Hierarchical Bayesian Inference – Its Application to Dust Emission Modelling

Frédéric GALLIANO

AIM, CEA/Saclay, France

Outline of the Talk

1. **Motivations & Principles of Bayesian Inference**
   - The Trickiness of Dust SED Fitting
   - Principles of Bayesian Sampling
   - Formalism & Numerical Implementation

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3. **Examples of Applications to Real Astrophysical Data**
   - Spinning Grains in λ-Orionis
   - Dust Evolution in Galaxies

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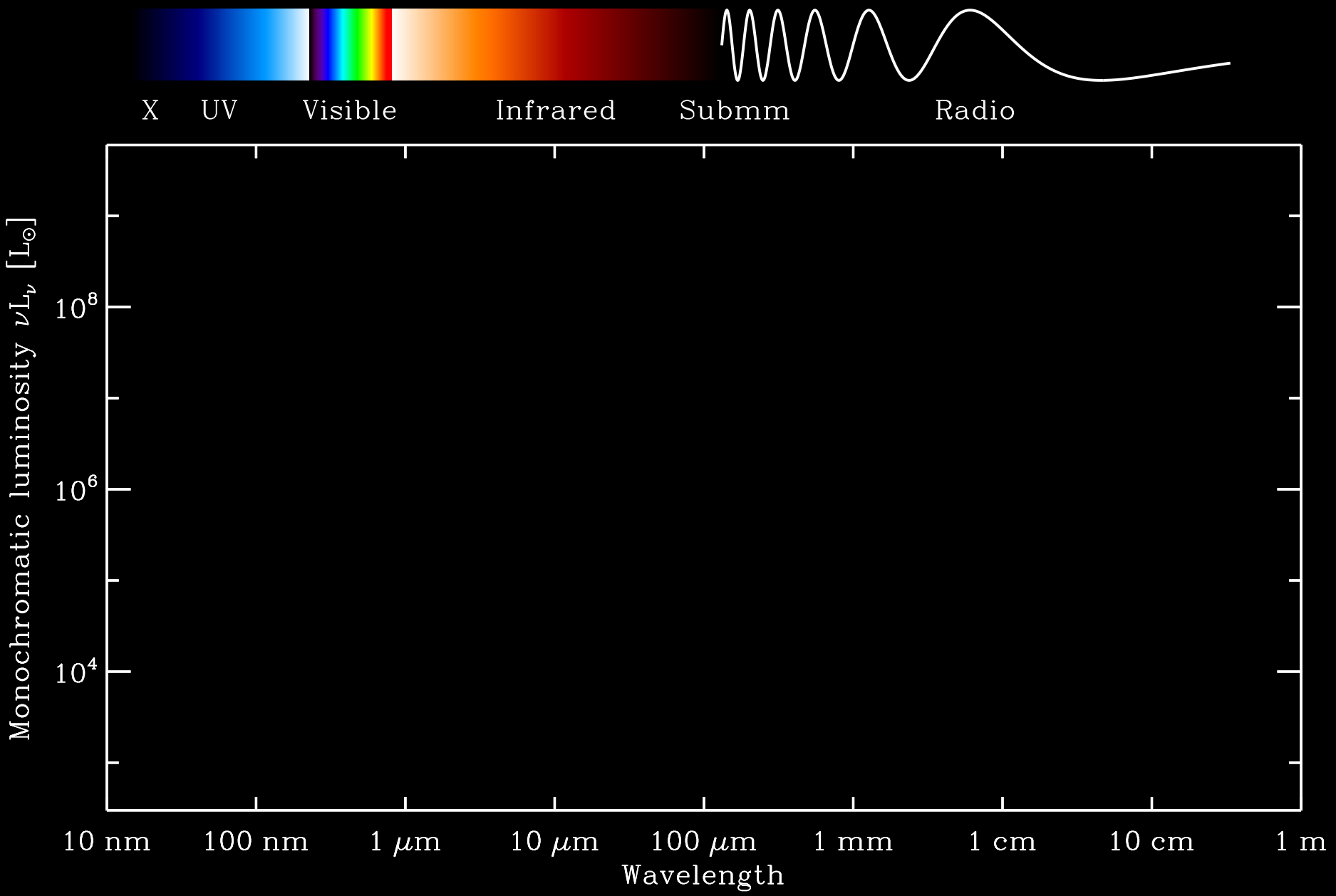

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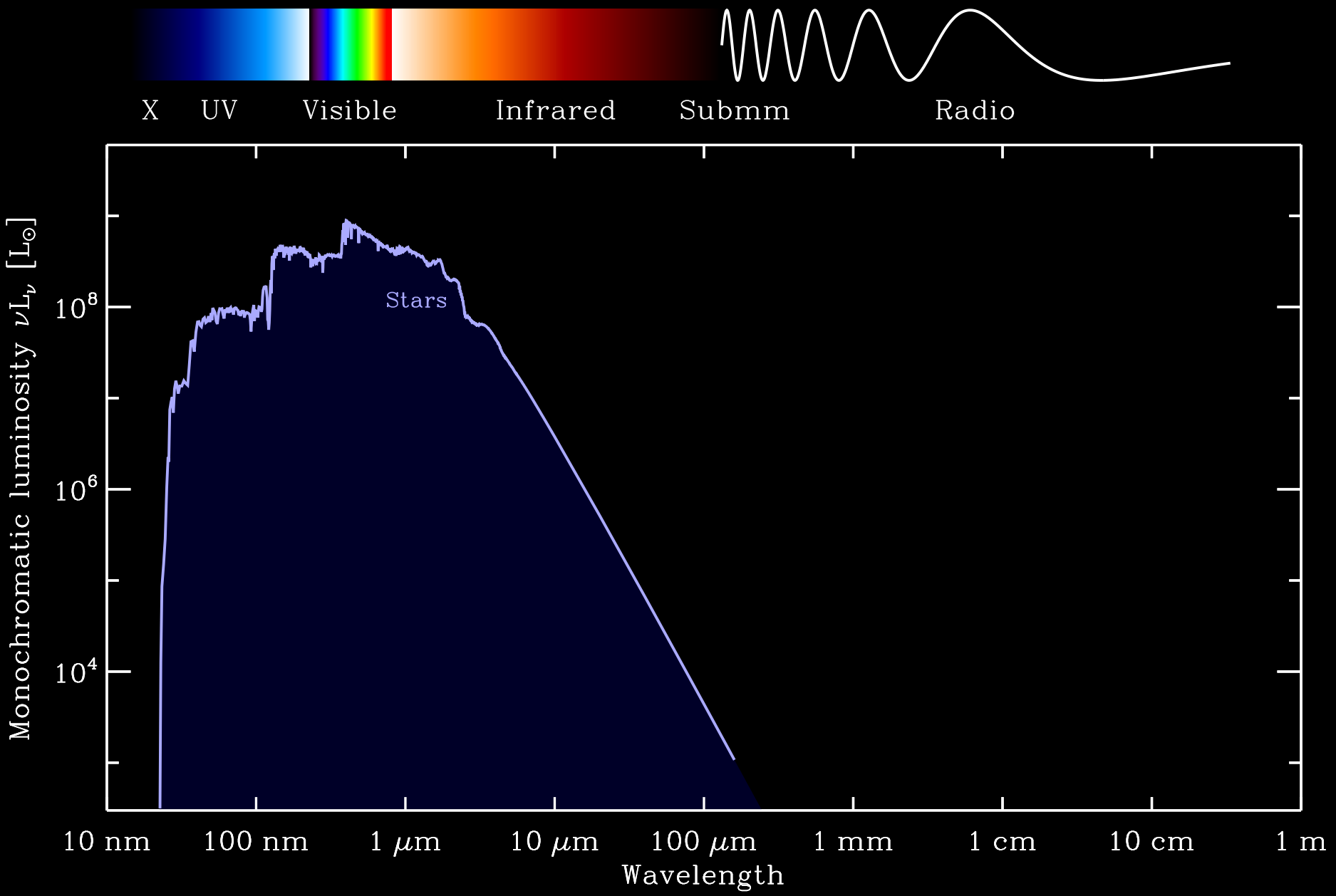

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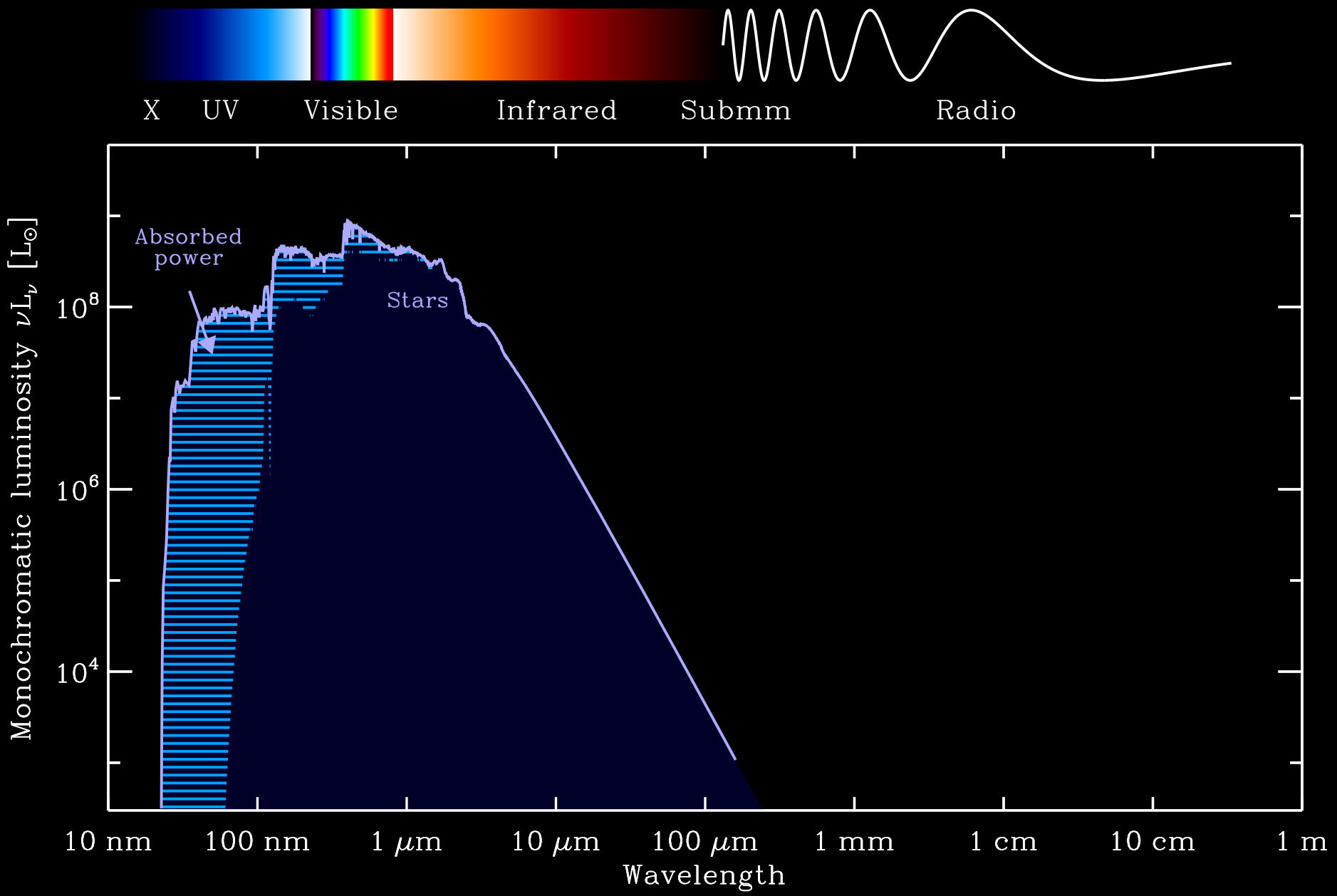

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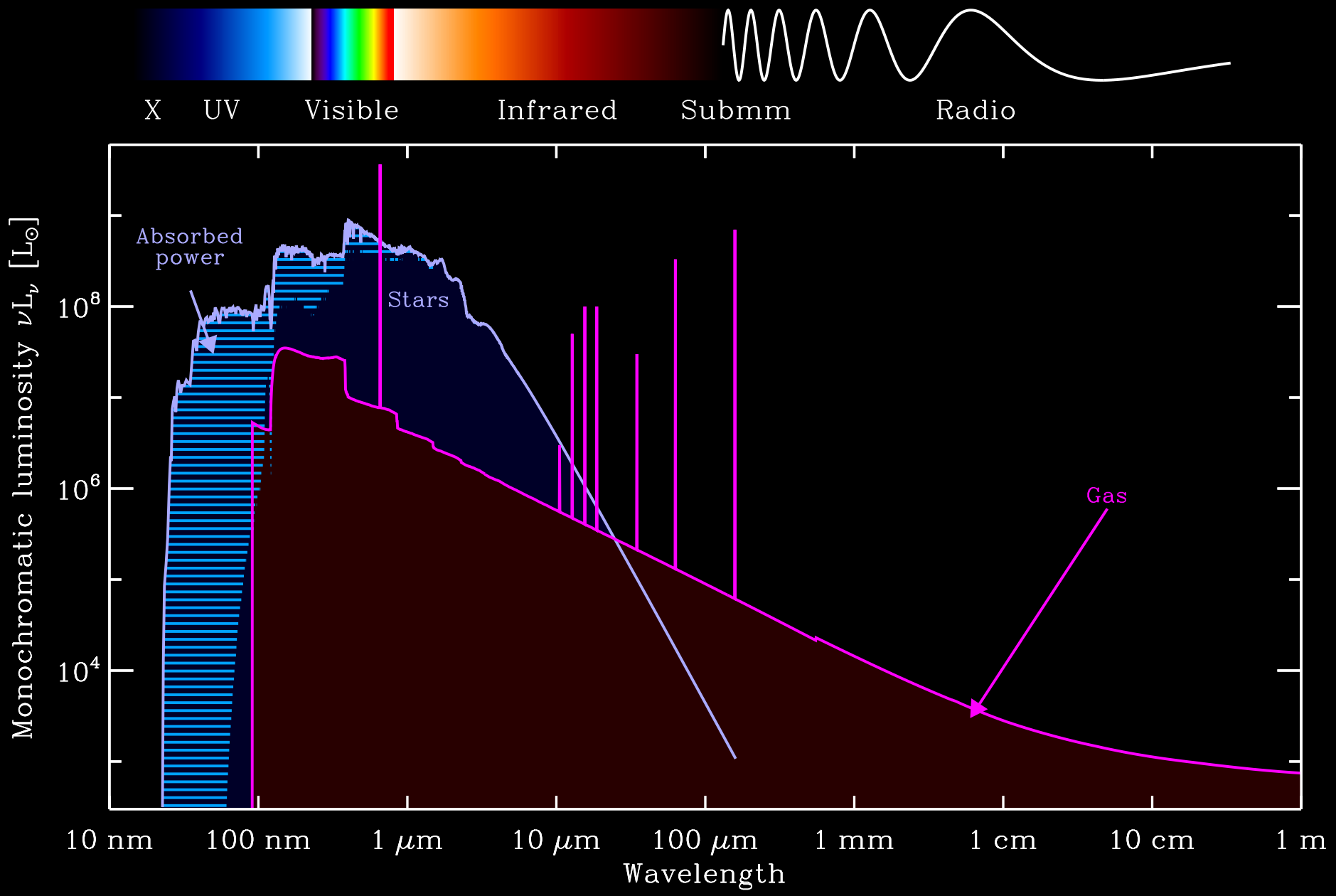

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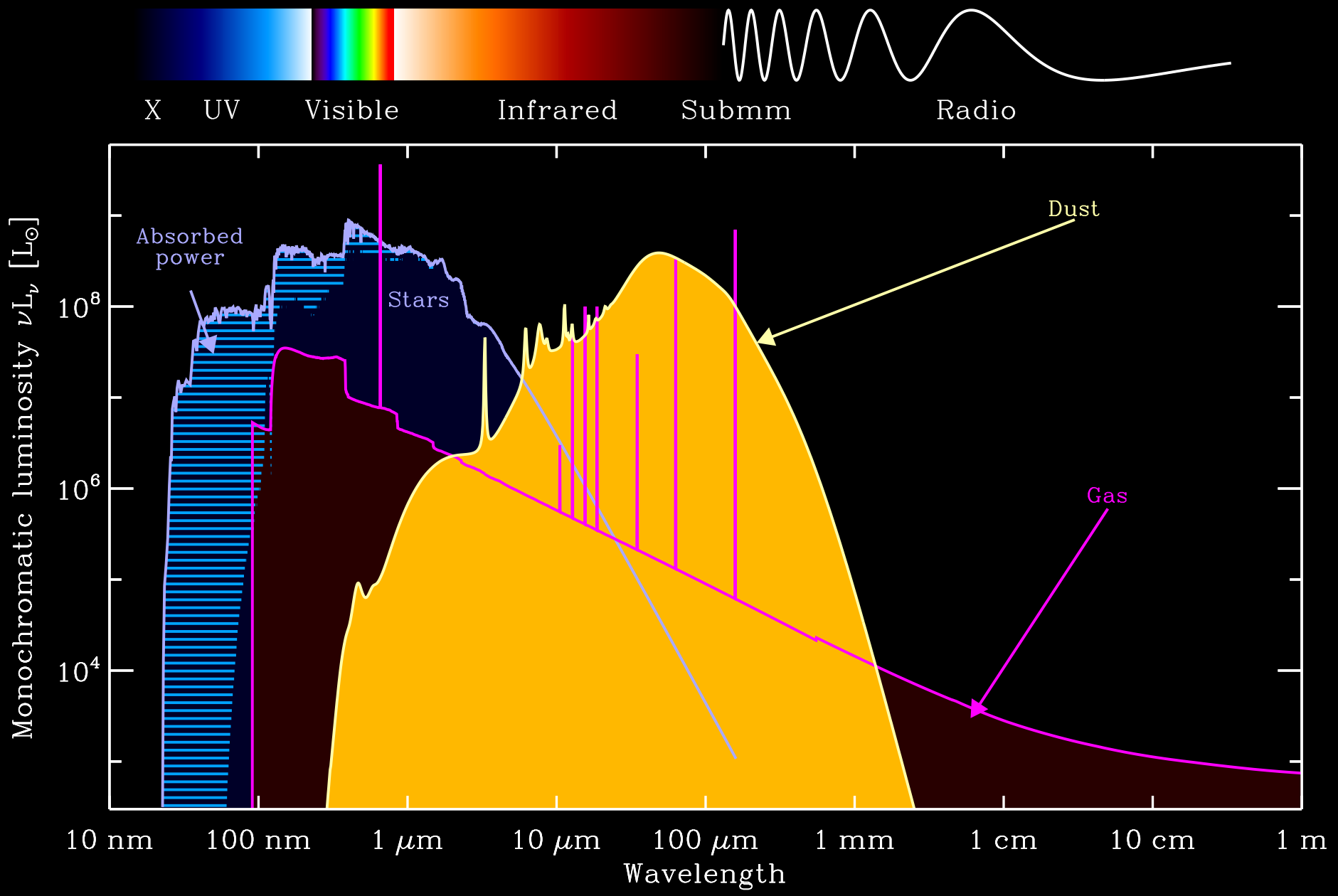

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Sampling the distribution of parameters:

The most common way: Markov Chain Monte-Carlo (MCMC) $\Rightarrow$ randomly drawing parameter values from the posterior.

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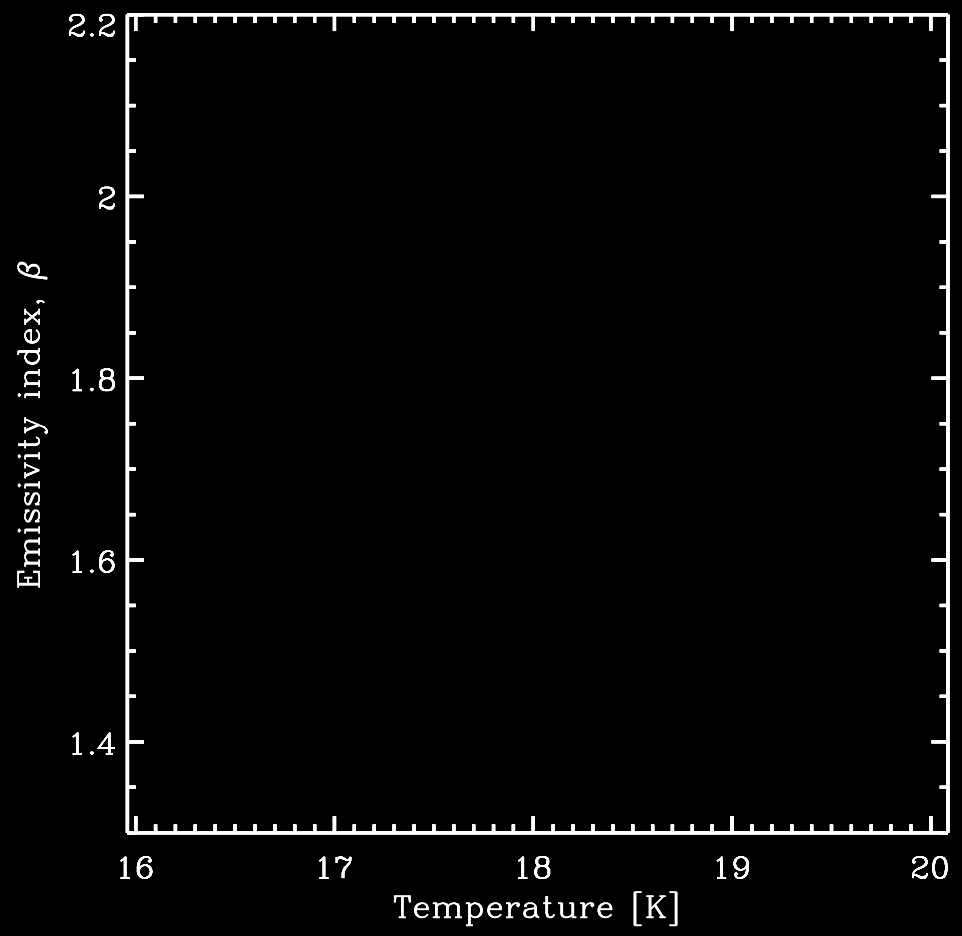

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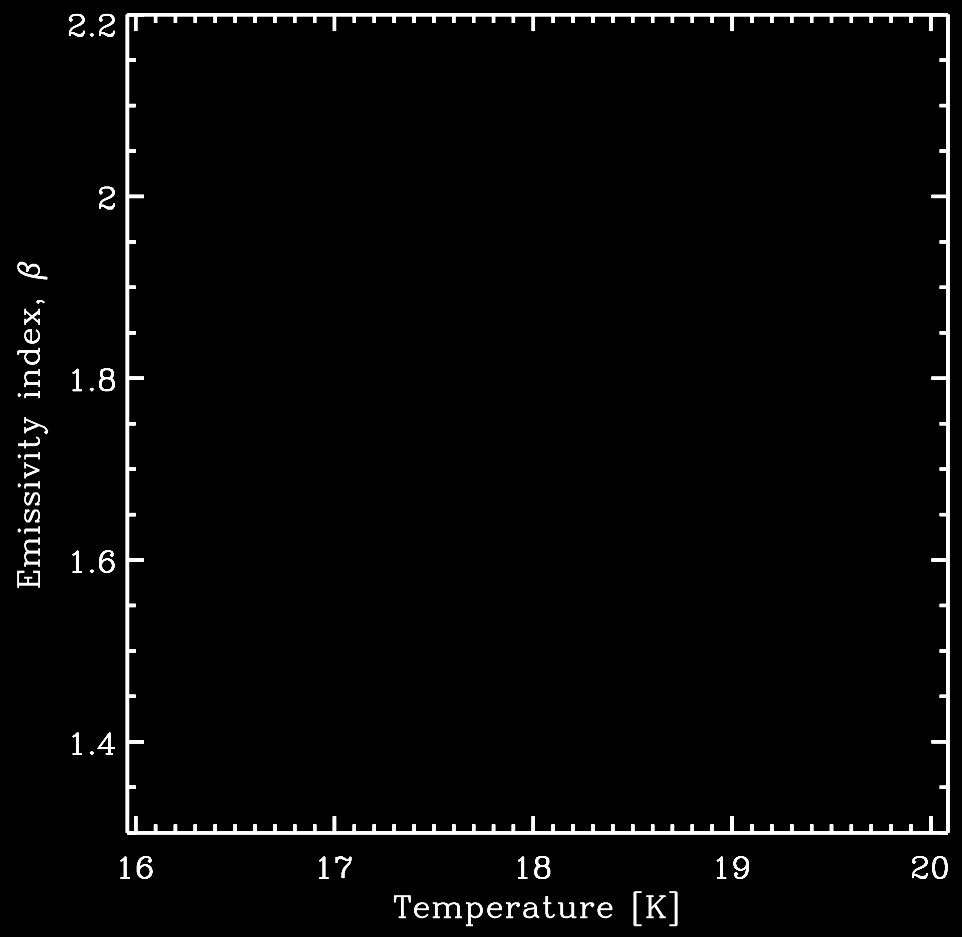

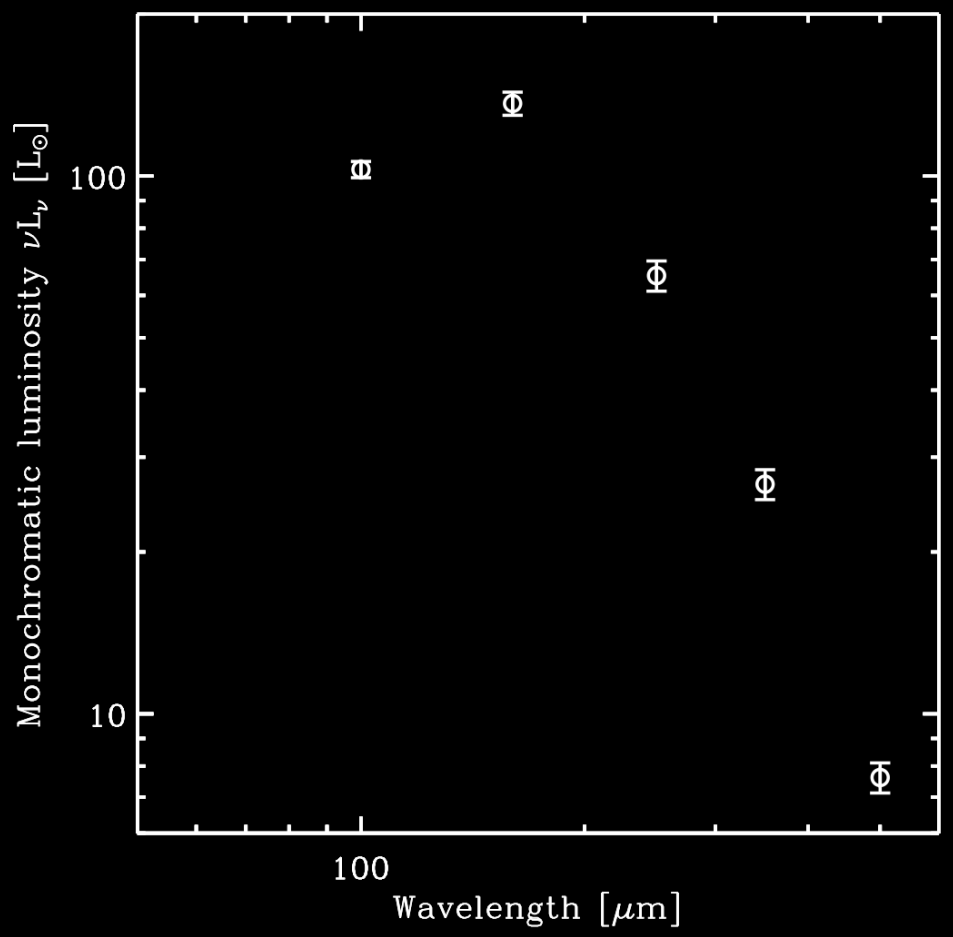

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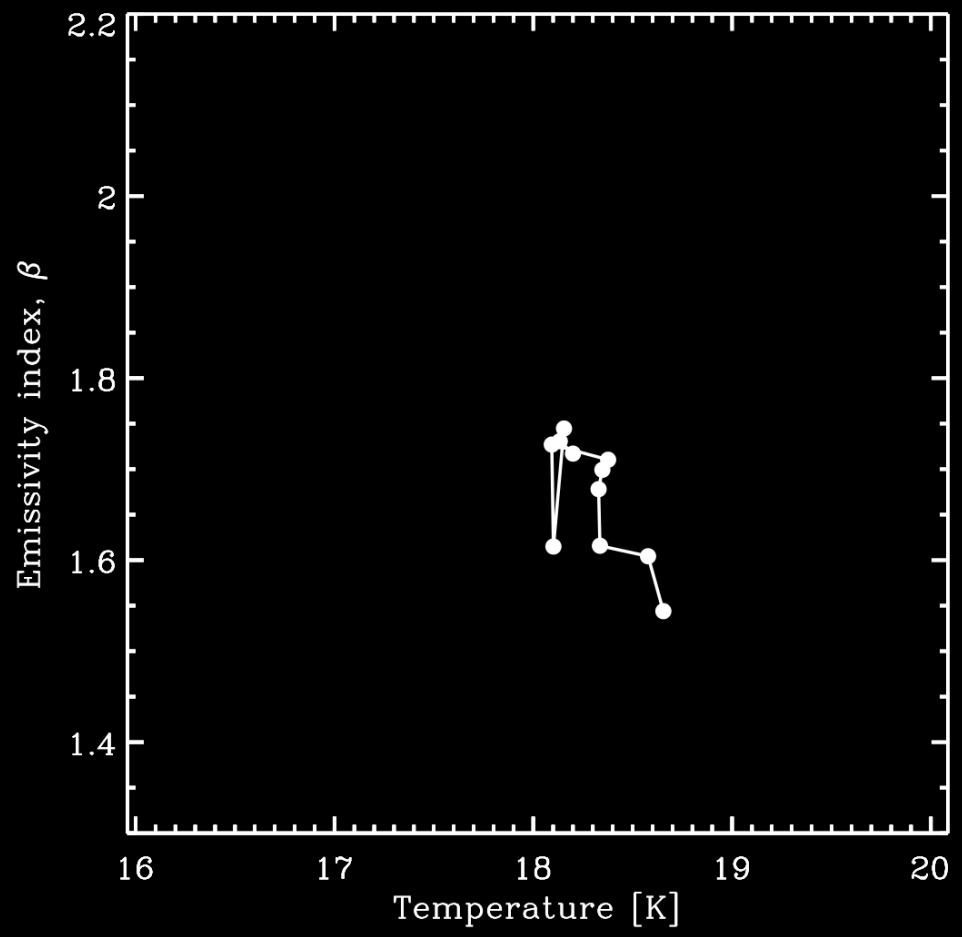

