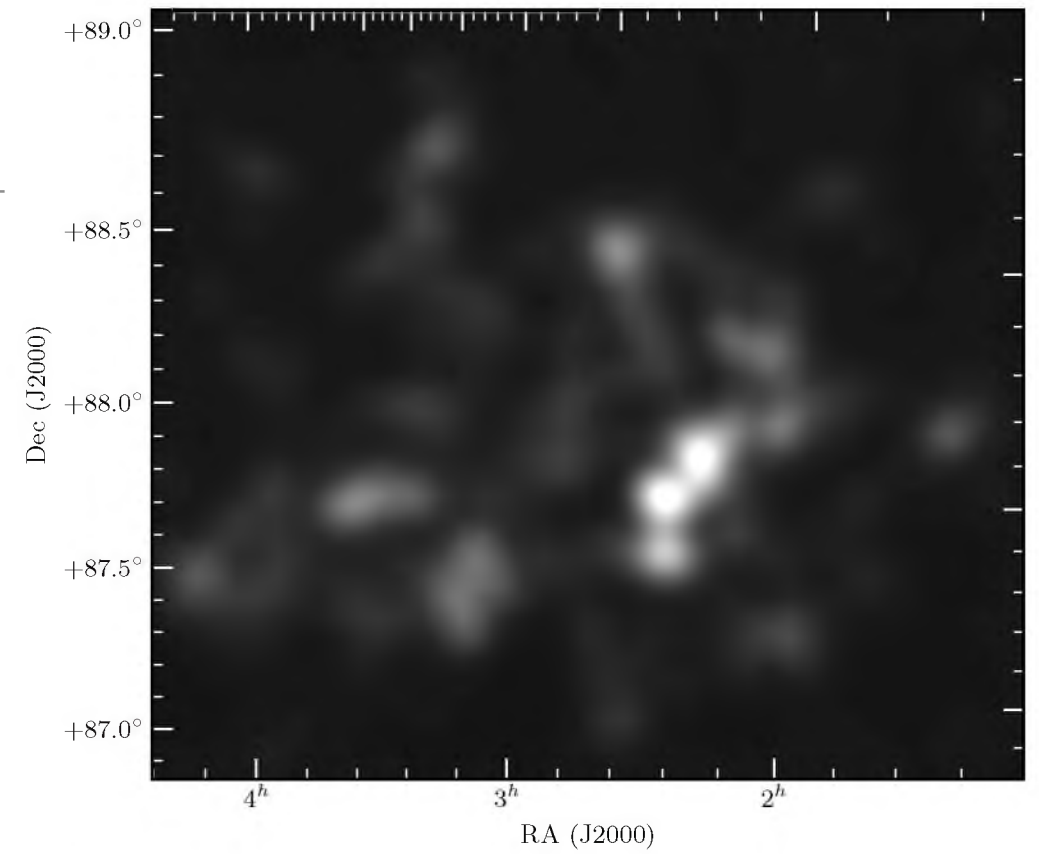
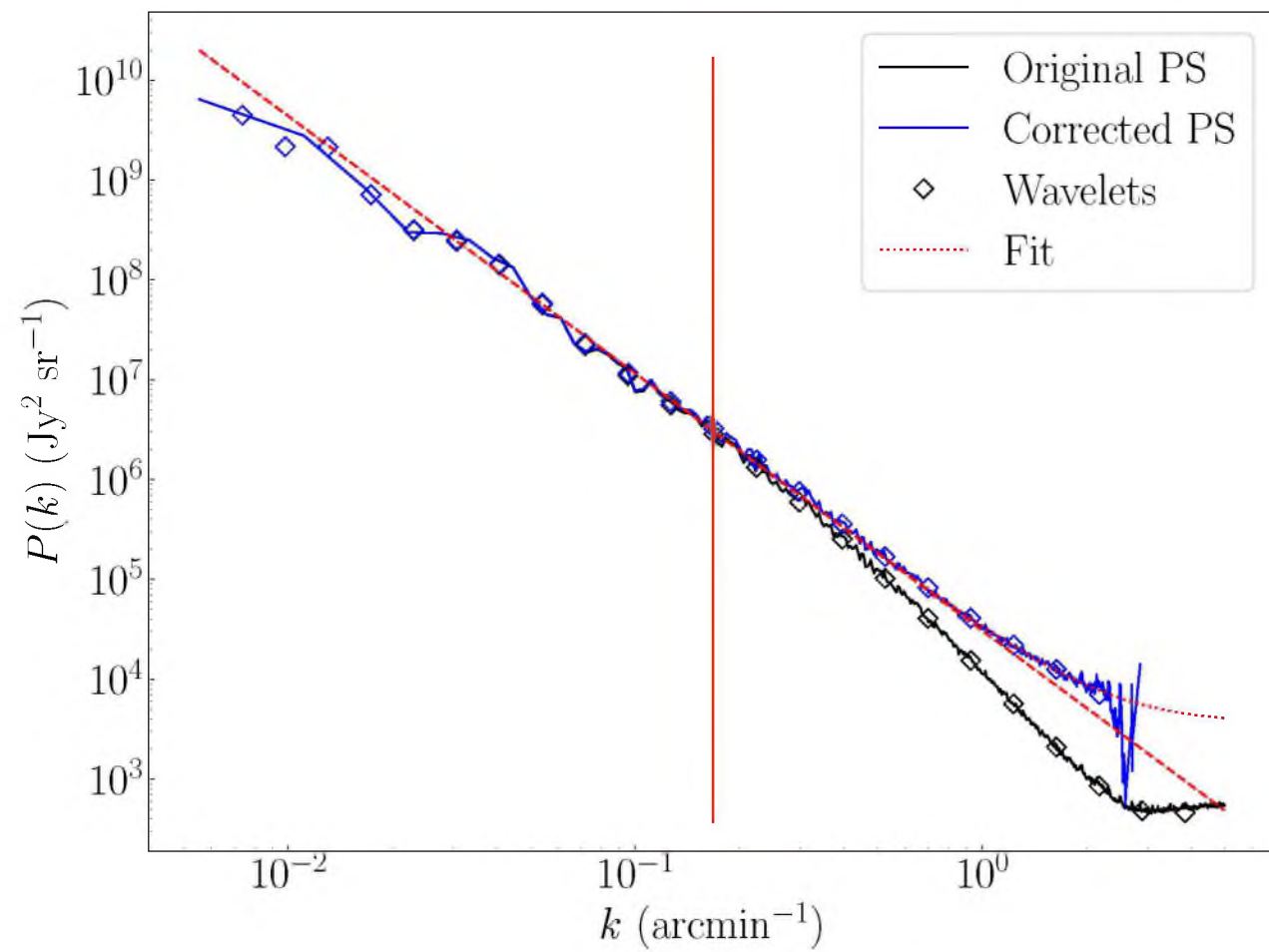
Polaris 250 μm



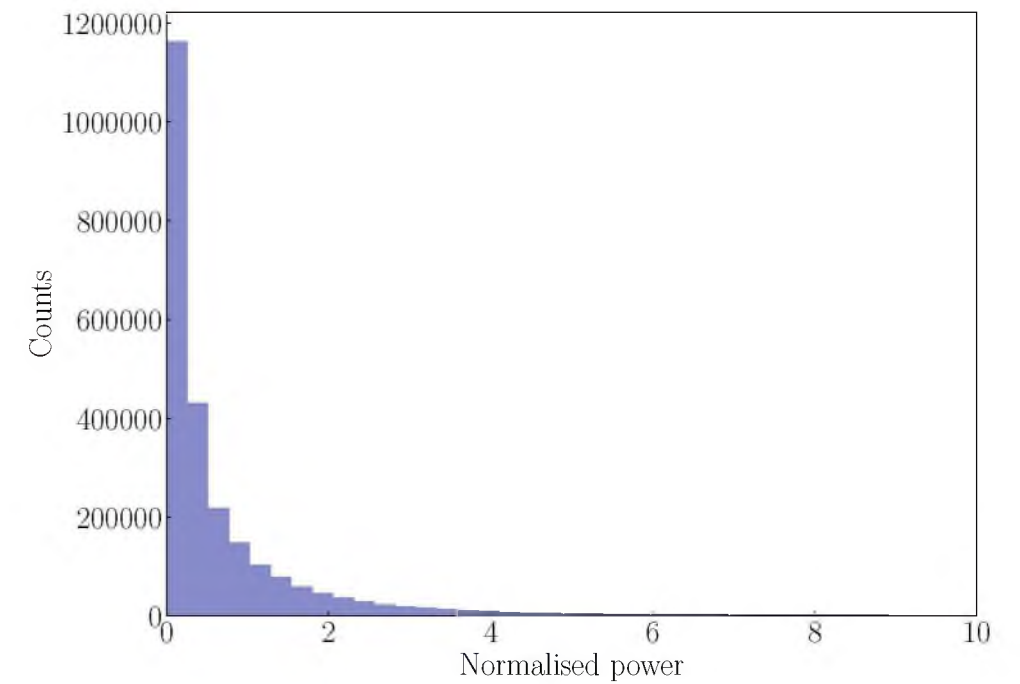
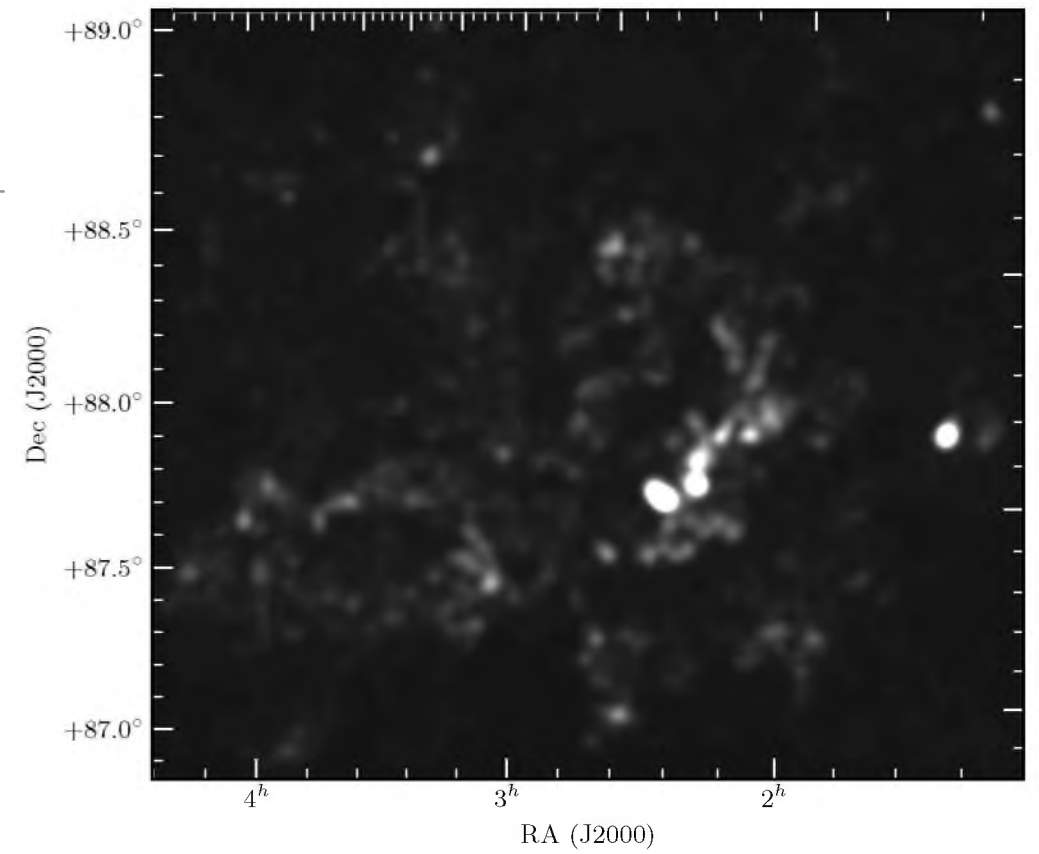
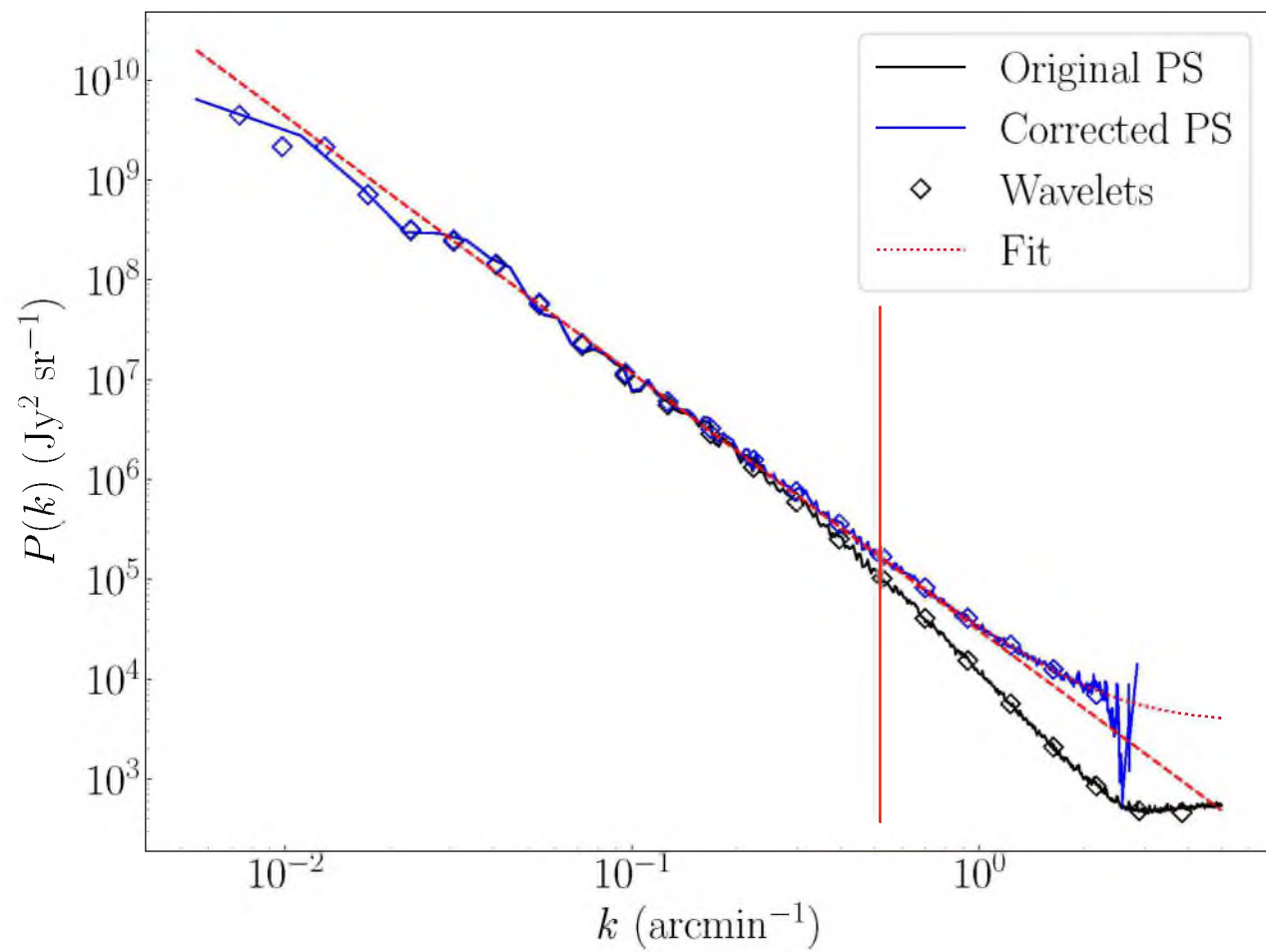
Polaris 250 μm



