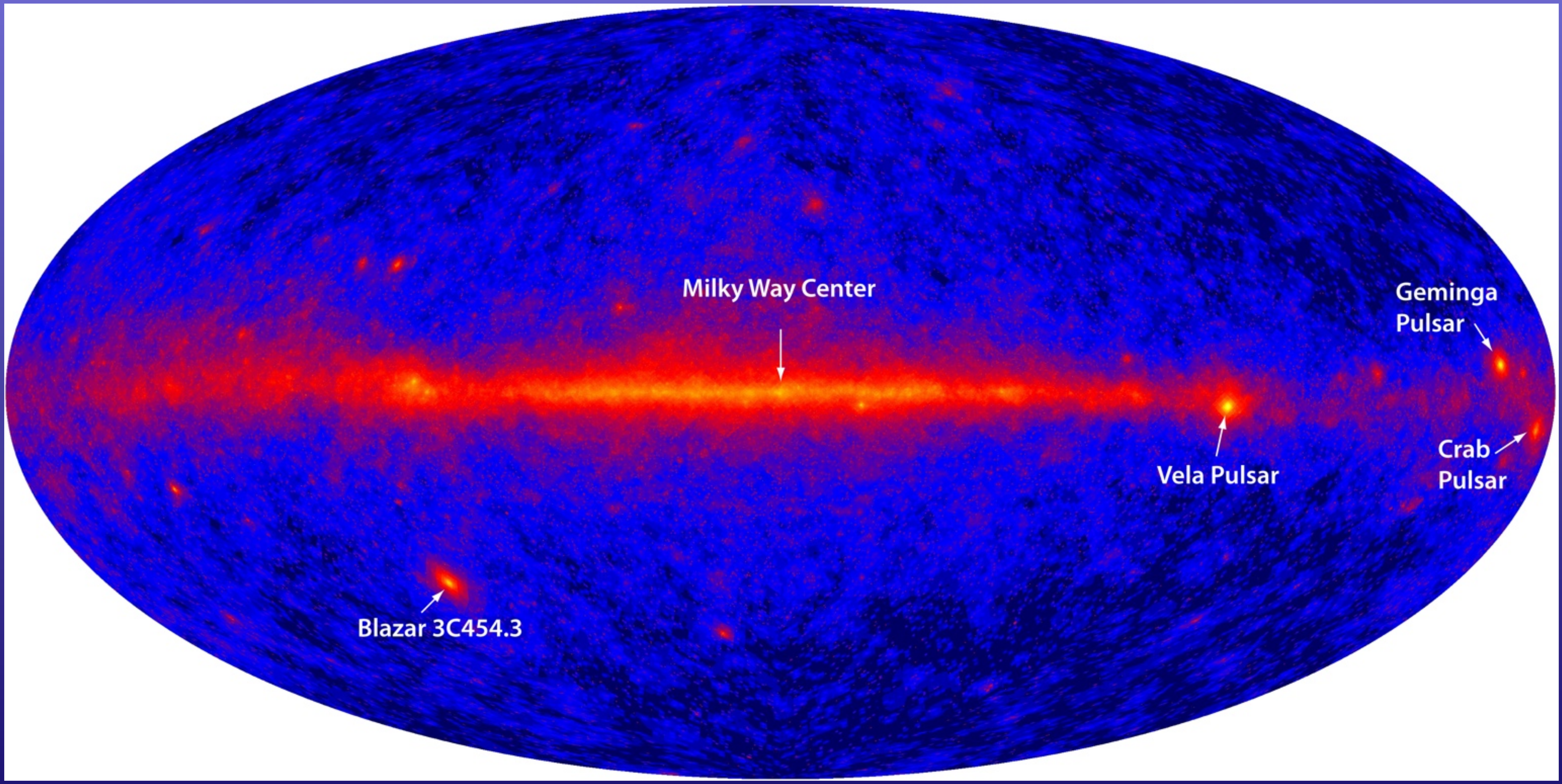
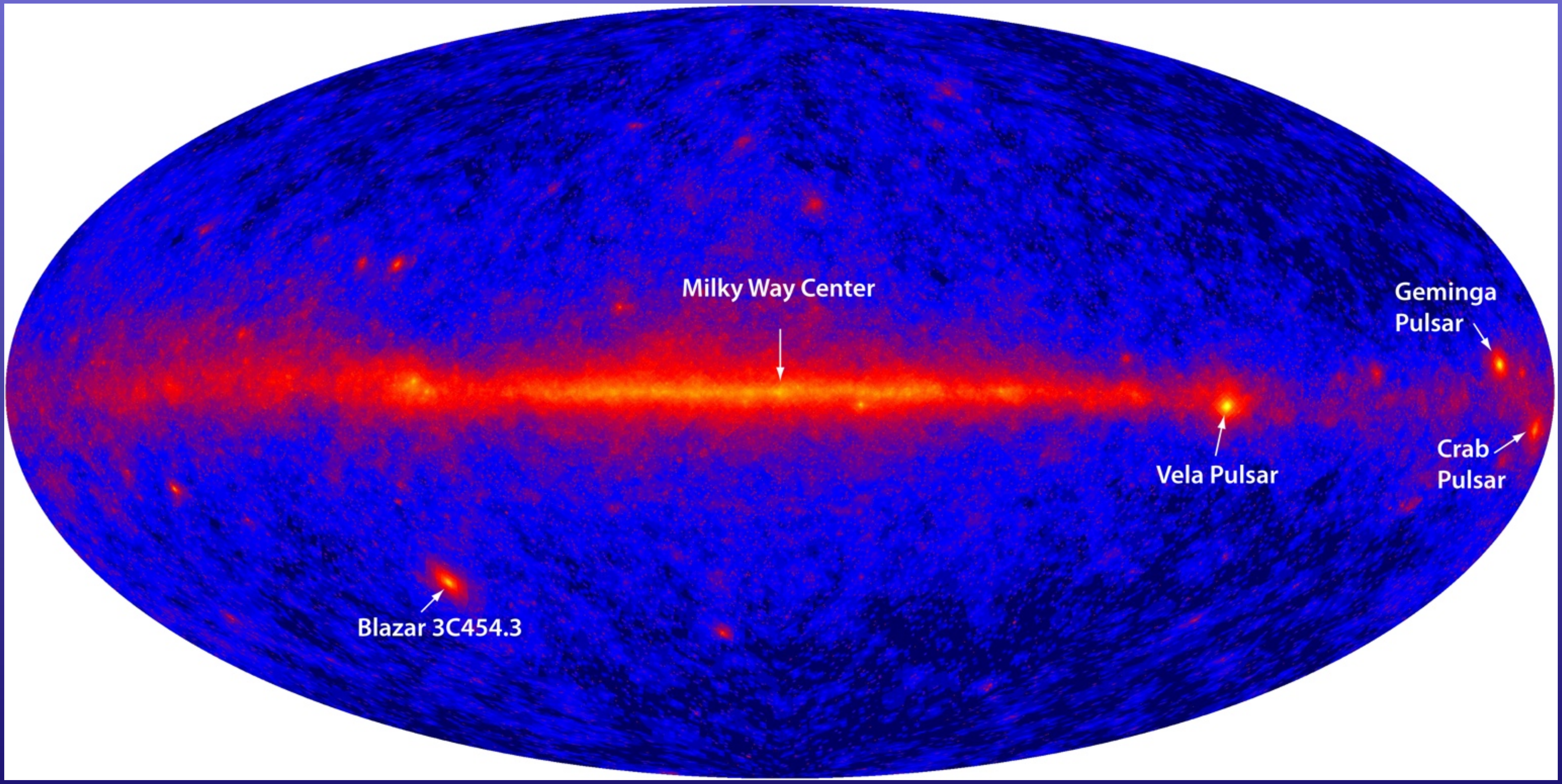
QUANTIFYING, SUMMARIZING, AND REPRESENTING 'TOTAL' UNCERTAINTIES IN IMAGE (AND SPECTRAL) 'DECONVOLUTION'