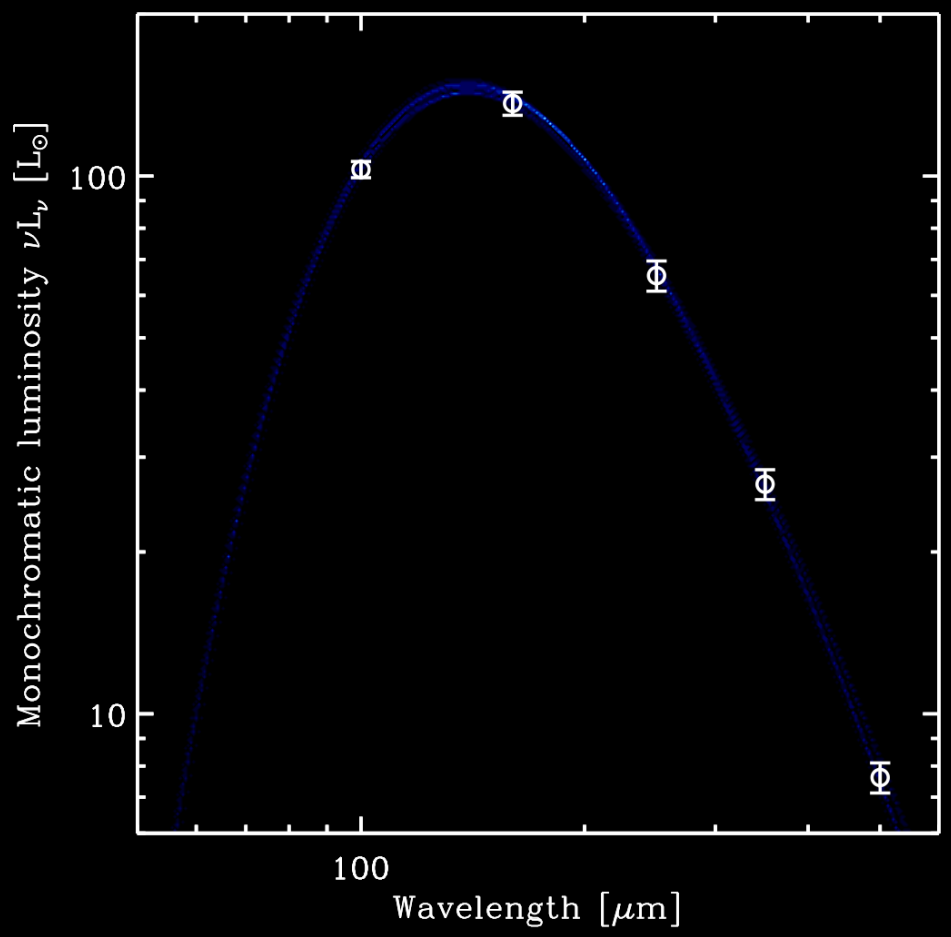

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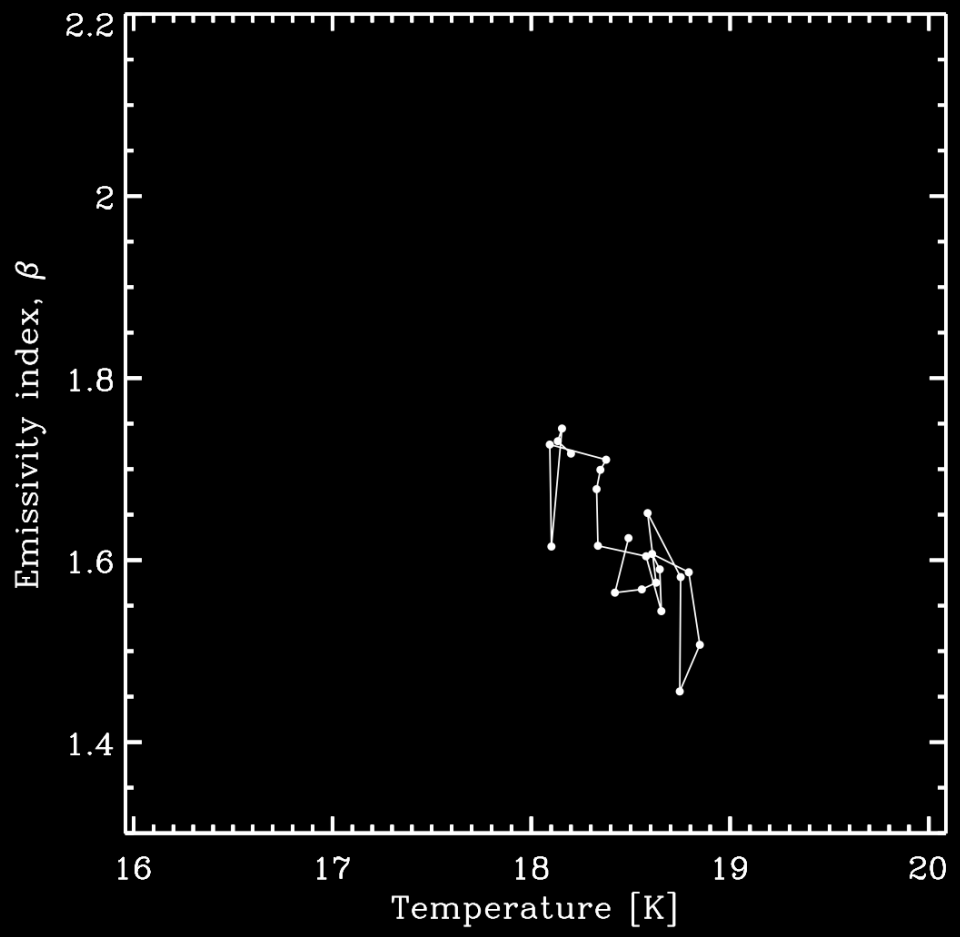

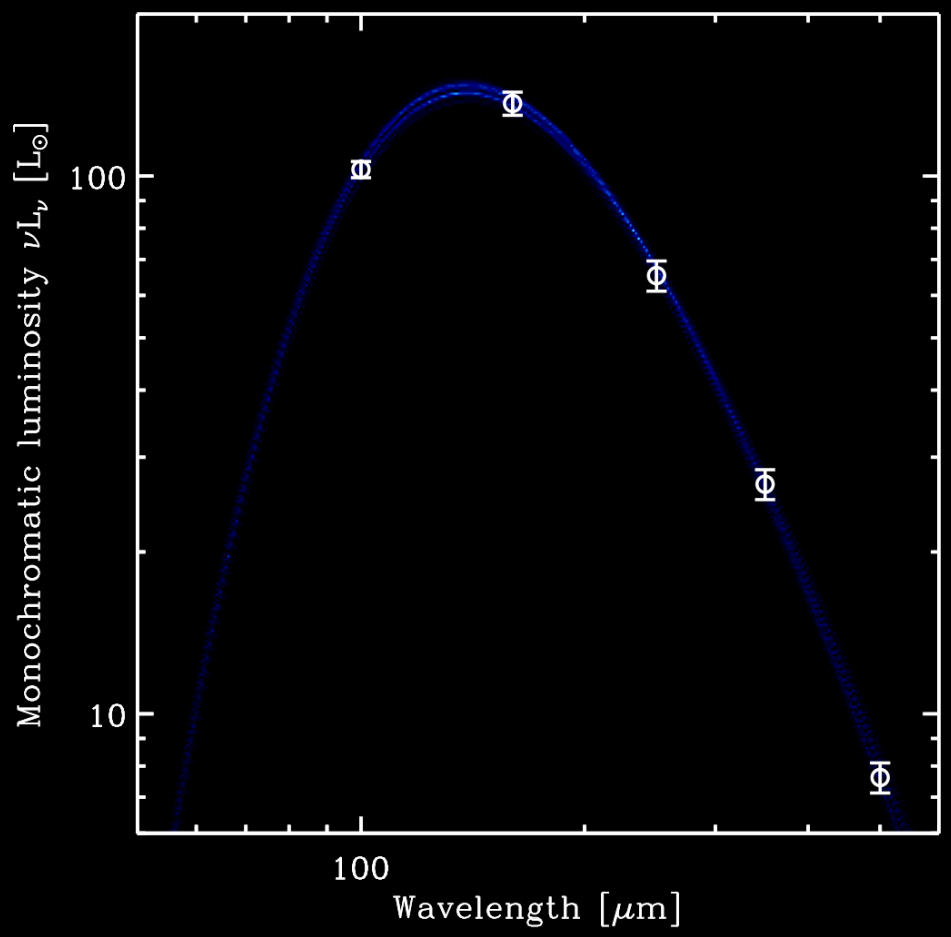

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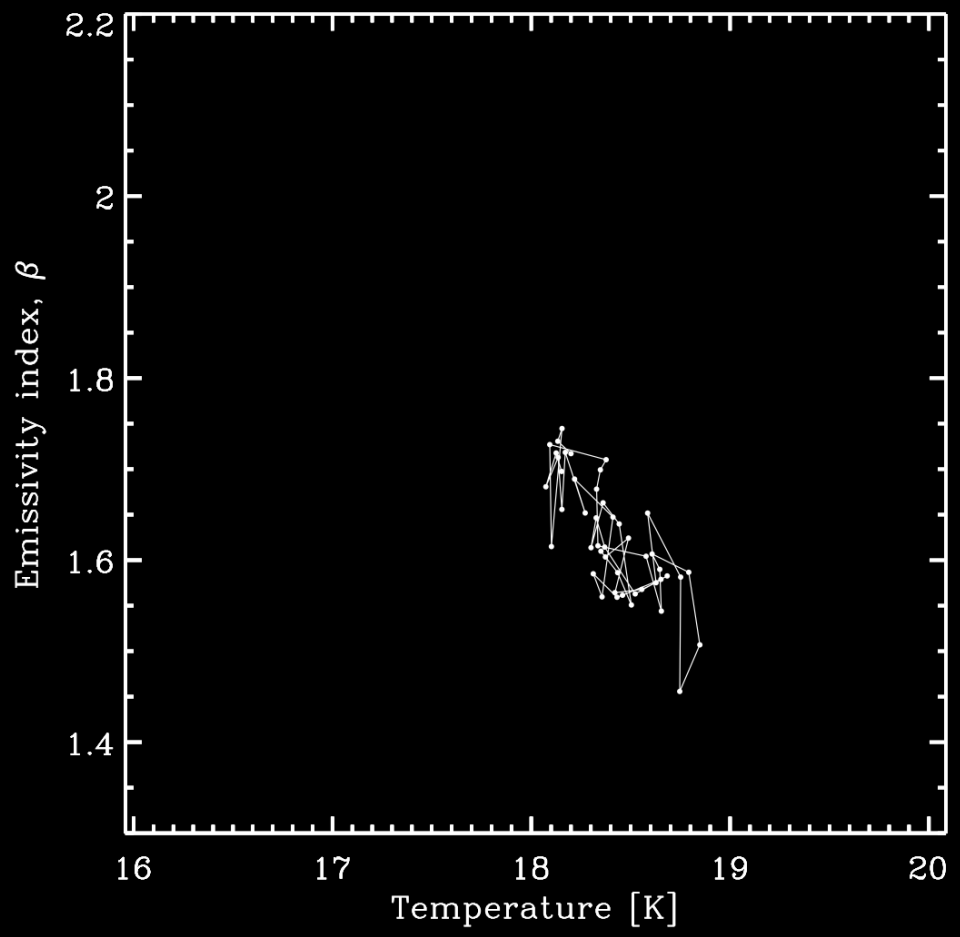

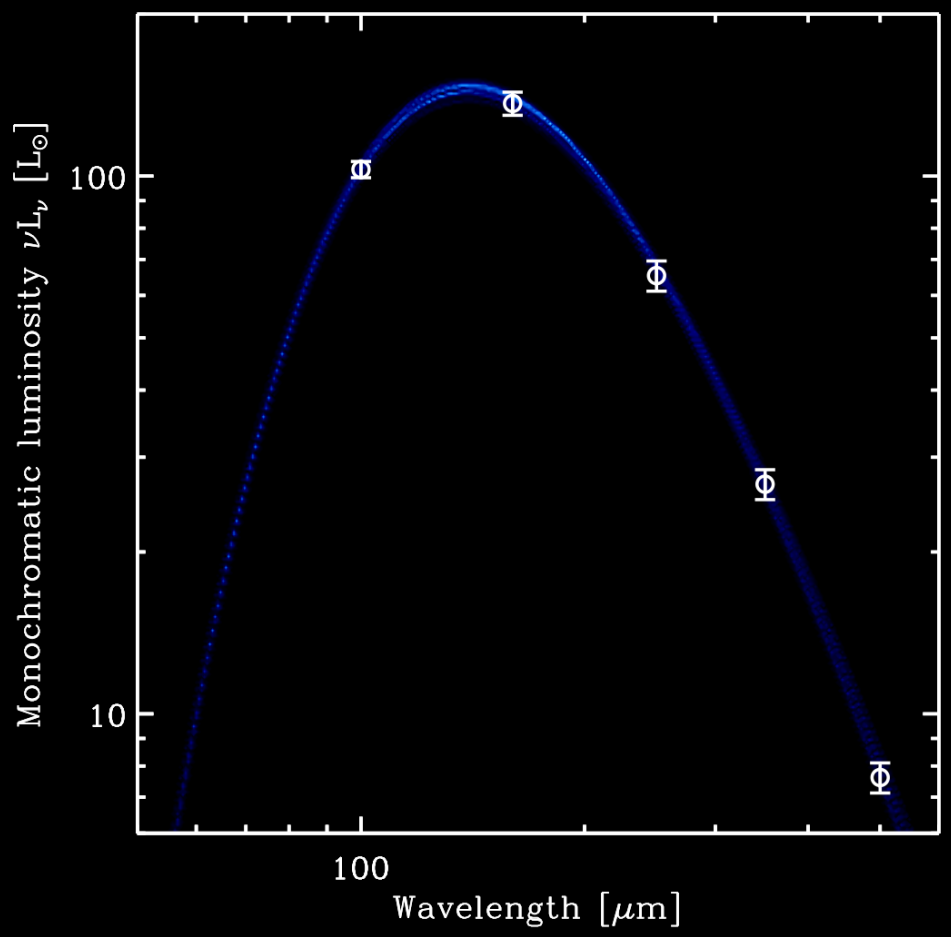

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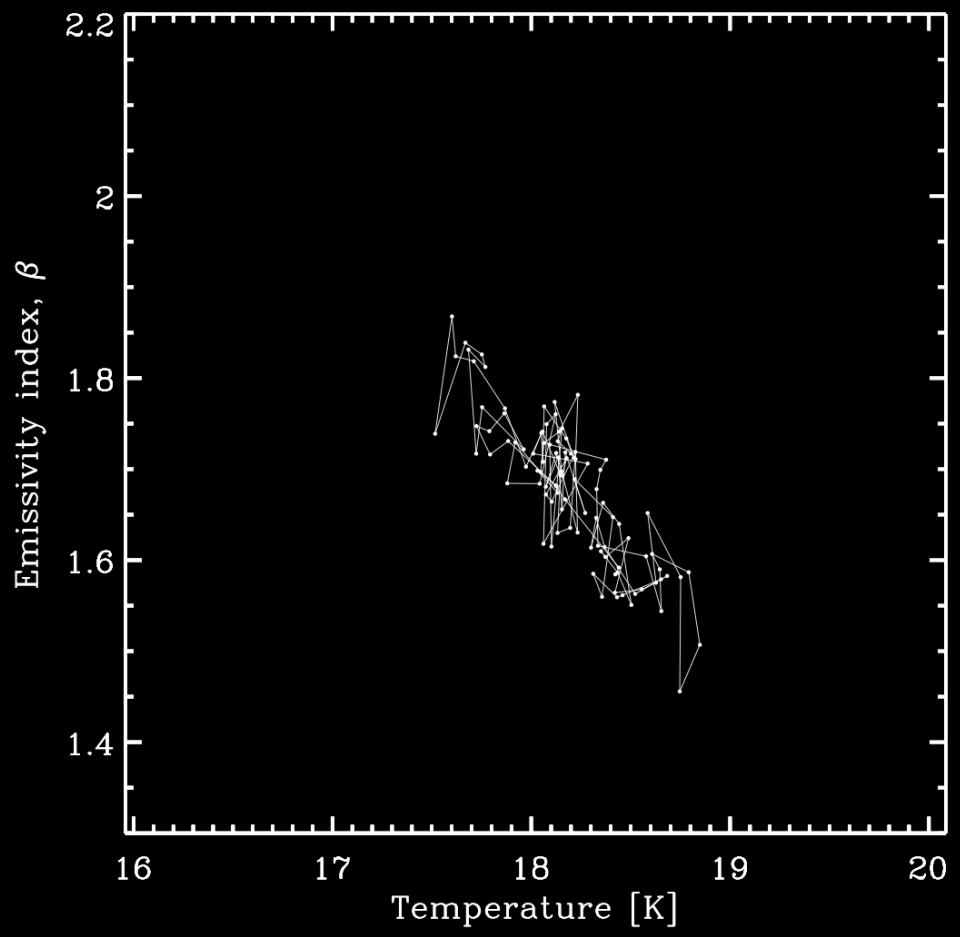

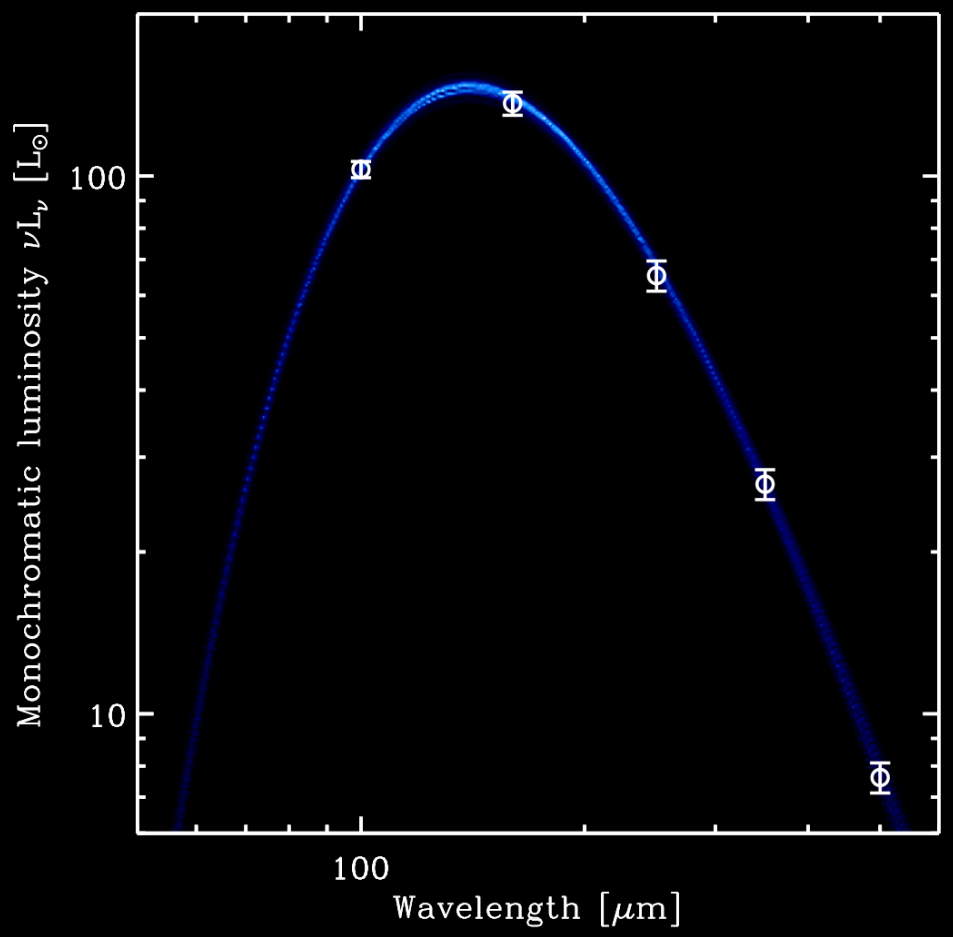

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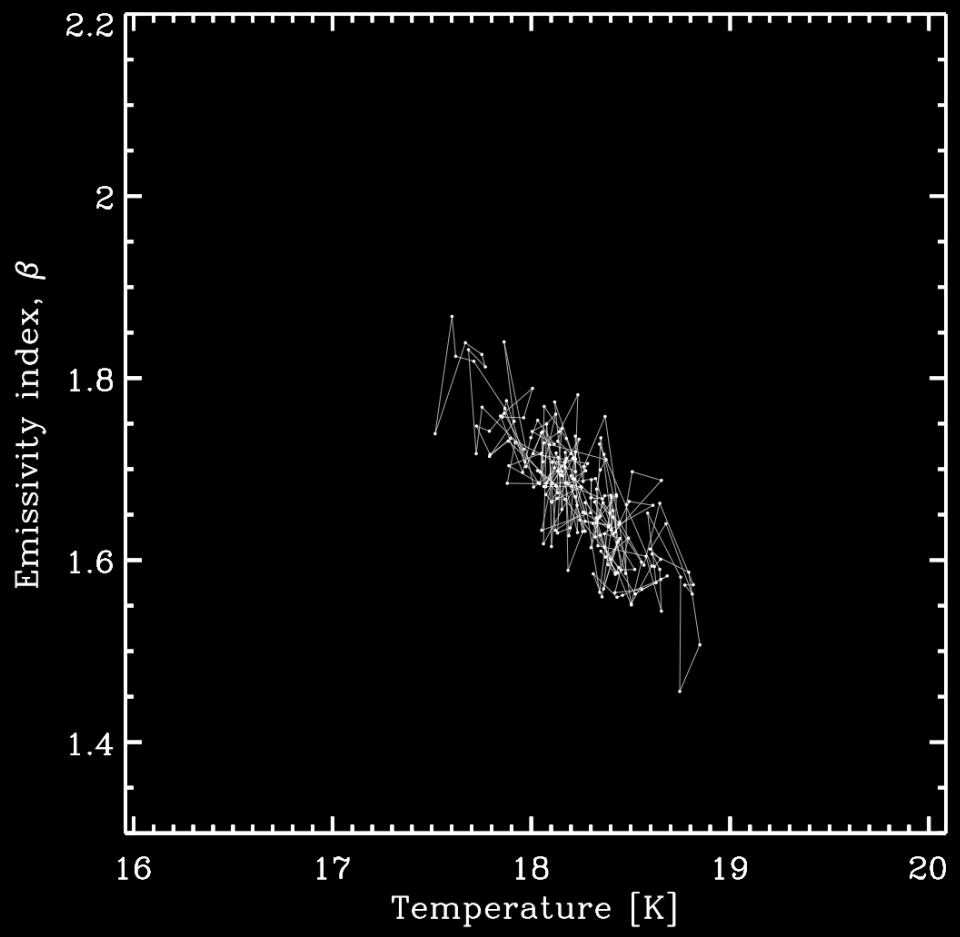

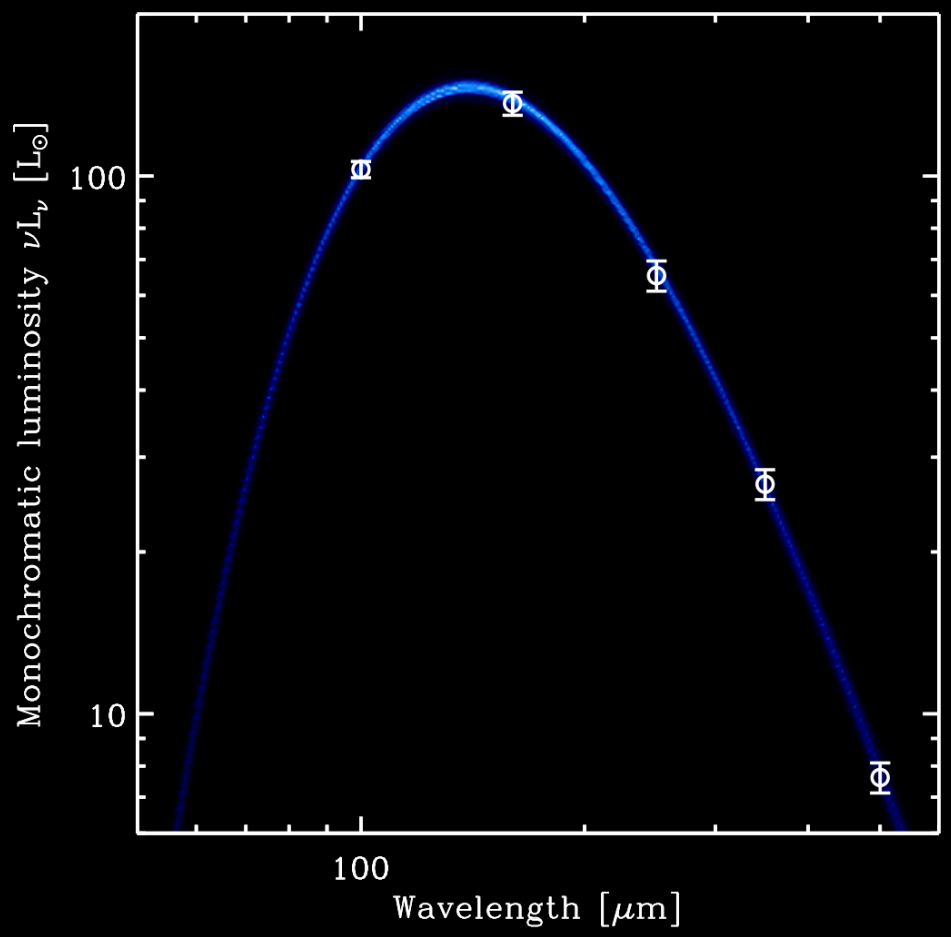

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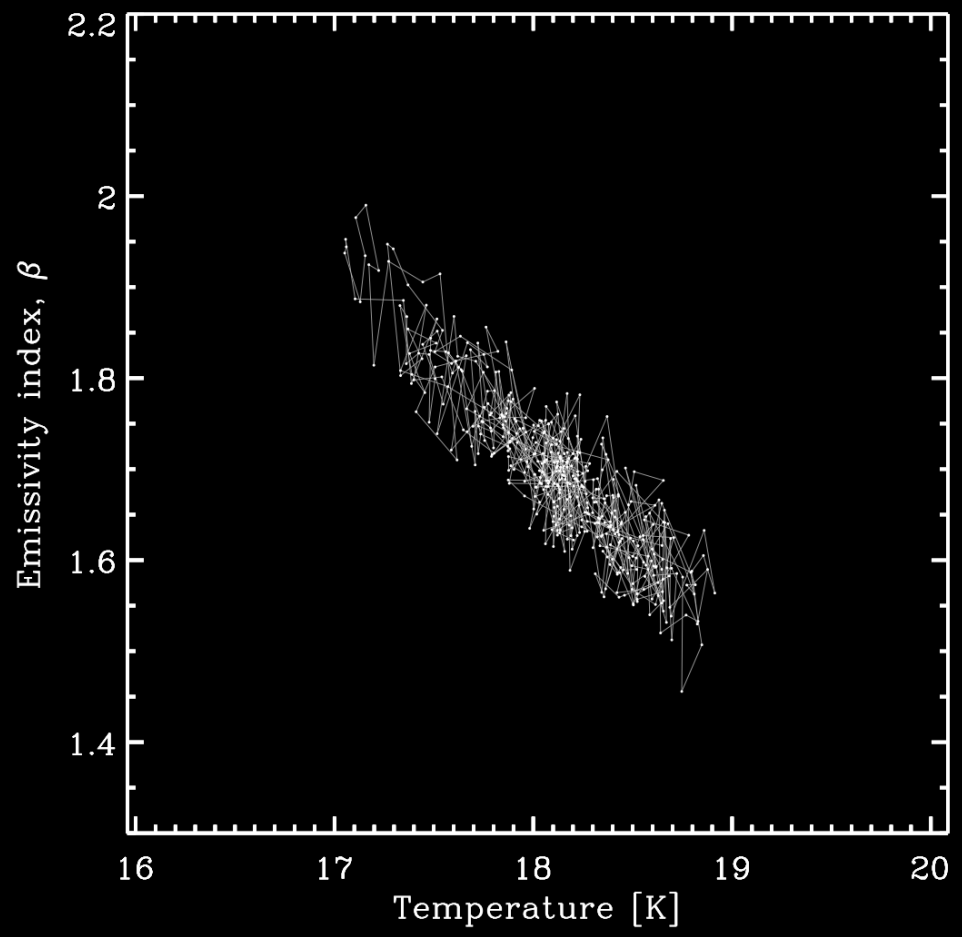