Polaris 250 μm



Polaris 250 μm



Multi-scale Non-Gaussian Segmentation

Multi-scale non-Gaussian segmentation (MnGSeg)

Denoising algorithm

Azzalini, A., Farge, M., & Schneider, K. 2005
Applied and Computational Harmonic Analysis, 18, 177

$$\sigma_{l,\theta}^2(\Phi) = \frac{1}{N_{l,\theta}(\Phi)} \sum_{\vec{x}} \mathbb{L}_{\Phi}(|\tilde{f}_{l,\theta}(\vec{x})|) |\tilde{f}_{l,\theta}(\vec{x})|^2$$

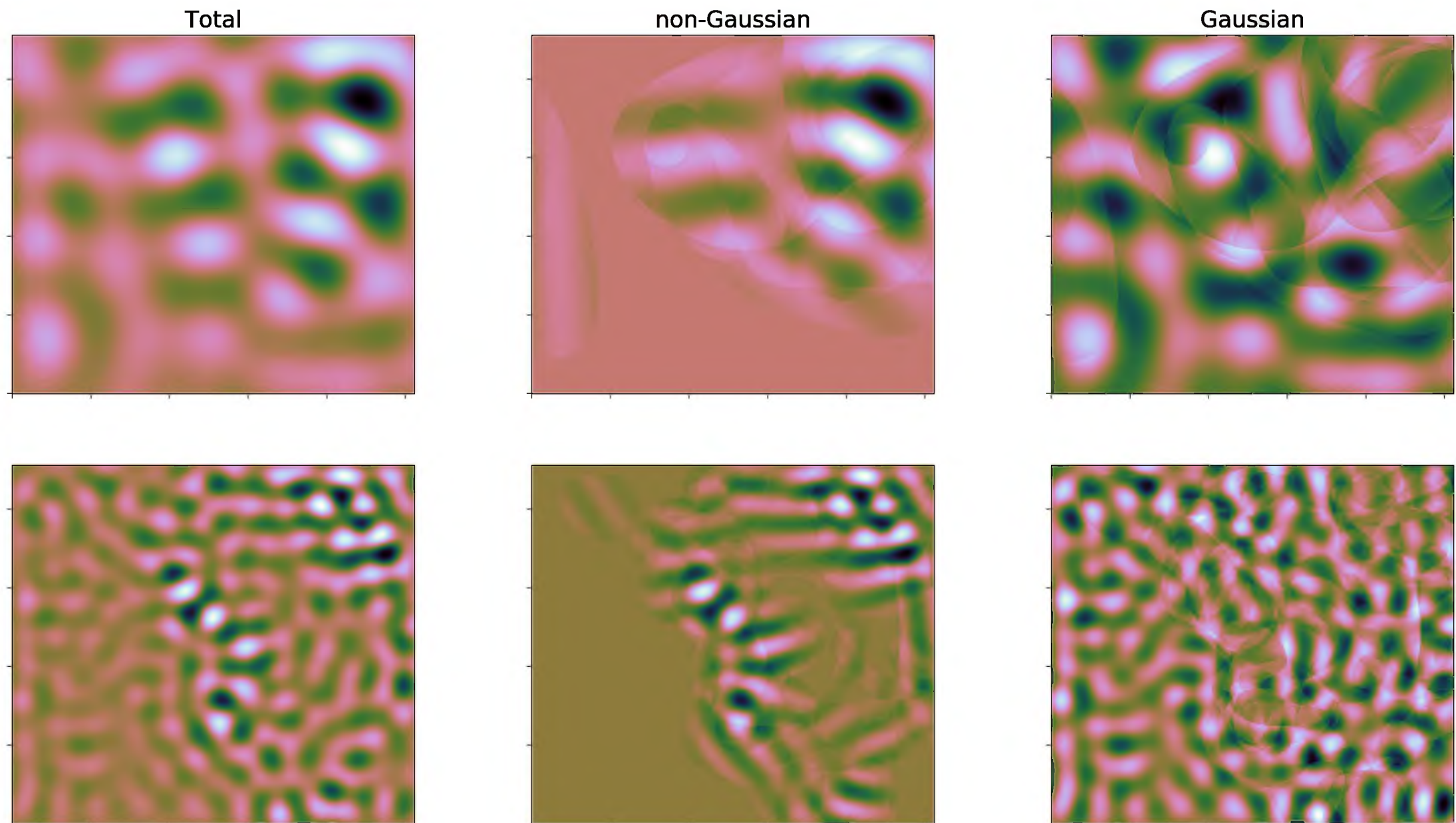
$$\mathbb{L}_{\Phi}(|\tilde{f}_{l,\theta}(\vec{x})|) = \begin{cases} 1 & \text{if } |\tilde{f}_{l,\theta}(\vec{x})| < \Phi \\ 0 & \text{else.} \end{cases}$$

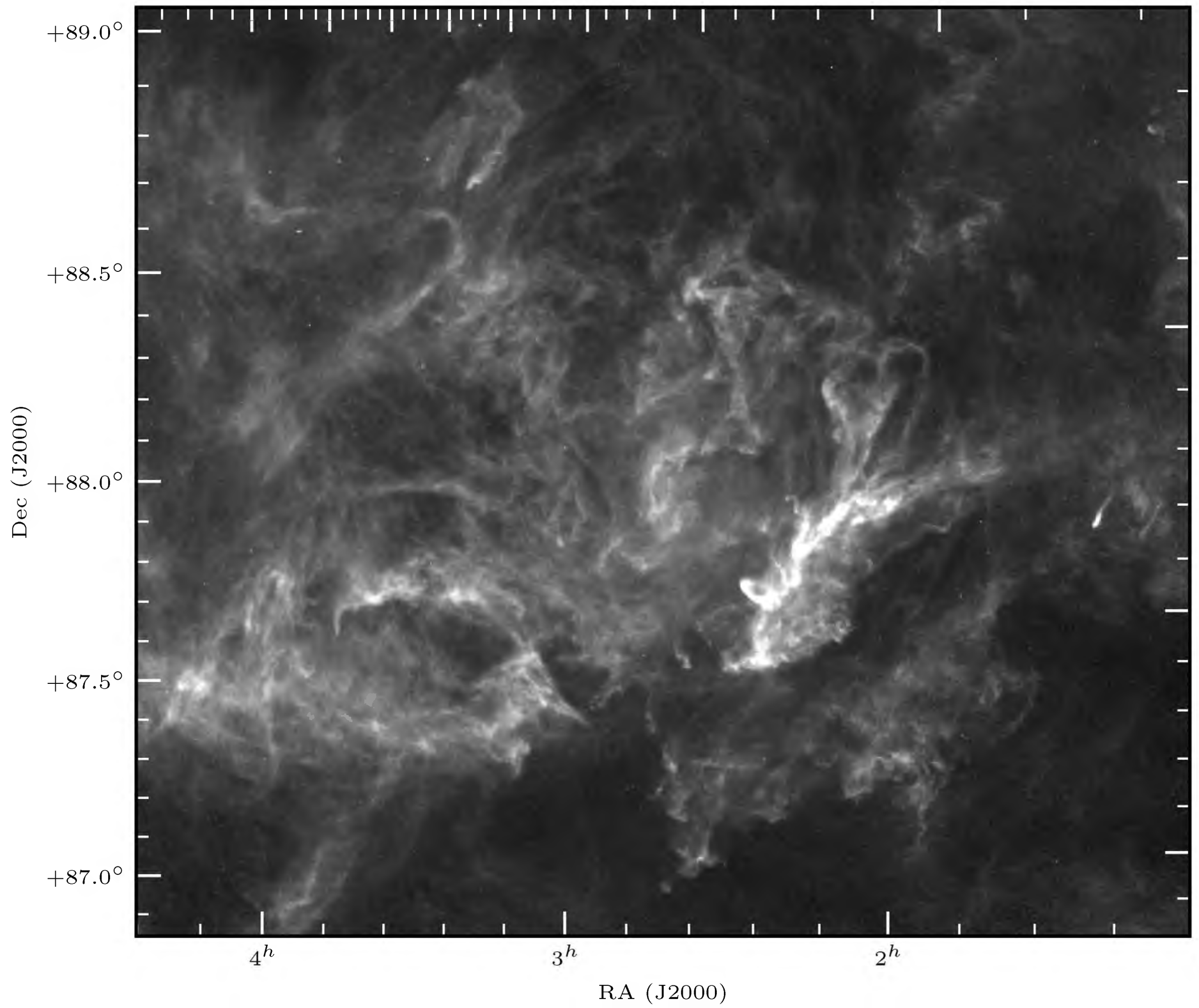
$$N_{l,\theta}(\Phi) = \sum_{\vec{x}} \mathbb{L}_{\Phi}(|\tilde{f}_{l,\theta}(\vec{x})|)$$