A. Connors for 'CHASC' or CBASC

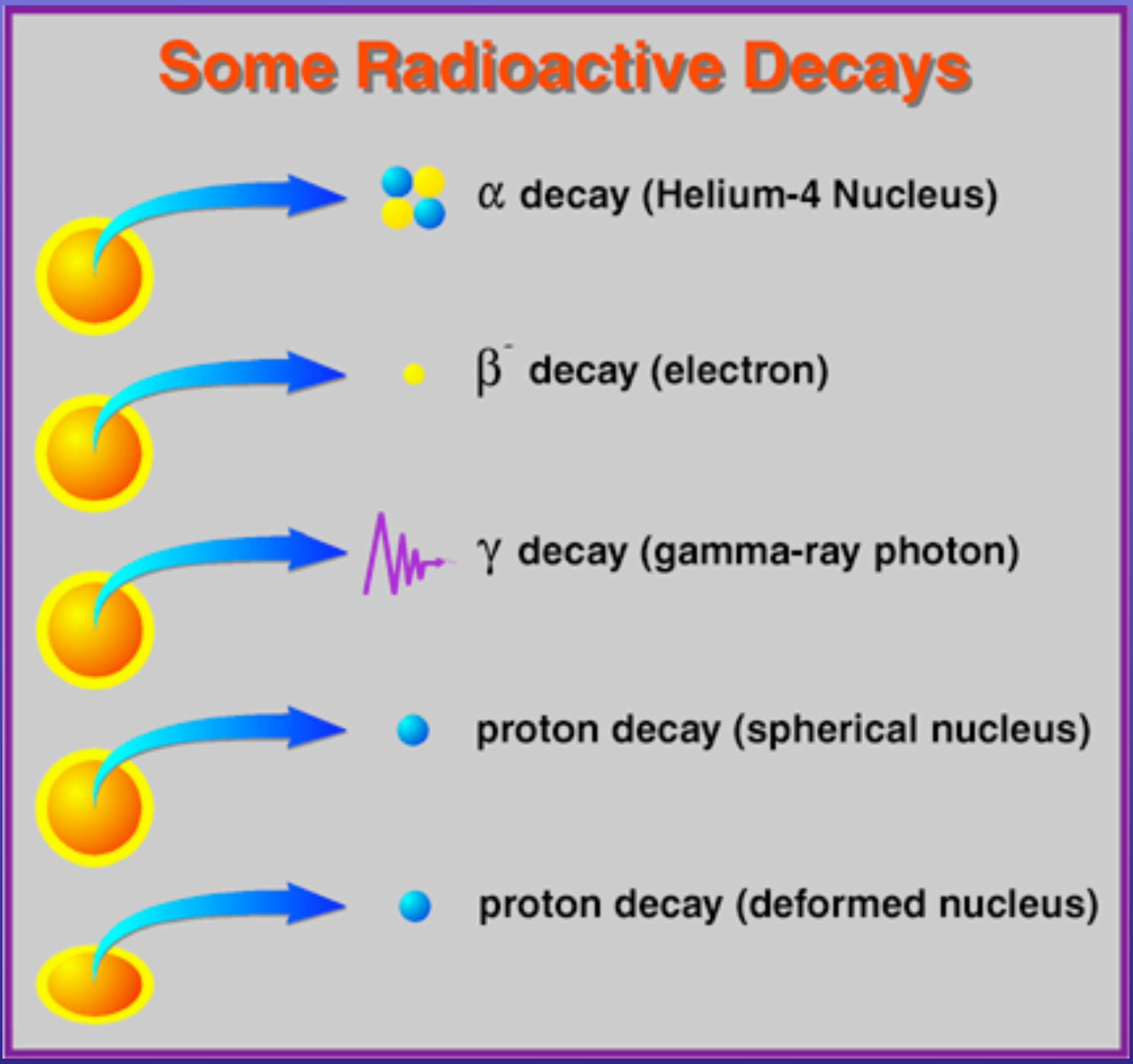


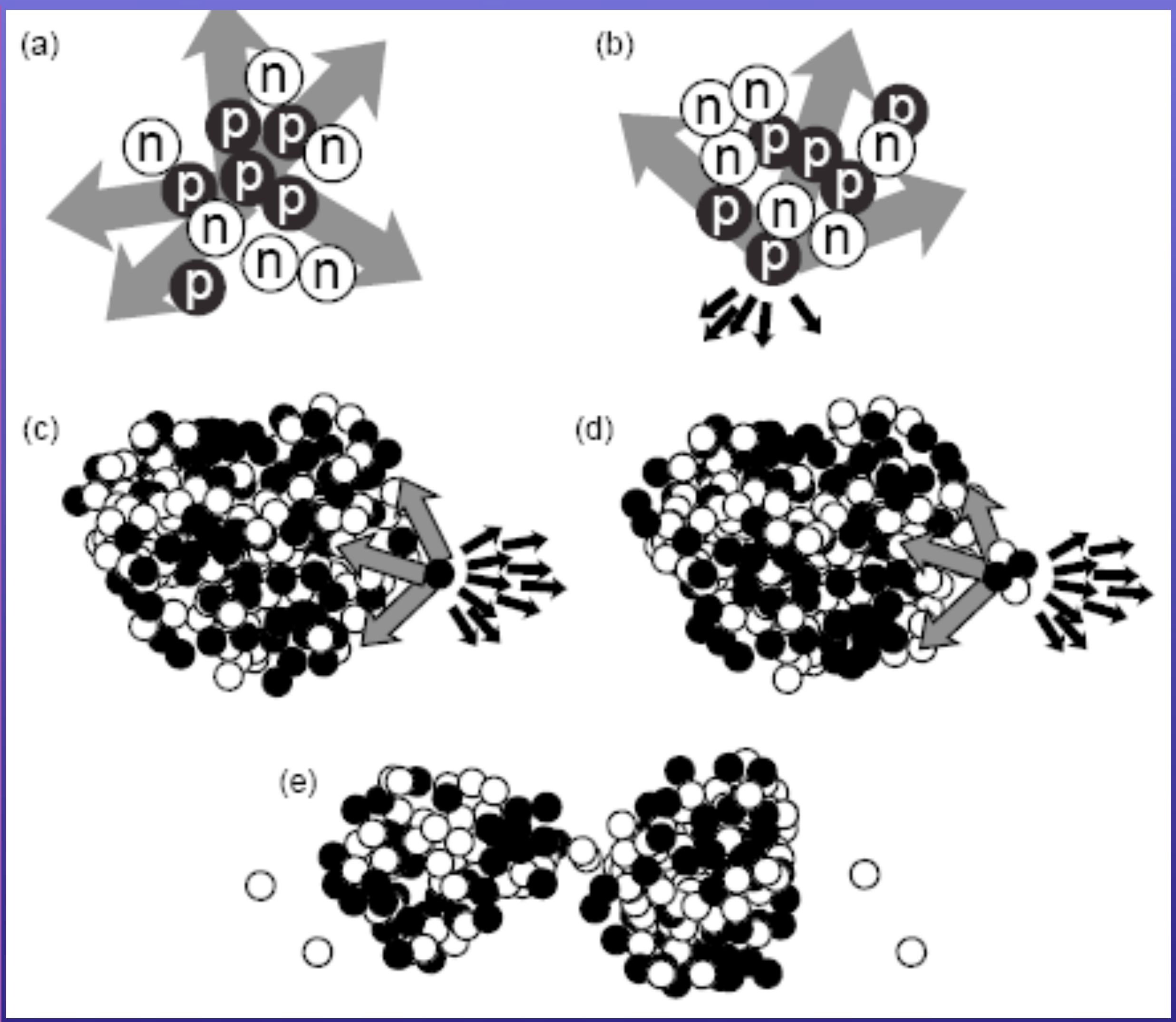
PART II: DOUBT

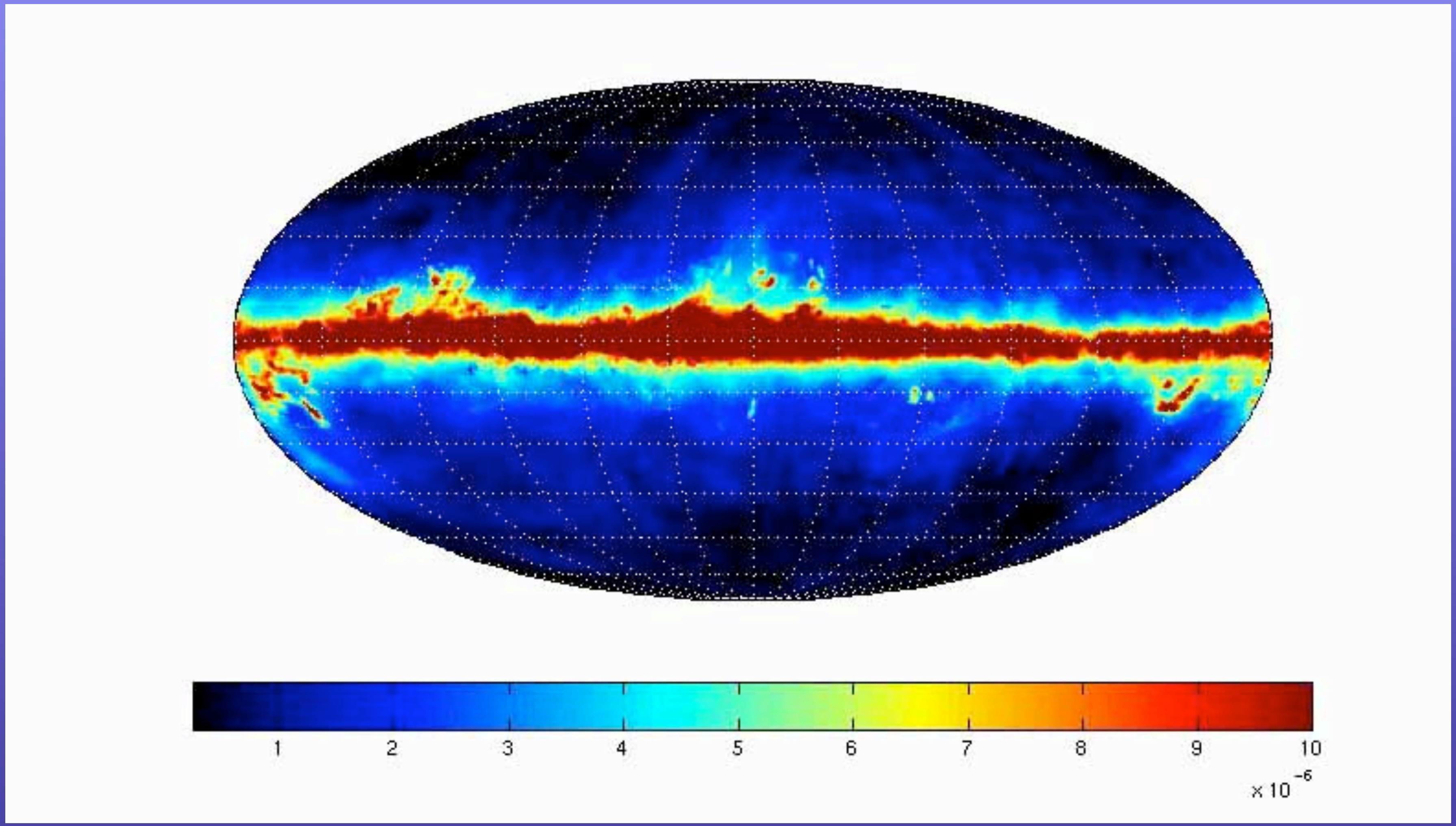
A. Connors for 'CHASC' or CBASC



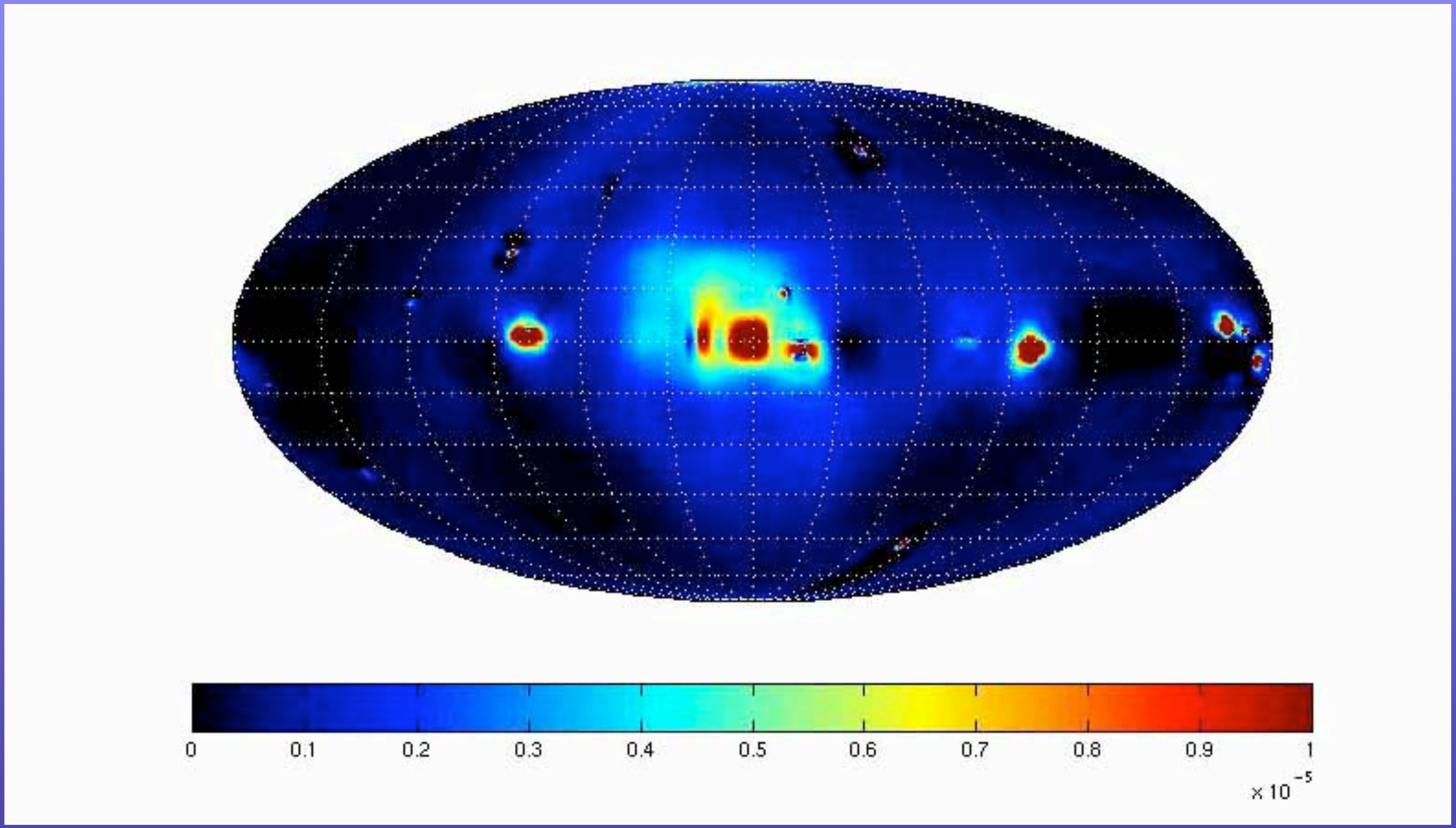
INSIDE the source: Intrinsically Multinomial/Poisson?







`The immediate question arises as to the statistical significance of this feature... quantification of object-wise significance (e.g., "this blob is significant at the n-sigma level") are difficult.' (Dixon et al. 1998 New Astronomy 3, 539)



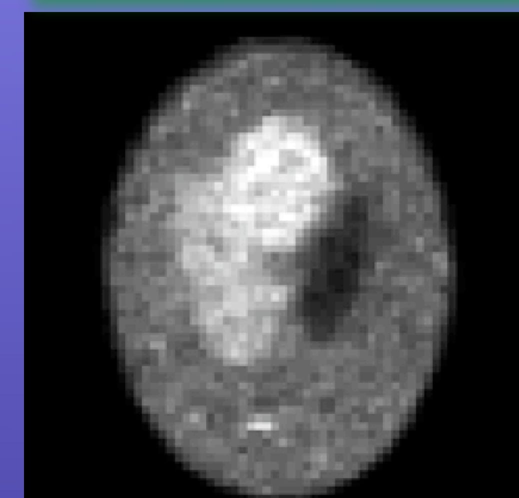
`The immediate question arises as to the statistical significance of this feature... quantification of object-wise significance (e.g., "this blob is significant at the n-sigma level") are difficult.' (Dixon et al. 1998 New Astronomy 3, 539)

Tomographic Reconstruction: Comparing Examples (from Willett et al.)

True image

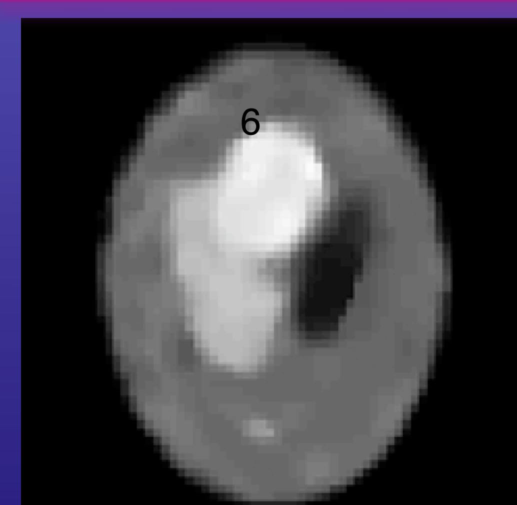
Filtered back projection

MLE reconstruction



Fessler's PWLS

Wedgelet reconstruction



What's the significance of / uncertainty on features?