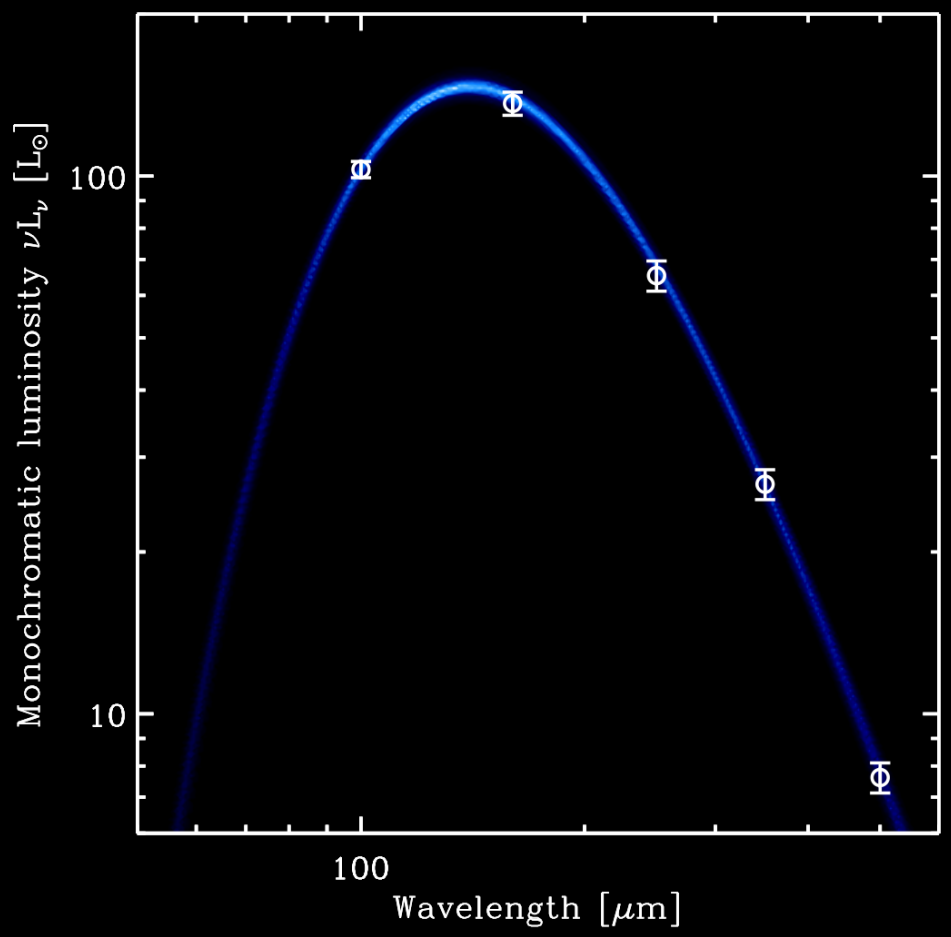

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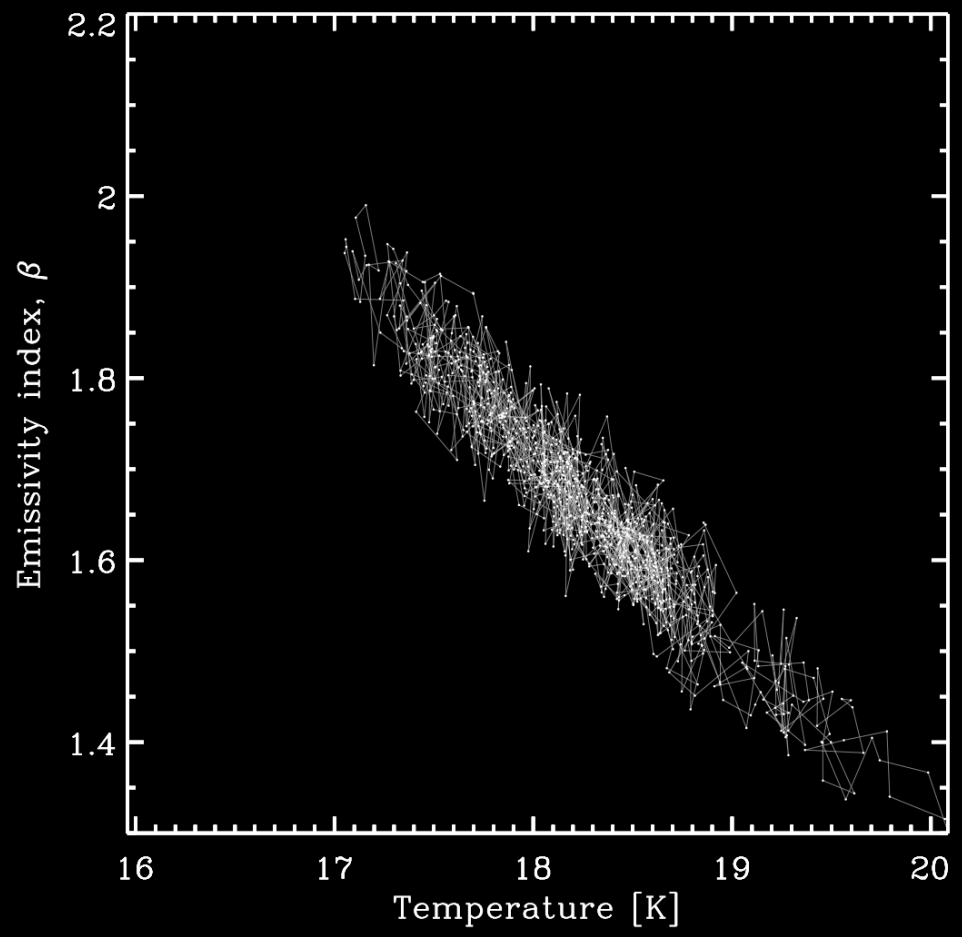

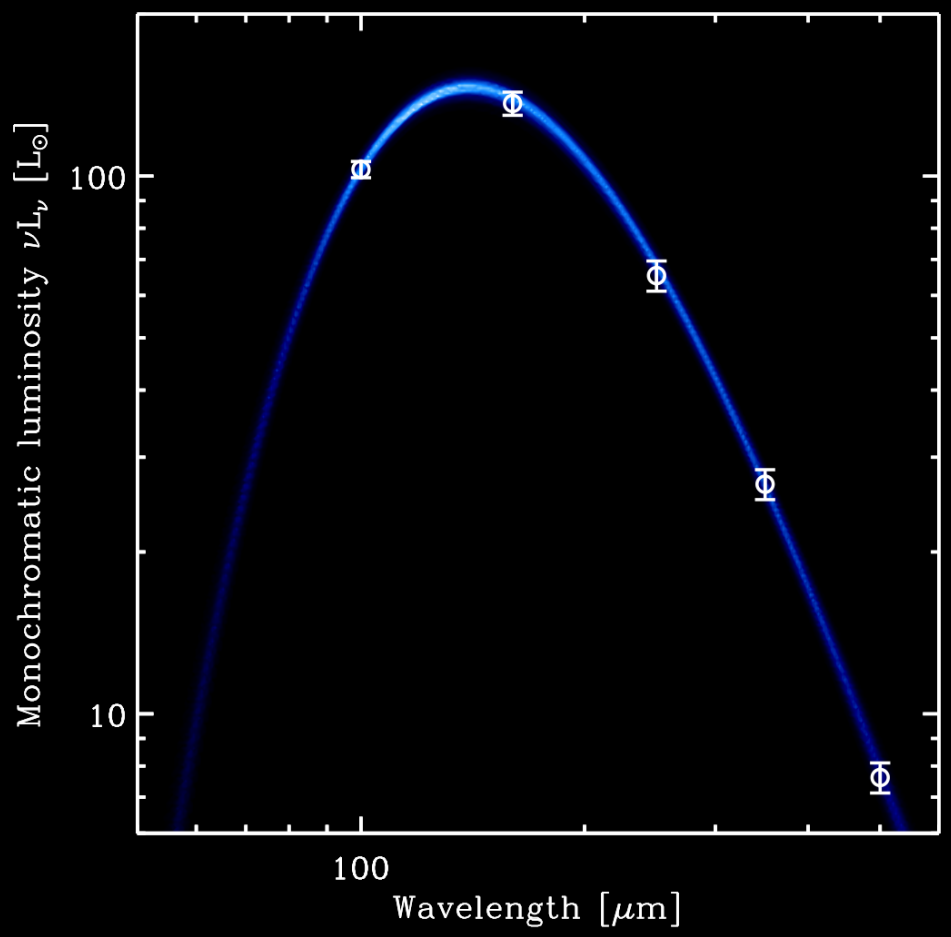

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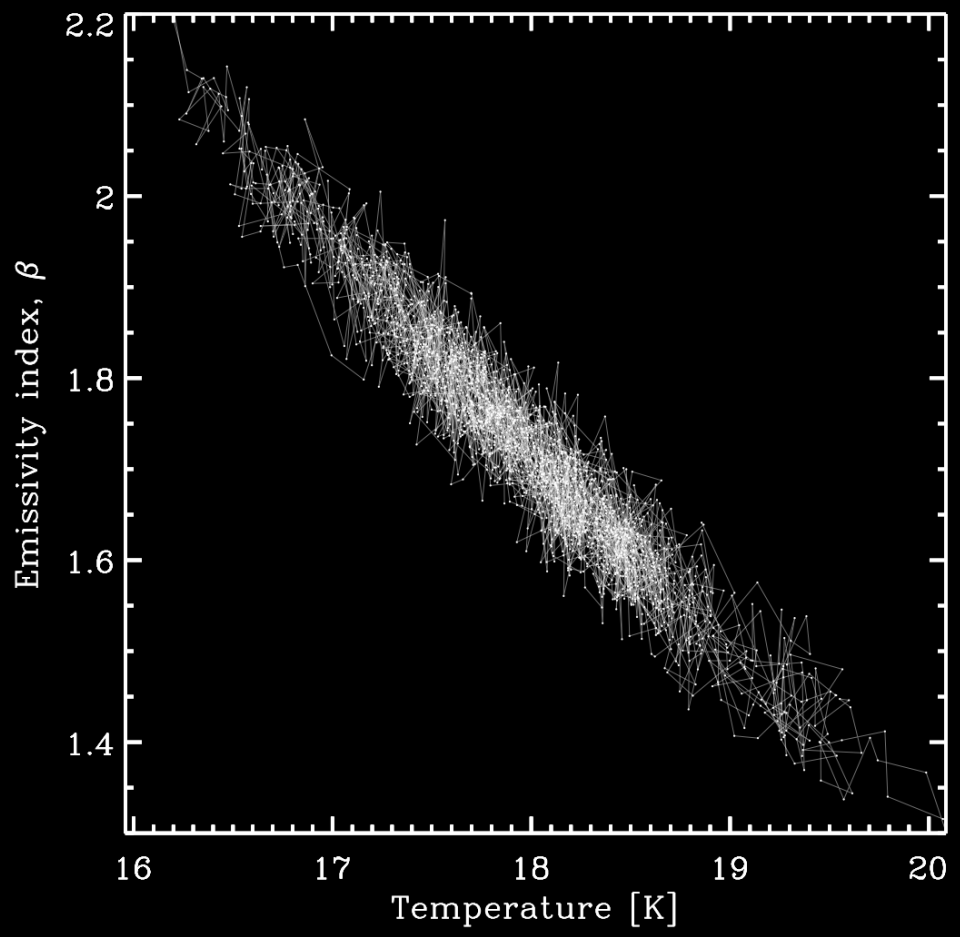

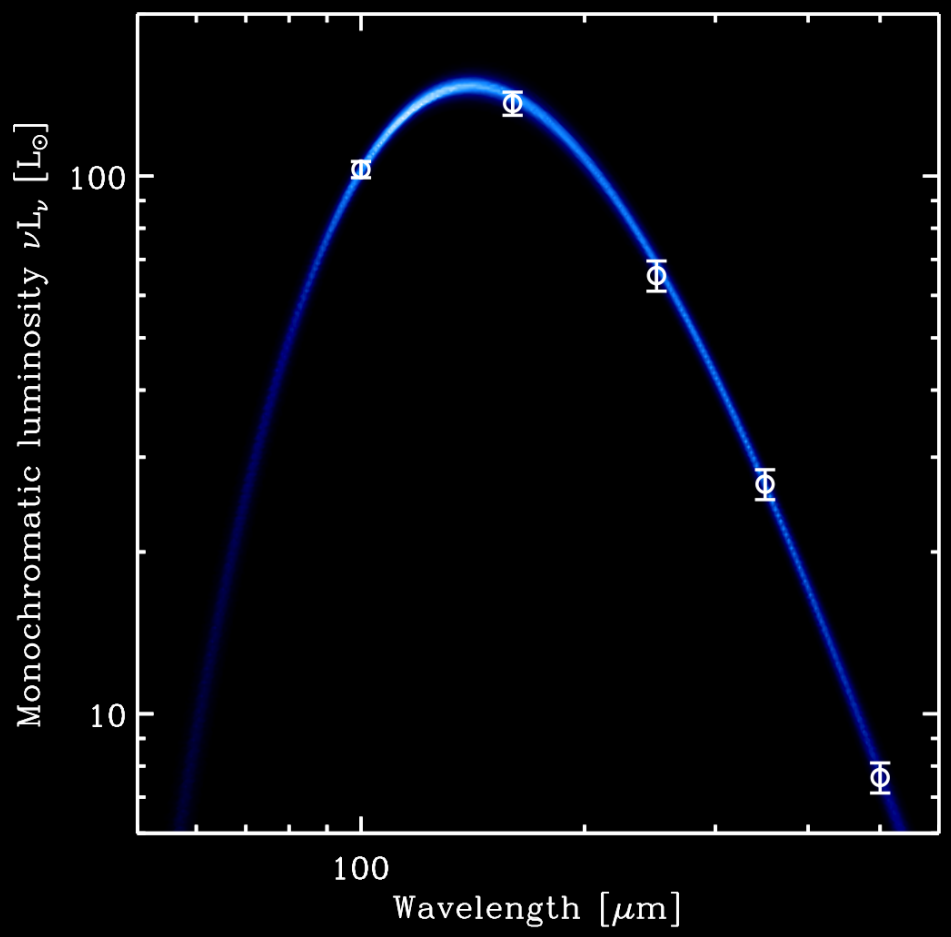

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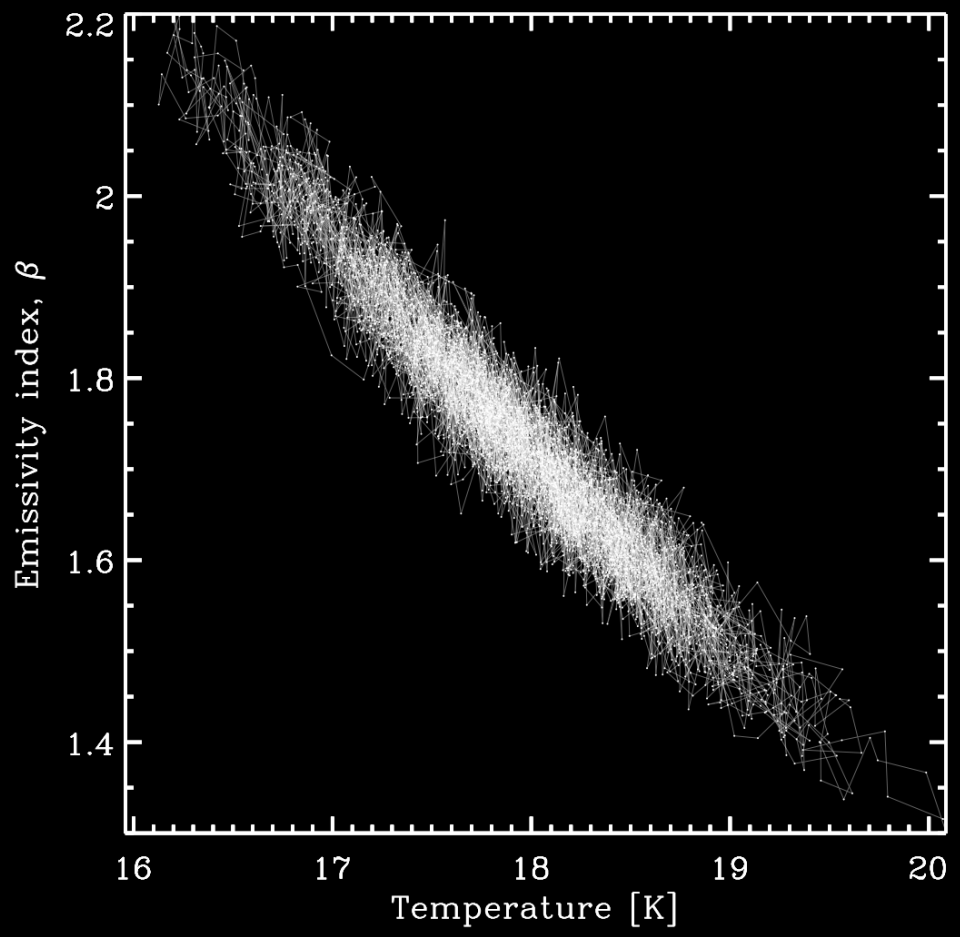

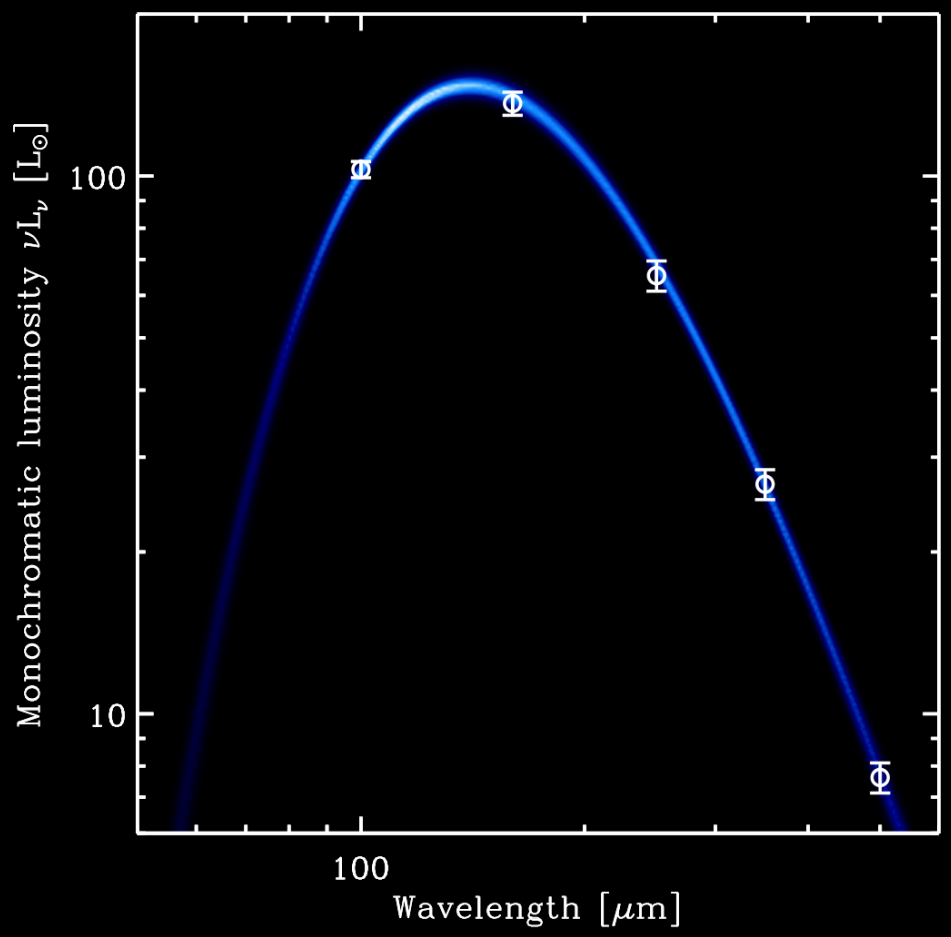

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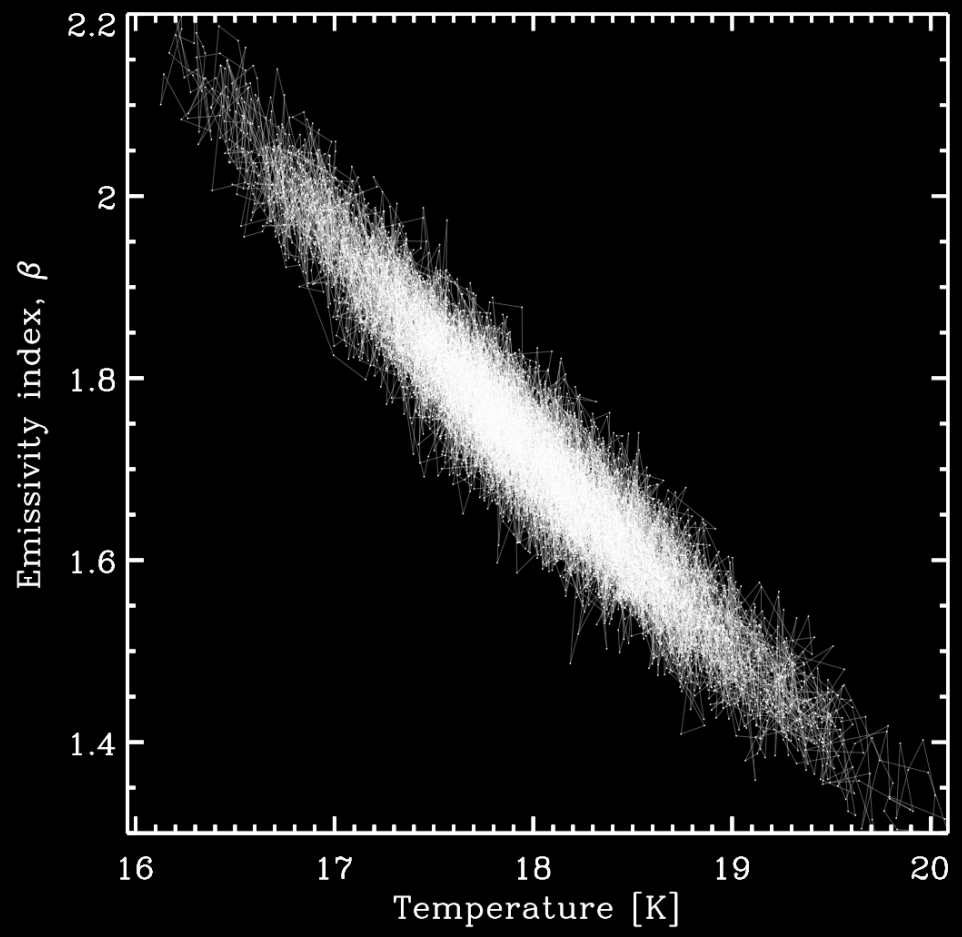

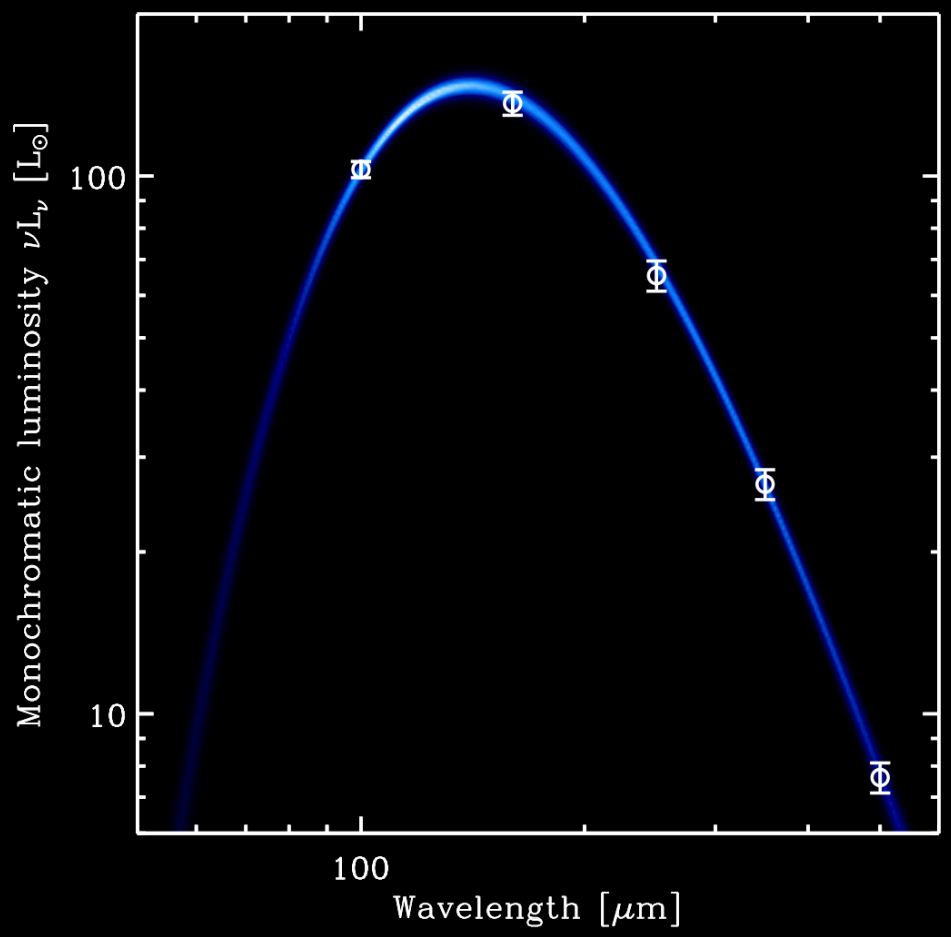

The Principle of Hierarchical Bayesian Inference

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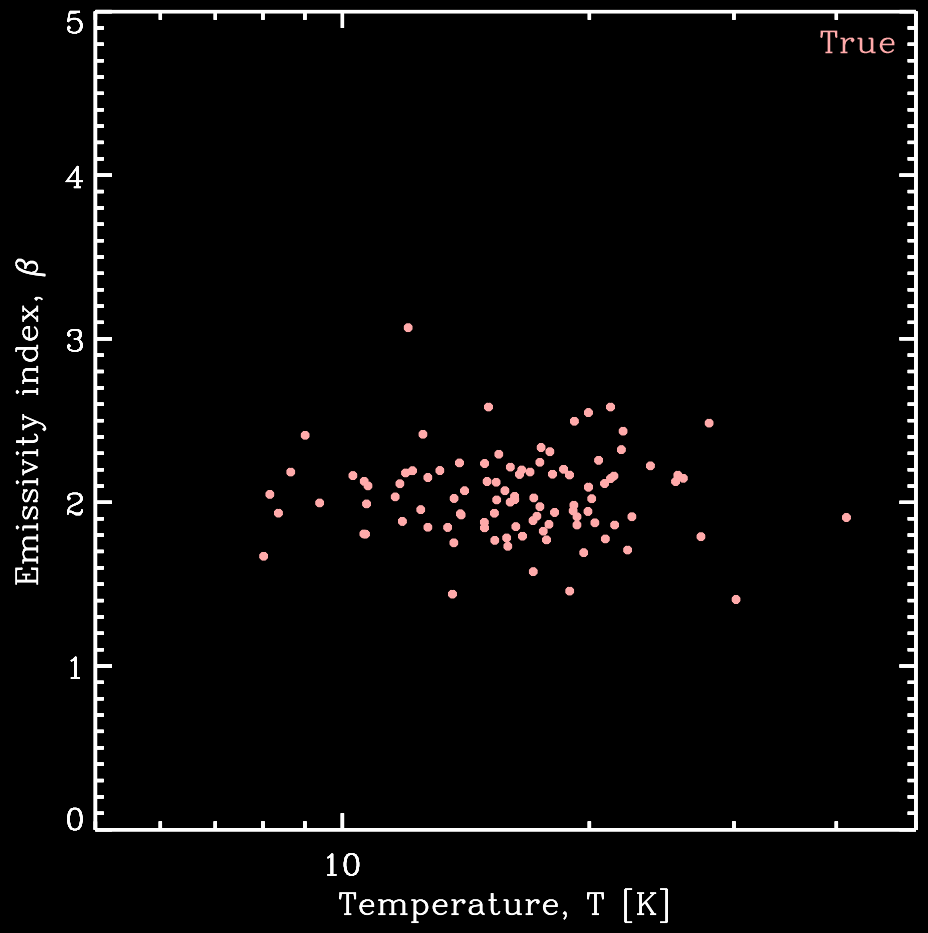