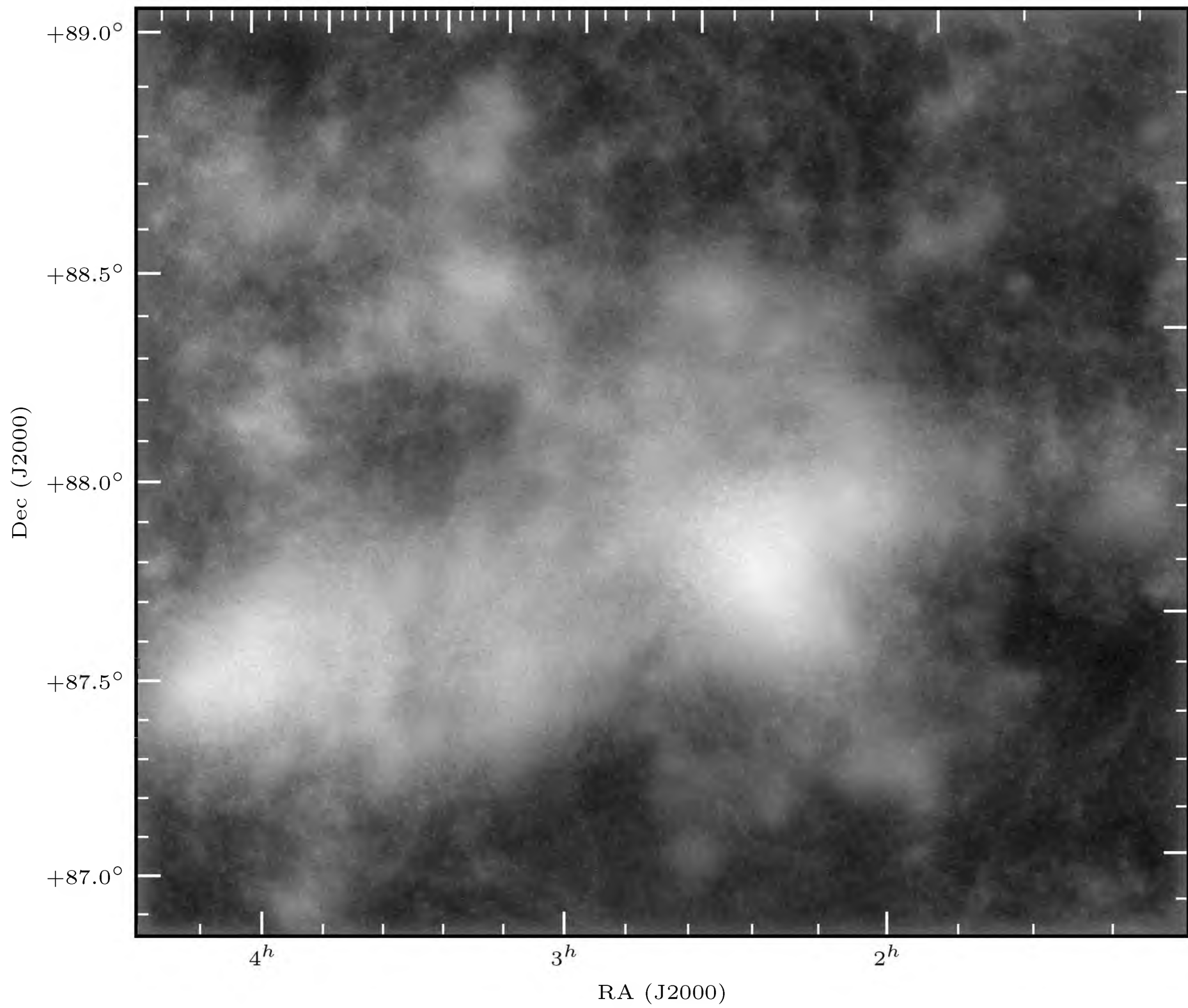
$$\begin{cases} \Phi_0(l, \theta) = \infty \\ \Phi_{n+1}(l, \theta) = q\sigma_{l,\theta}(\Phi_n(l, \theta)), \end{cases}$$

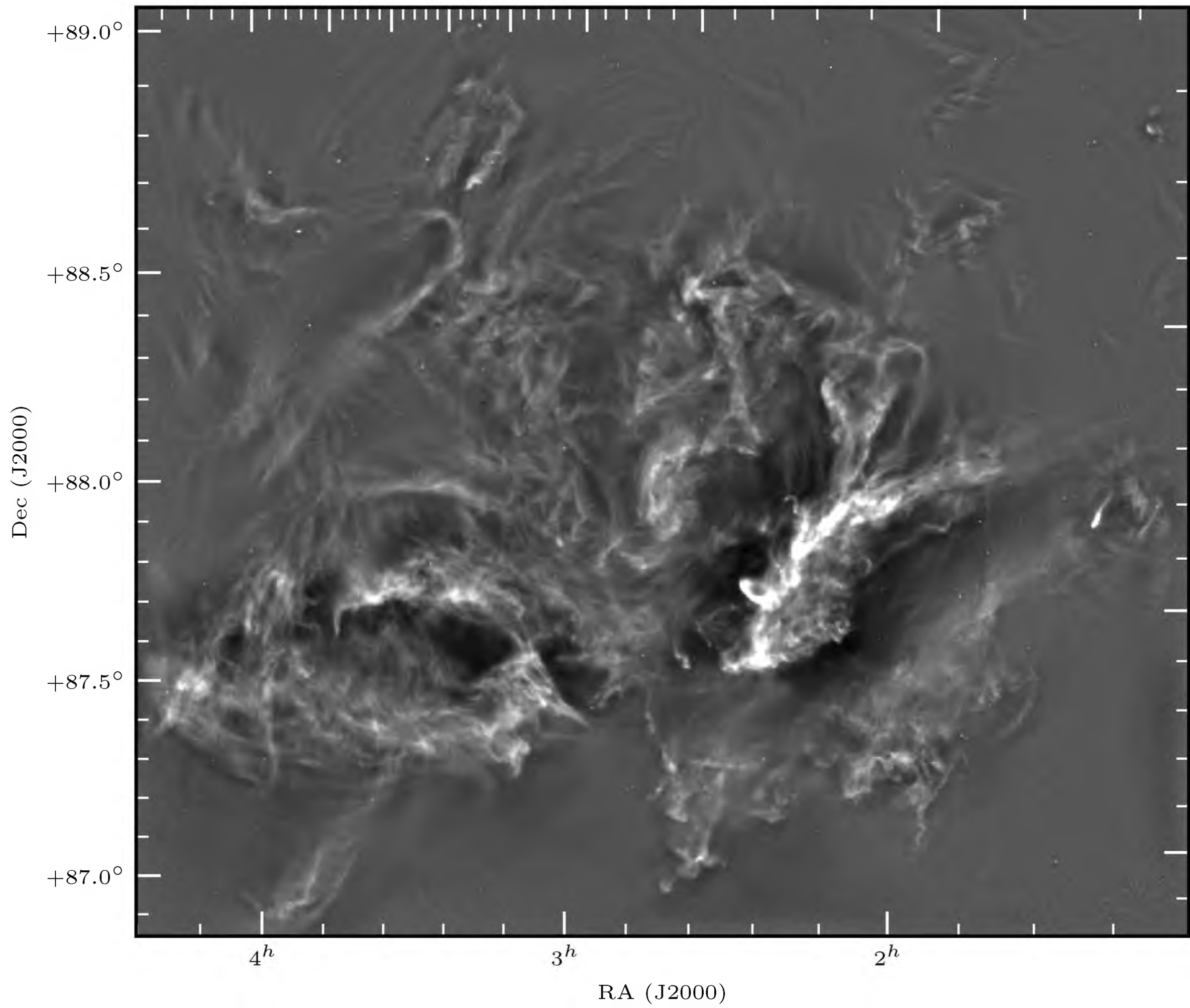
Multi-scale non-Gaussian segmentation (MnGSeg)

Apply an iterative algorithm as a function of scales and angles.