Talk Outline (Parallel pieces):

0. What/Why: Demos, Definitions

1. What/Why: Problem Definition:
   - 1.1 Goodness-of-fit and feature-detection
   - 1.2 Mismatch significance, shape error bars
   - 1.3 All uncertainties: instrument, physics

2. How/Why: History/Methods
   - 2.1 Frequentist Multiscale, Bayesian Structure
   - 2.2 DA/MCMC
   - 2.3 Comparisons of Null (simulations) vs Data

3. Current Examples
   - Varying signal to noise: “E” and Gamma-ray sky

4. Current Challenges

How/Why: History/Methods

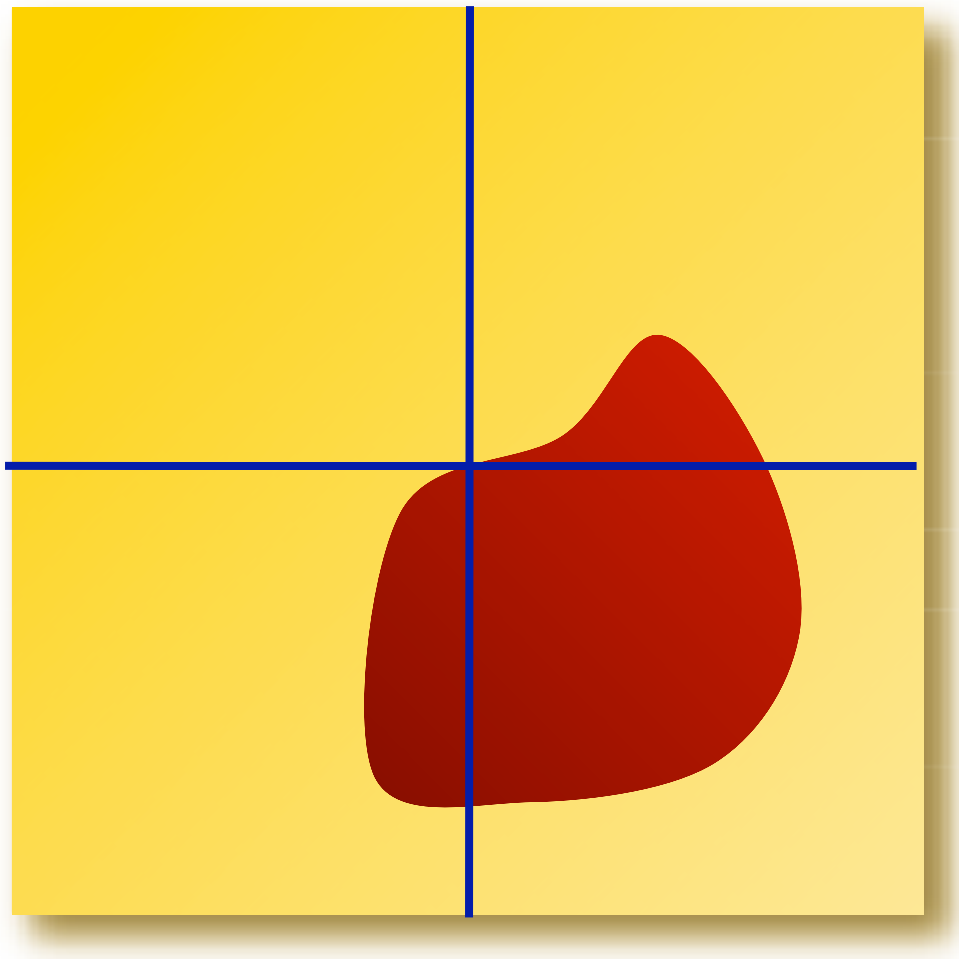
* Putting Flexible/Multiscale ‘NP’ models
* Together with parametrized physics-based models
* Full Bayesian Posterior framework

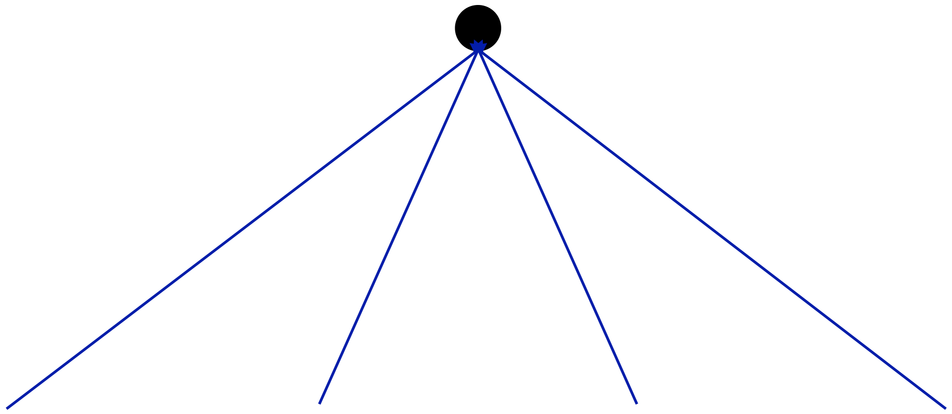
* ‘Likelihoodist’ (Tanner); Priors ~ Complexity Penalty
* Bayes allows Modularity: Data Augmentation,
* Bayes allows complex, high-dimensions: MCMC

Multiplicative Multiscale Innovation Models

Timmermann & Nowak, 1999
Kolaczyk, 1999

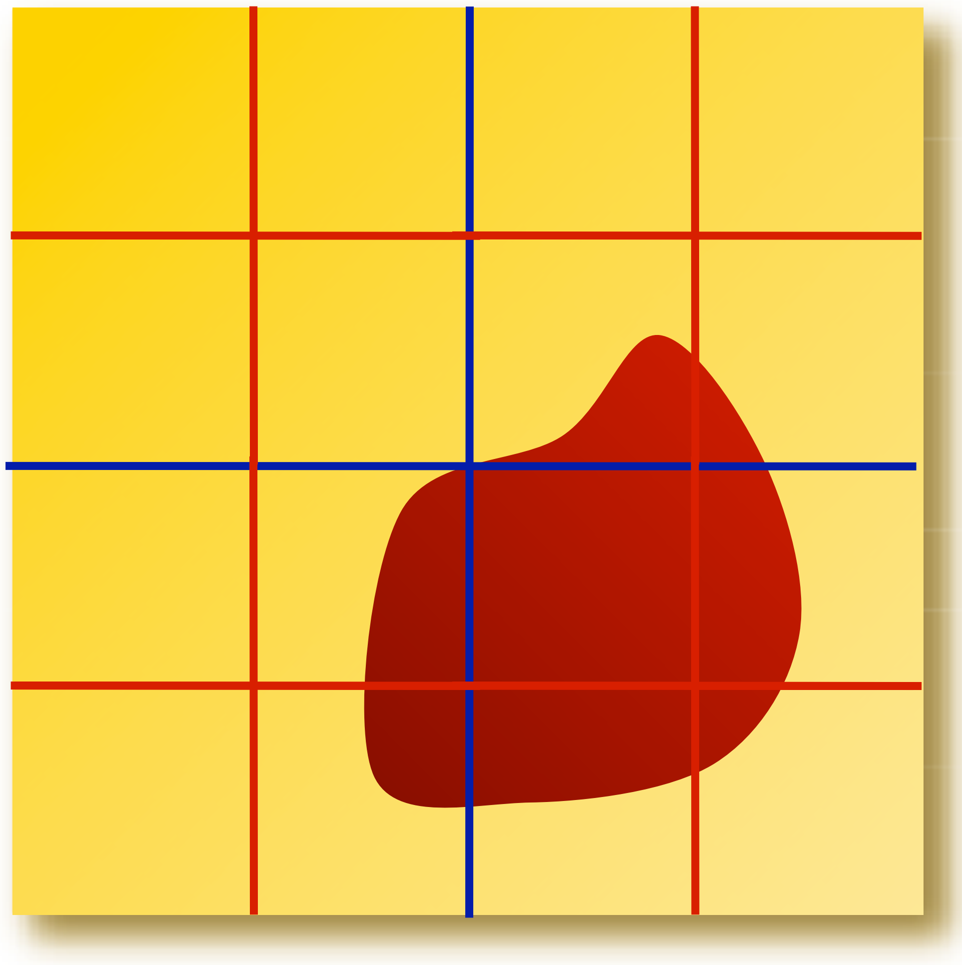
Multiplicative Multiscale Innovation Models

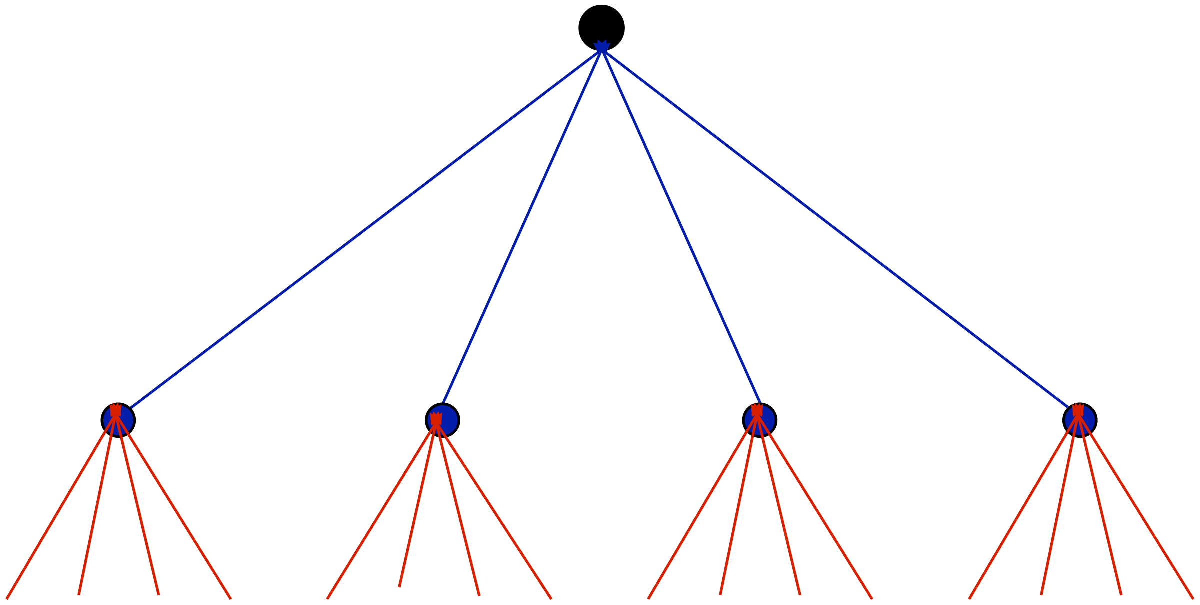




Timmermann & Nowak, 1999
Kolaczyk, 1999

Multiplicative Multiscale Innovation Models





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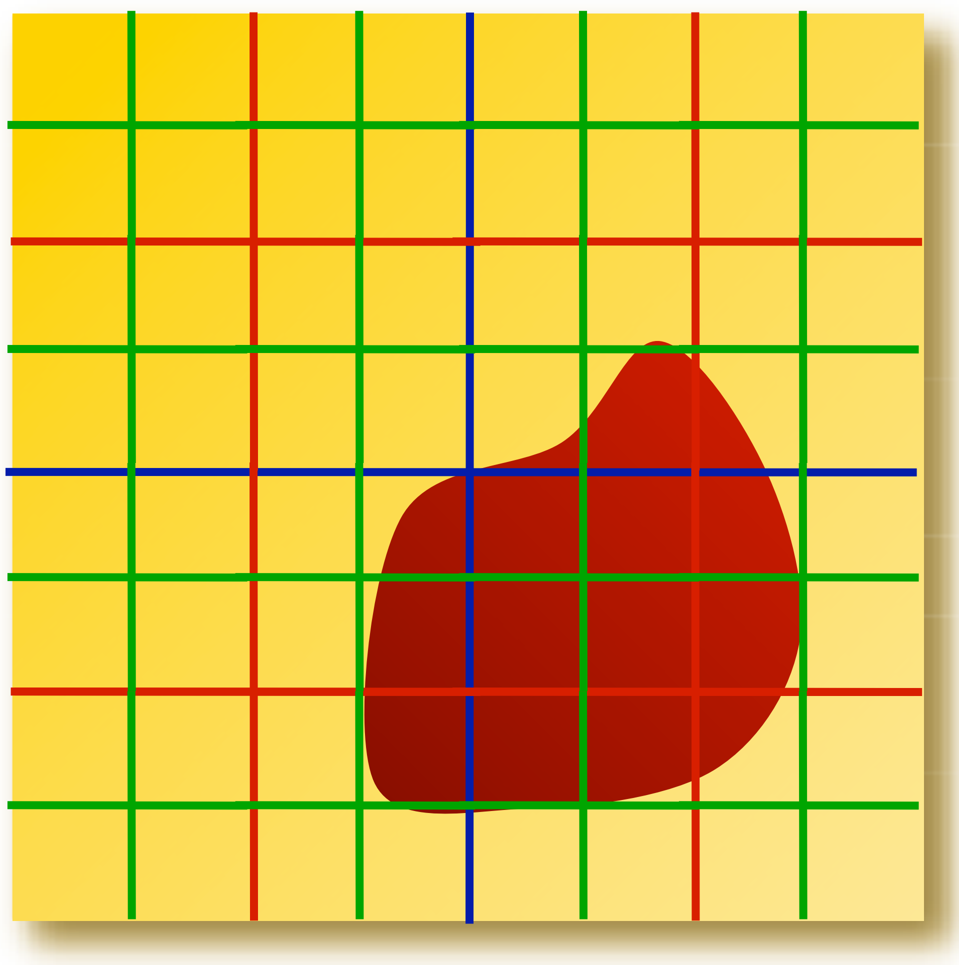
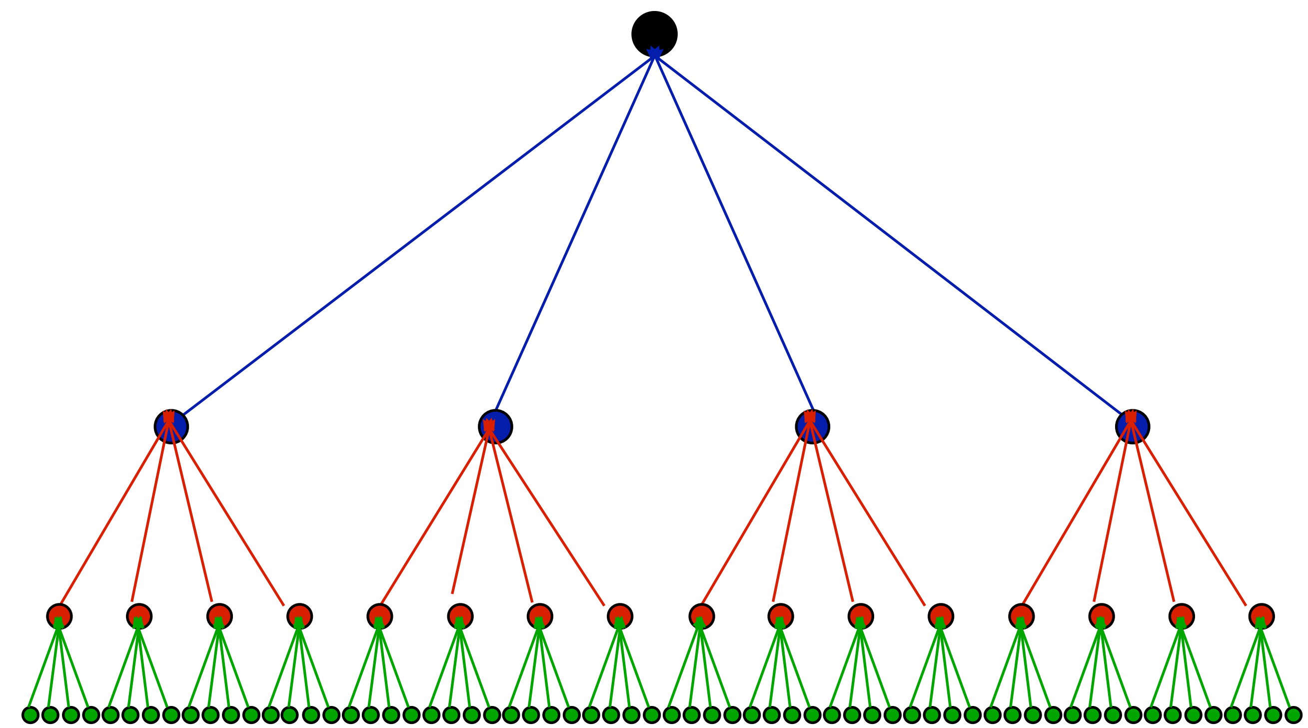
Multiplicative Multiscale Innovation Models