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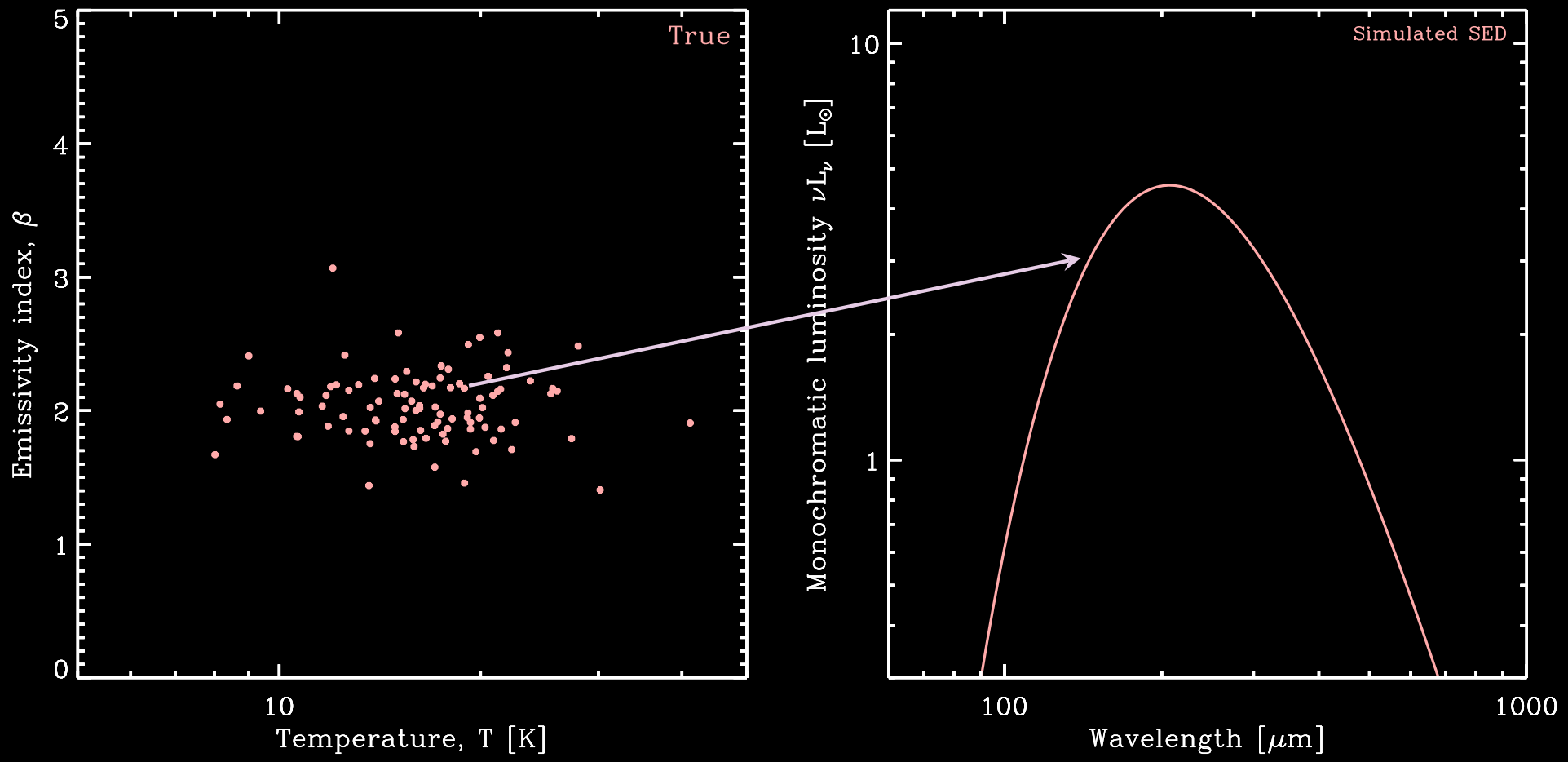

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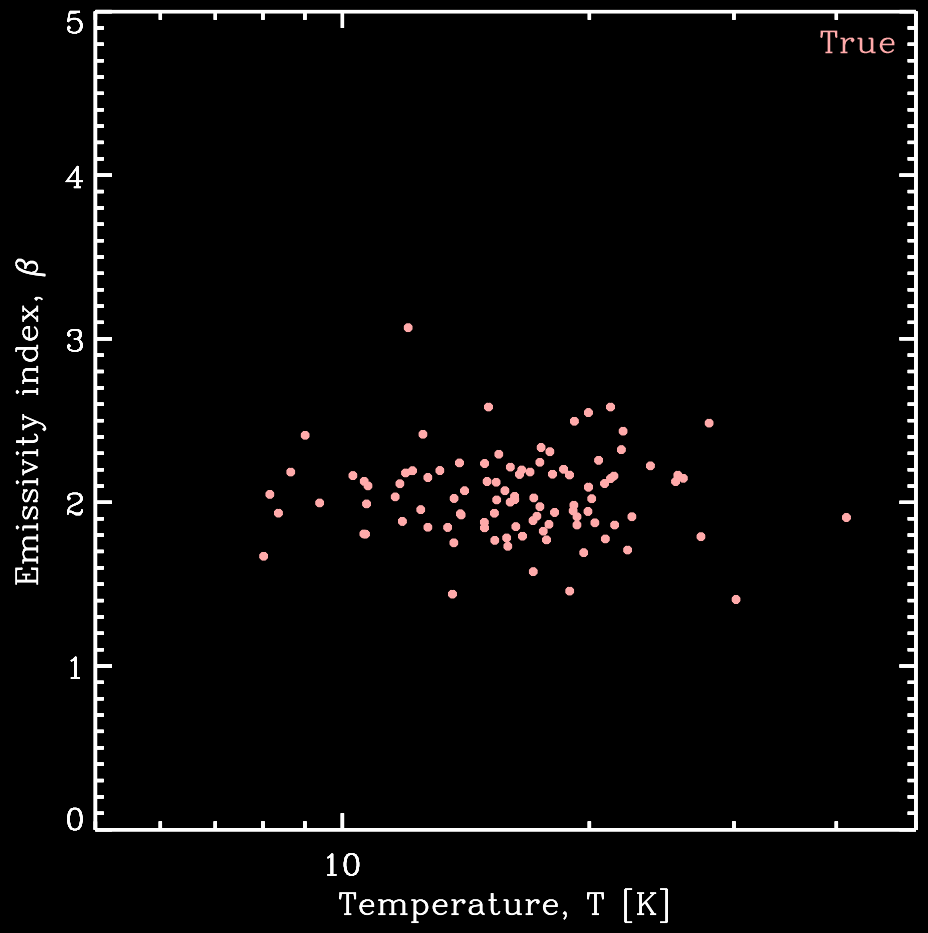

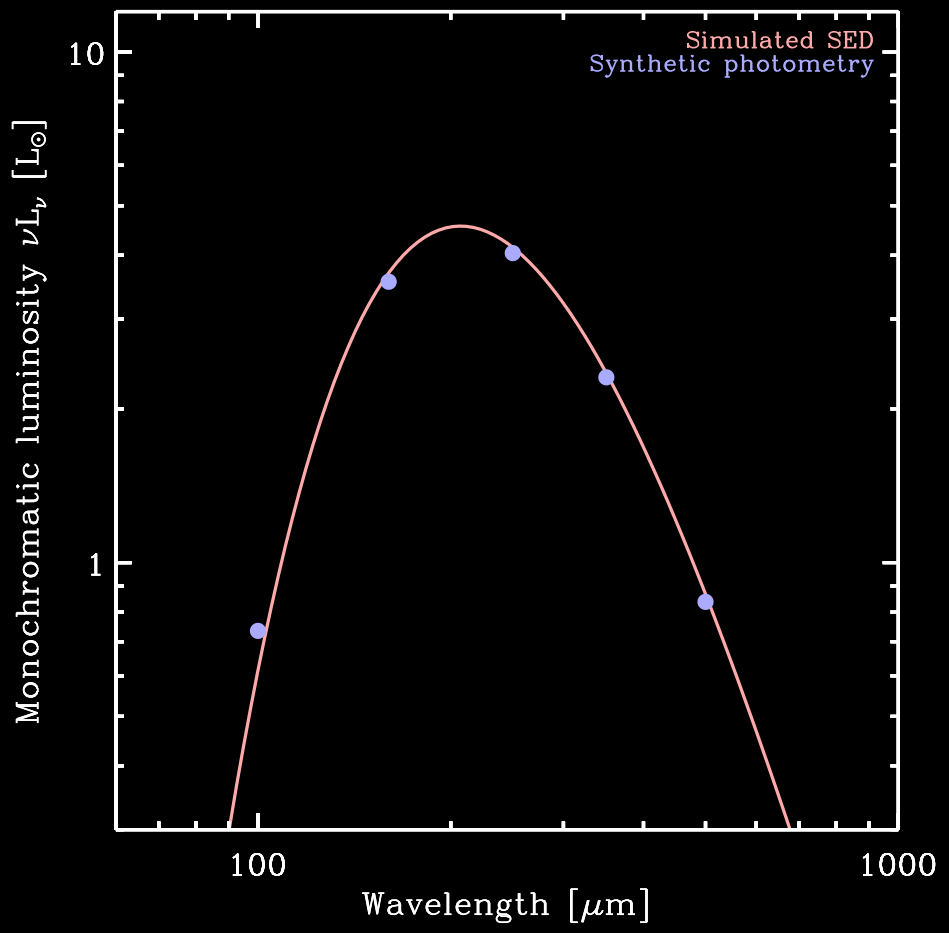

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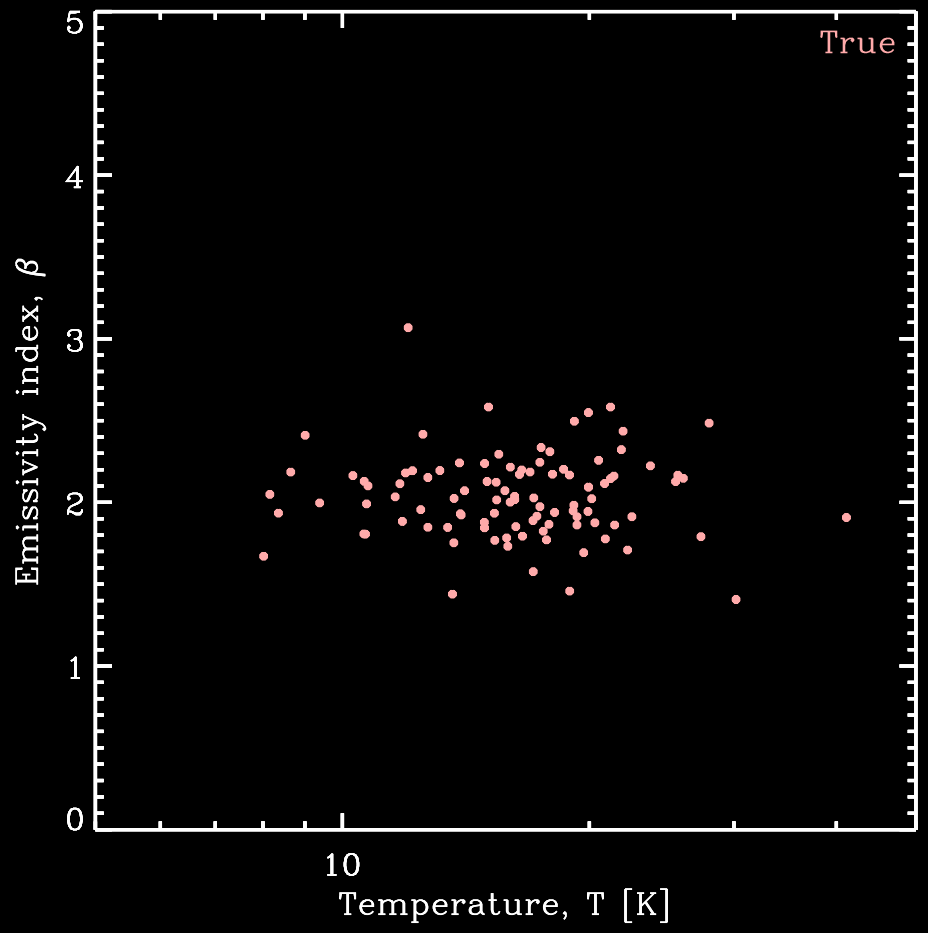

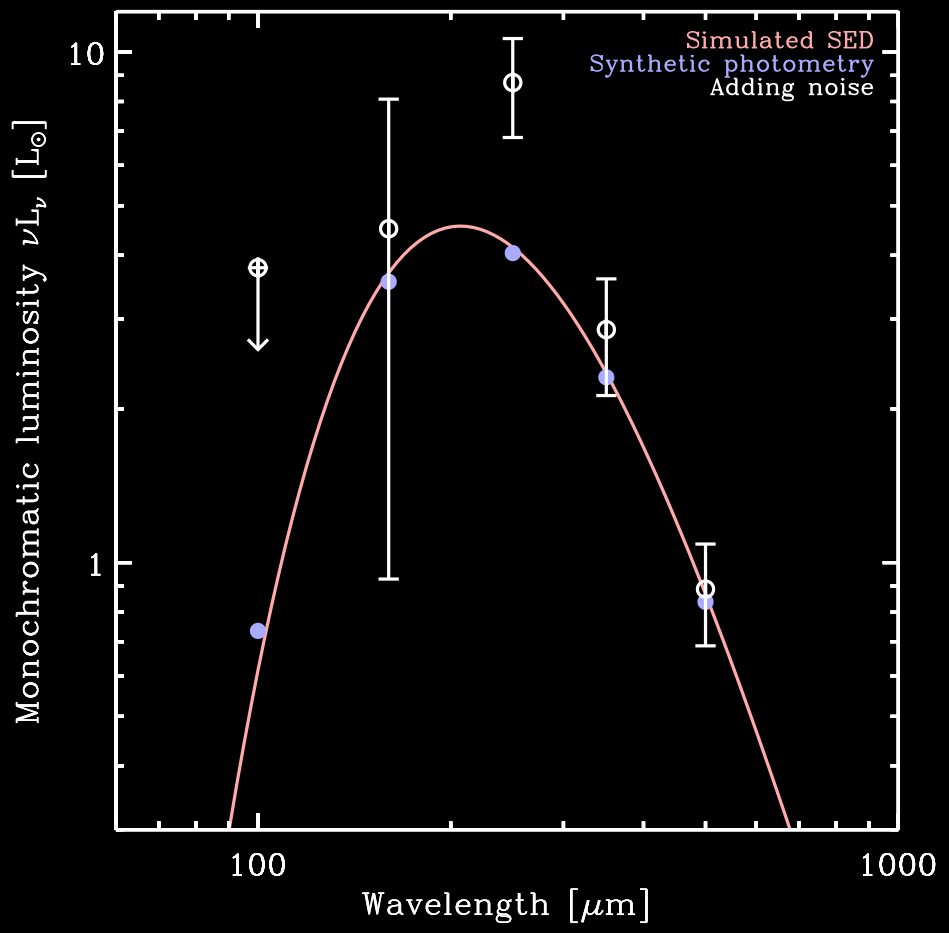

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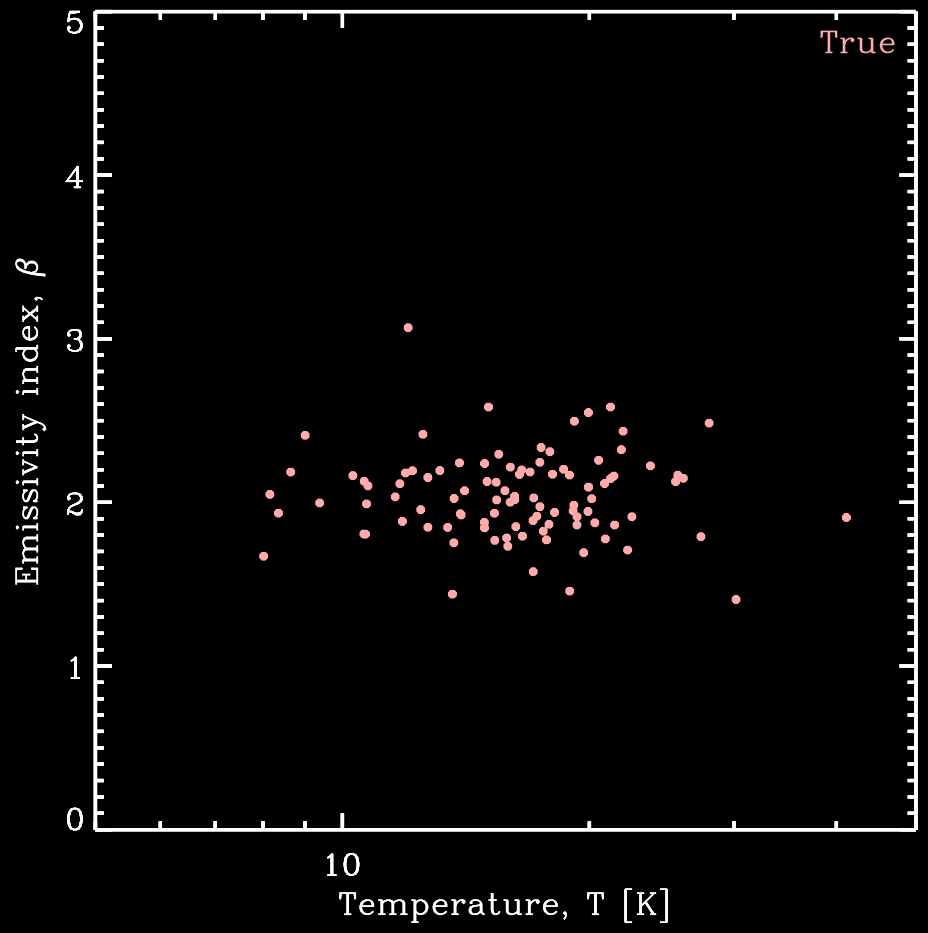

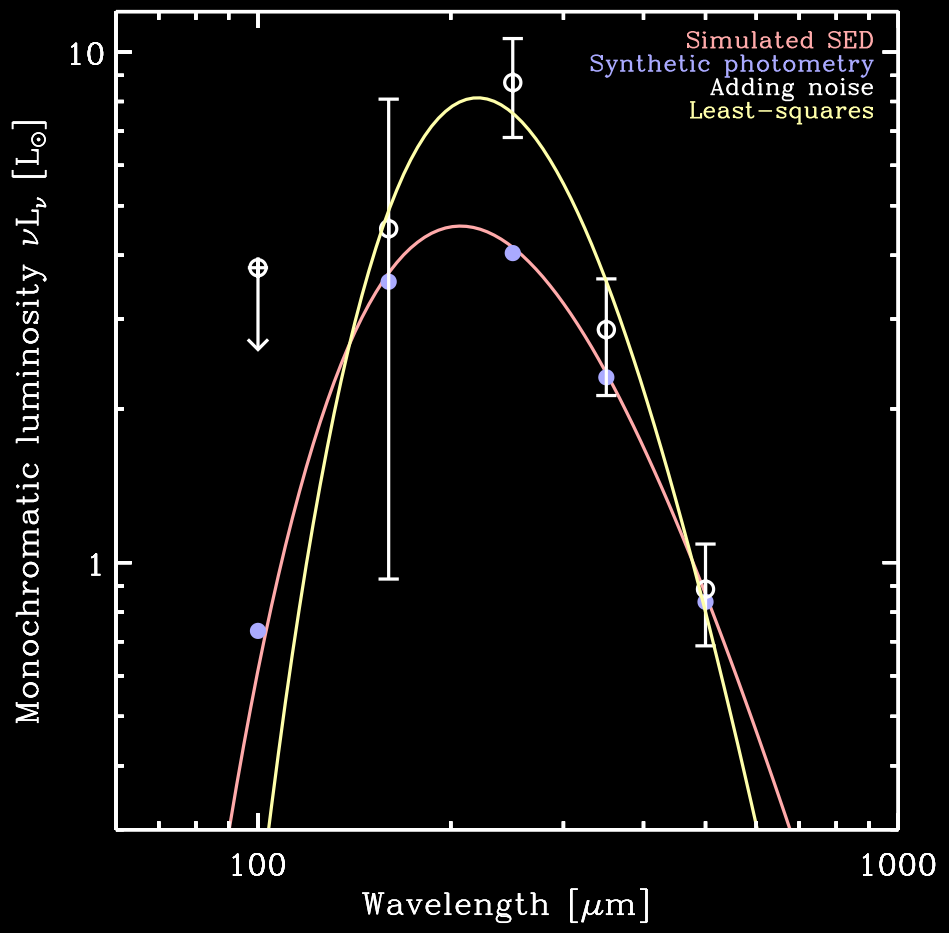

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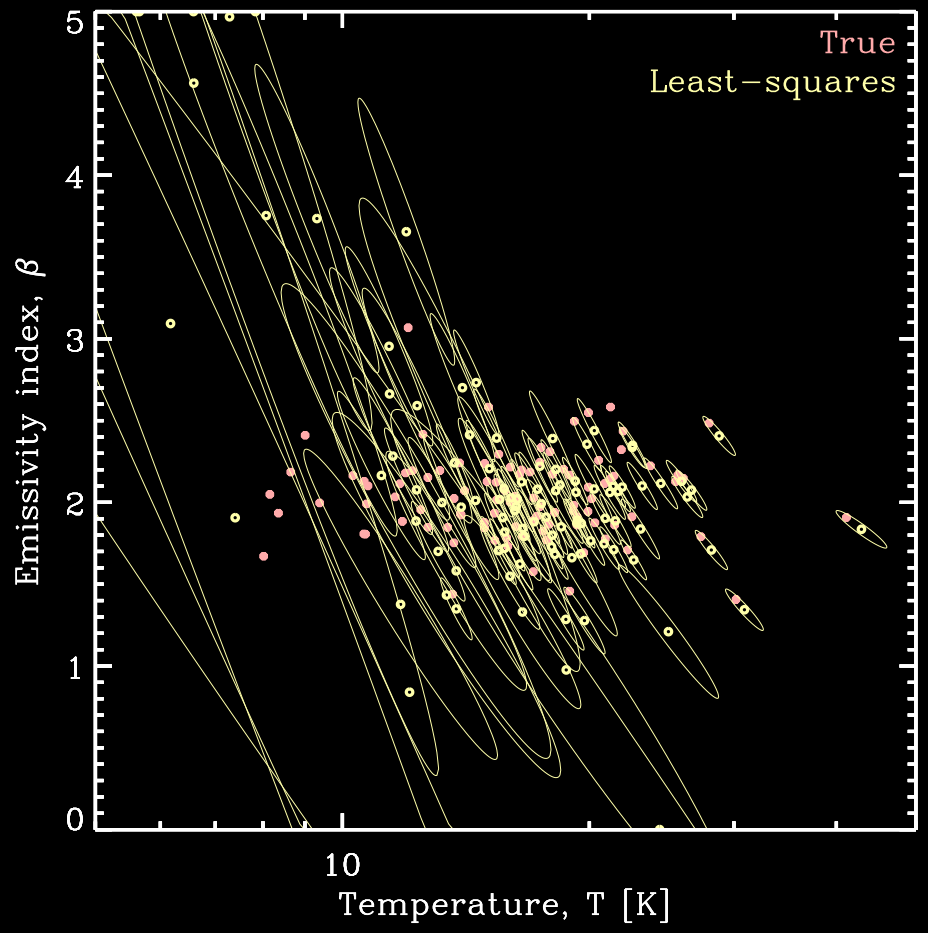

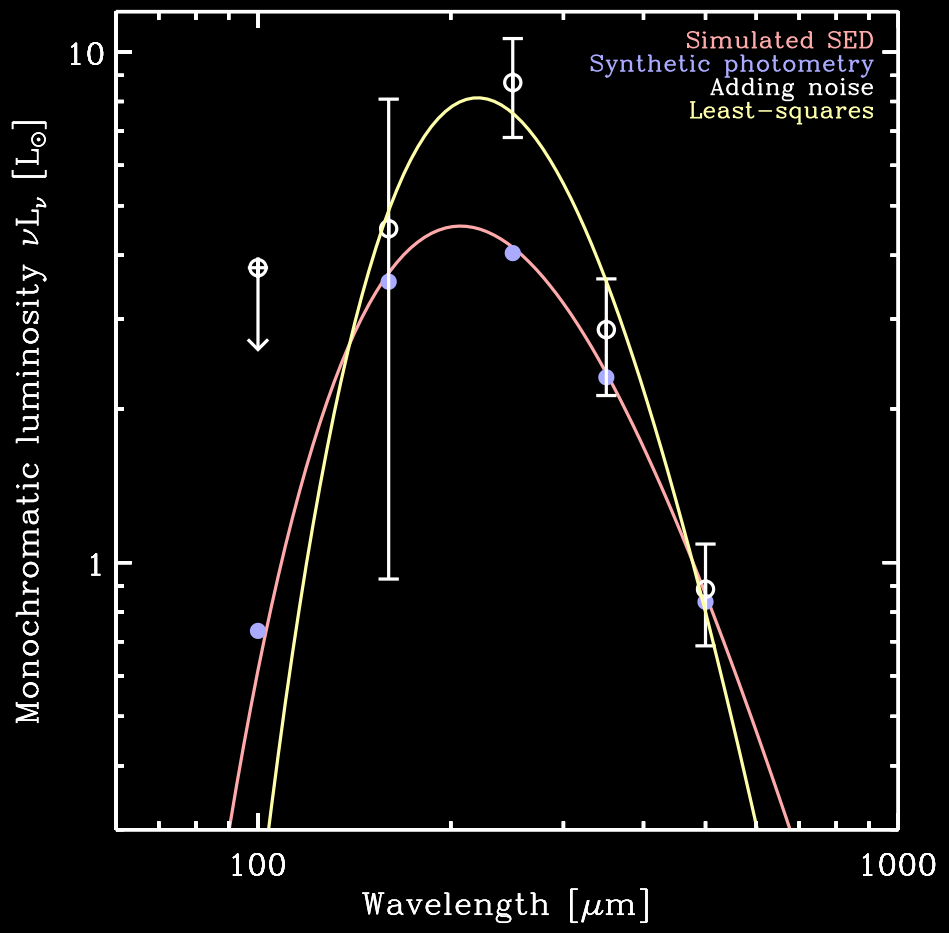

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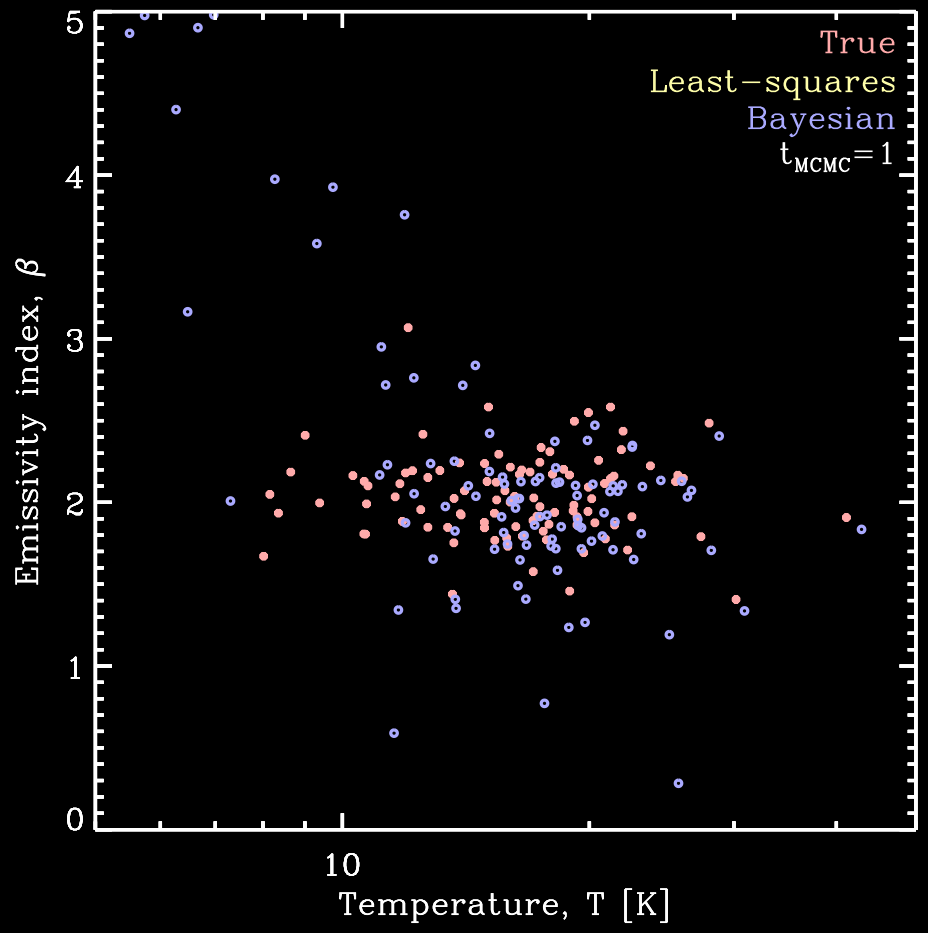