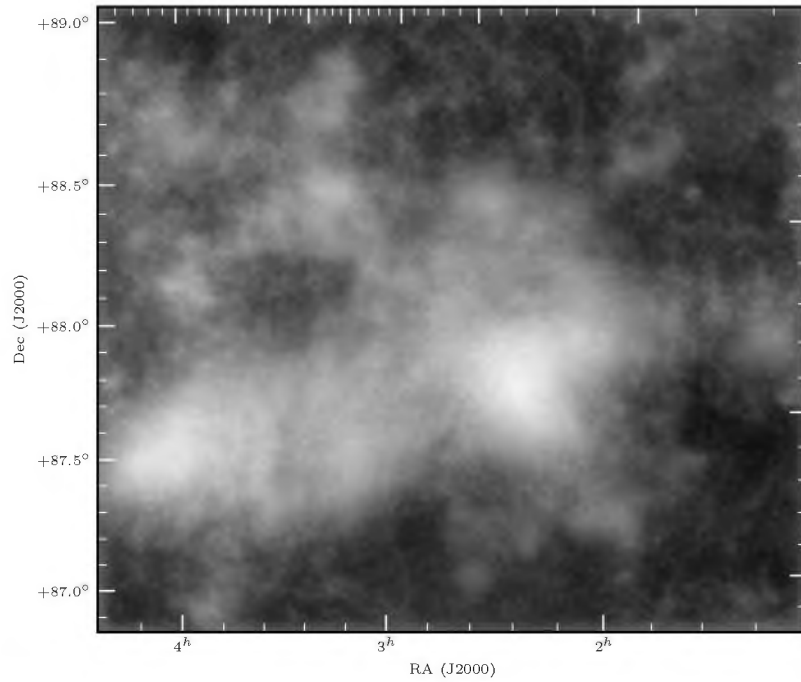




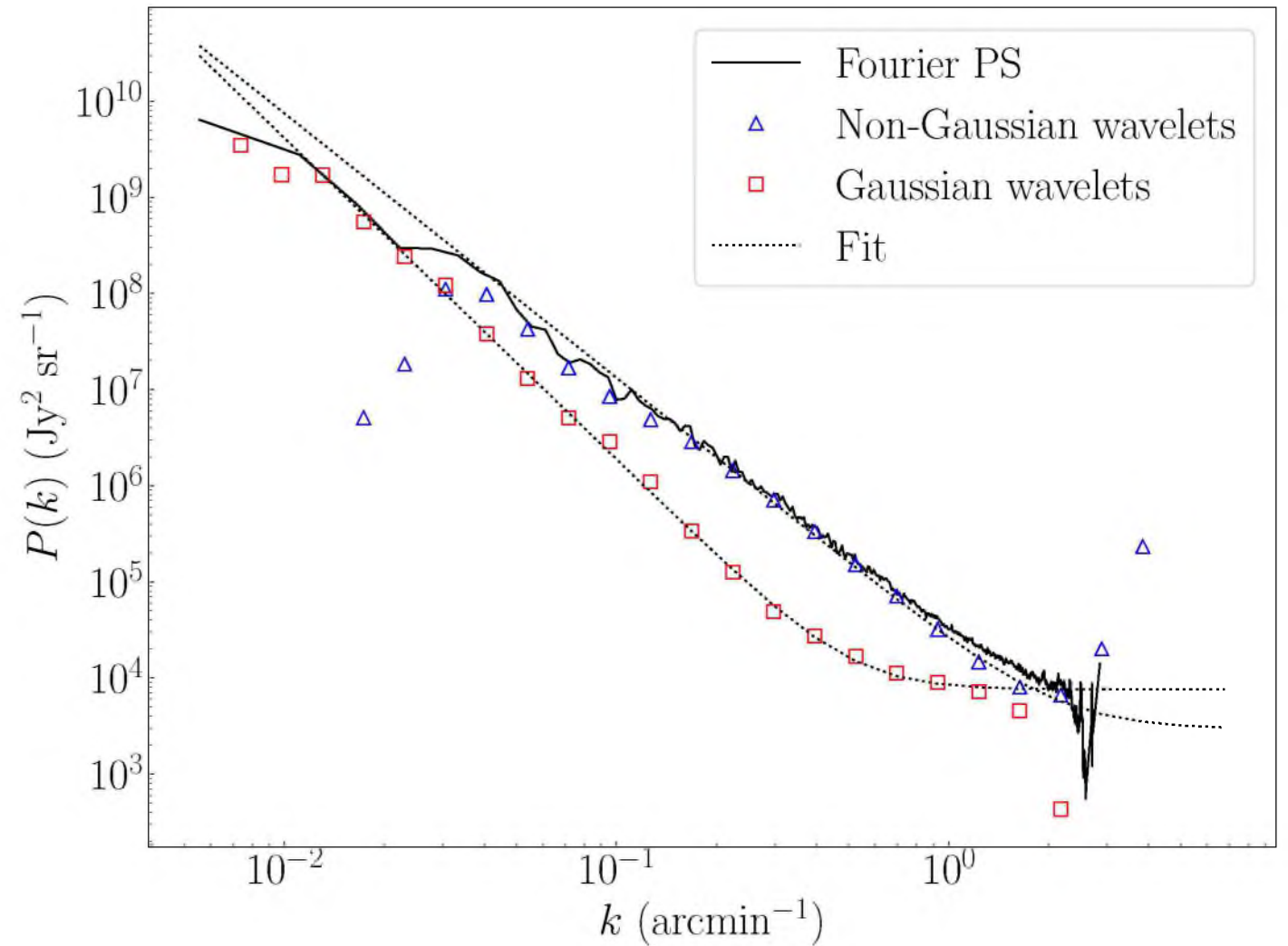
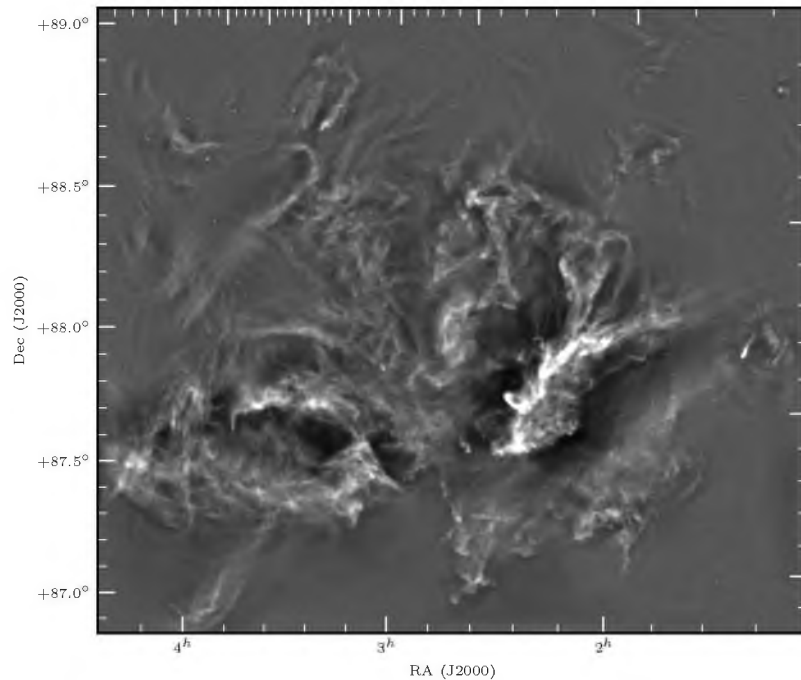


Multi-scale non-Gaussian segmentation (MnGSeg)

Gaussian

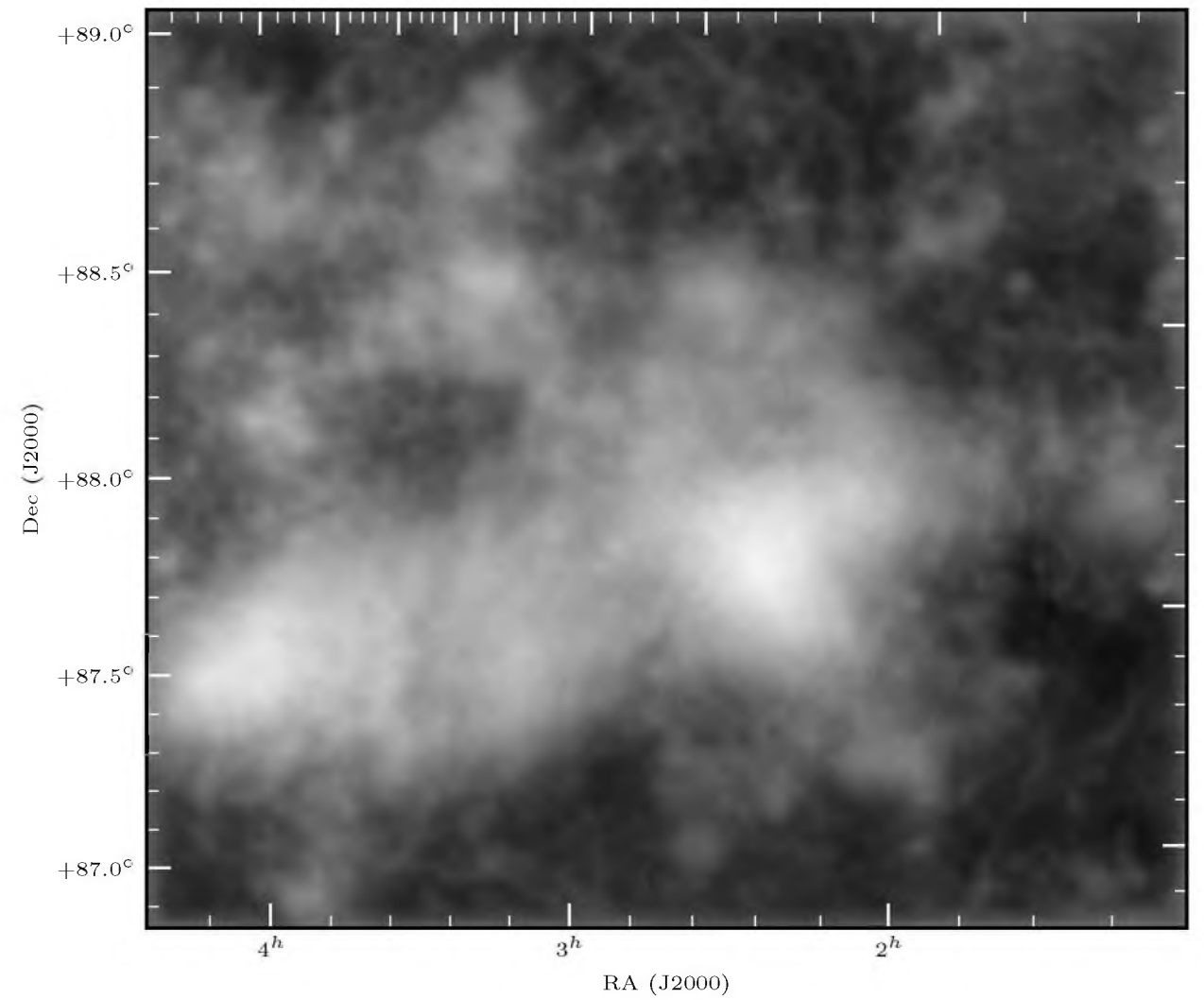
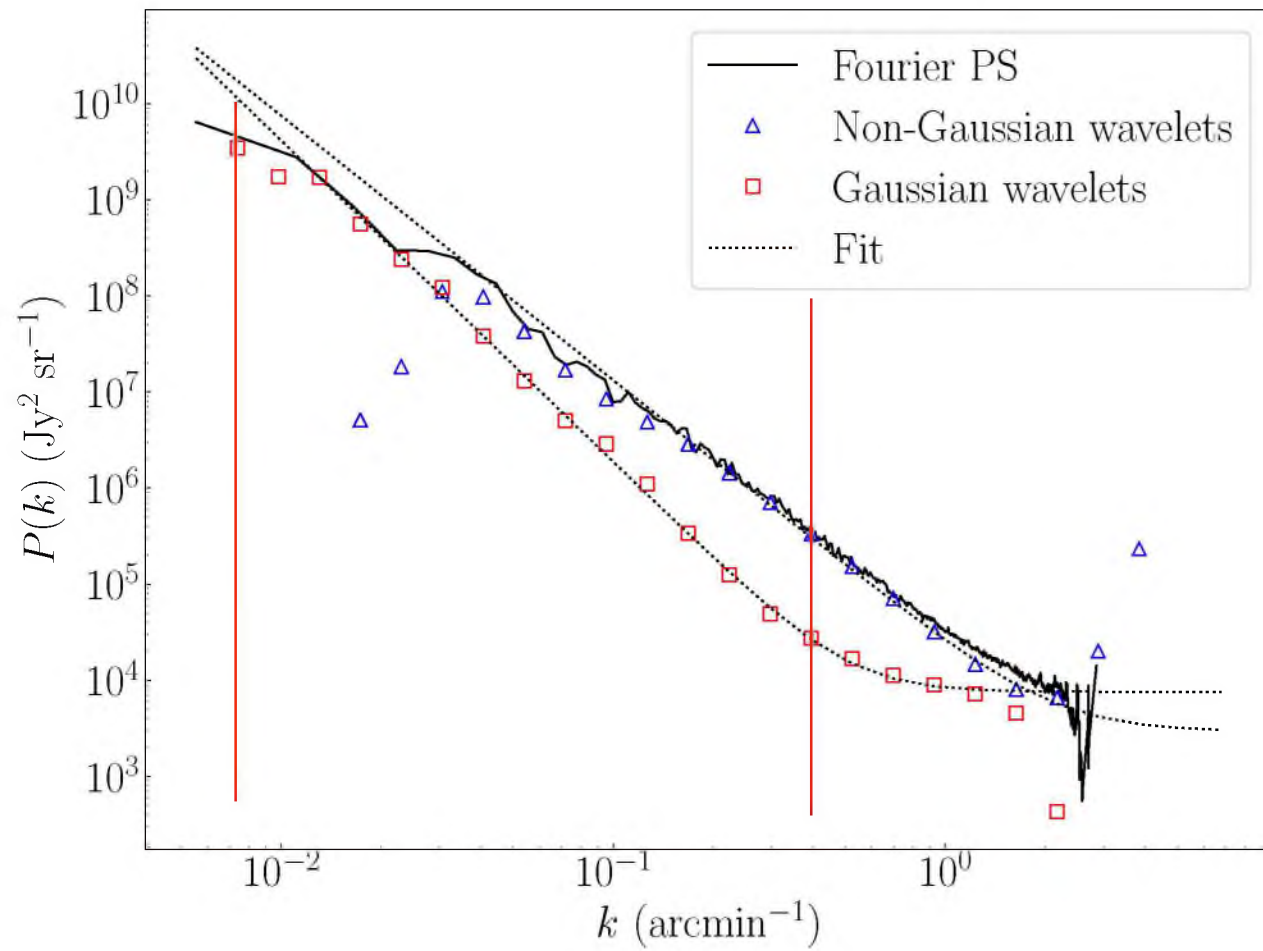