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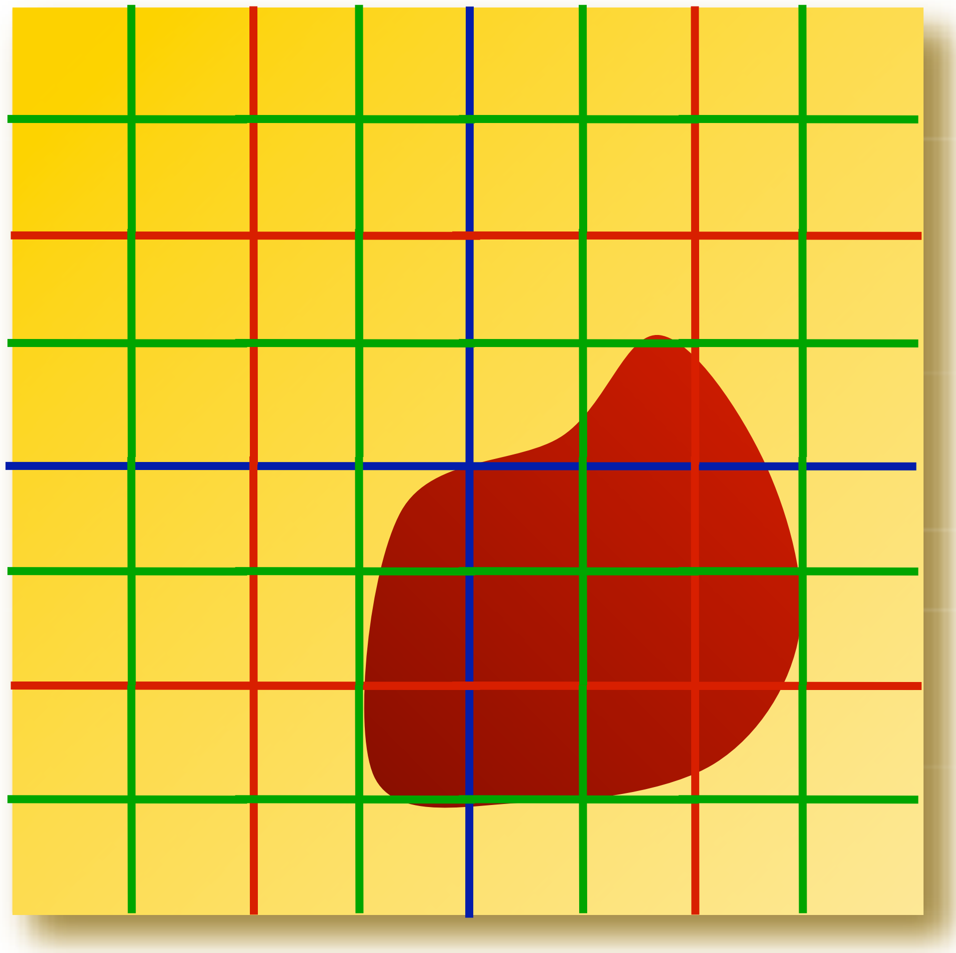
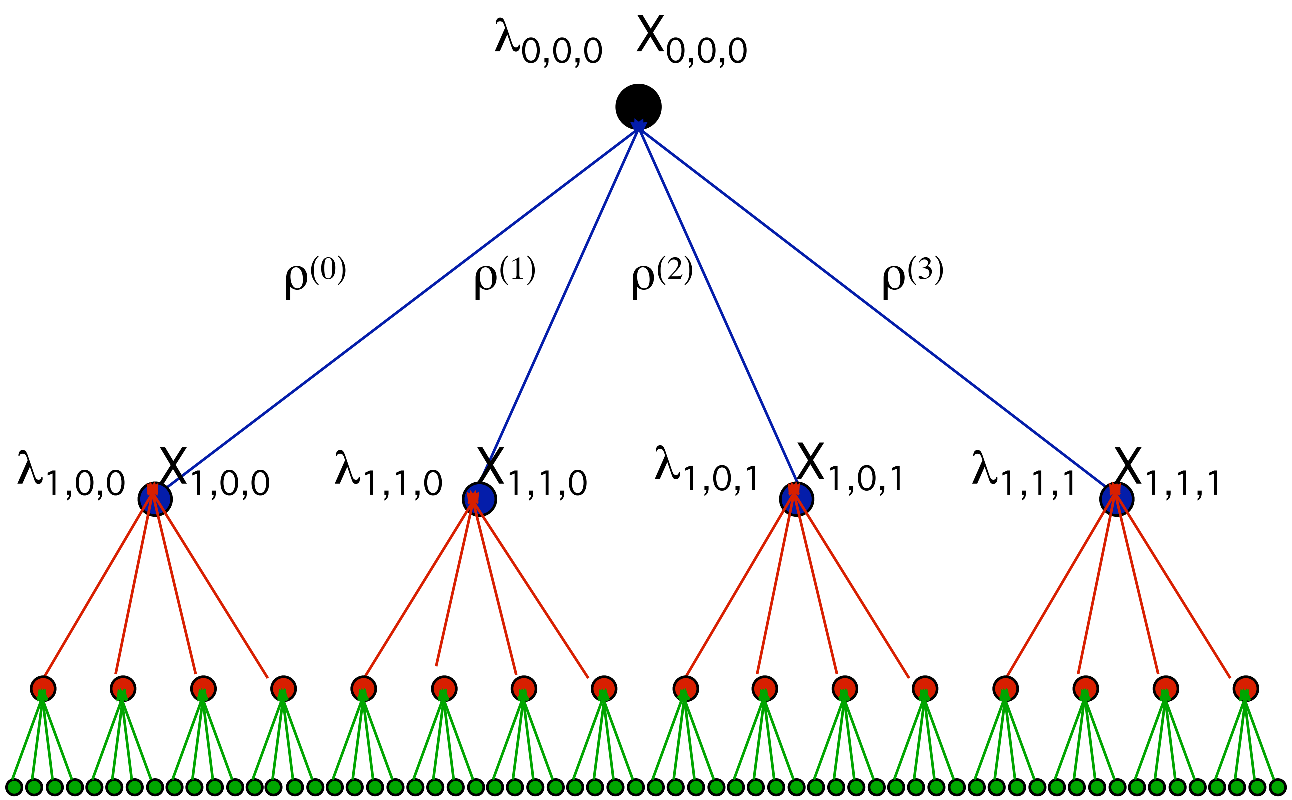
Multiplicative Multiscale Innovation Models





- Recursively subdivide image into squares
- Let $\{\rho\}$ denote the ratio between child and parent intensities
- Knowing $\{\rho\} \Leftrightarrow$ Knowing $\{\lambda\}$
- Estimate $\{\rho\}$ from empirical estimates based on counts in each partition square

Timmermann & Nowak, 1999
Kolaczyk, 1999

Usual Equations for 'True' Intensity, Instrument, Data:

$S(l,b,e,t,\theta)$ = Expected 'True' Source Intensity

$E(l,b,e,t,\varphi)$ = 'True' Effective Area

$PSF(x,y \mid l,b,e,t,\xi)$ = 'True' instrument smearing

$\Lambda(x,y,e,t,\theta,\varphi,\xi)$ = 'True' Expected counts in detector

$D(x,y,e,t,\theta,\varphi,\xi)$ = measured counts in detector

$$\Lambda(x,y,e,t,\theta,\varphi,\xi) = PSF(x,y|l,b,e,t,\xi) @ E(l,b,e,t,\varphi) * S(l,b,e,t,\theta)$$

$$D(x,y,e,t,\theta,\varphi,\xi) \sim \text{Poisson}(\Lambda(x,y,e,t,\theta,\varphi,\xi))$$

Usual Equations for 'Model' Intensity, Instrument, Data:

$s(l,b,e,t,\theta)$ = Expected 'Model' Source Intensity

$\epsilon(l,b,e,t,\varphi)$ = 'Model' Effective Area

$psf(x,y \mid l,b,e,t,\xi)$ = 'Model' instrument smearing

$\lambda(x,y,e,t,\theta,\varphi,\xi)$ = 'Model' Expected counts in detector

$D(x,y,e,t,\theta,\varphi,\xi)$ = measured counts in detector

$$\lambda(x,y,e,t,\theta,\varphi,\xi) = psf(x,y|l,b,e,t,\xi) @ \epsilon(l,b,e,t) * s(l,b,e,t,\theta)$$

$$D\,(x,y,e,t,\theta,\varphi,\xi) \sim \text{Poisson}\,(\,\lambda(x,y,e,t,\theta,\varphi,\xi)\,)$$

Our Equations for 'Model' Intensity, Instrument, Data:

$s(l,b,e,t,\theta)$ = Expected 'Physics Model' Source Intensity

$m(l,b,e,t,\alpha,\kappa)$ = Expected Multiscale Source Counts

α = Smoothing Parameters for each scale

κ = 'Range' parameter for Hyper-priors on α

β = 'Scale Factor' for Physics Model

$\epsilon(l,b,e,t,\varphi)$ = 'Model' Effective Area

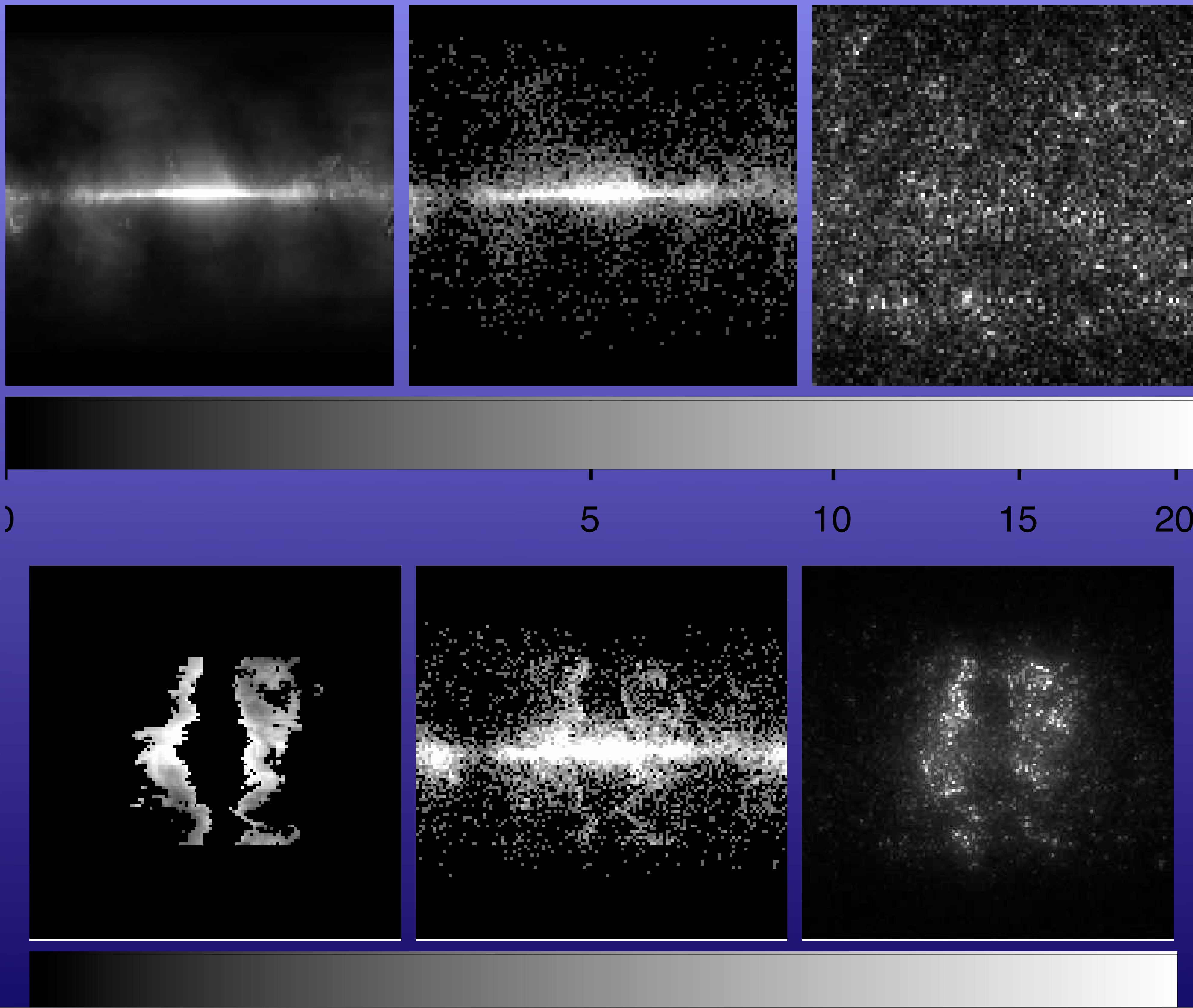
$psf(x,y \mid l,b,e,t,\xi)$ = 'Model' instrument smearing