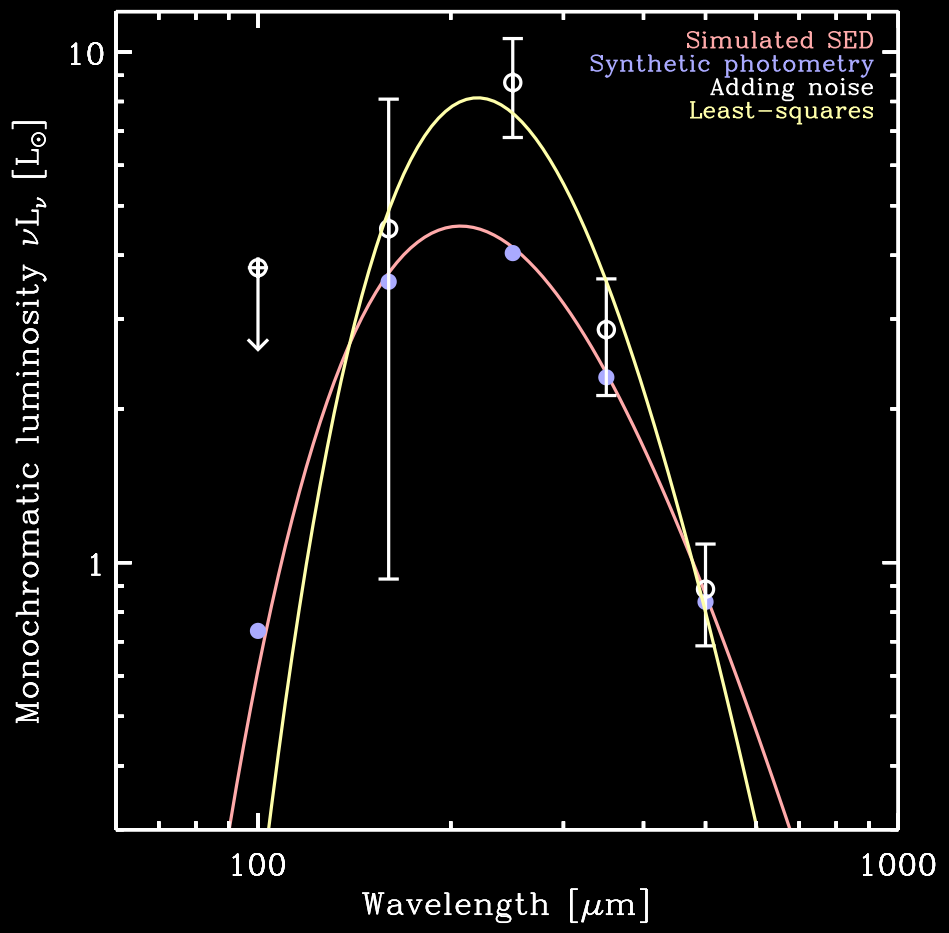

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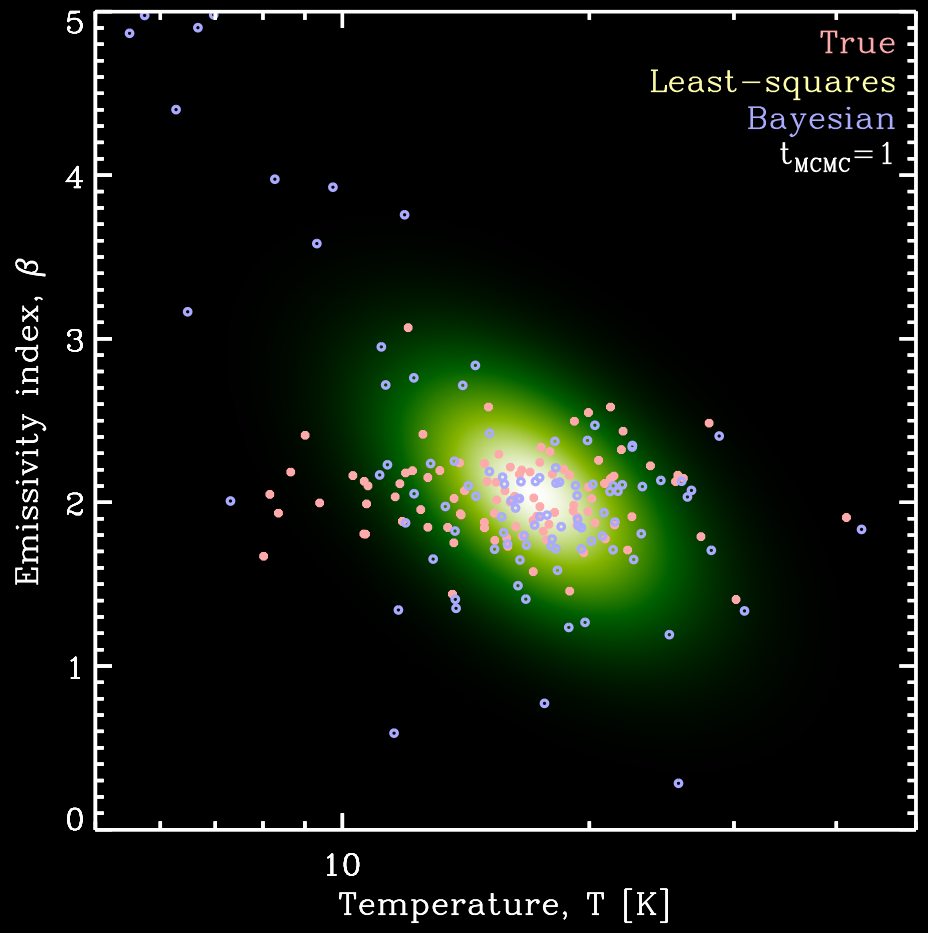

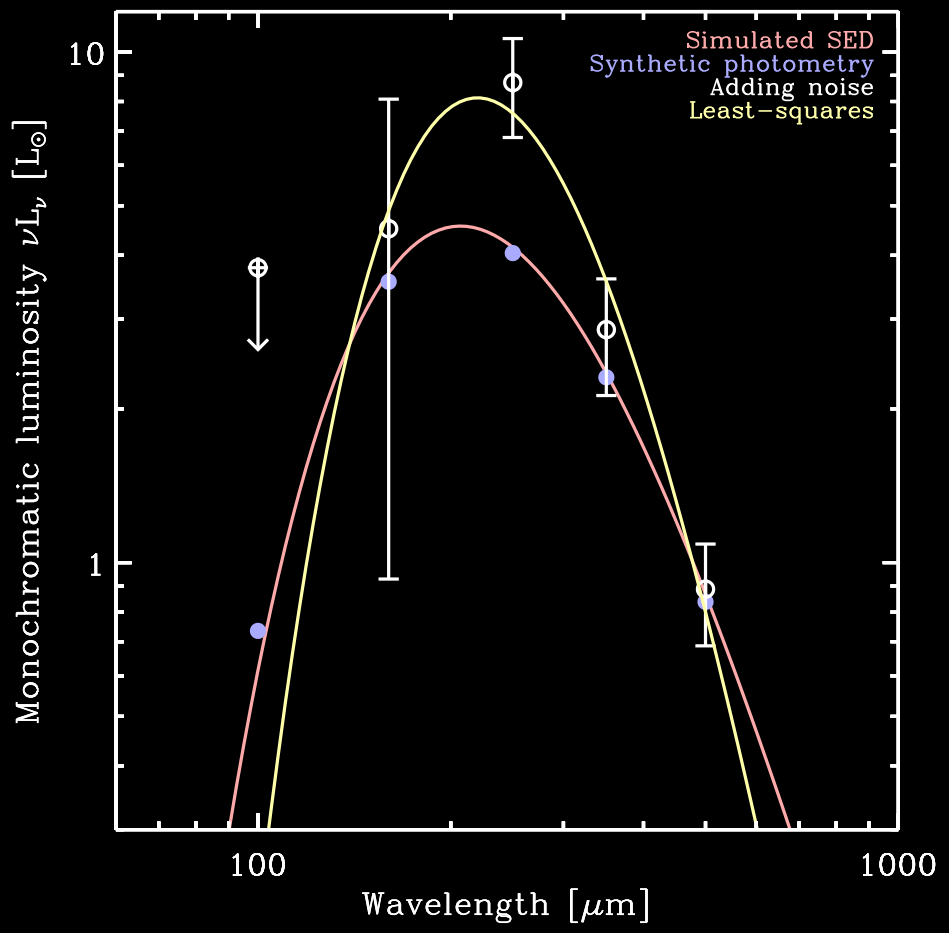

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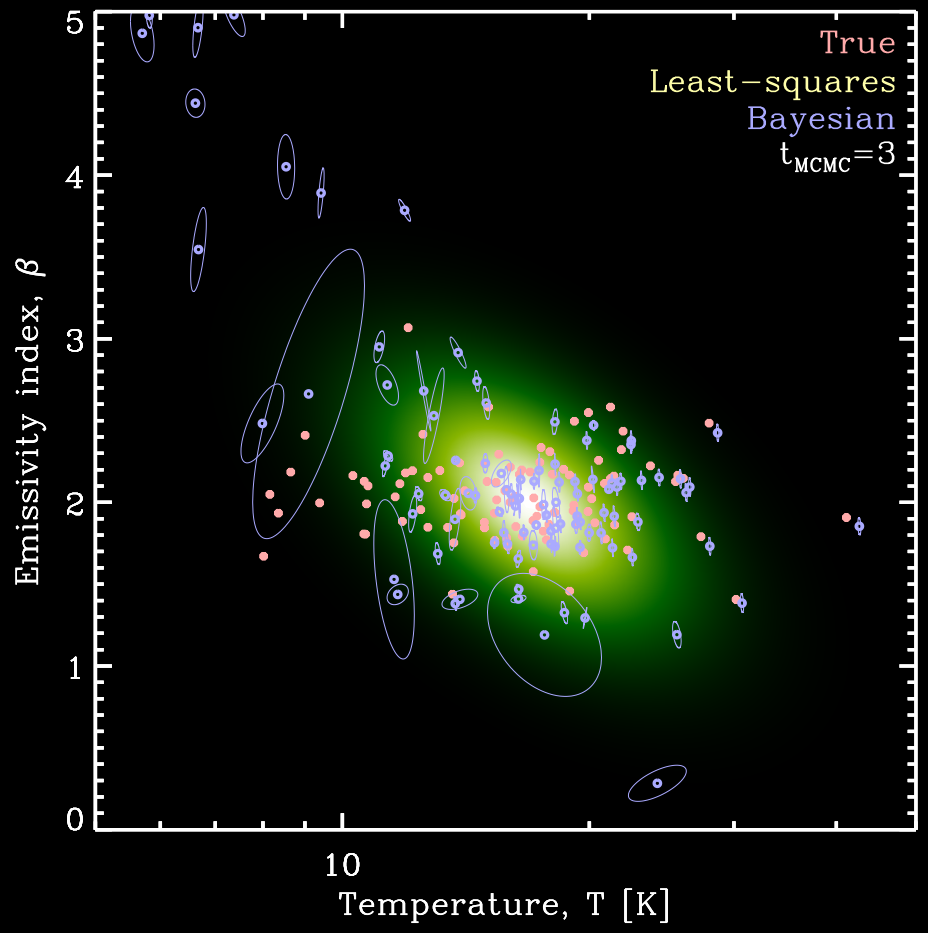

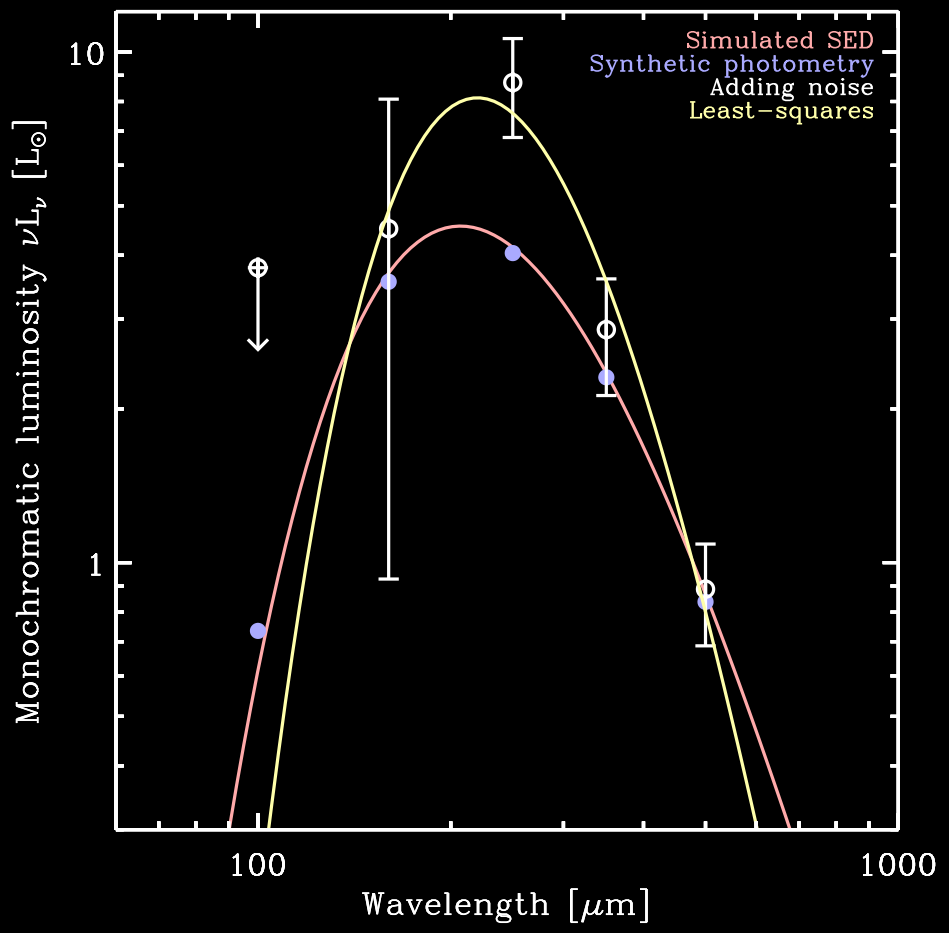

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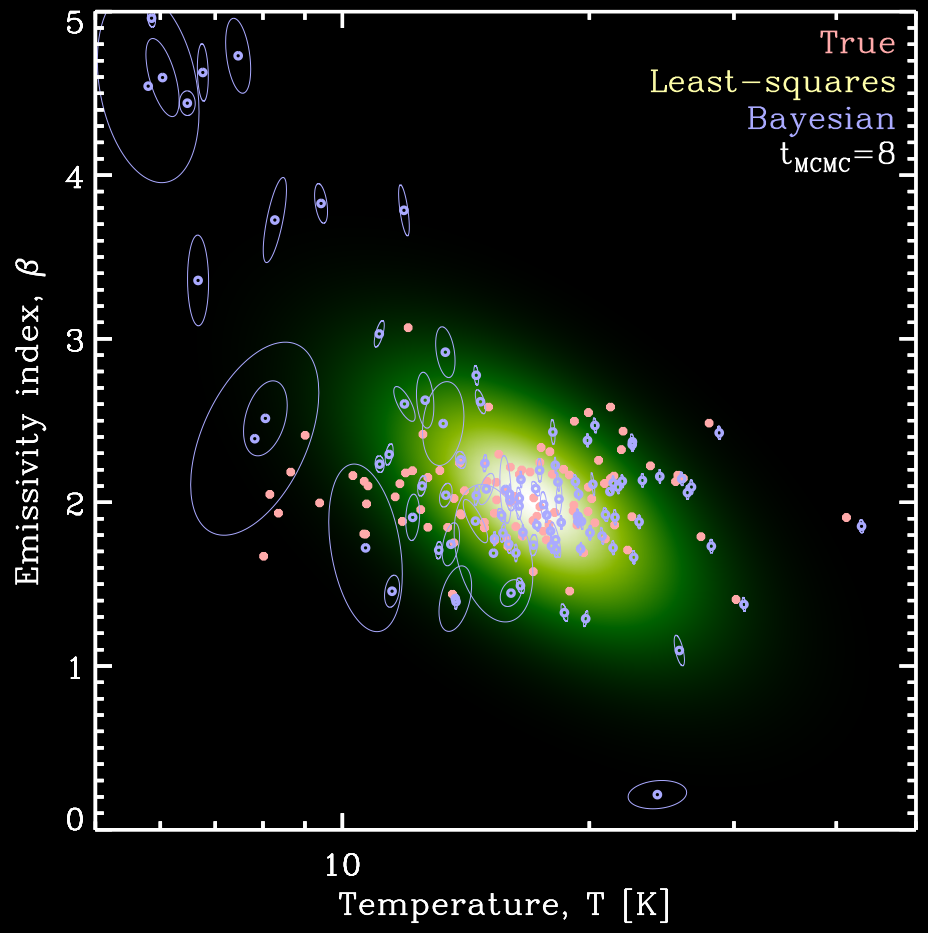

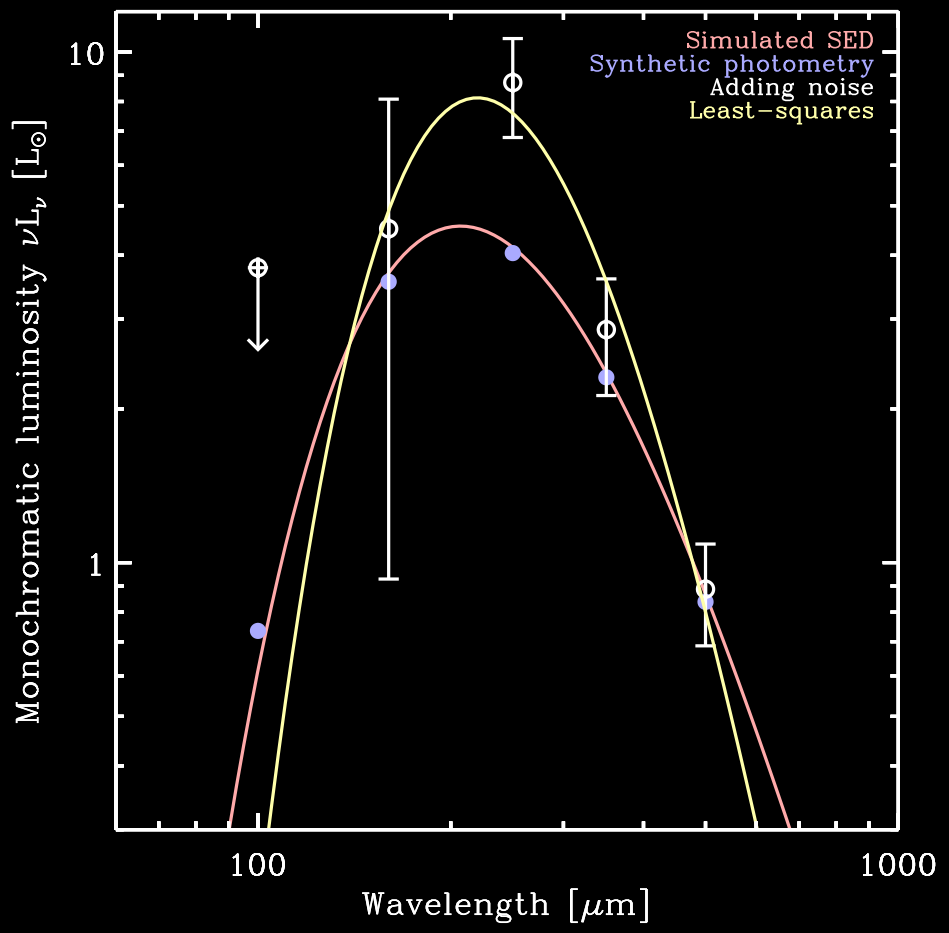

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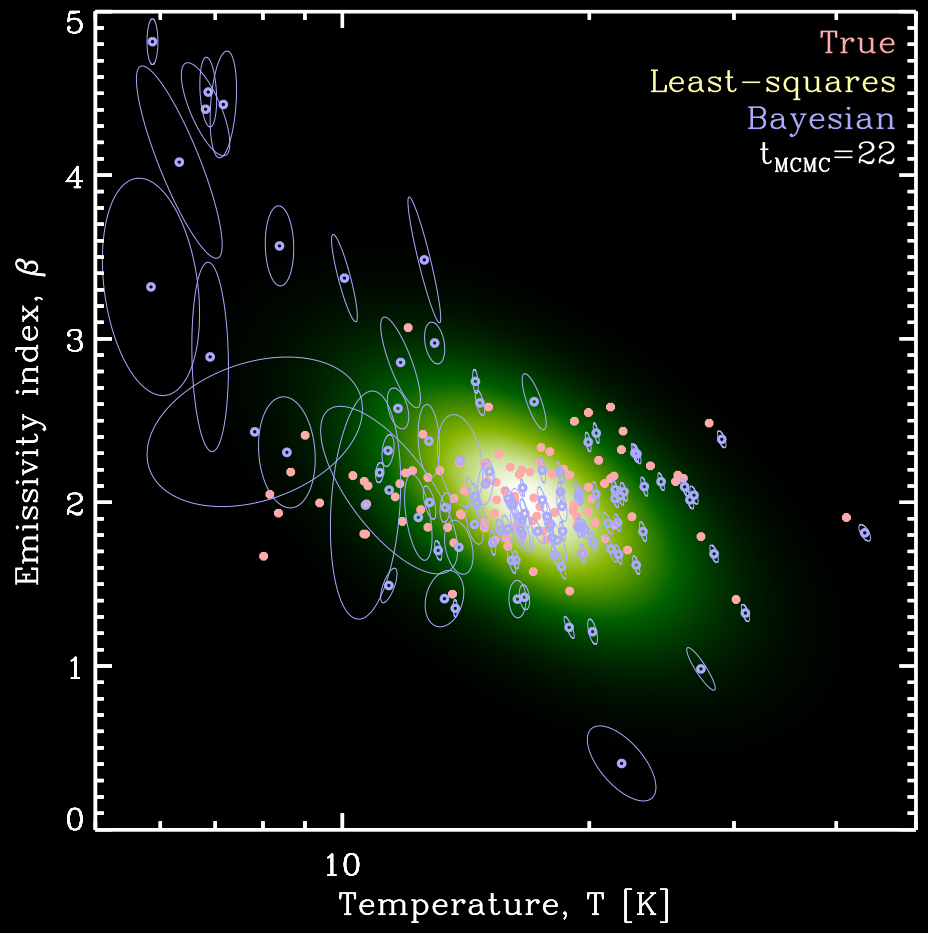

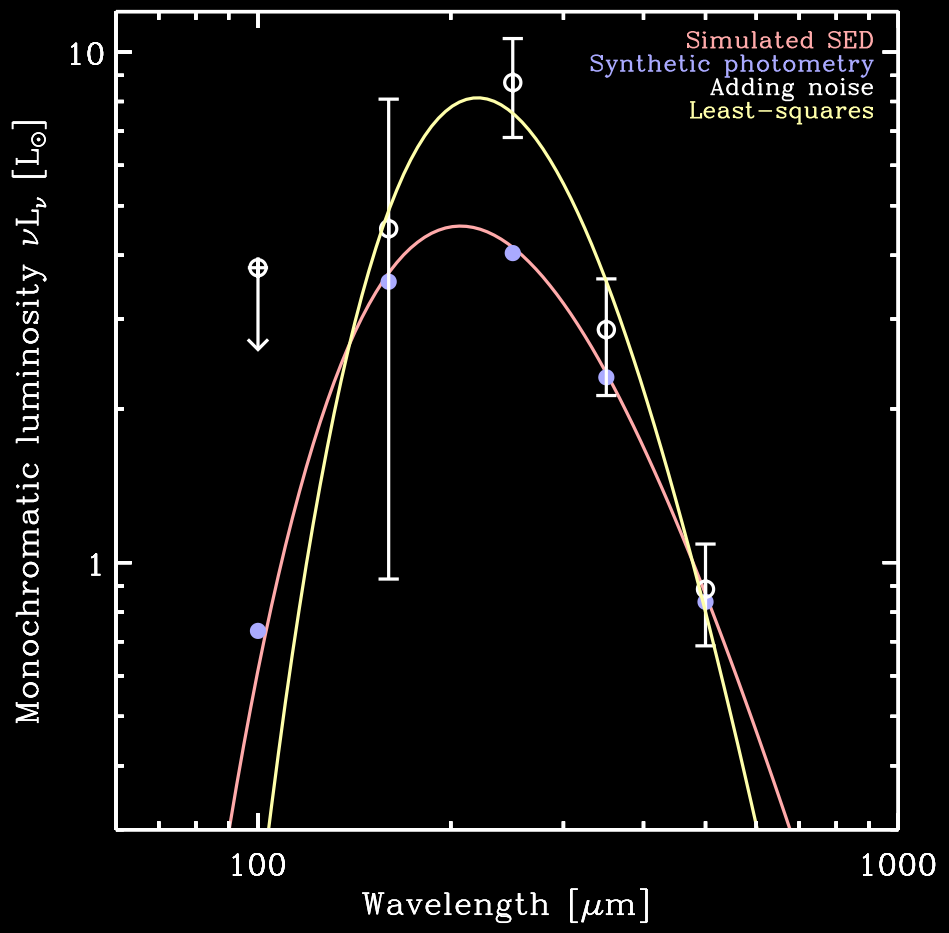

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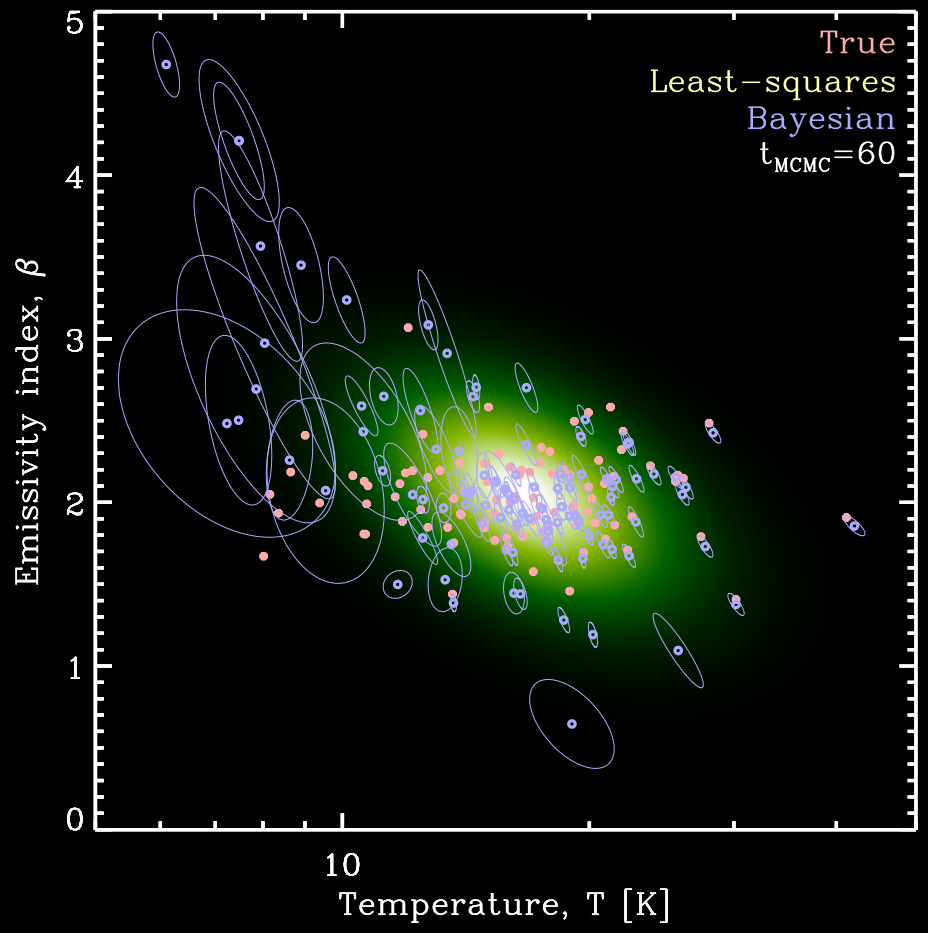