non-Gaussian

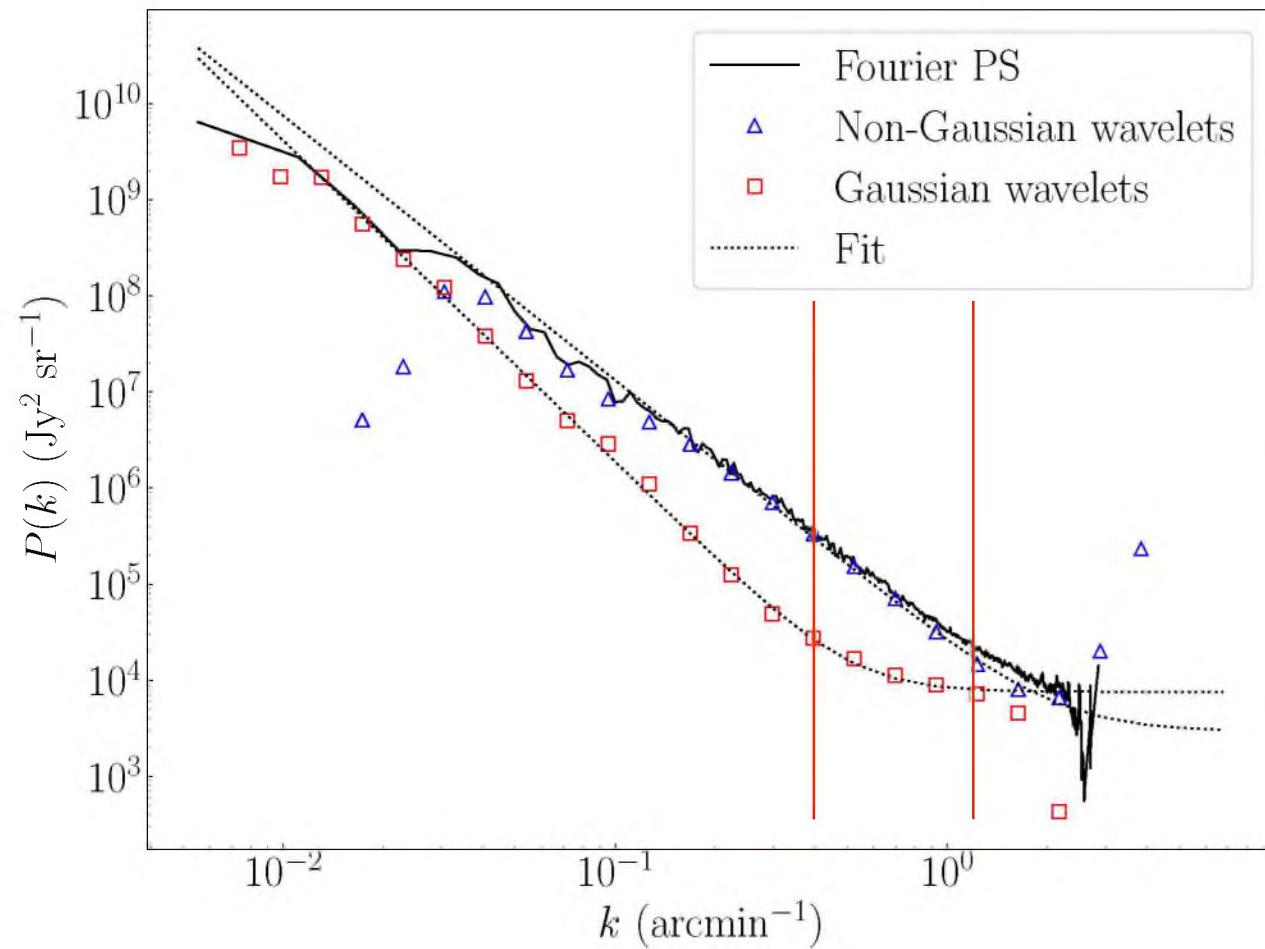


	A_{ISM} ($\text{Jy}^2 \text{sr}^{-1}$)	Power-Law (γ)	P_0 ($\text{Jy}^2 \text{sr}^{-1}$)
Total	$(3.1 \pm 0.3) \times 10^4$	-2.58 ± 0.01	$(3.5 \pm 0.1) \times 10^3$
Gaussian	$(8 \pm 1) \times 10^2$	-3.34 ± 0.05	$(7.6 \pm 0.7) \times 10^3$
non-Gaussian	$(2.3 \pm 0.2) \times 10^4$	-2.75 ± 0.07	$(2.9 \pm 0.8) \times 10^3$

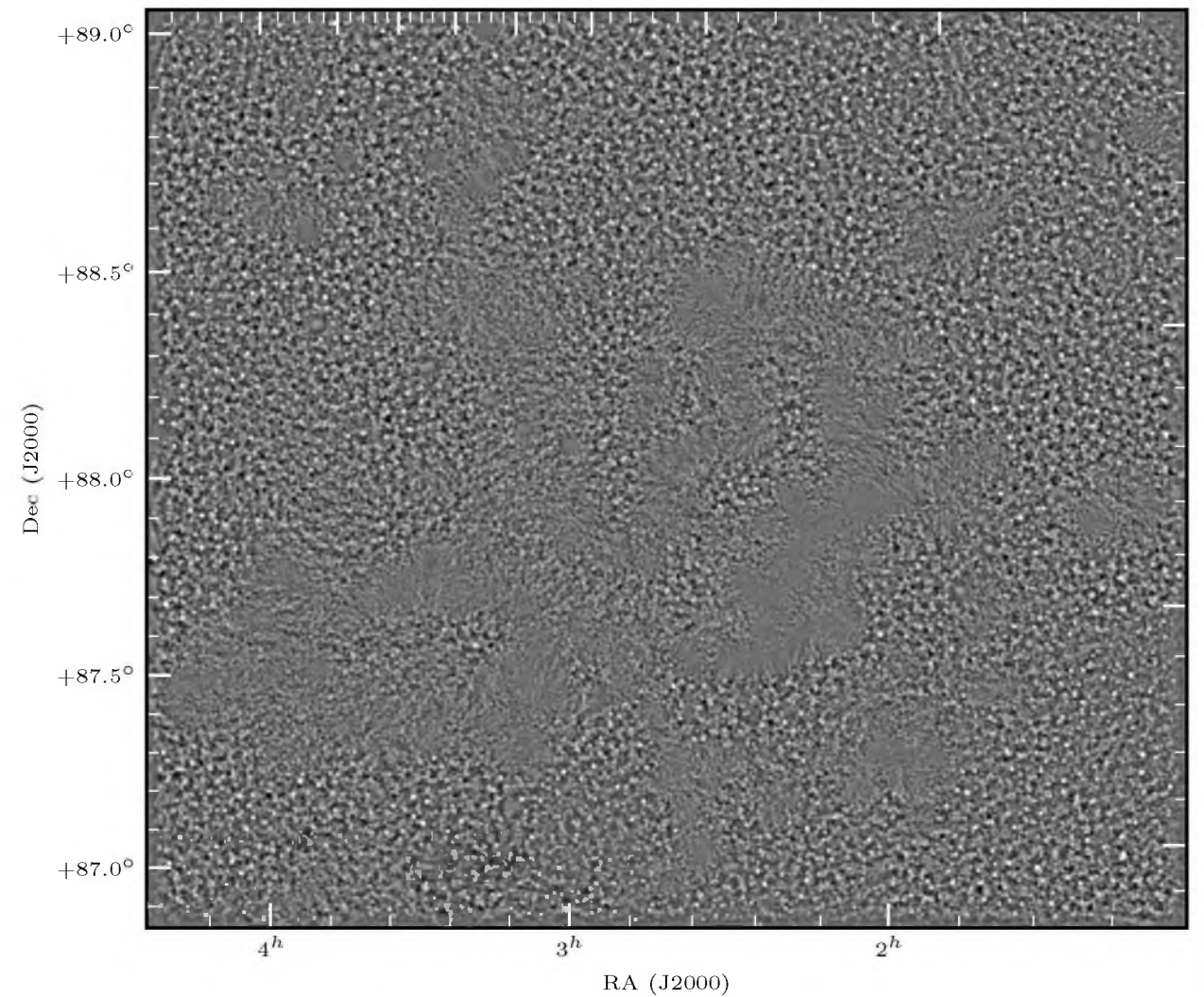
Polaris 250 μm (Gaussian part)



Polaris 250 μm (Gaussian part)