$\lambda(x,y,e,t,\theta,\varphi,\xi)$ = 'Model' Expected counts in detector

$D(x,y,e,t,\theta,\varphi,\xi)$ = measured counts in detector

$$\lambda(x,y,e,t,\theta,\varphi,\xi) = psf(x,y|l,b,e,t,\xi)@$$
$$(\ \beta*\epsilon(l,b,e,t)*s(l,b,e,t,\theta) + m\ (l,b,e,t,\alpha,\kappa)\ )$$

3. Moderate Signal-To-Noise Examples:Gamma-Ray Sky:



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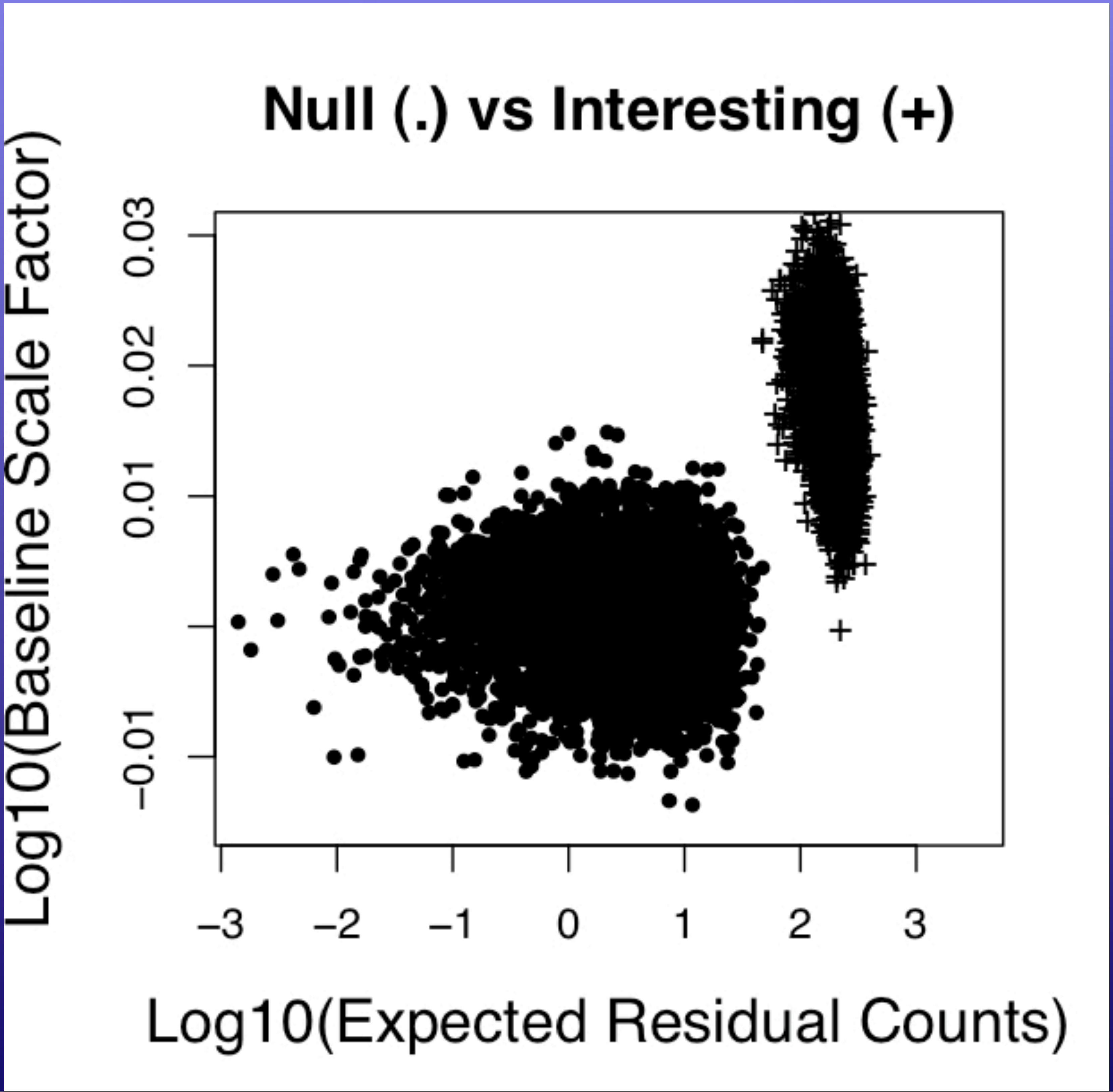

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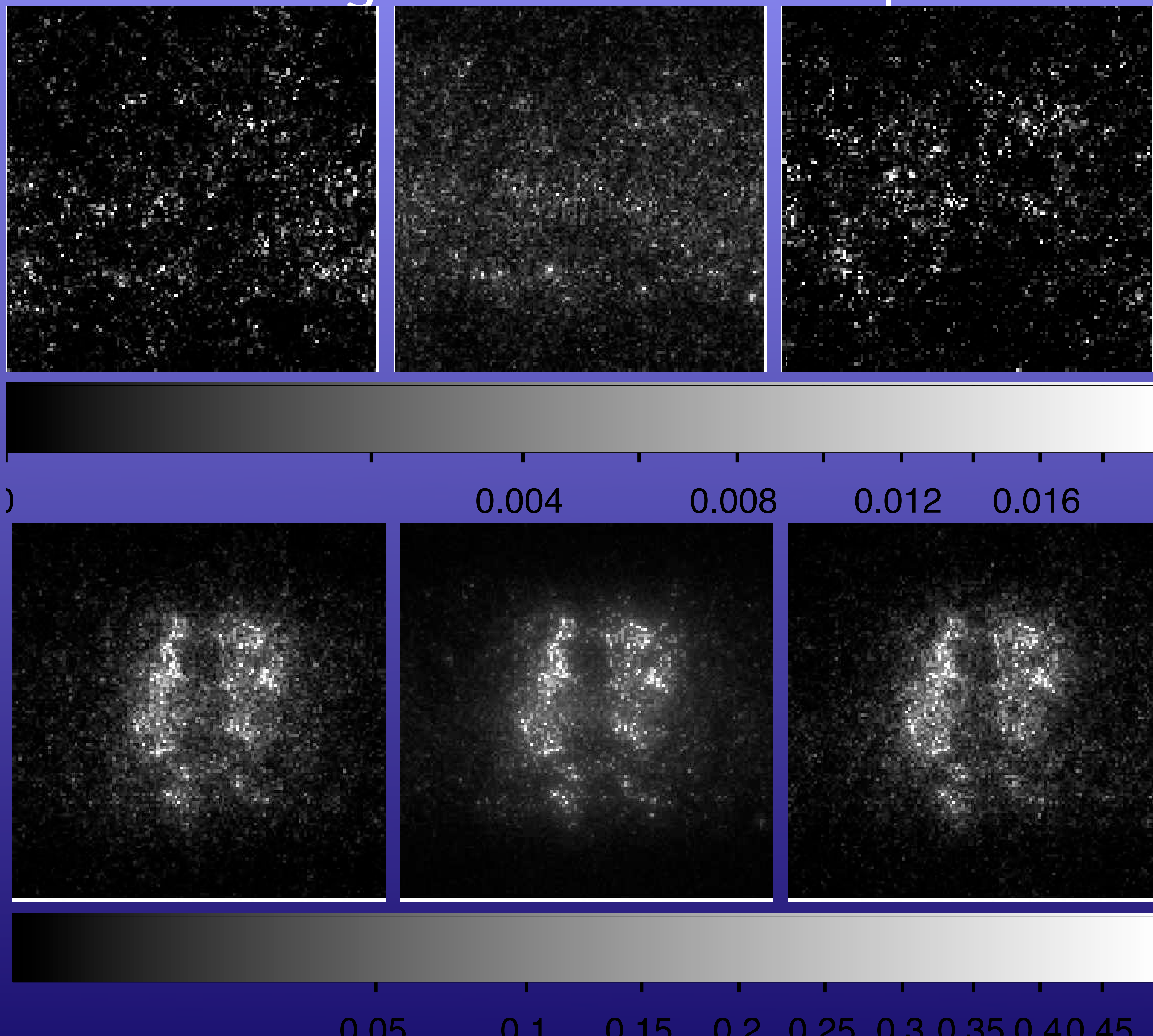
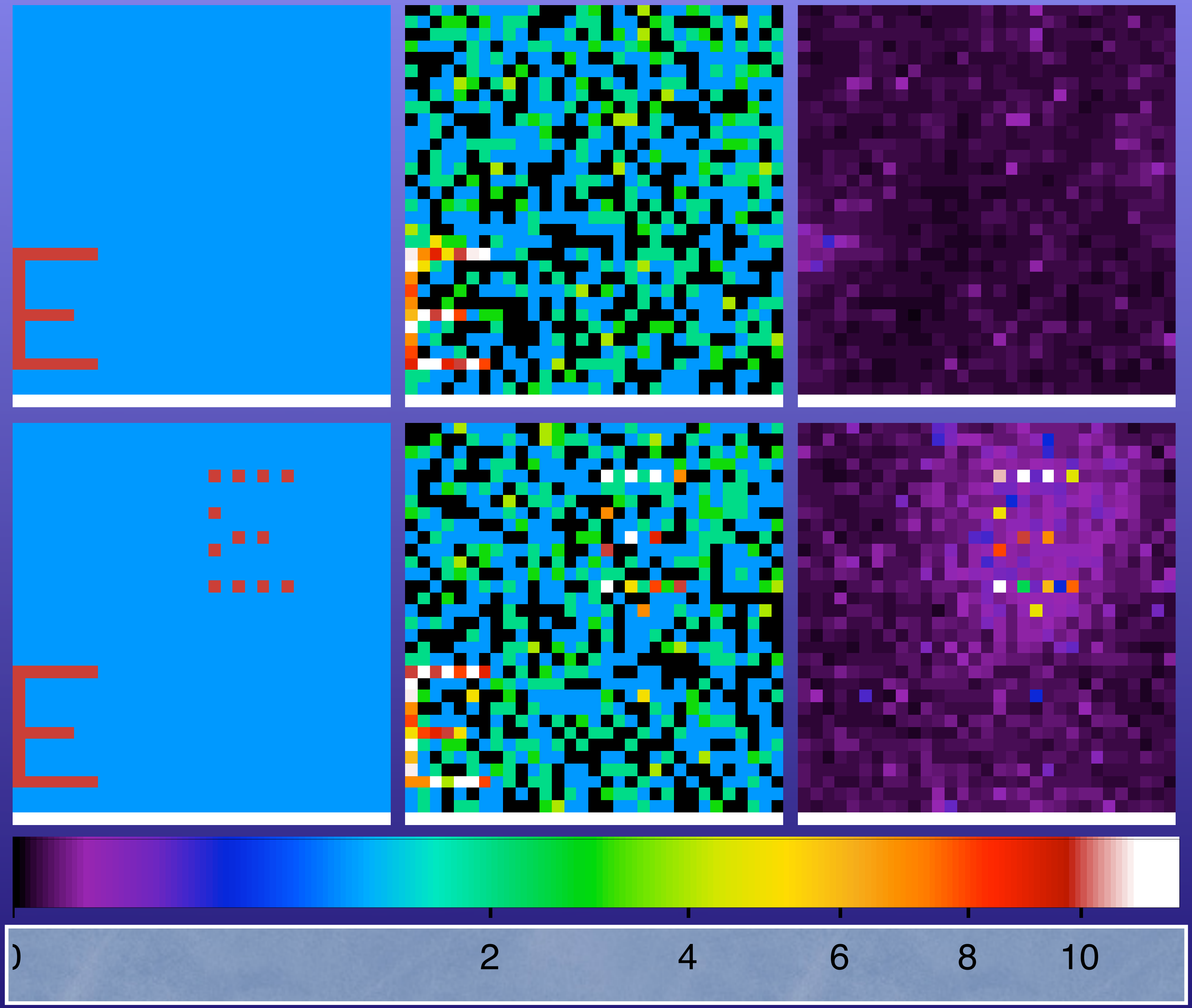