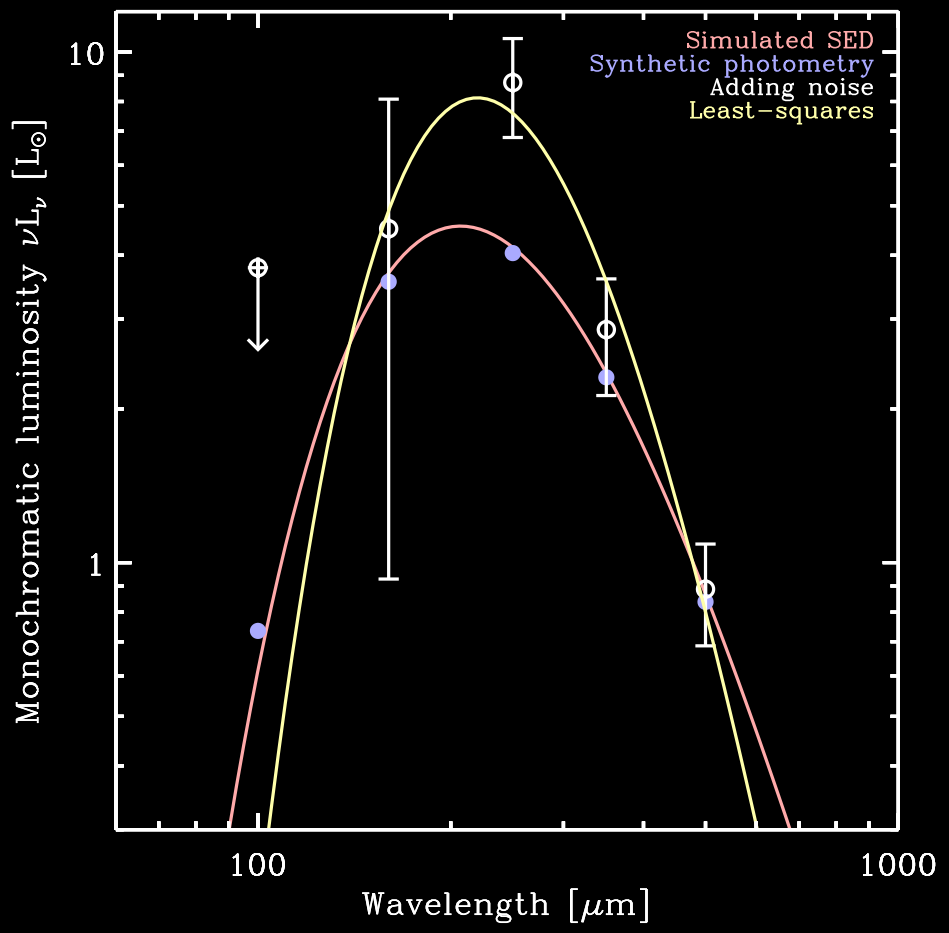

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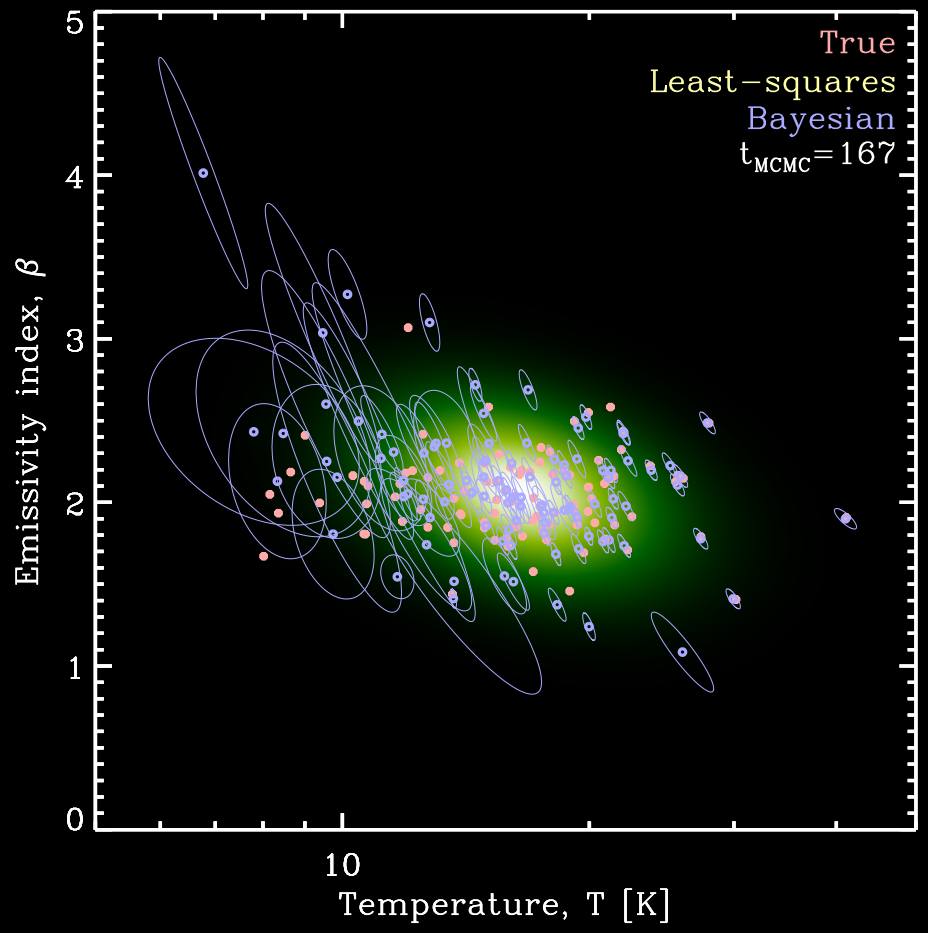

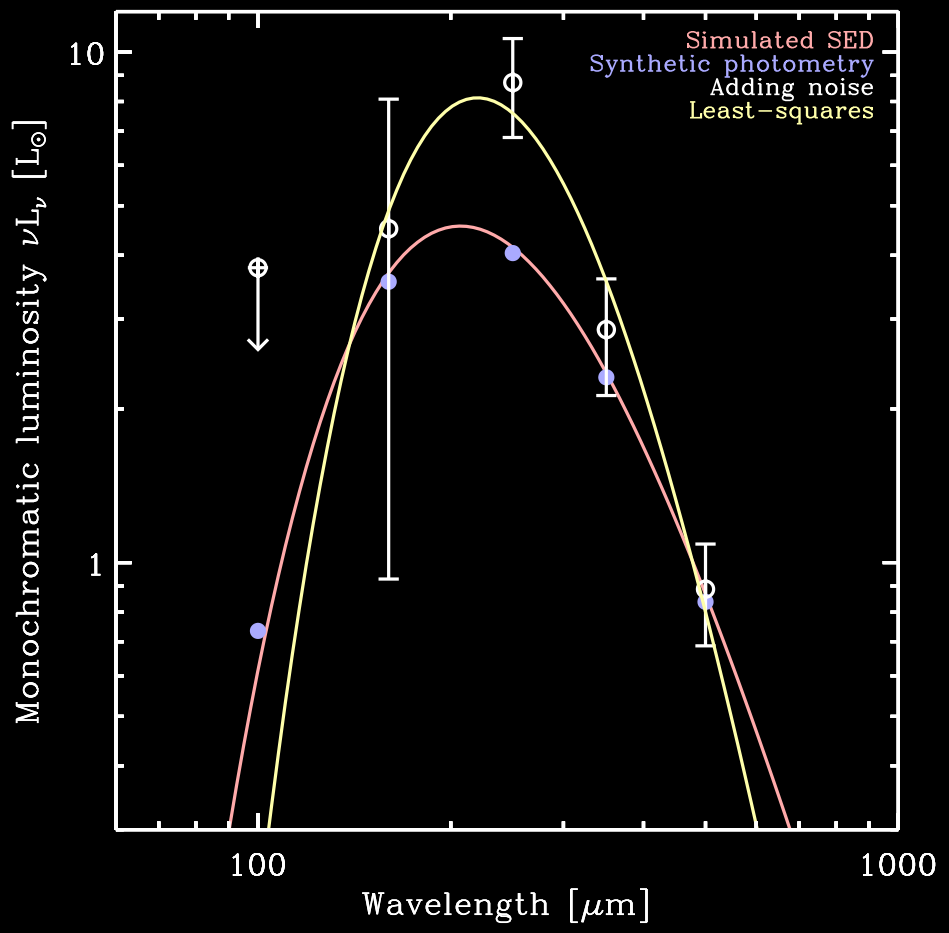

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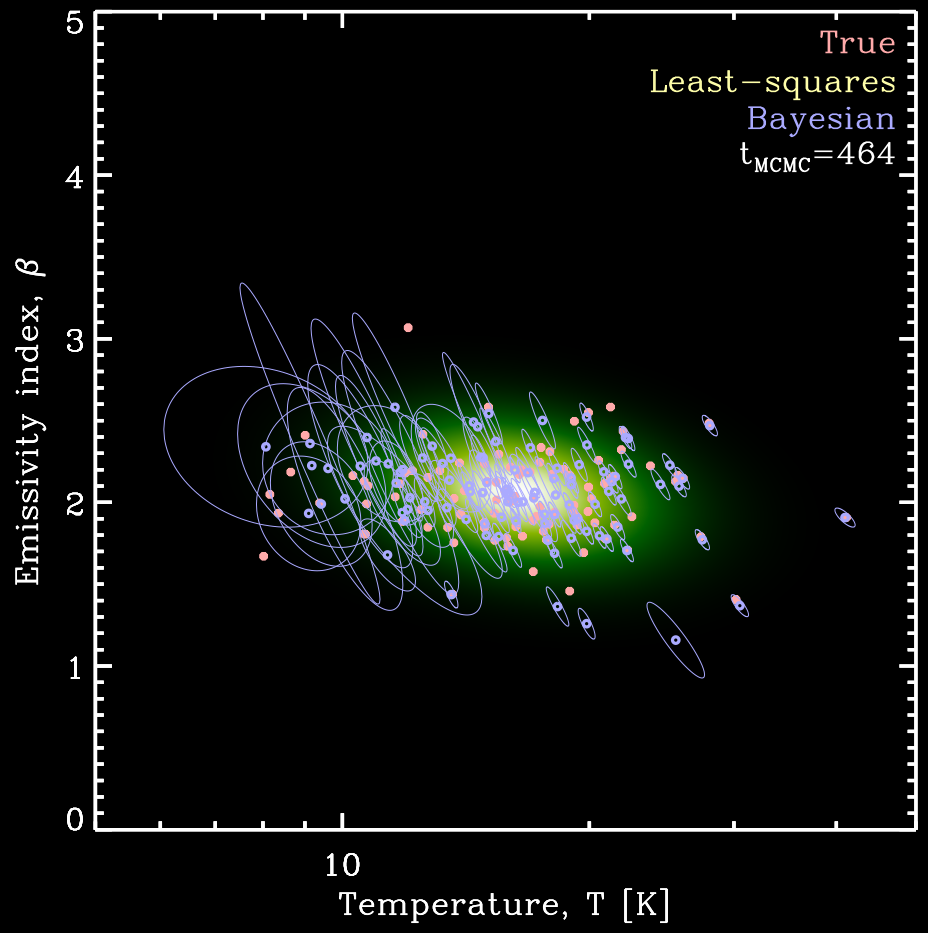

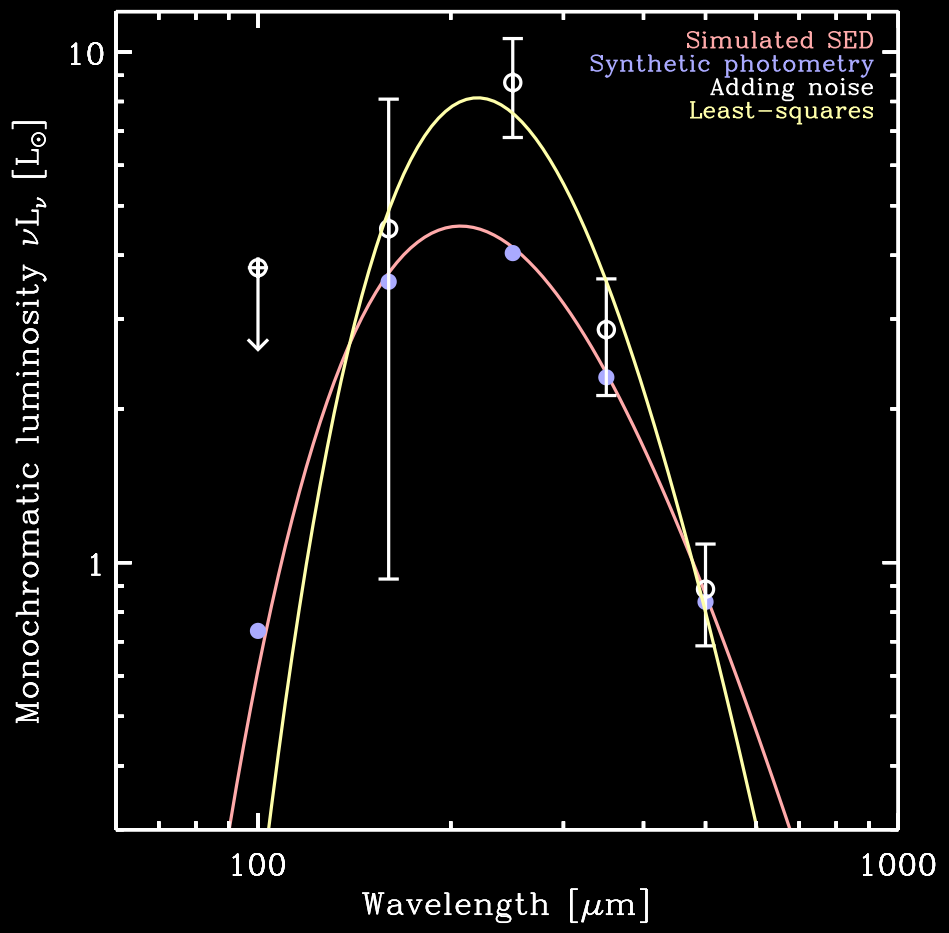

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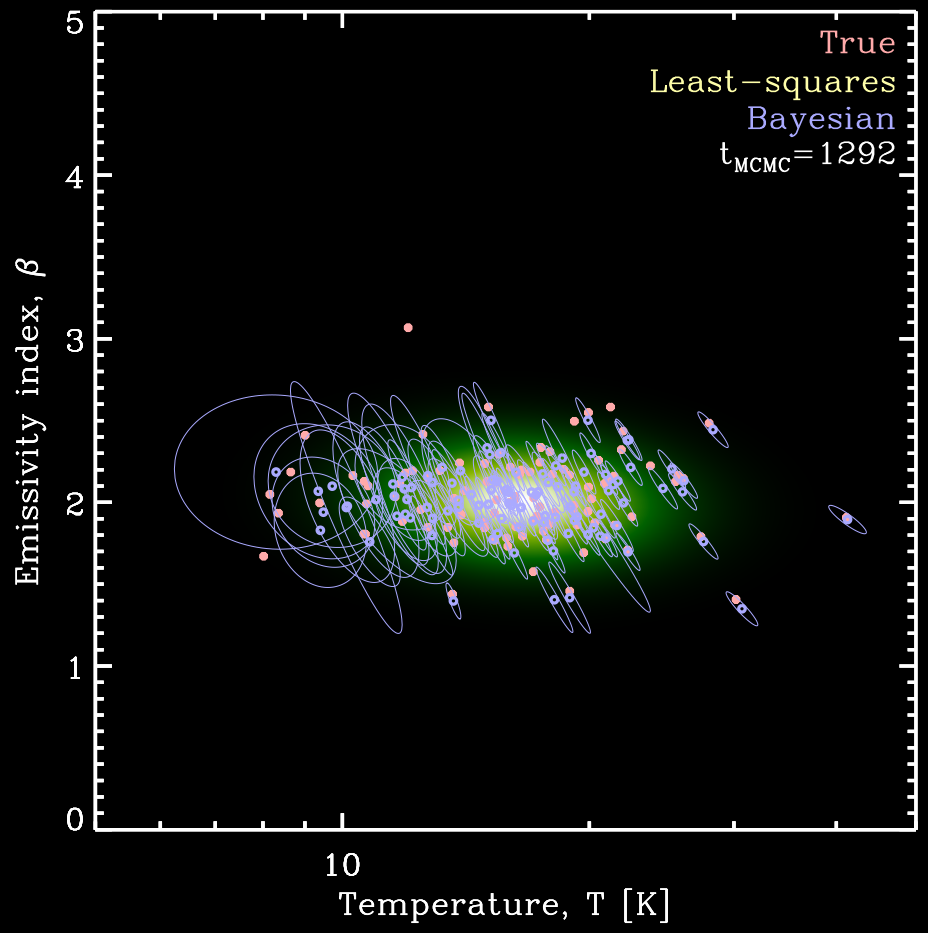

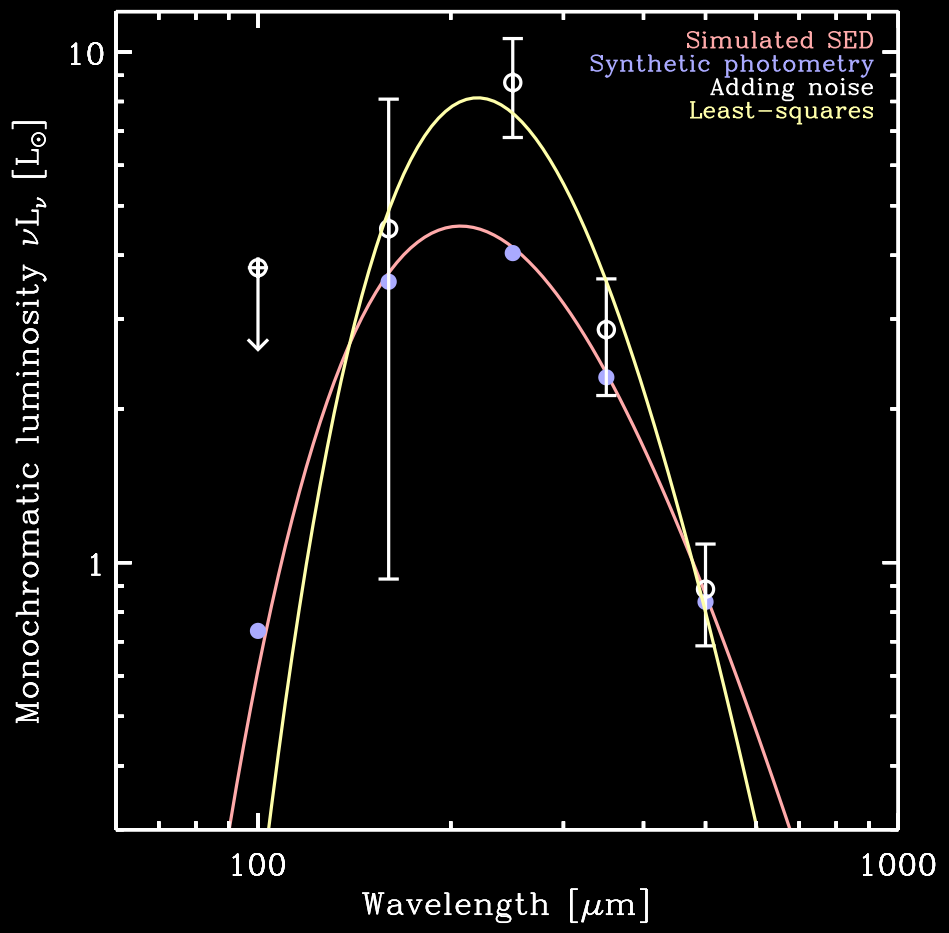

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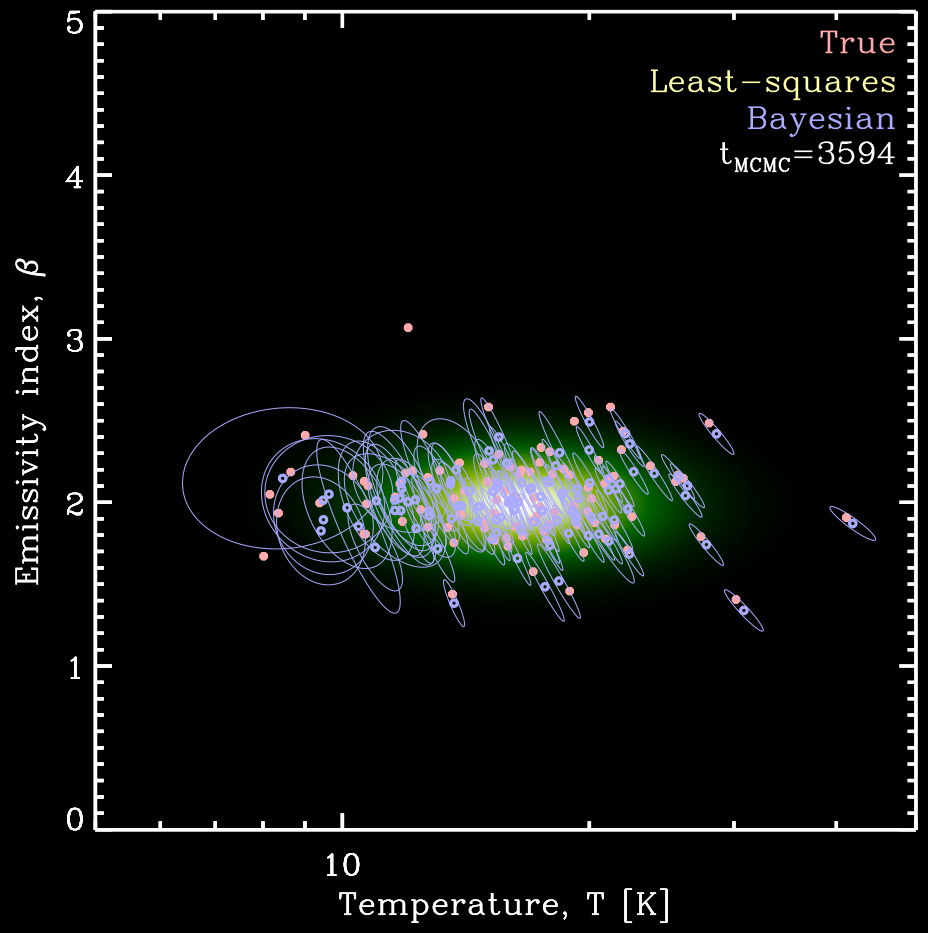

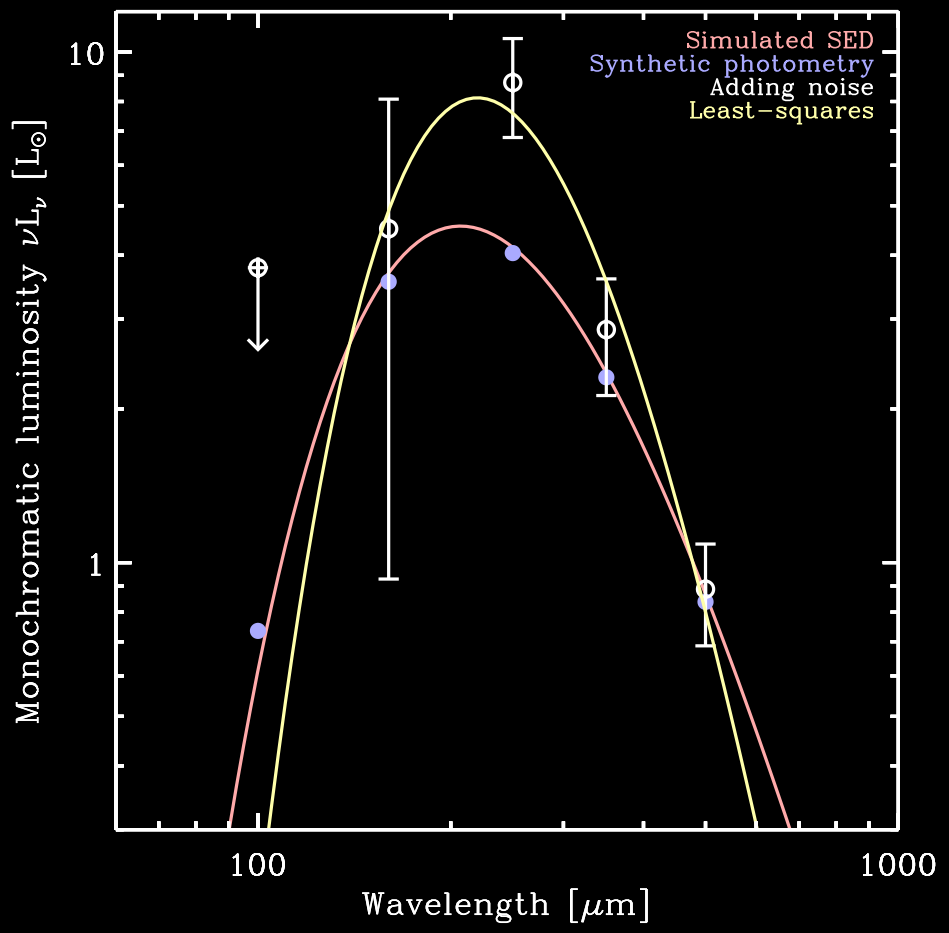

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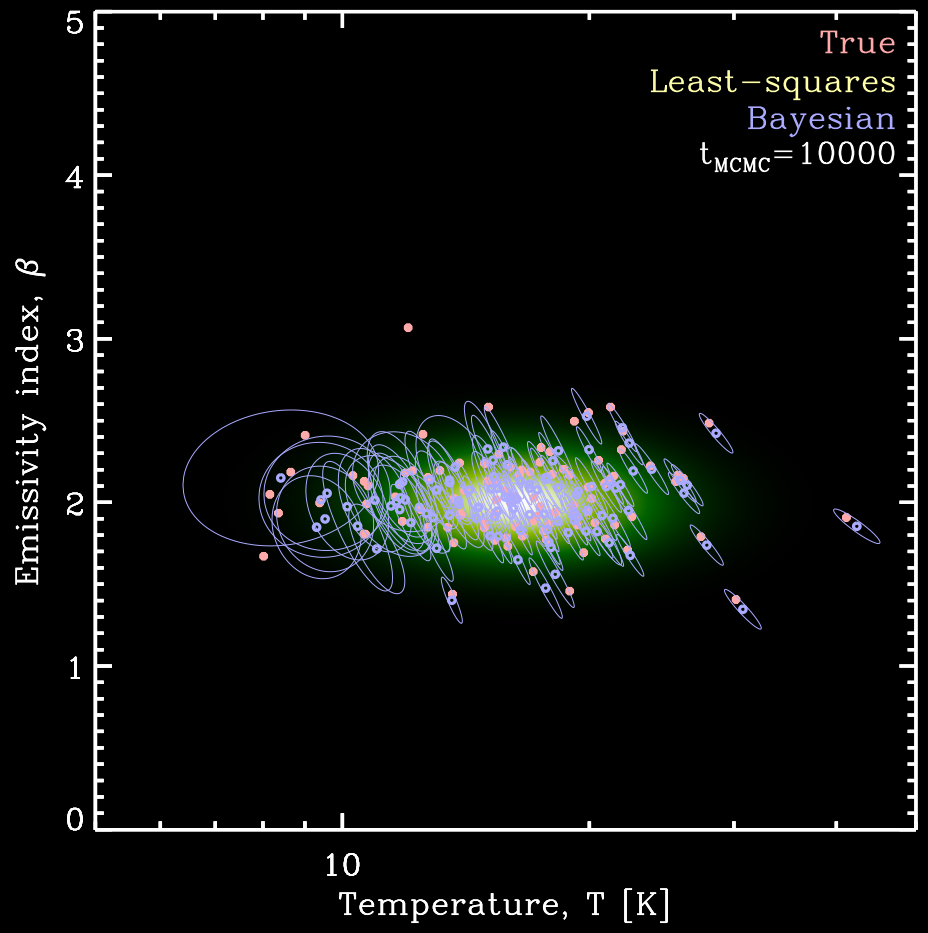