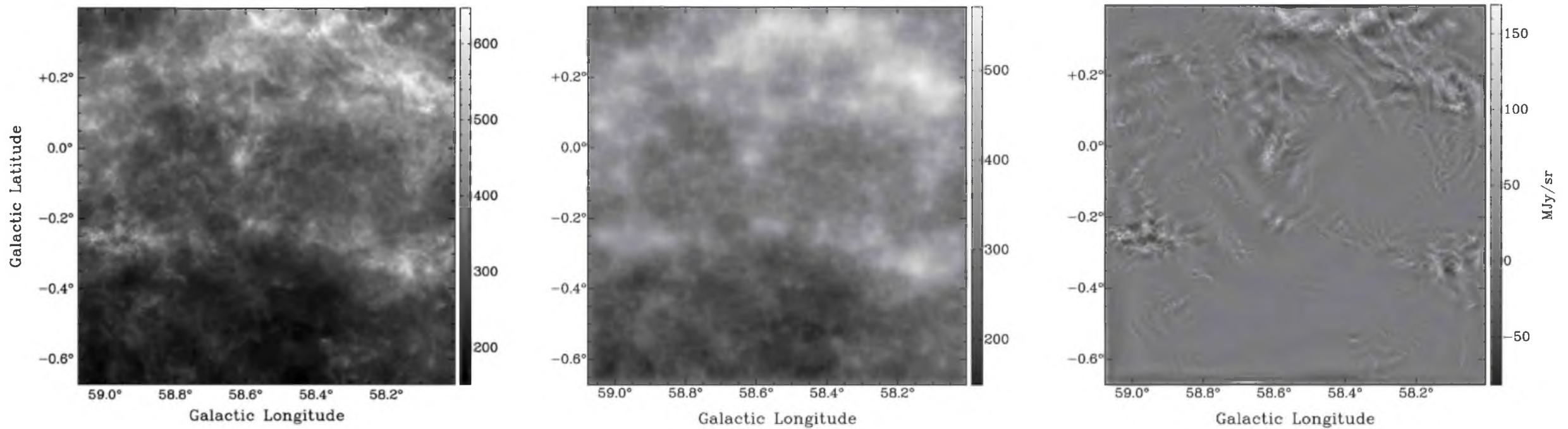


CIB - Cosmic Infrared Background

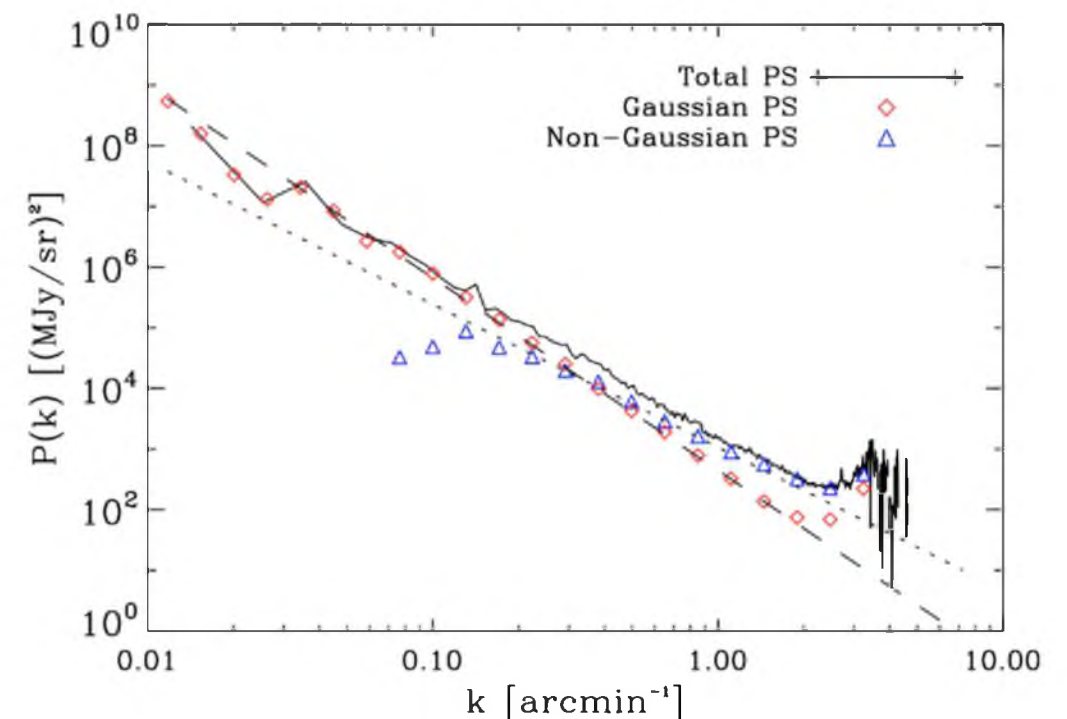


The lack of a characteristic scale

Robitaille et al. 2014



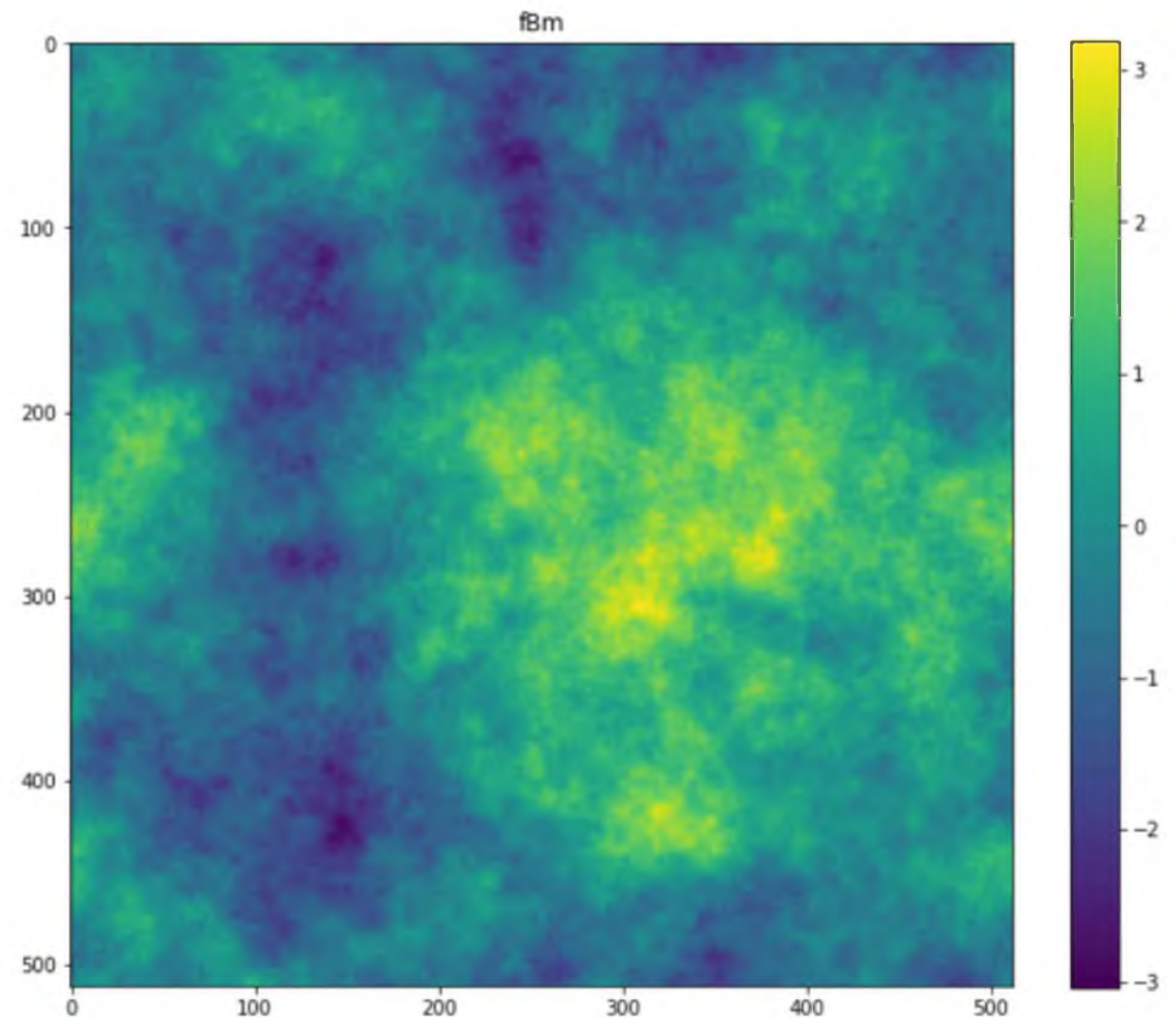
- Even when coherent structures appear at smaller scales, filaments produce no break in the power spectrum.
- Coherent structures demonstrate a spatial hierarchical scaling, i.e. filaments inside filaments, which “induces” a power law in the power spectrum.
- Filaments are well embedded in the diffuse background.



Multiplicative random cascade model

Vázquez-Semadeni 1994

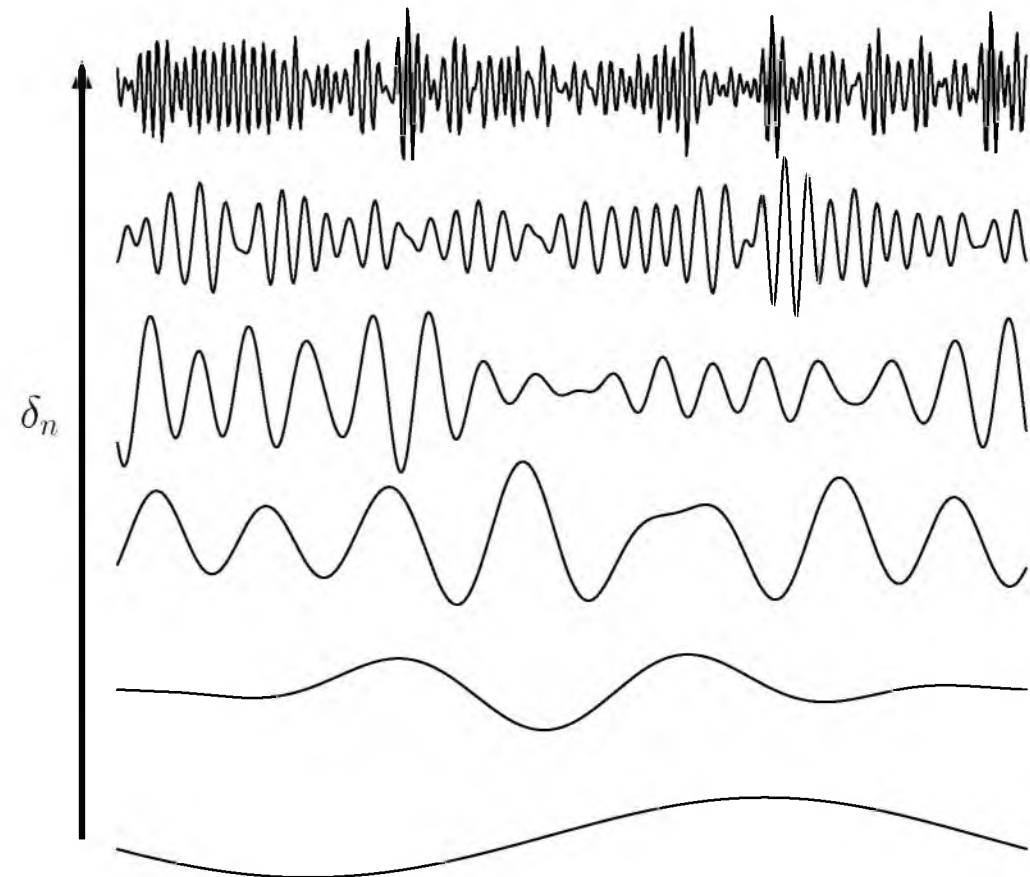
In particular, a lognormal pdf appears to be a likely candidate for the density distribution in fully turbulent flows, in which each new value of the local density is essentially random. In this case the density after a finite time can be considered to be the product of a large number of random fluctuations $[\rho(t_n) = \delta_n \delta_{n-1} \dots \delta_1 \delta_0 \rho(t_0)]$. If these fluctuations are independent of one another, then the local density $\rho(x, t)$ should have a lognormal distribution in time.



Multiplicative random cascade model

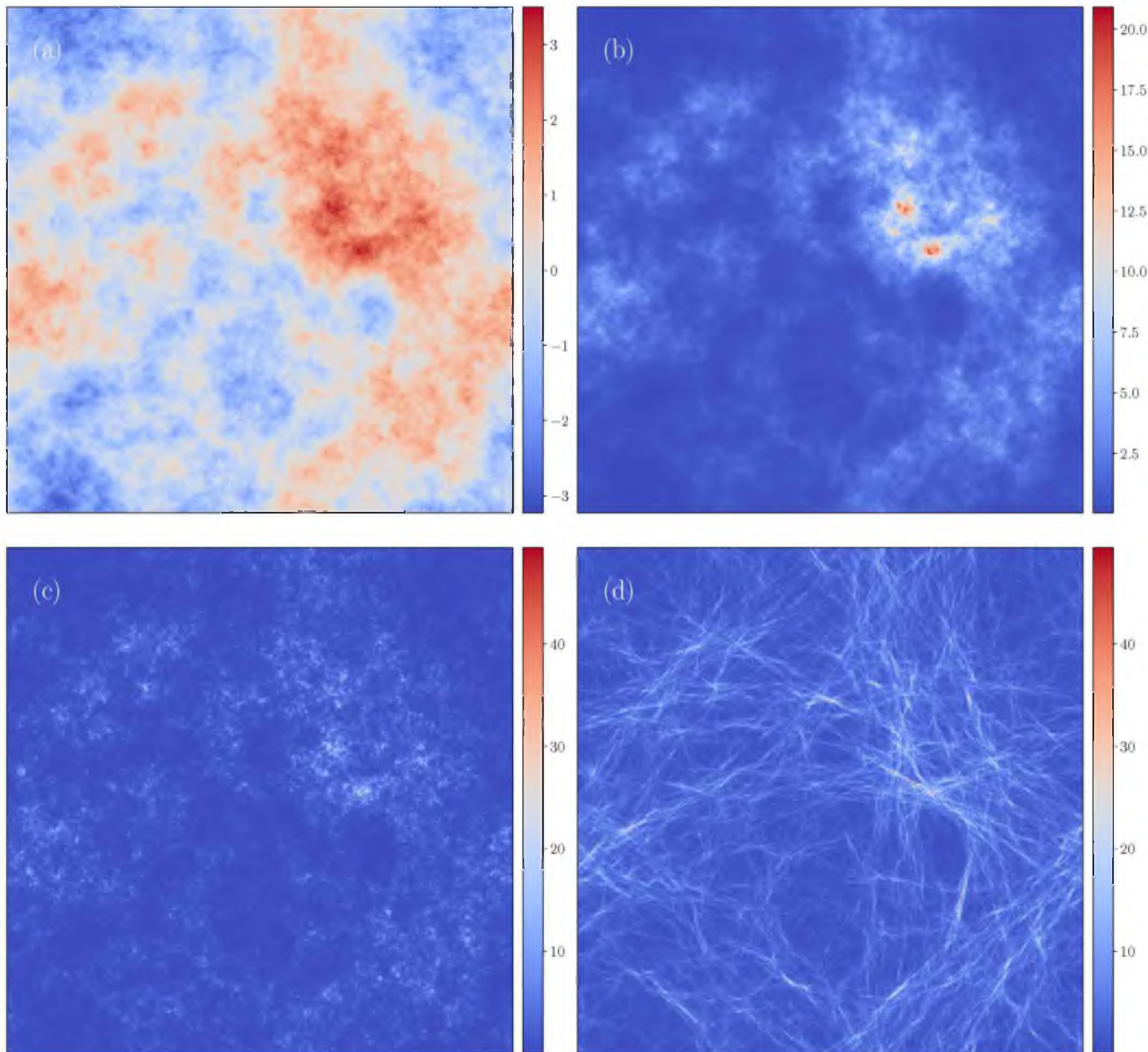
Vázquez-Semadeni 1994

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“One of the simplest methods — and historically the first — for obtaining multifractal dissipation measures” (Frisch 1995 — on intermittency models)