4. Moderate Signal-To-Noise Examples: 2 "E":



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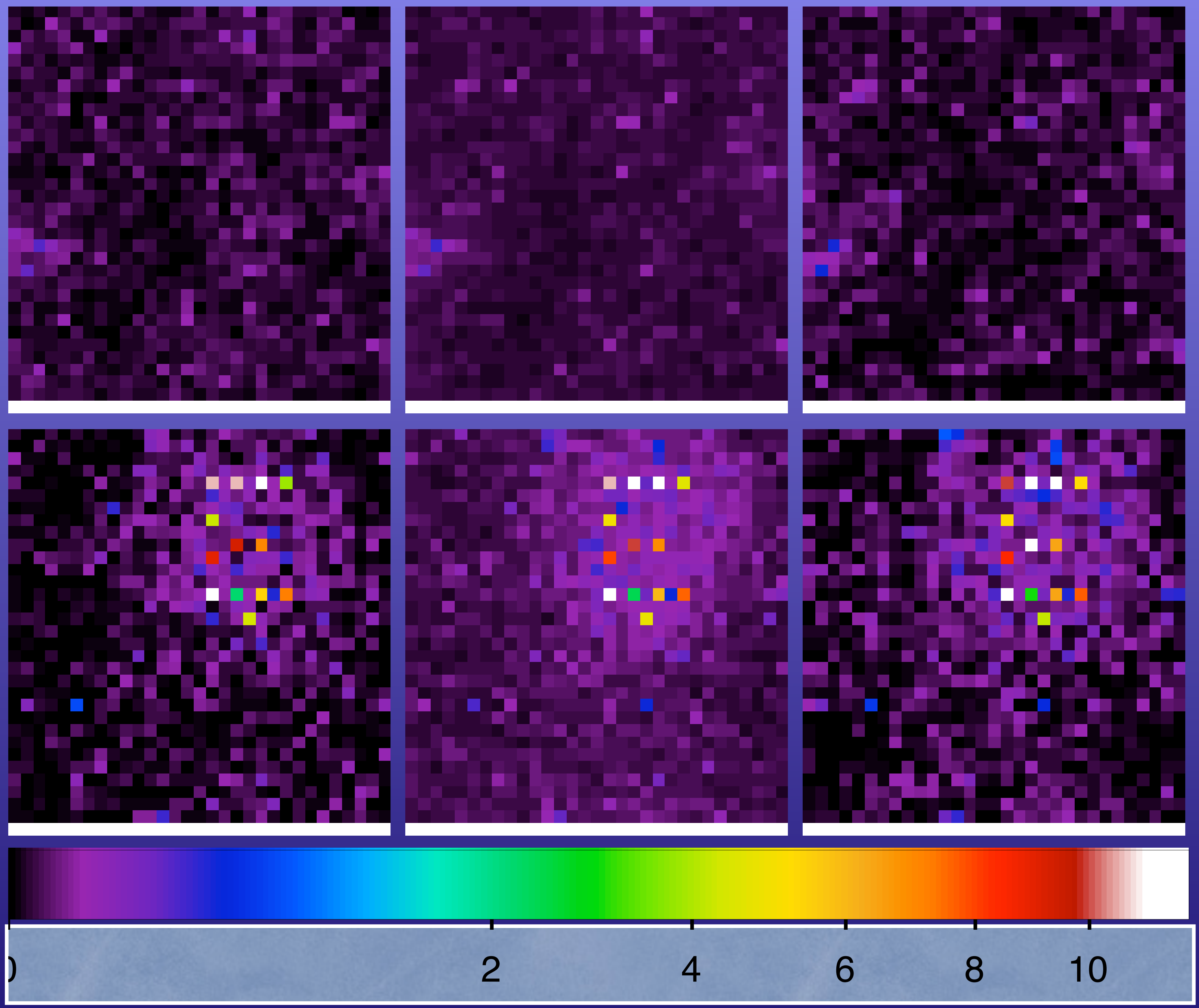
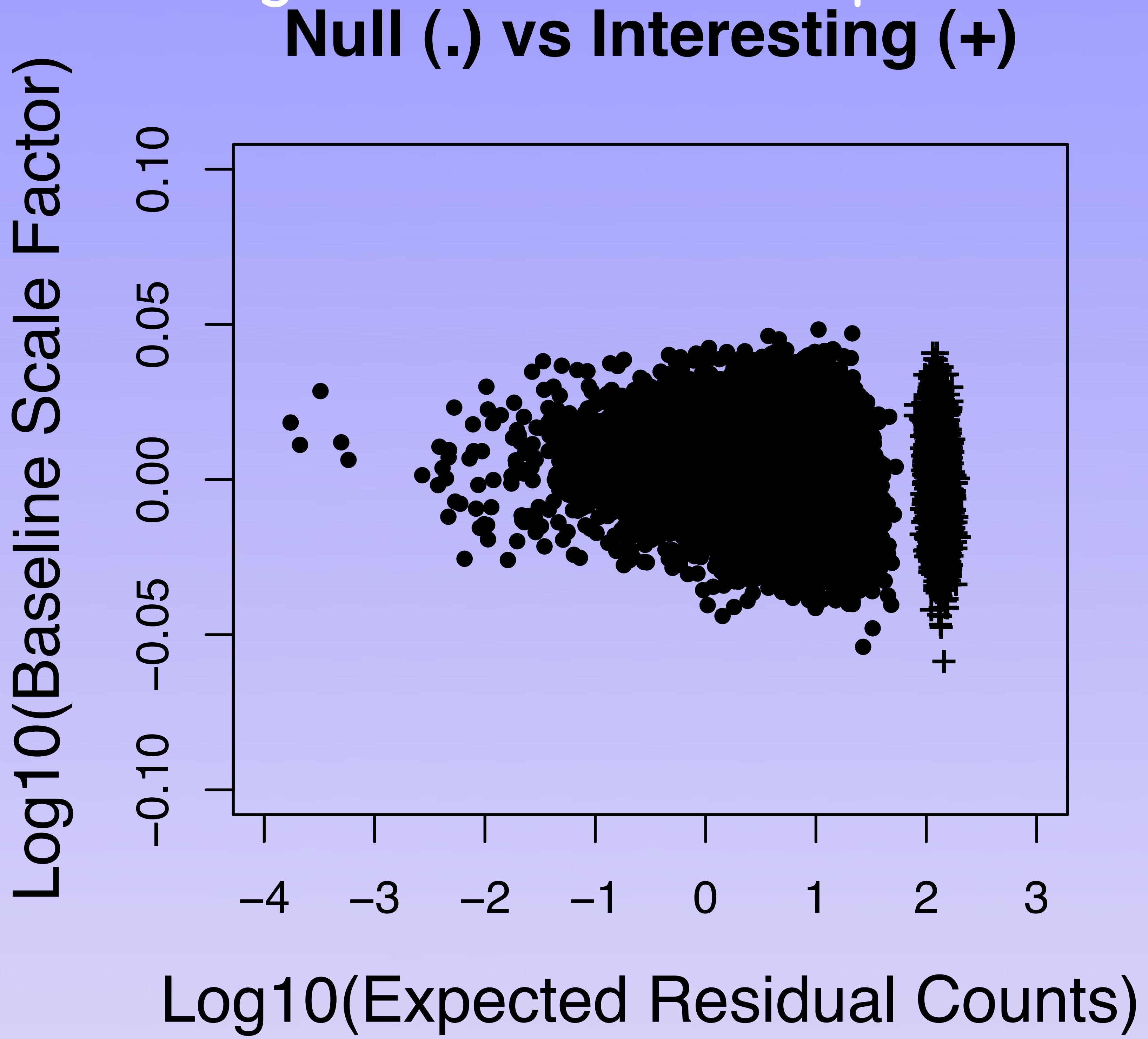
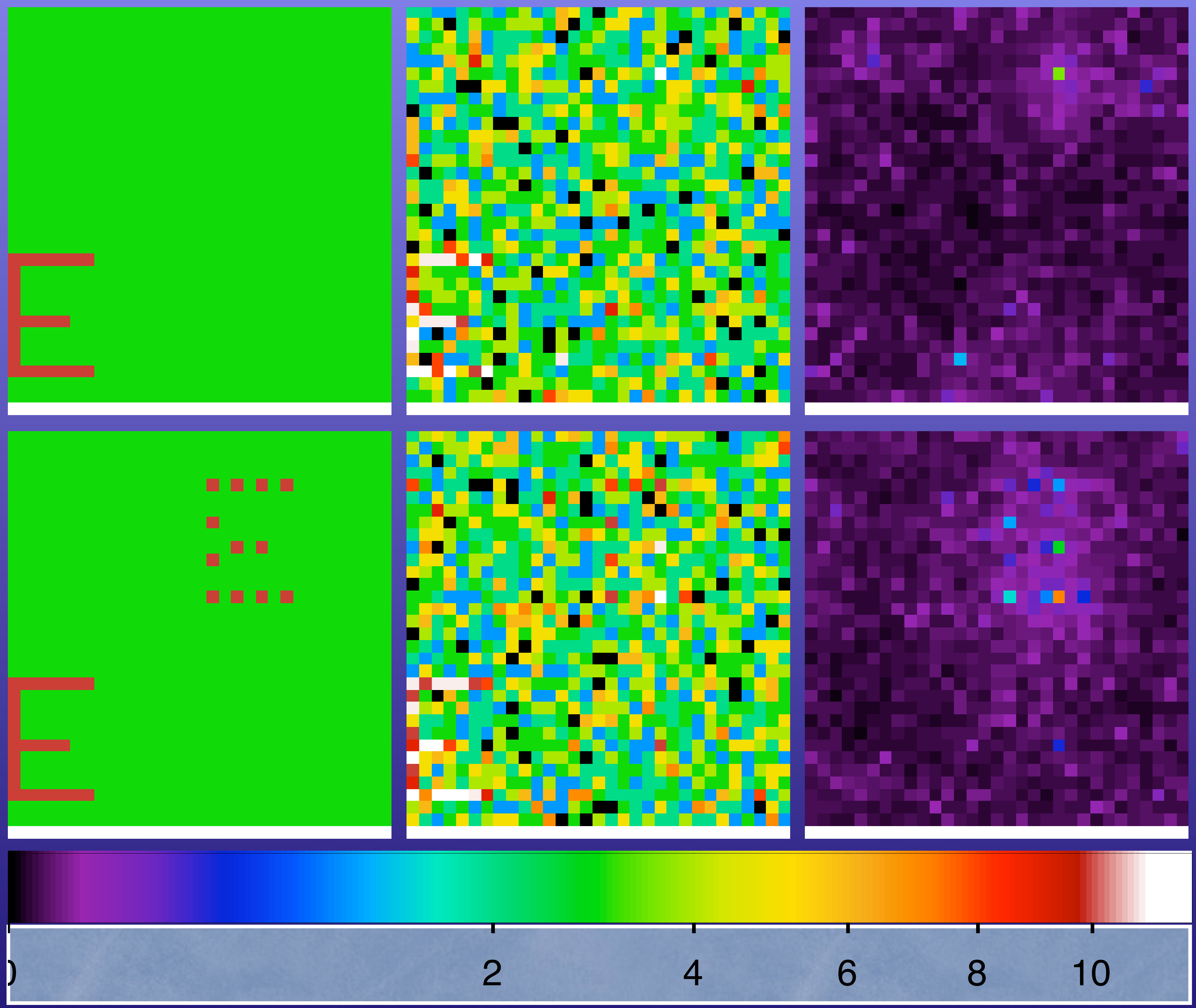