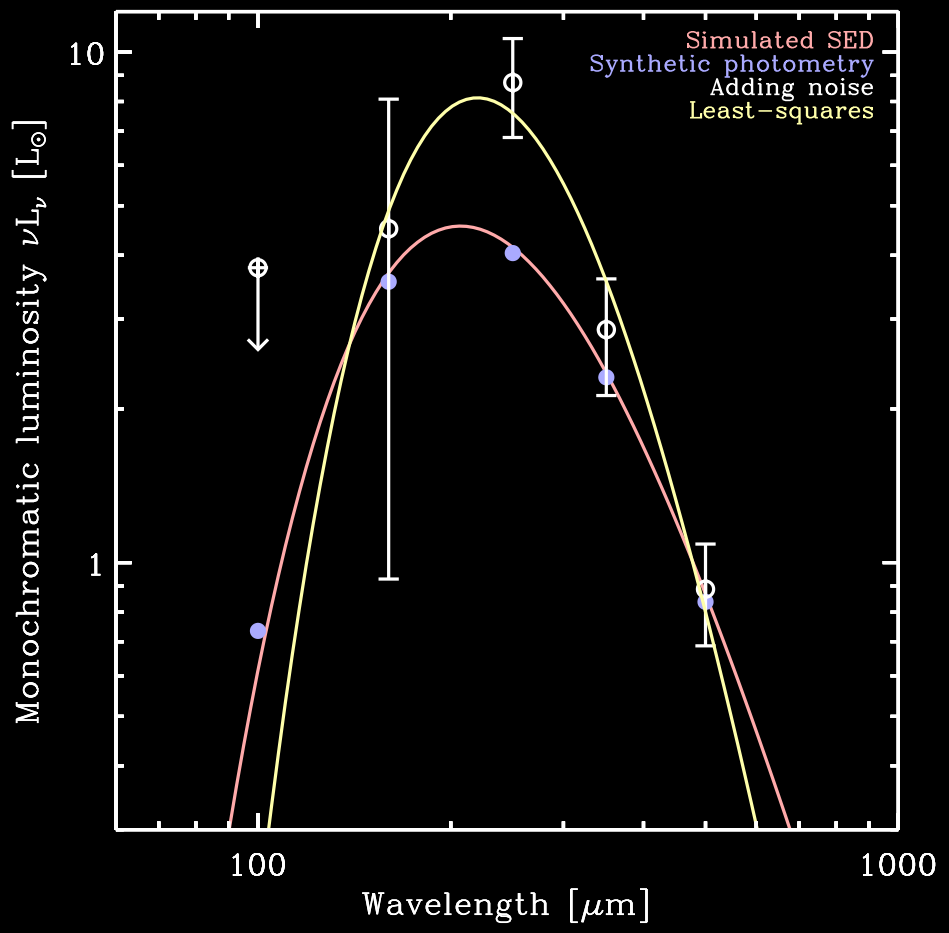

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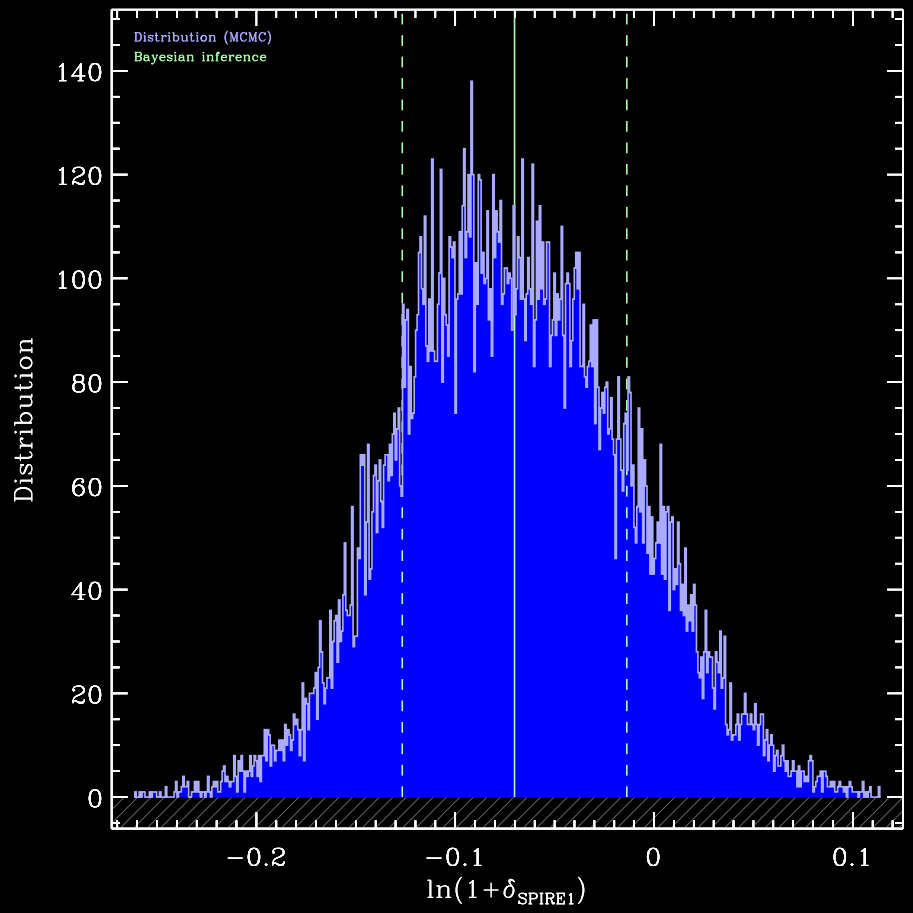

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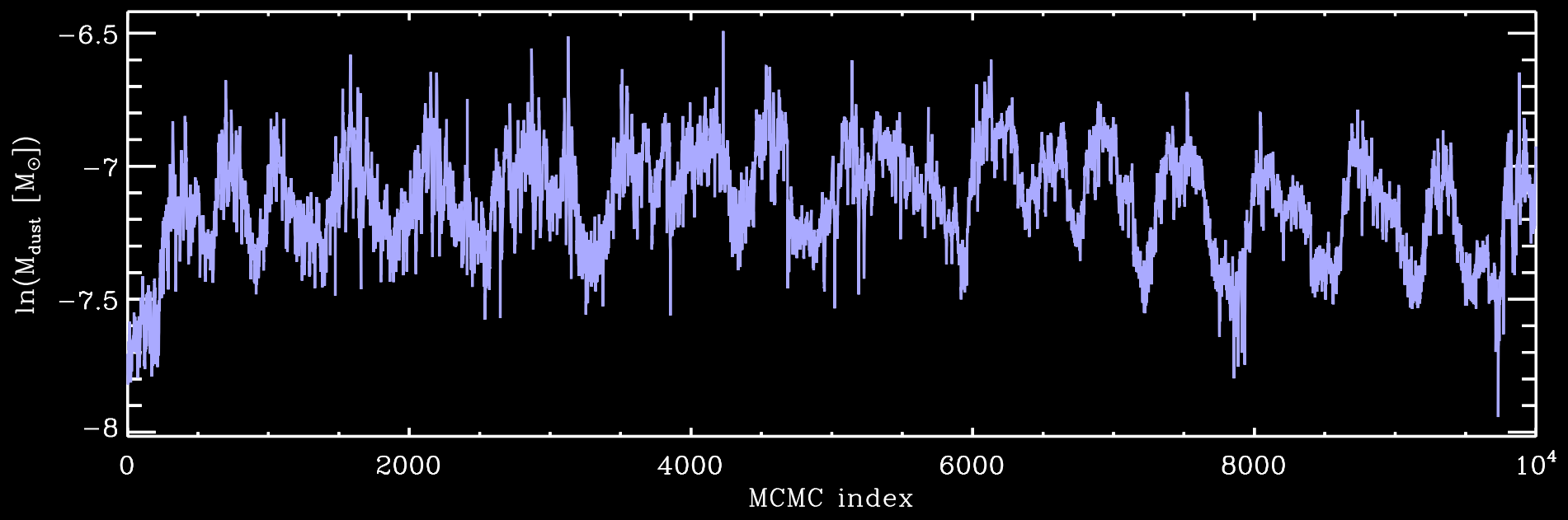

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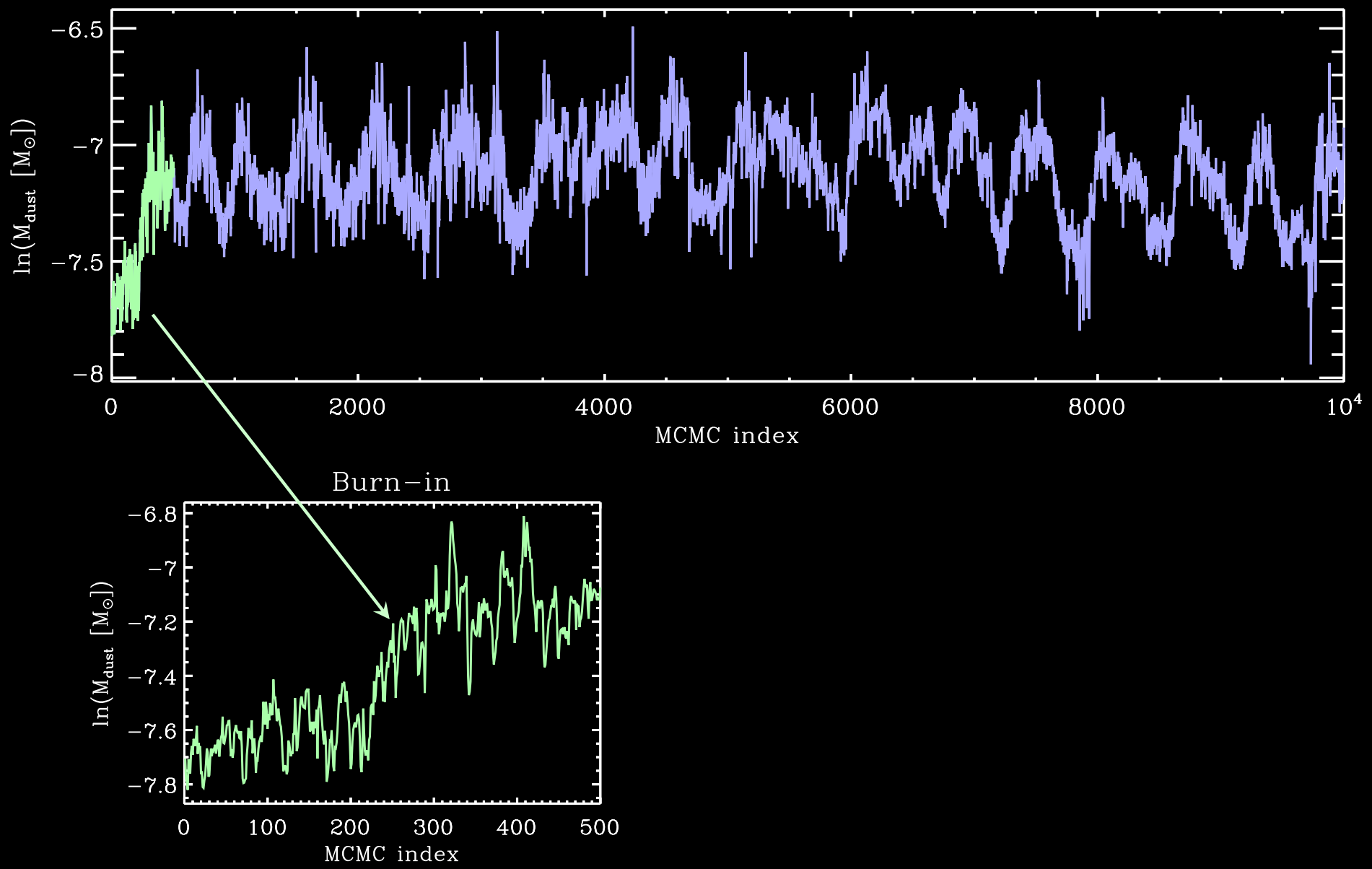

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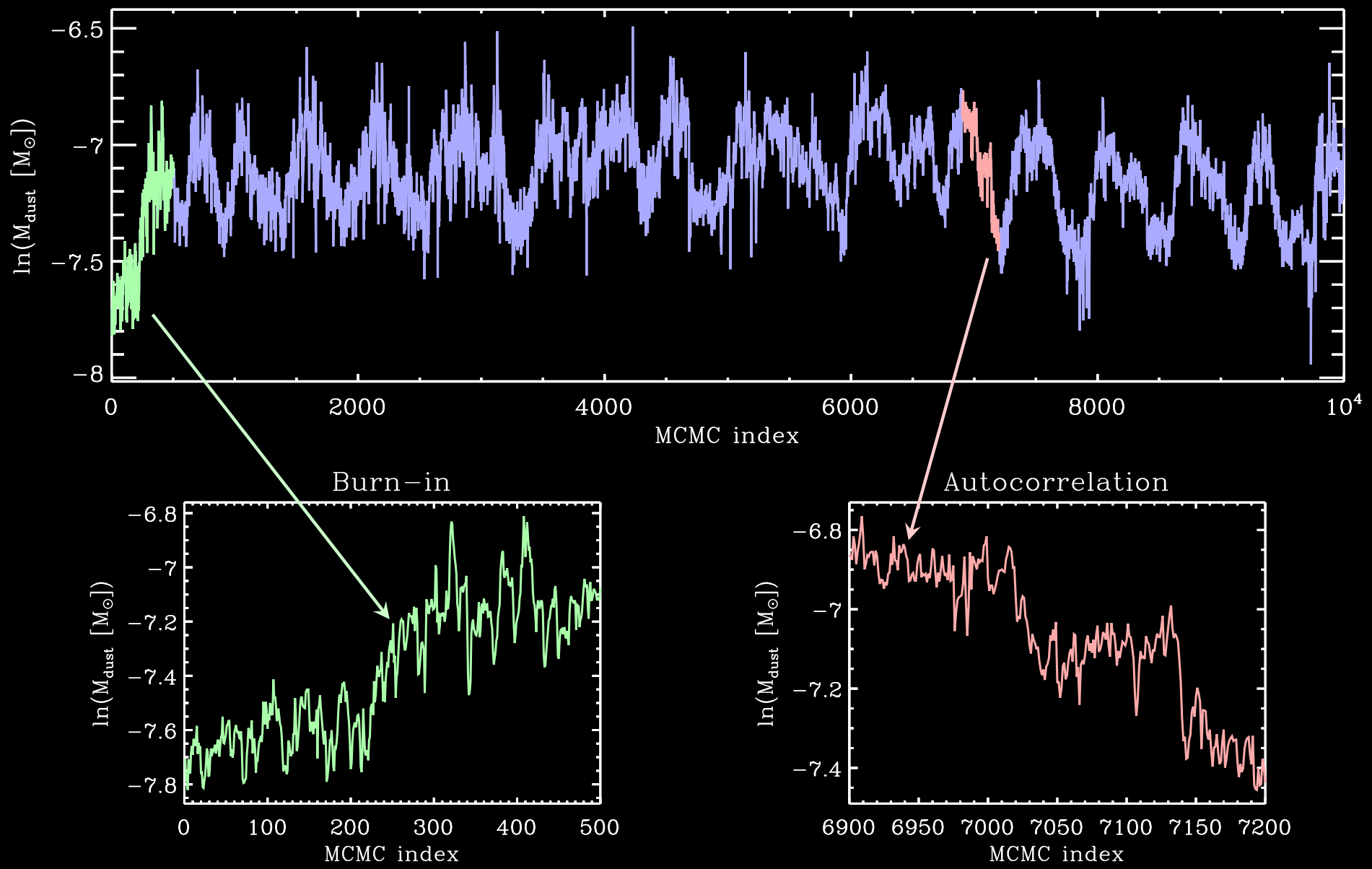

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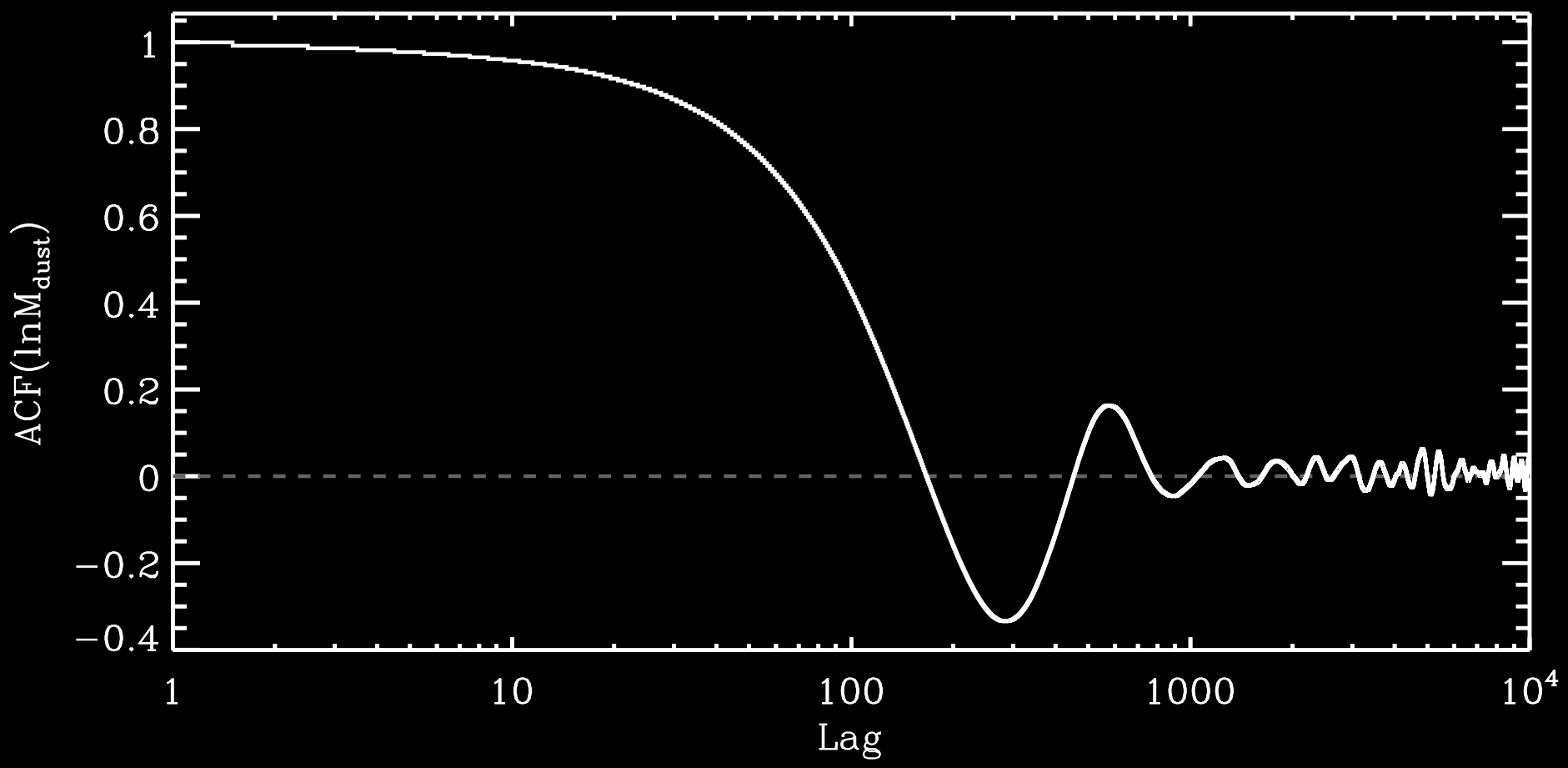

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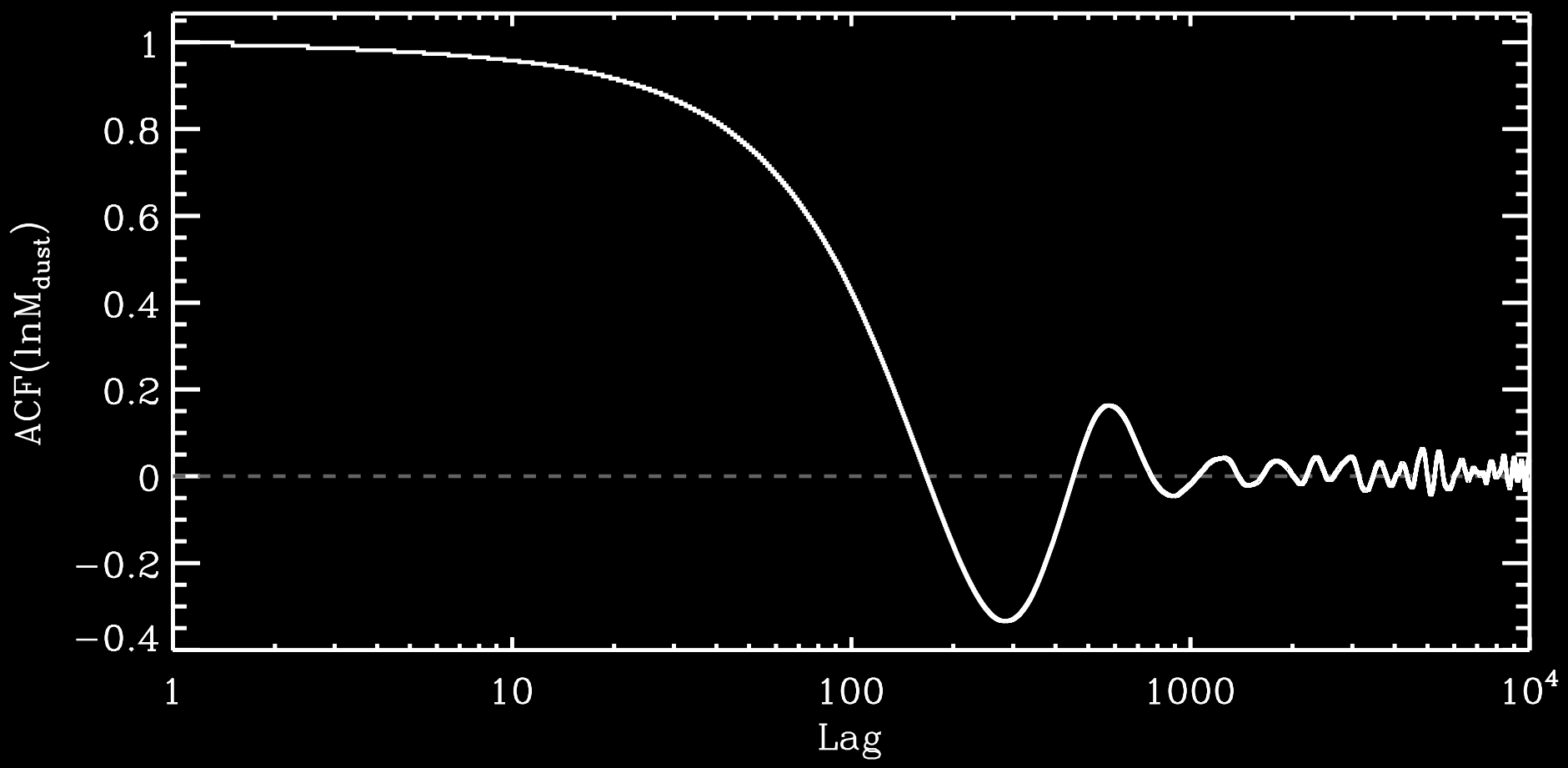

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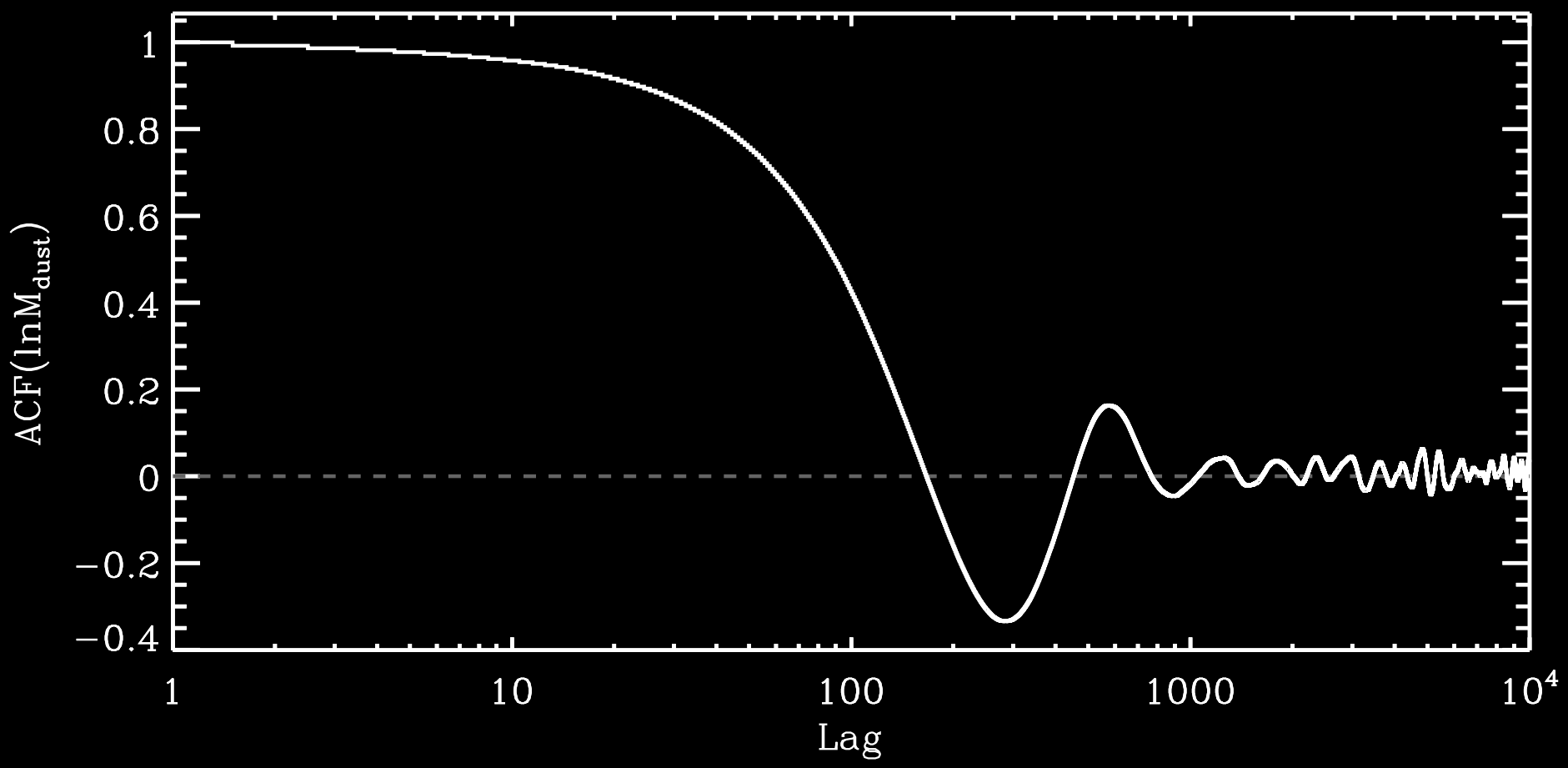

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Outline of the Talk

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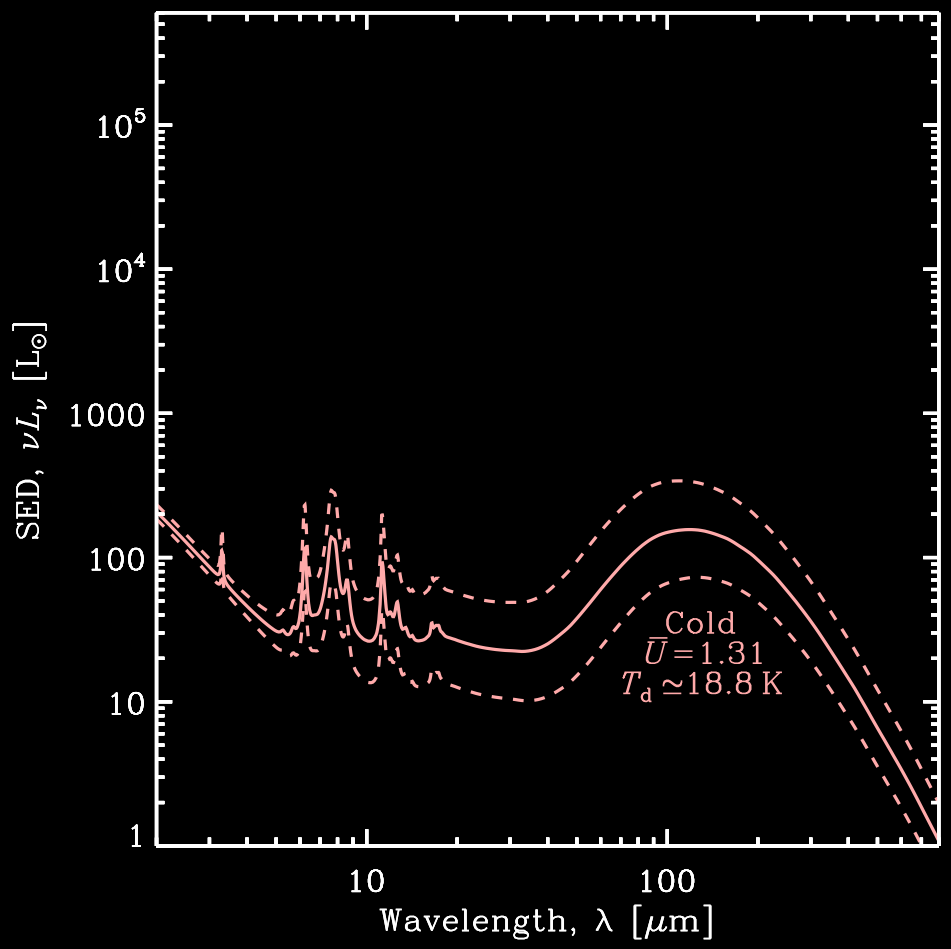