Multiplicative random cascade model



$$\rho_a(\mathbf{x}) = f(\mathbf{x}) \\ = \mathbf{fBm}$$

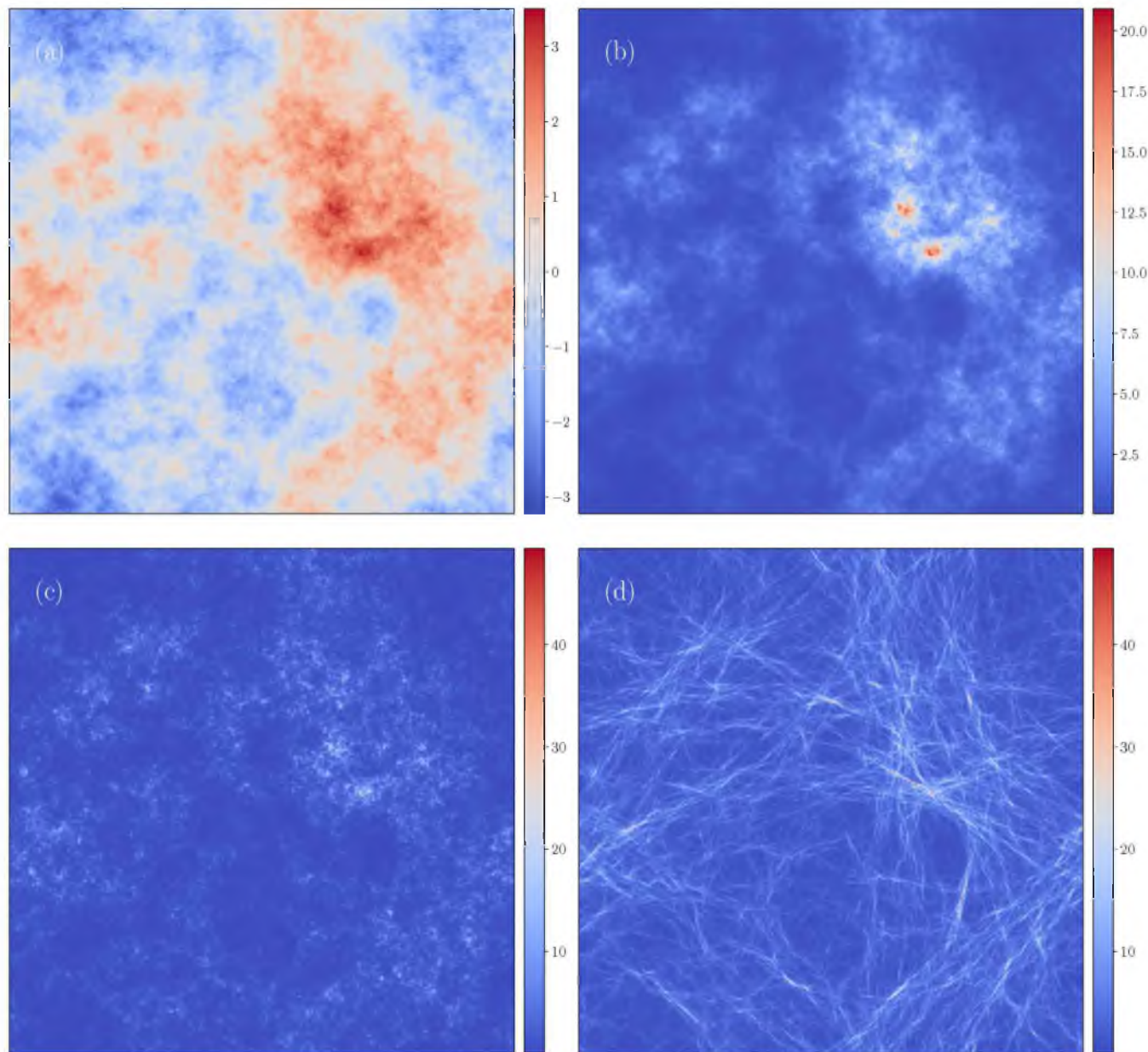
$$\rho_b(\mathbf{x}) = \exp[\sigma_\rho f(\mathbf{x})] \\ \sigma_\rho = (\ln[1 + 0.5\mathcal{M}^2])^{0.5}$$

$$\rho_c(\mathbf{x}) = \prod_{l,\theta} \exp[\sigma C_\ell \tilde{f}(\mathbf{x}, \ell, \theta)]$$

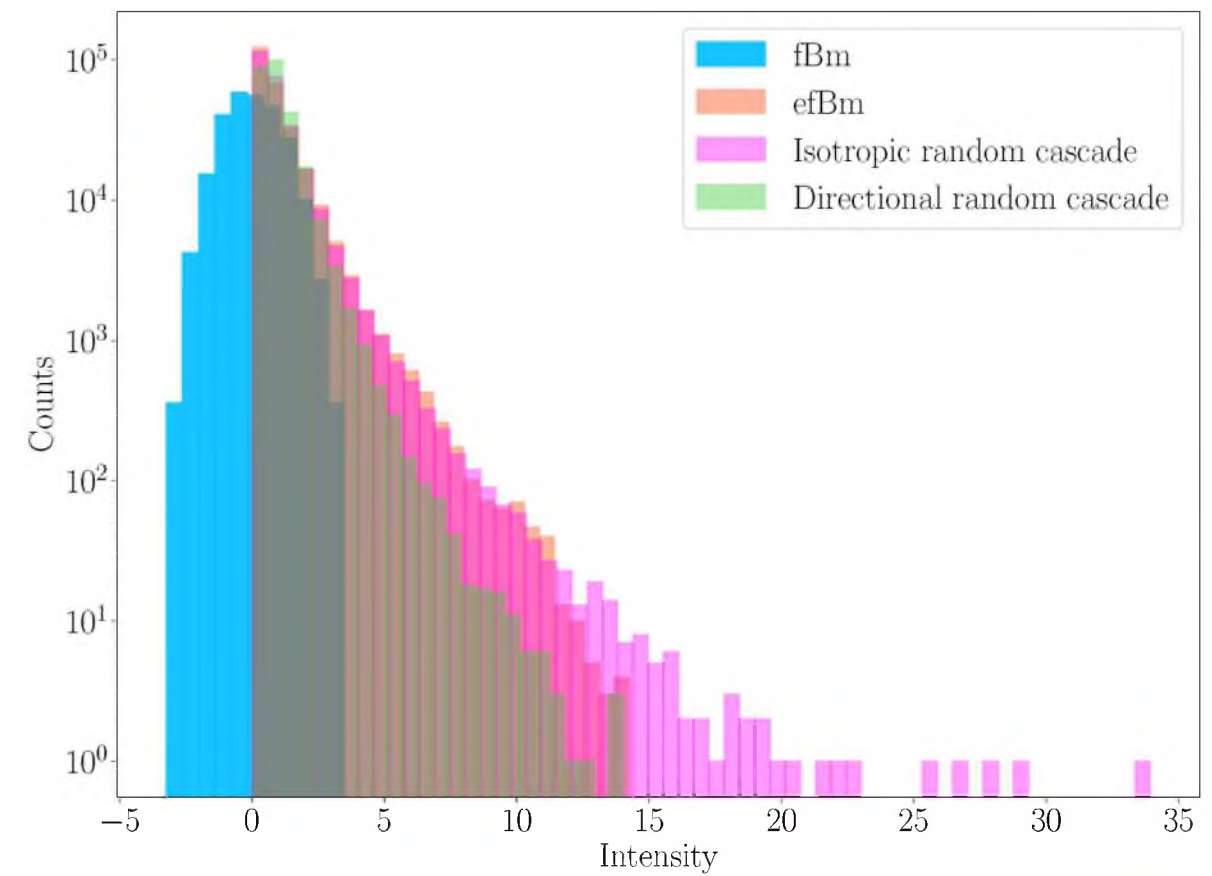
$$\rho_d(\mathbf{x}) = \frac{1}{N_\theta} \sum_{\theta} \left[\prod_l \exp[\sigma C_\ell \tilde{f}(\mathbf{x}, \ell, \theta)] \right]$$

“One of the simplest methods — and historically the first — for obtaining multifractal dissipation measures” (Frisch 1995 — on intermittency models)

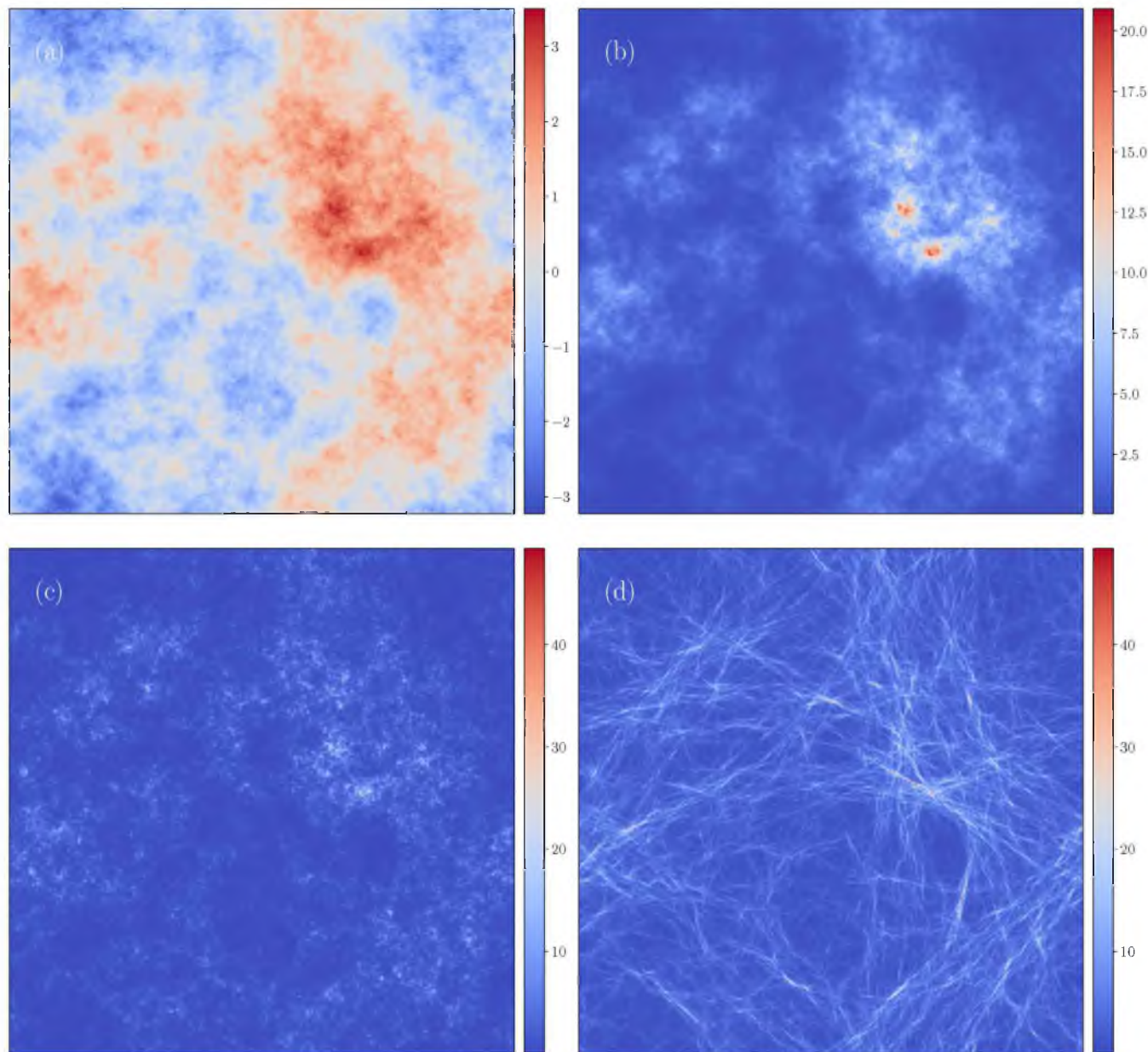
Multiplicative random cascade model



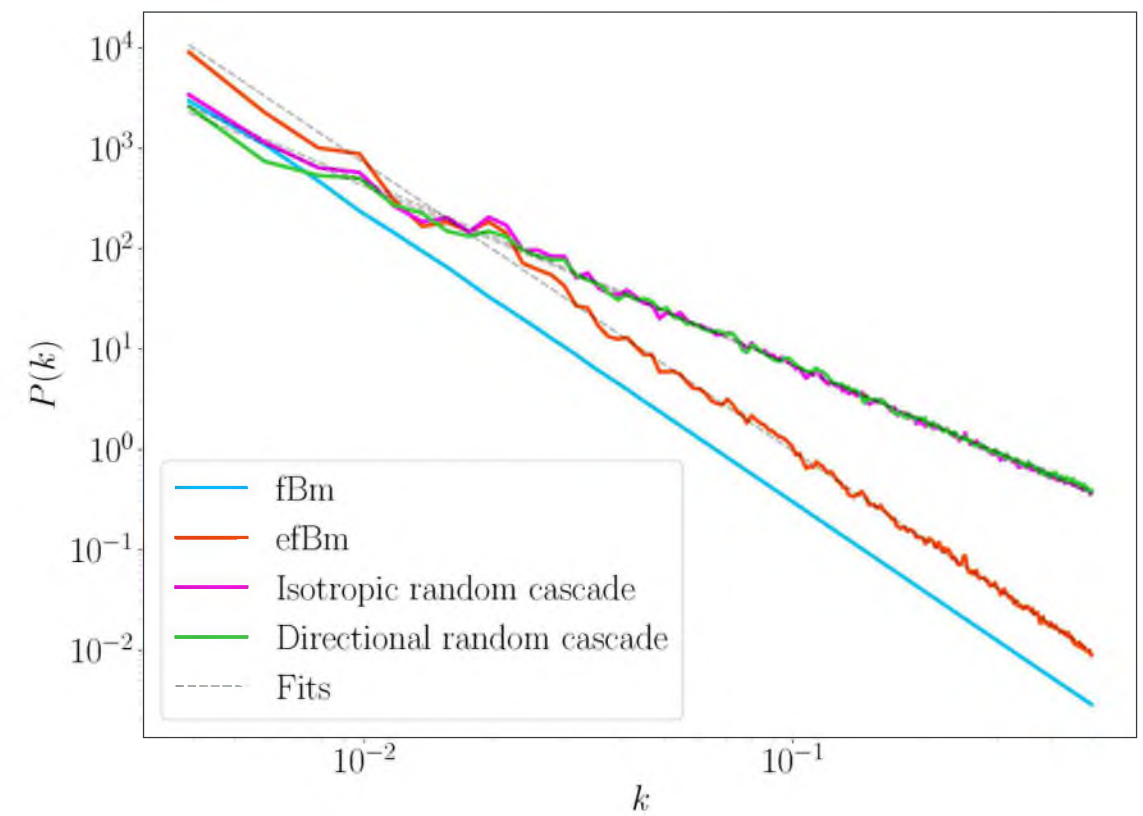
J.-F. Robitaille, A. Al-Rifai, I. Joncou
E. Moraux, P. Lesaffre, F. Motte
2019 (in prep.)