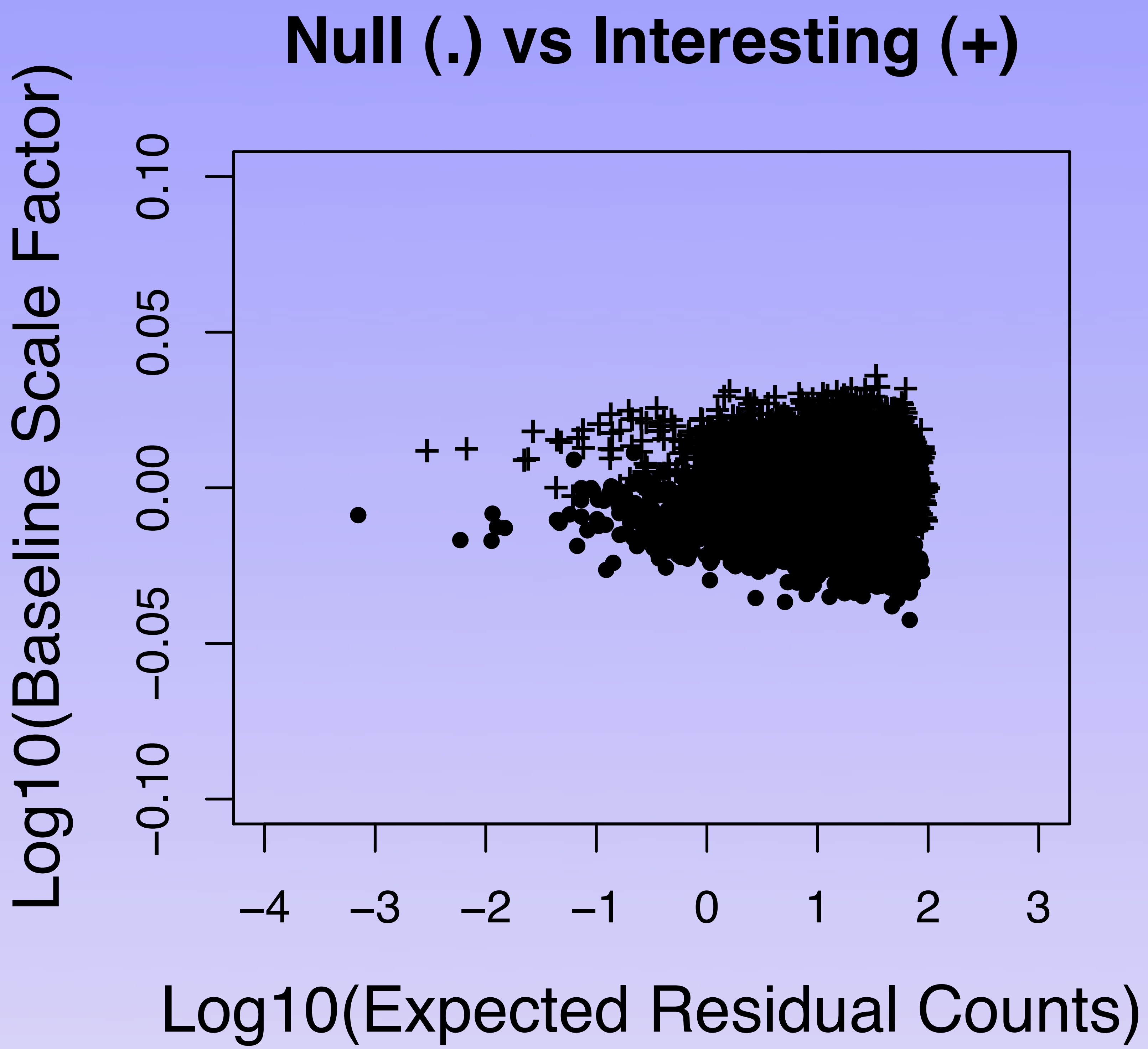
4. Moderate Signal-To-Noise Examples: 2 "E":



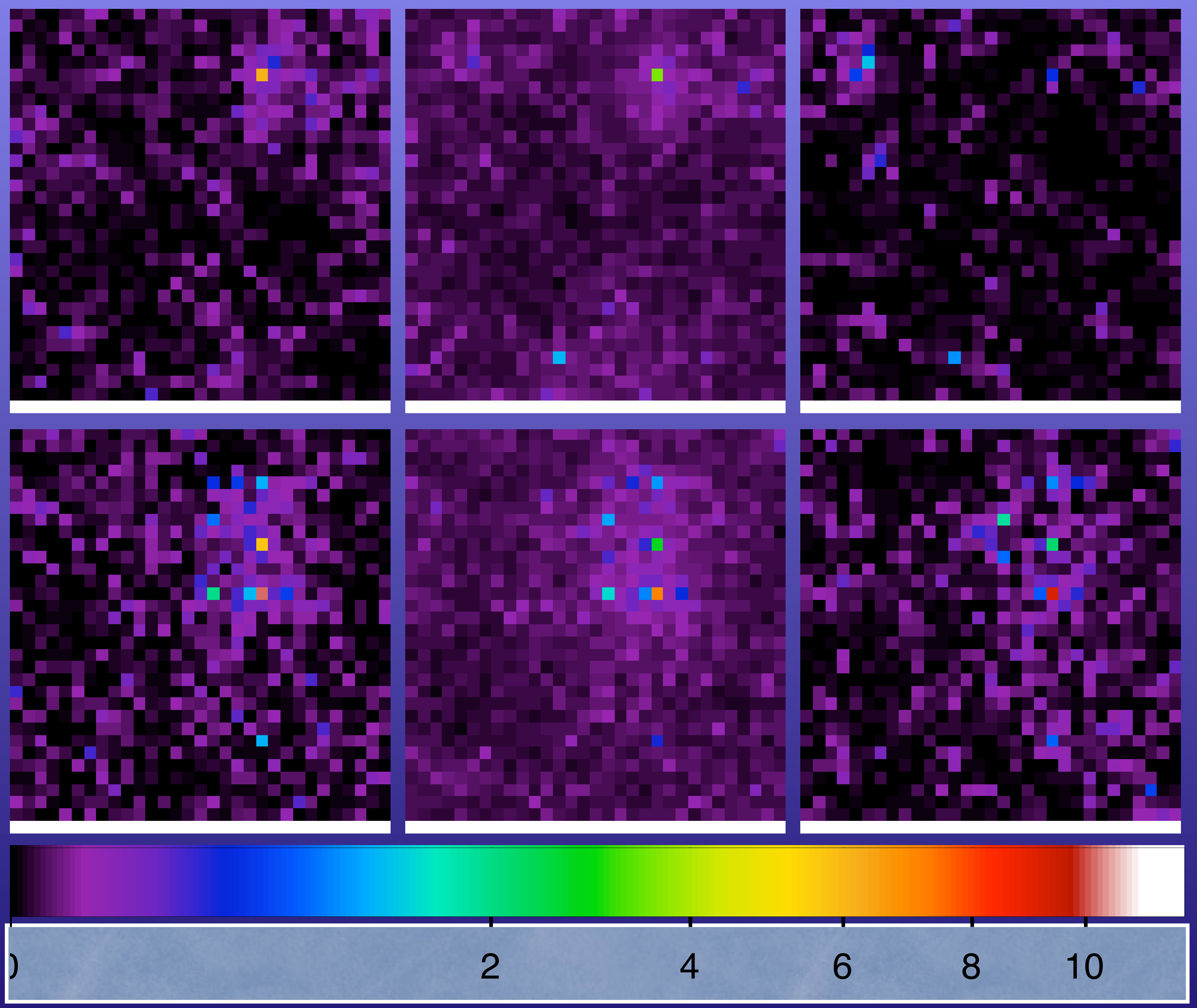
3. Low Signal-To-Noise Examples: 2 "E":



5. Low Signal-To-Noise Examples: 2 "E":



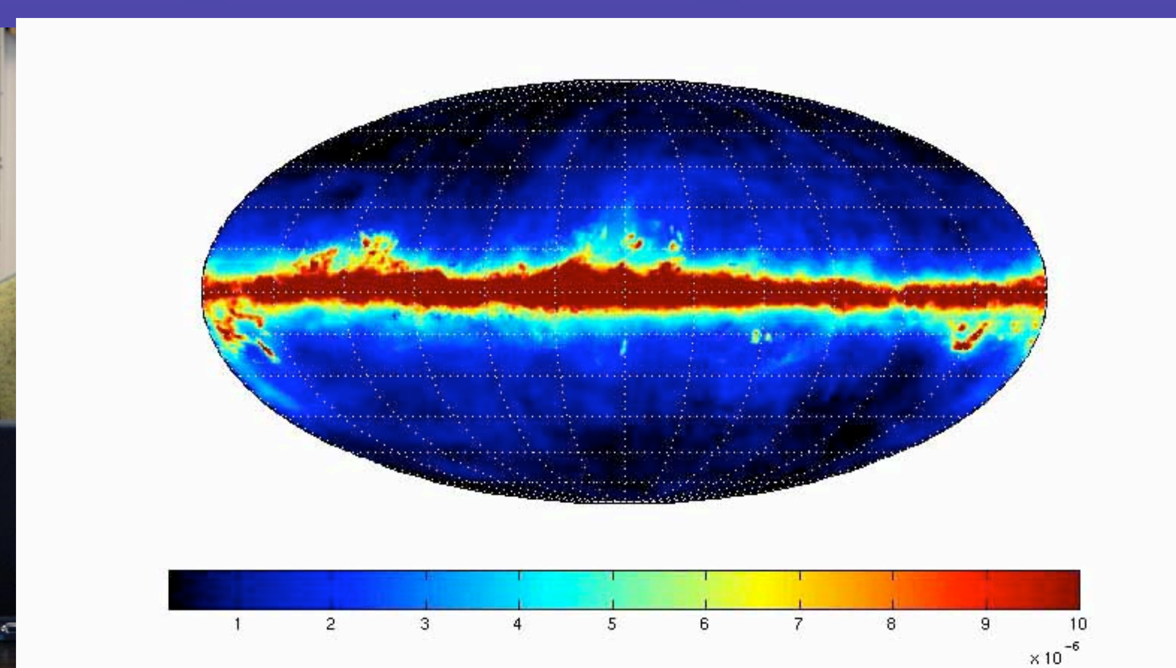
5. Low Signal-To-Noise Examples: 2 "E":



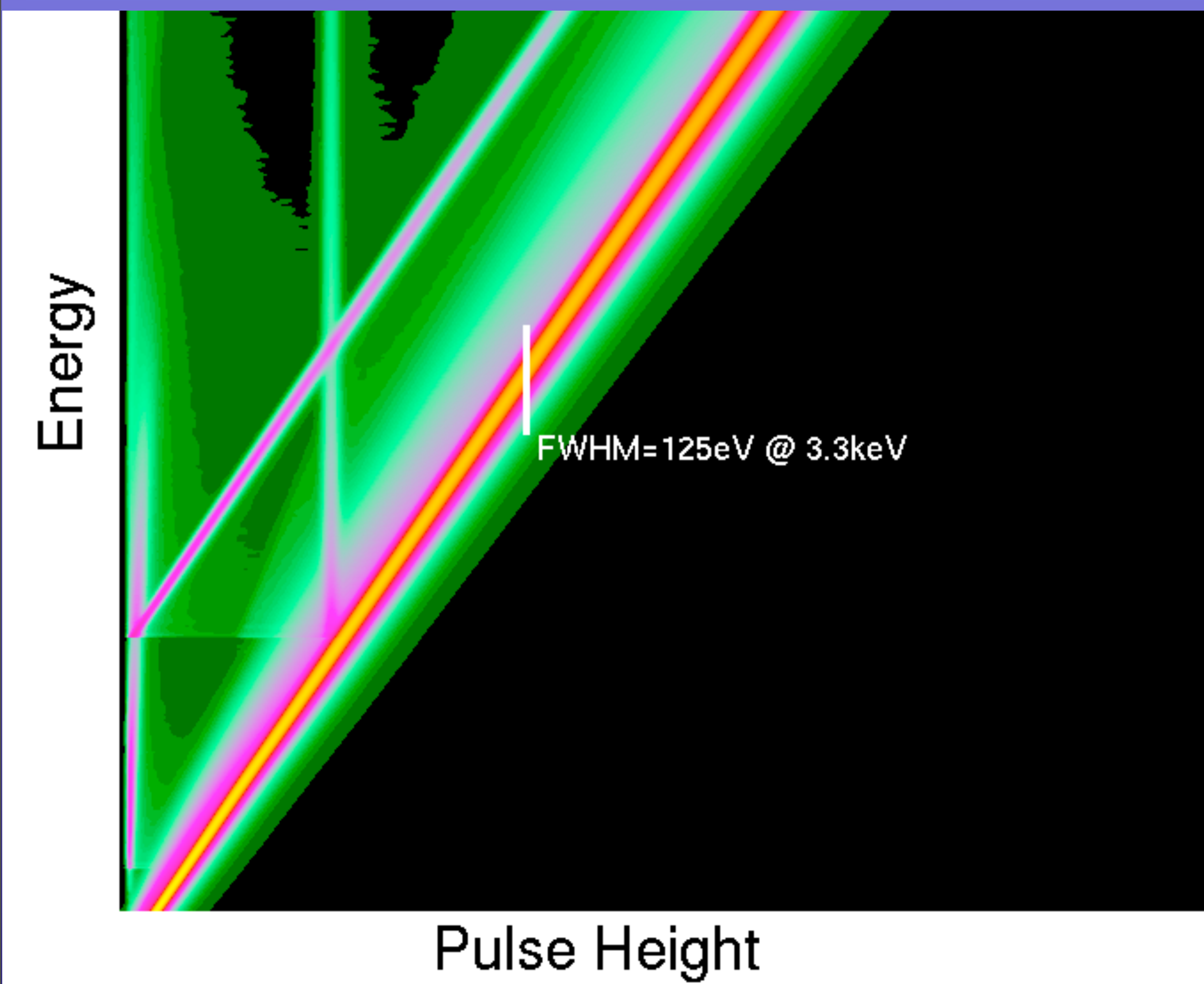
DOUBT: Skeptical Astronomers: Basic Physics??

V. Kashyap, N. Brickhouse : Atomic physics uncertainy

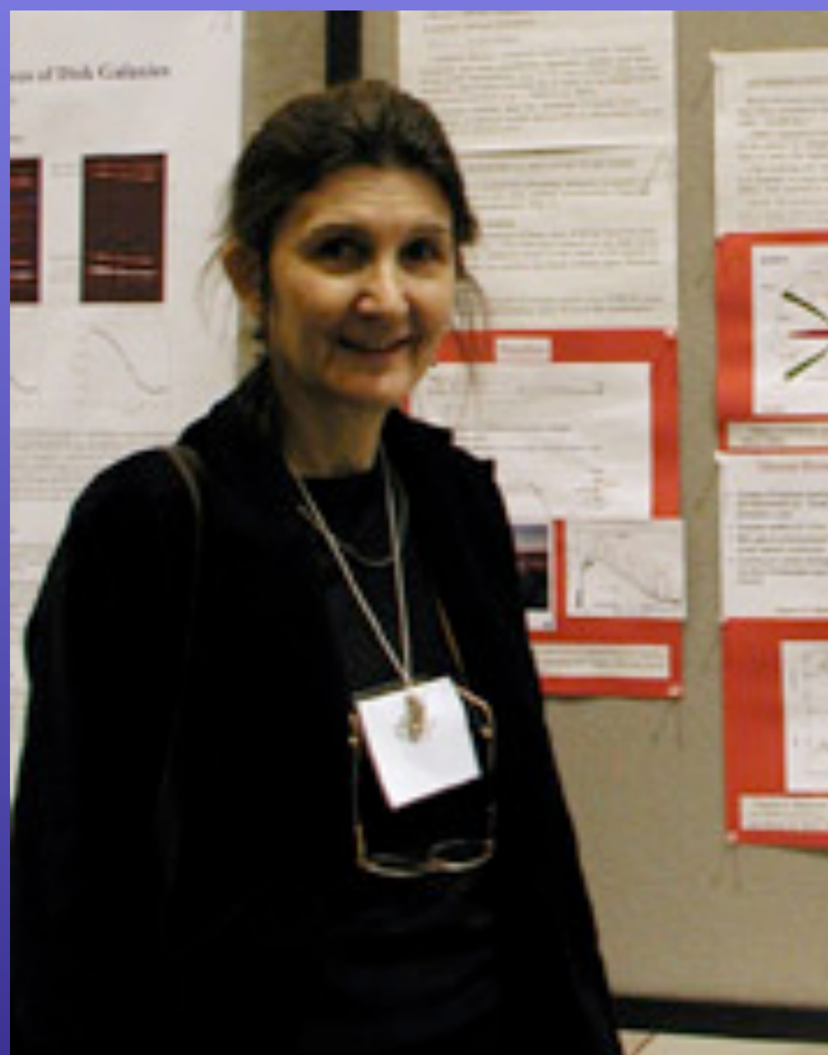
I. A. Grenier, J. M Casandjian : "GALPROP" uncertainy



DOUBT: Skeptical Astronomers.....
J. Drake, et al. : ARF/RMF uncertainy



DOUBT: Skeptical Astronomers.....
M. Karovska on PSF Variations/Uncertainty:



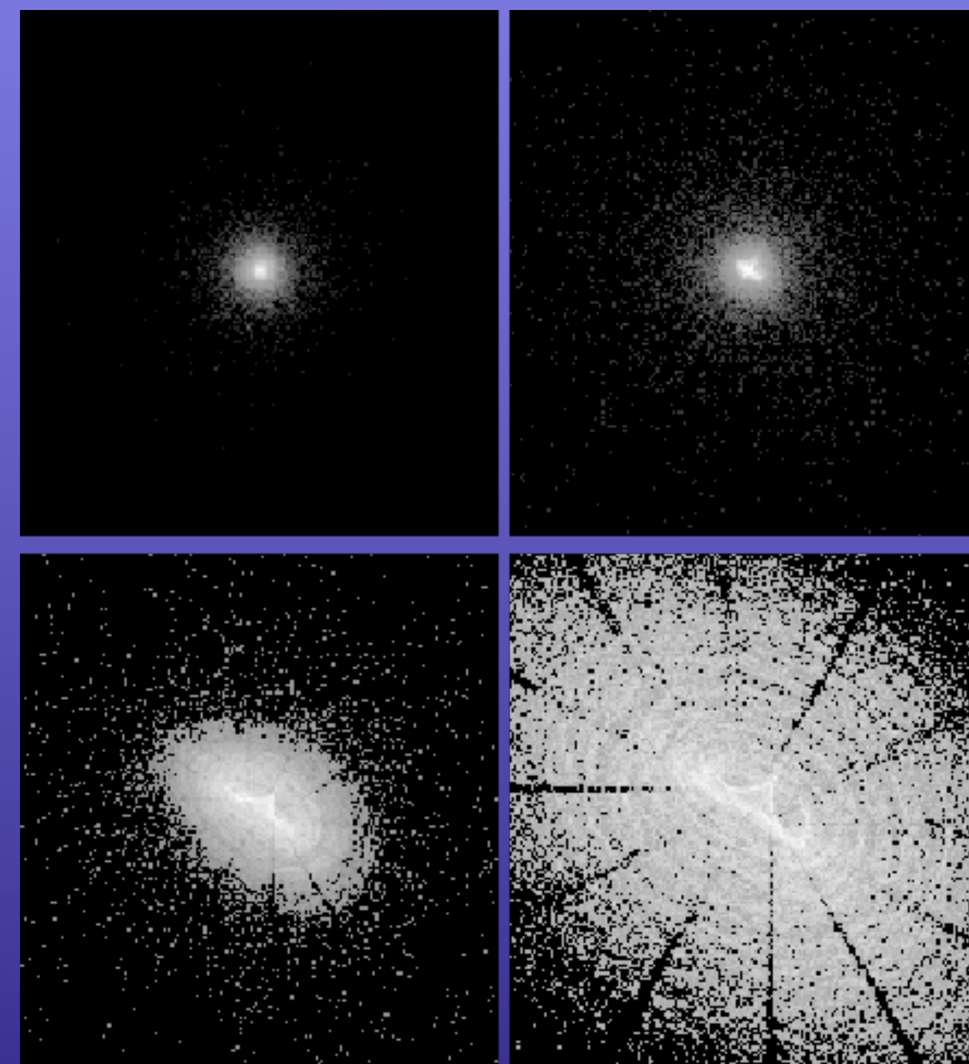
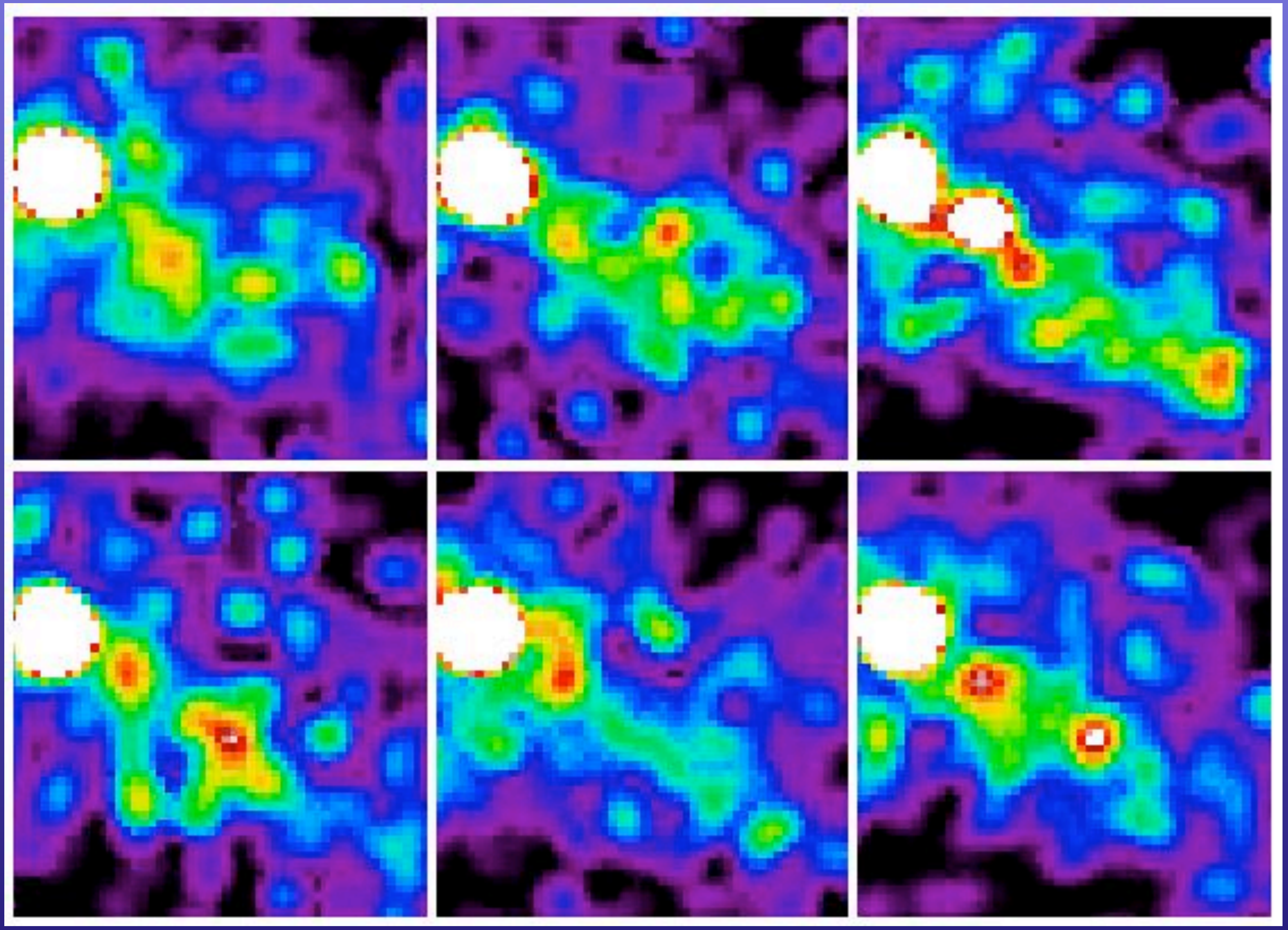
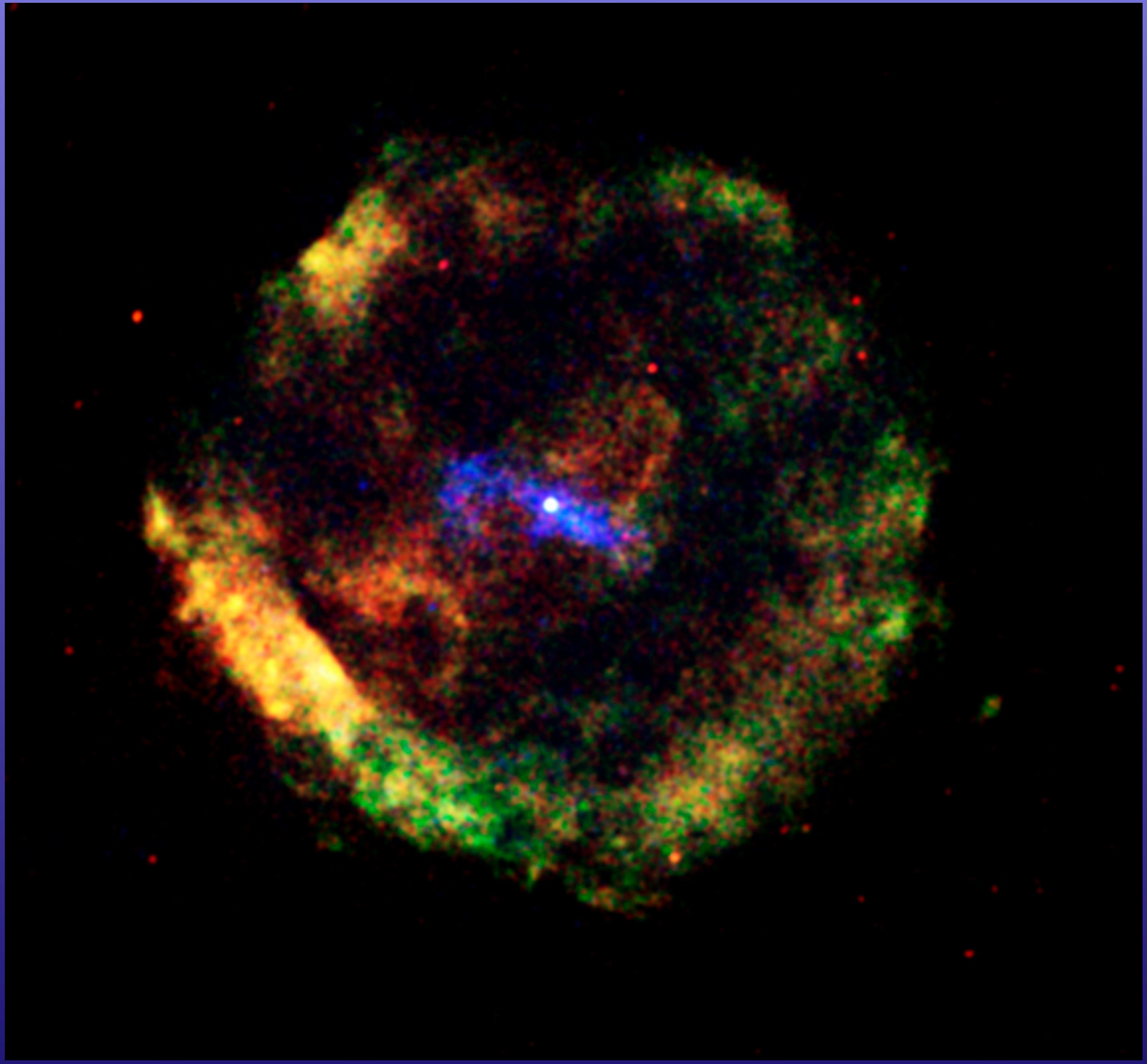


Figure: Model PSFs for the HRC-I instrument at 1.4967keV as a function of off-axis angles (log display); clockwise from the top, off-axis angles 0′ (on axis), 1.′5, 6′, and 12′. The size of the FOV is about 0.′5.

NEW CHALLENGES: Examples
(Mallory Roberts -Black Hole/Jet changes?)



NEW CHALLENGES: Examples
SNR G11.2-0.3 changes with energy?
Mallory Roberts



NEW CHALLENGES: Examples
X-ray vs optical jet??
Herman Marshall