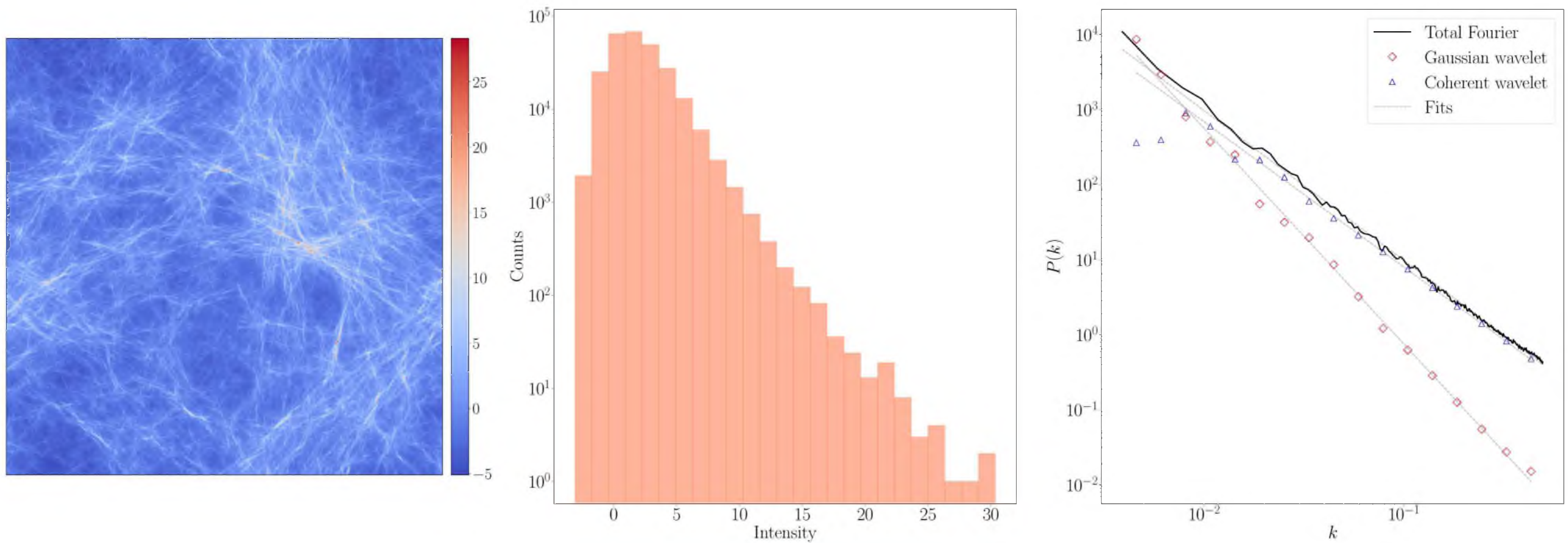
Multiplicative random cascade model



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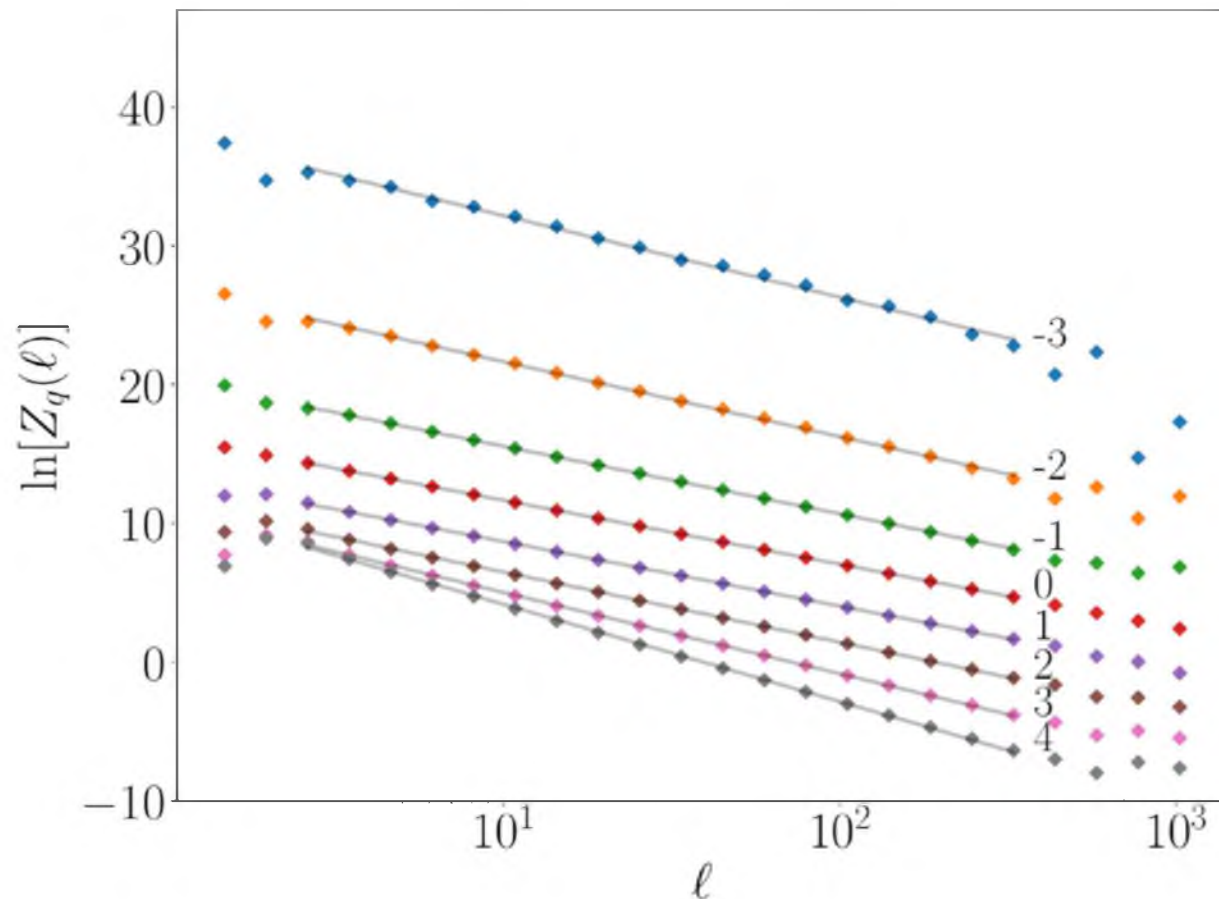


Multiplicative random cascade model



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2019 (in prep.)

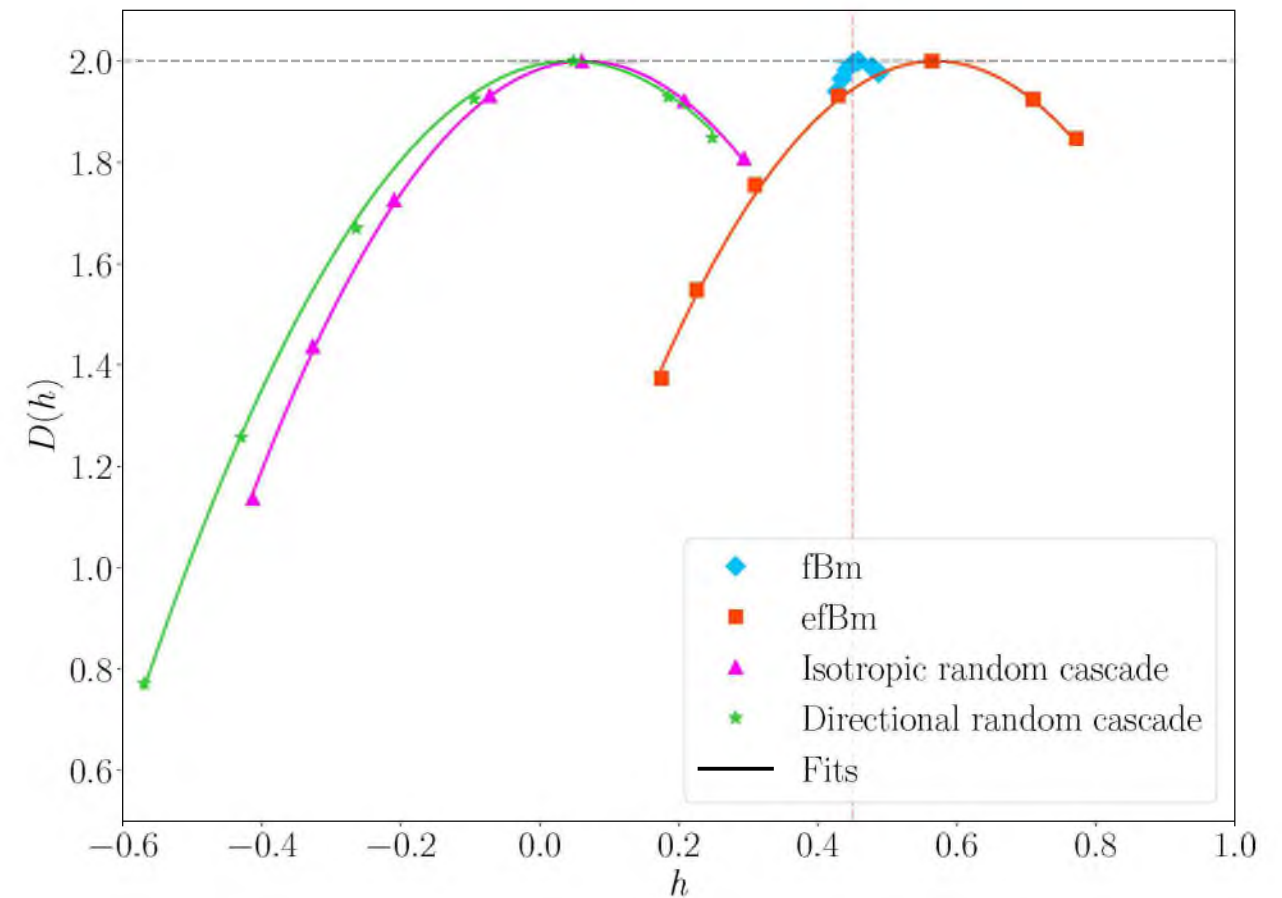
Multifractal analysis



Partition function

$$z(q, l) = \langle |\tilde{f}(l, \vec{x}, \theta)|^q \rangle_{\theta, x}$$

$$z(q, l) \sim l^{\tau(q)}$$



Multifractal spectrum

$$D(h) = qh - \tau(q)$$

$$h = \frac{d\tau(q)}{dq}$$

$$\gamma = 2 + 2h$$

Summary

- In-depth power spectrum analysis which take into account non-Gaussianities is possible (Robitaille et al. 2019).
- This technique naturally extracts filamentary structures associated with star formation from a non-uniform background... and the CIB!
- Coherent structures associated with star formation demonstrate a spatial hierarchical scaling well embedded in the diffuse background.
- The statistical properties respect a multifractal geometry, which may be associated with turbulence intermittency.
- MnGSeg code available at <https://github.com/jfrob27/pywavan>