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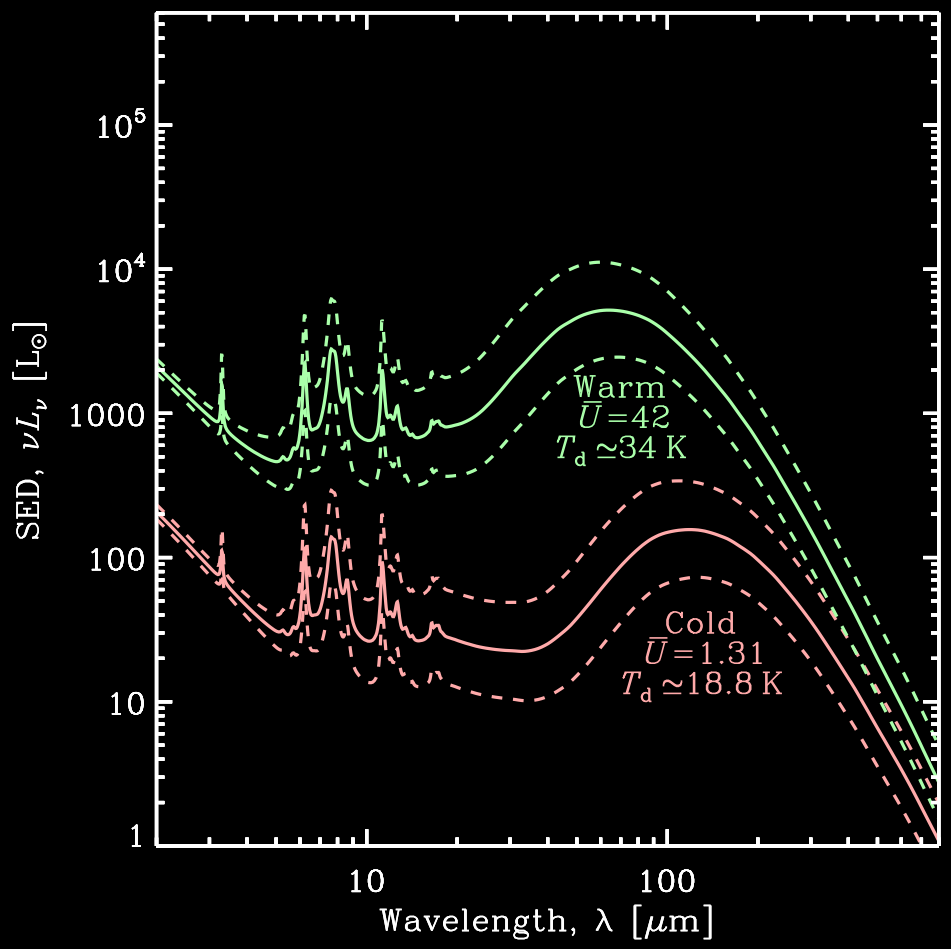

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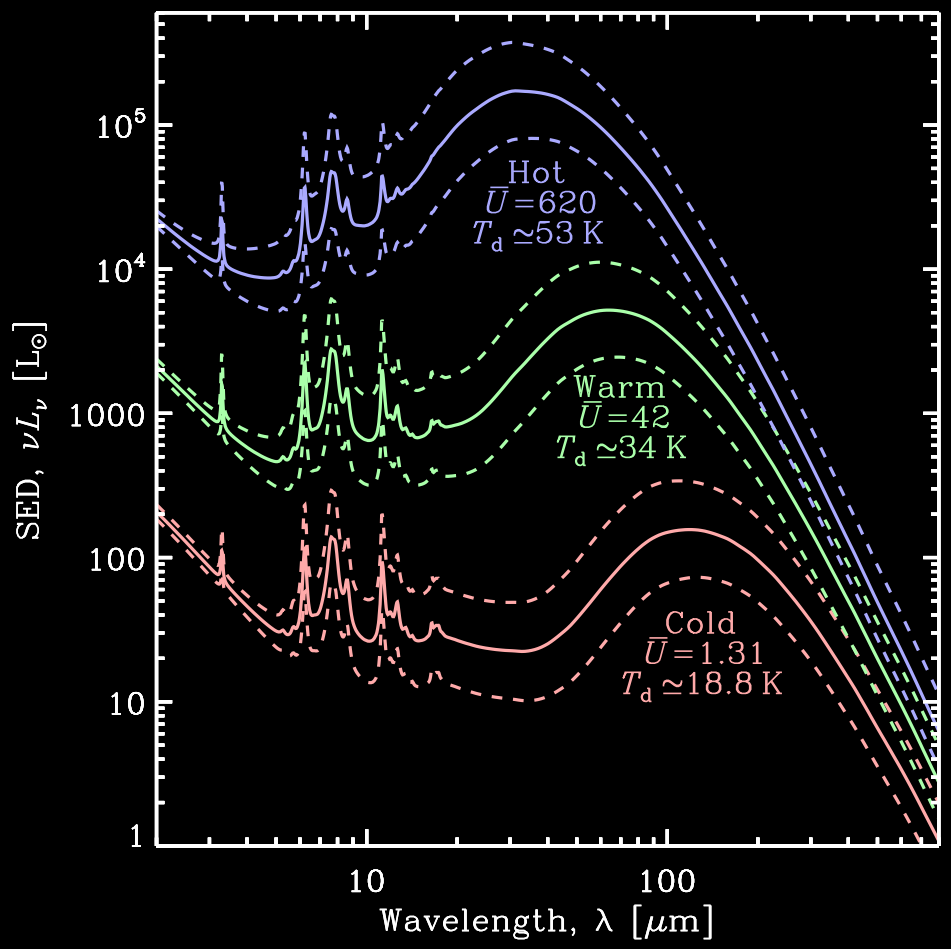

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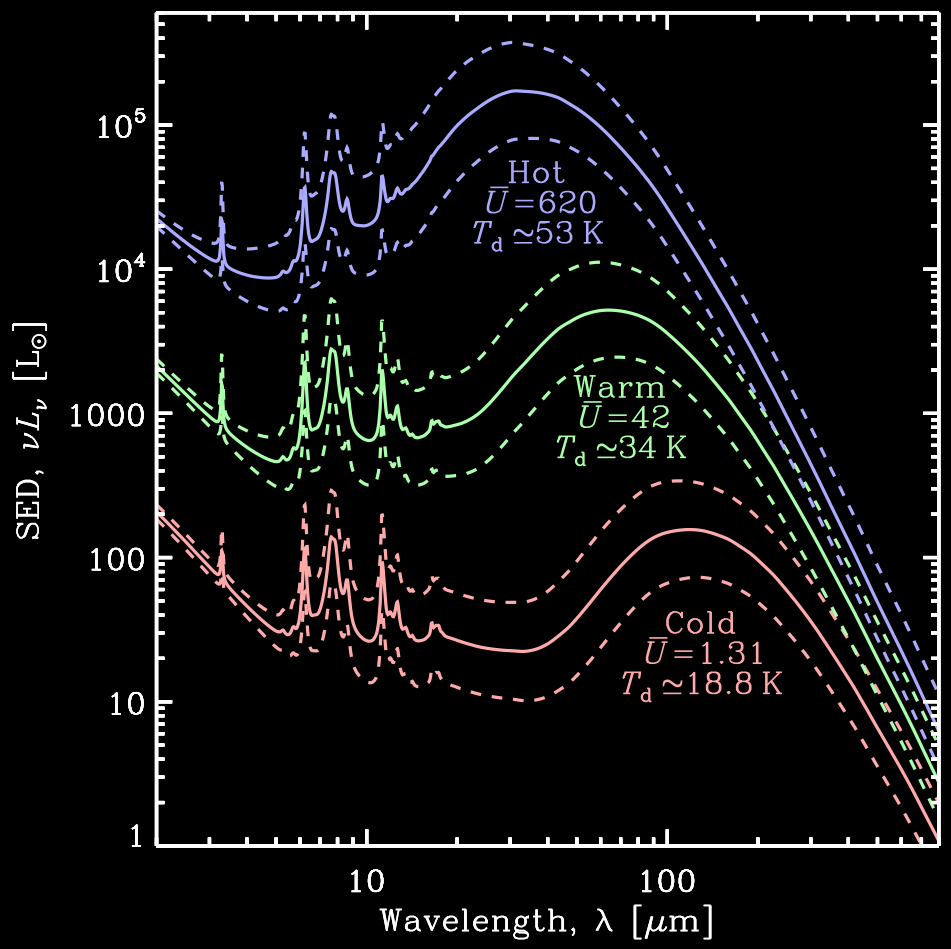

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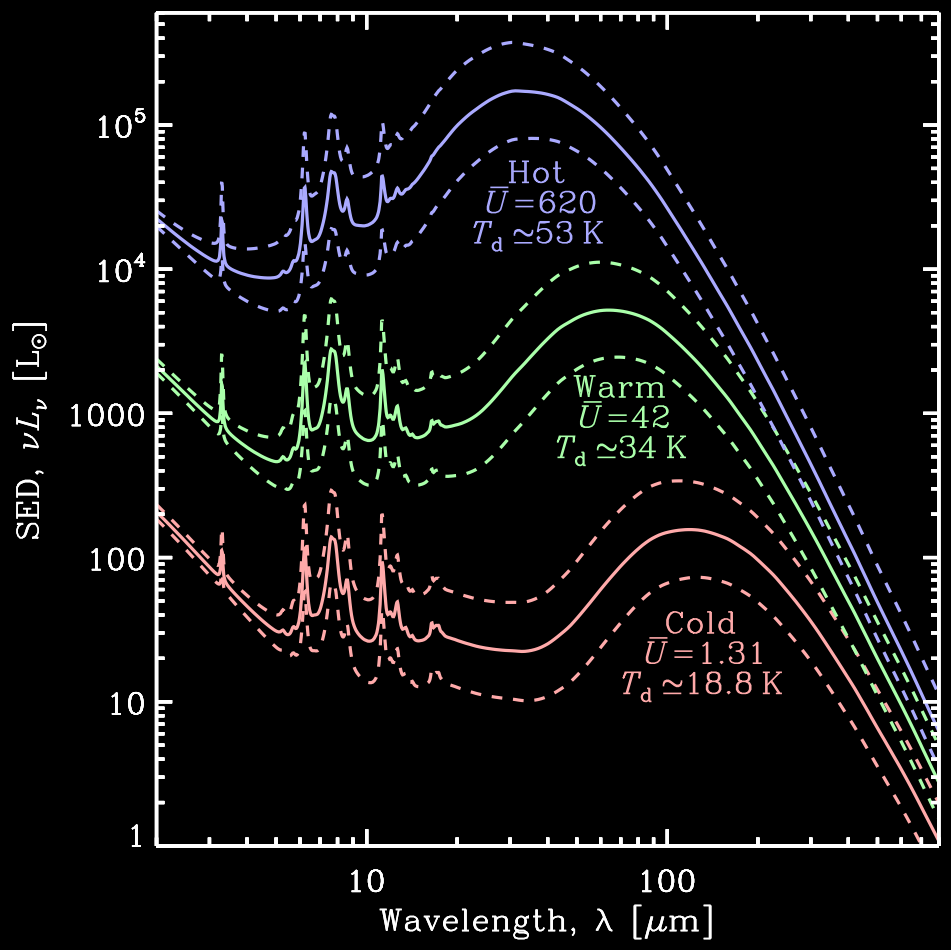

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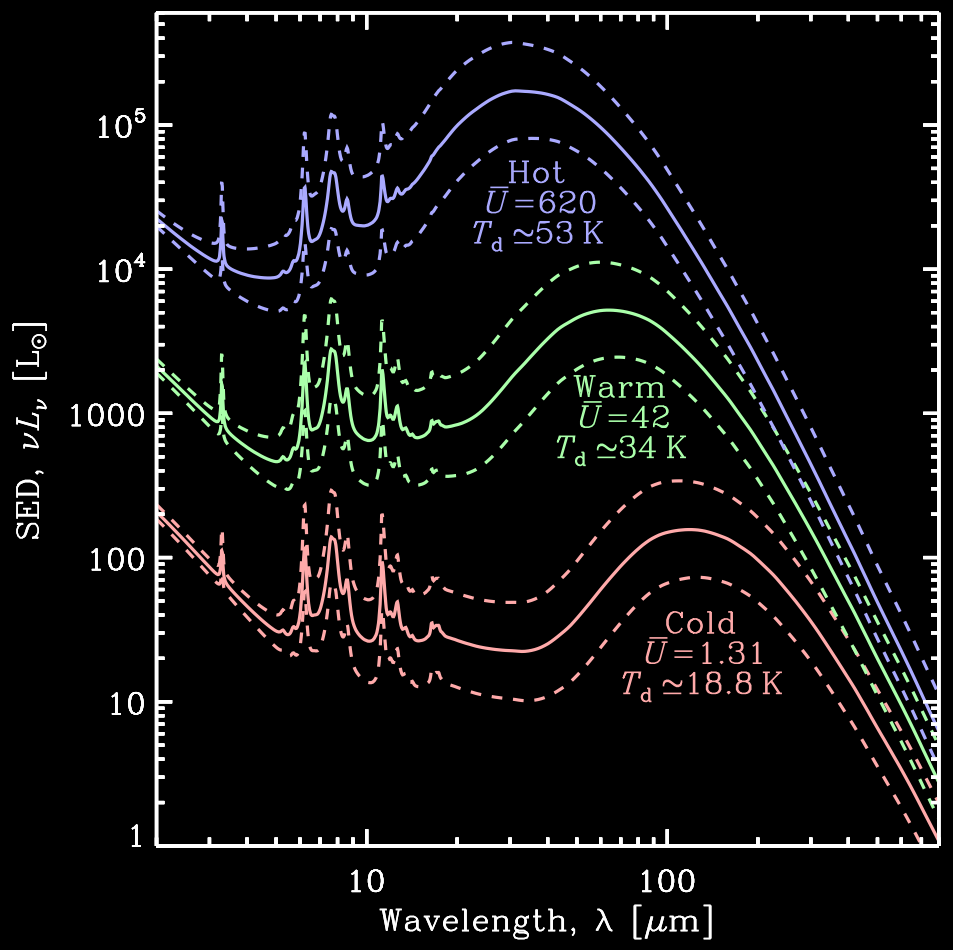

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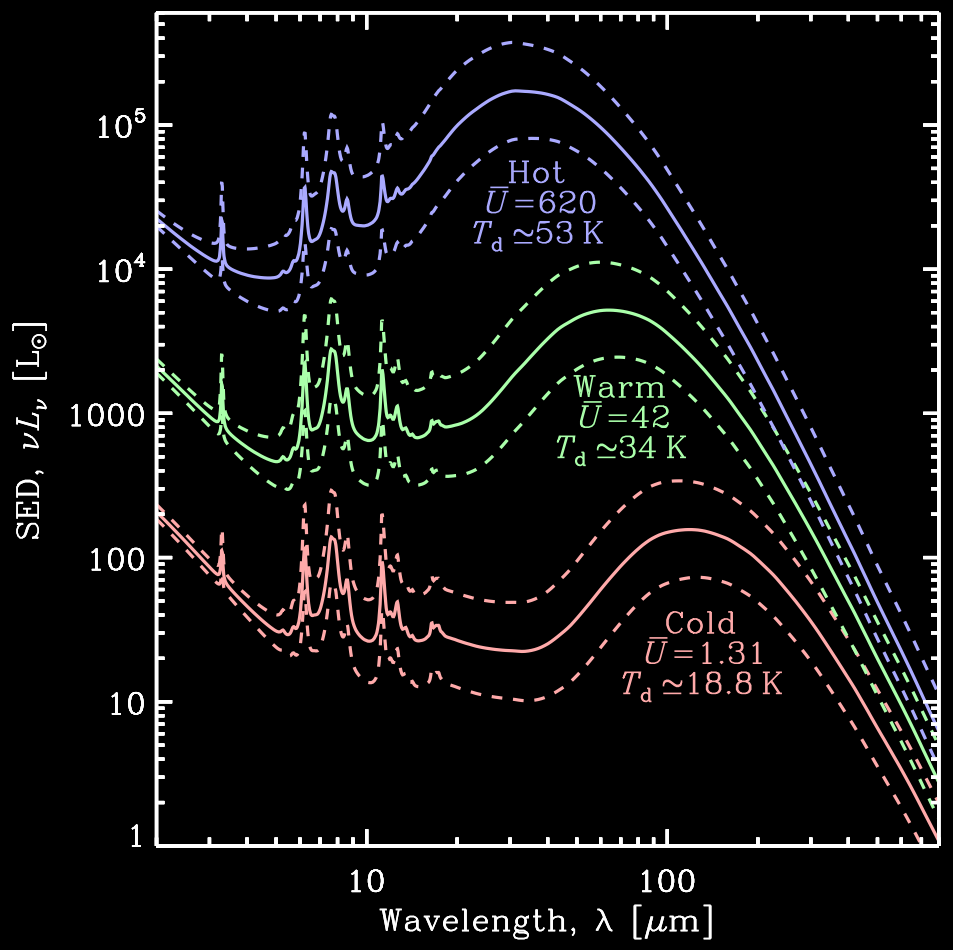

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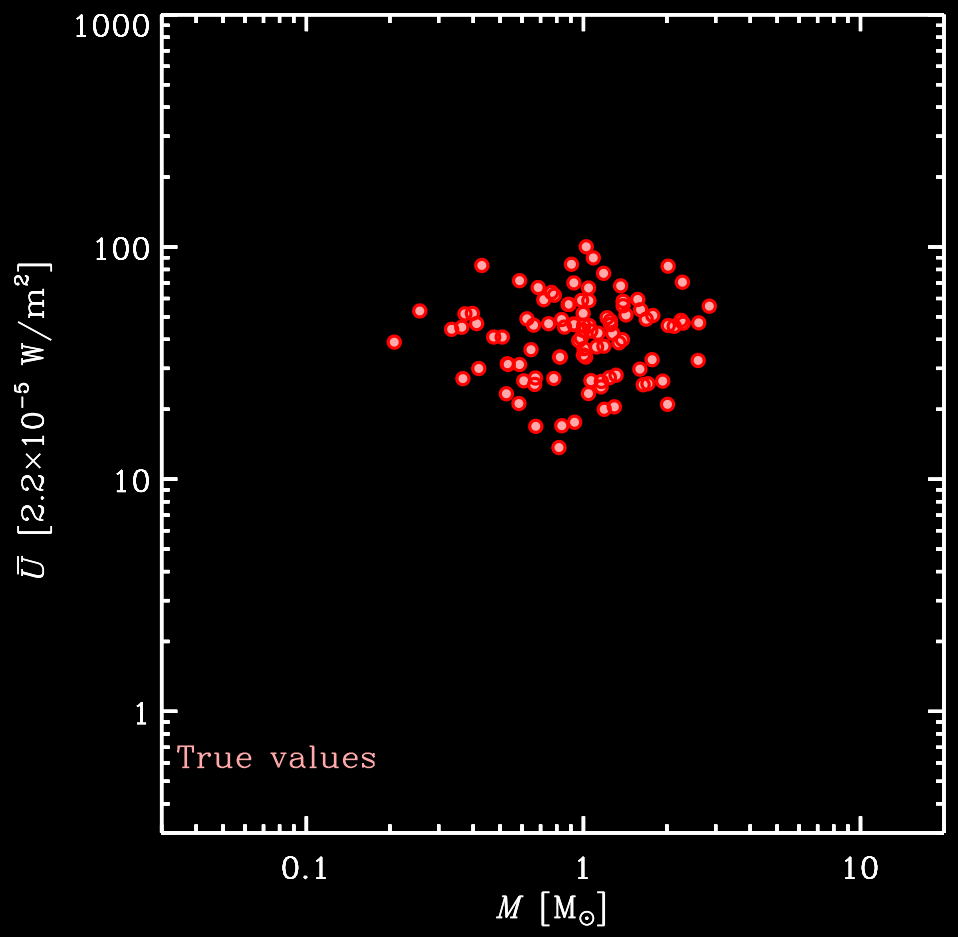

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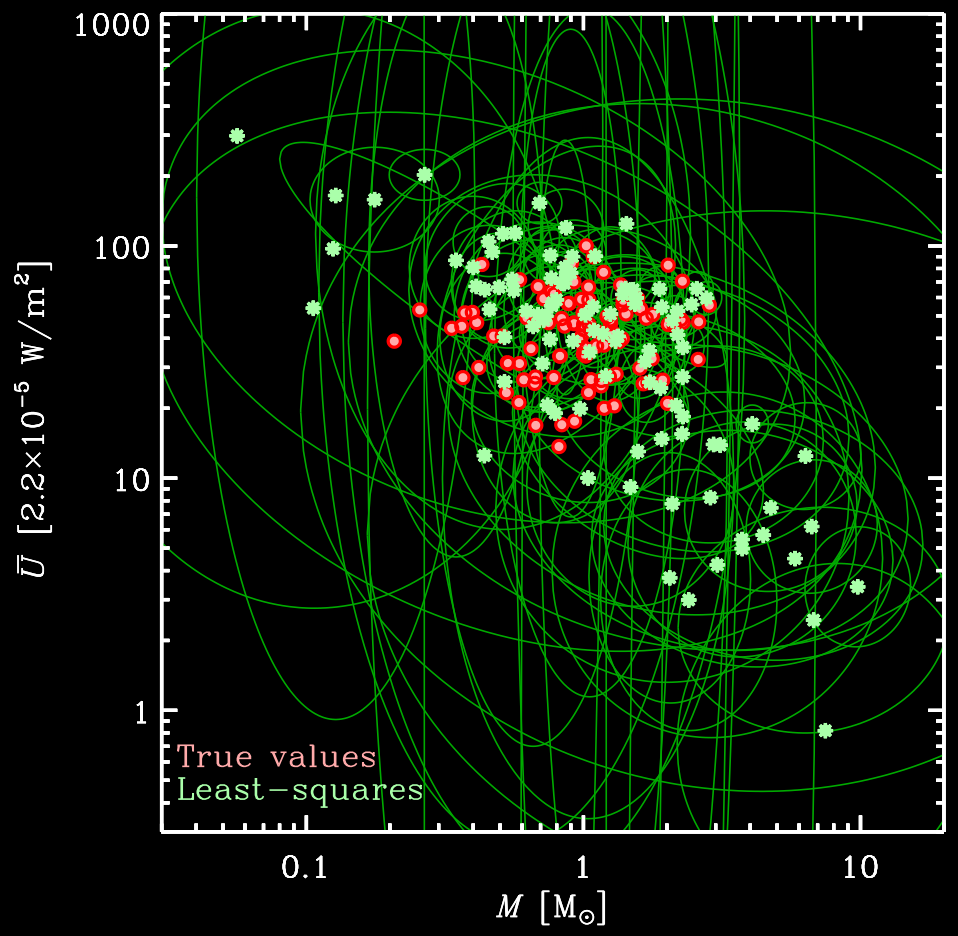

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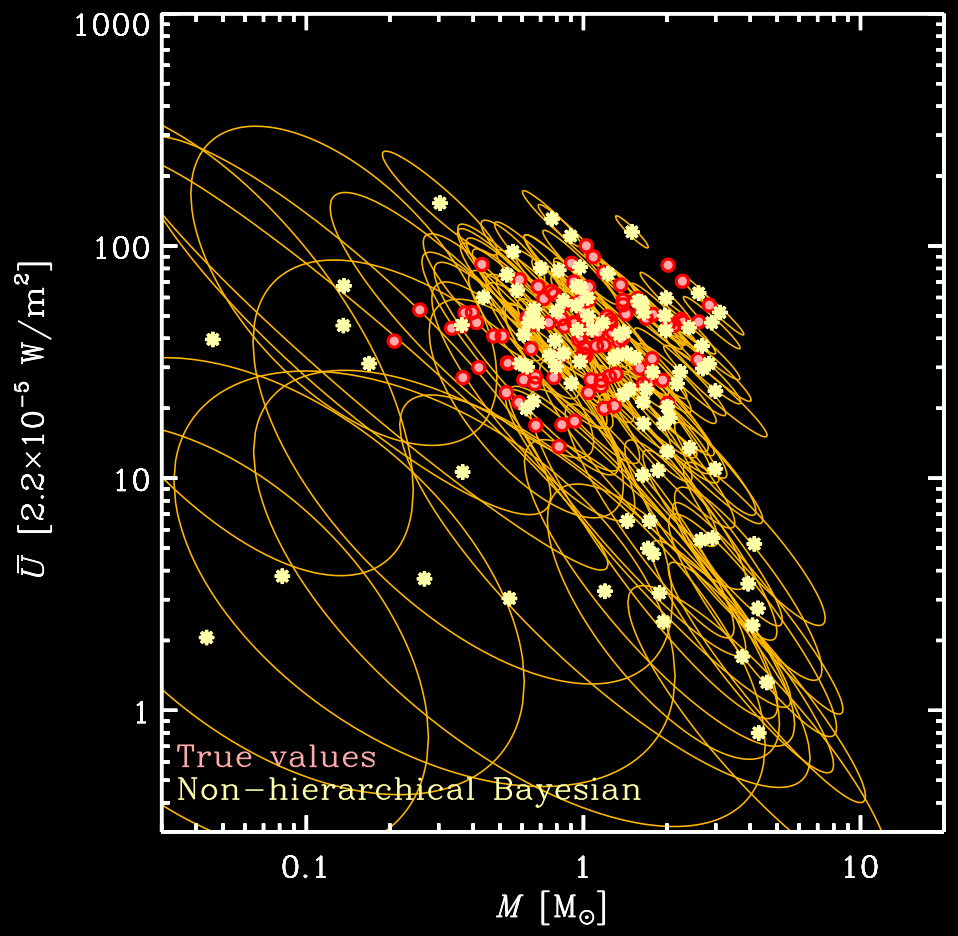

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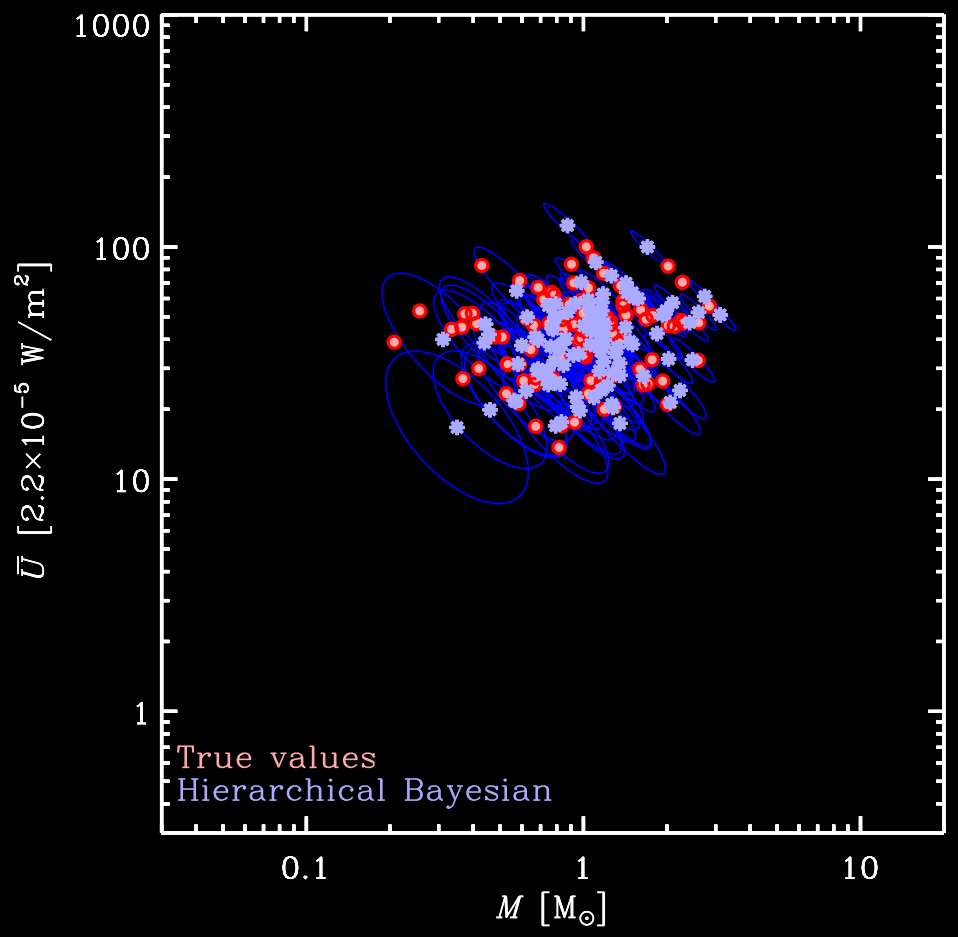

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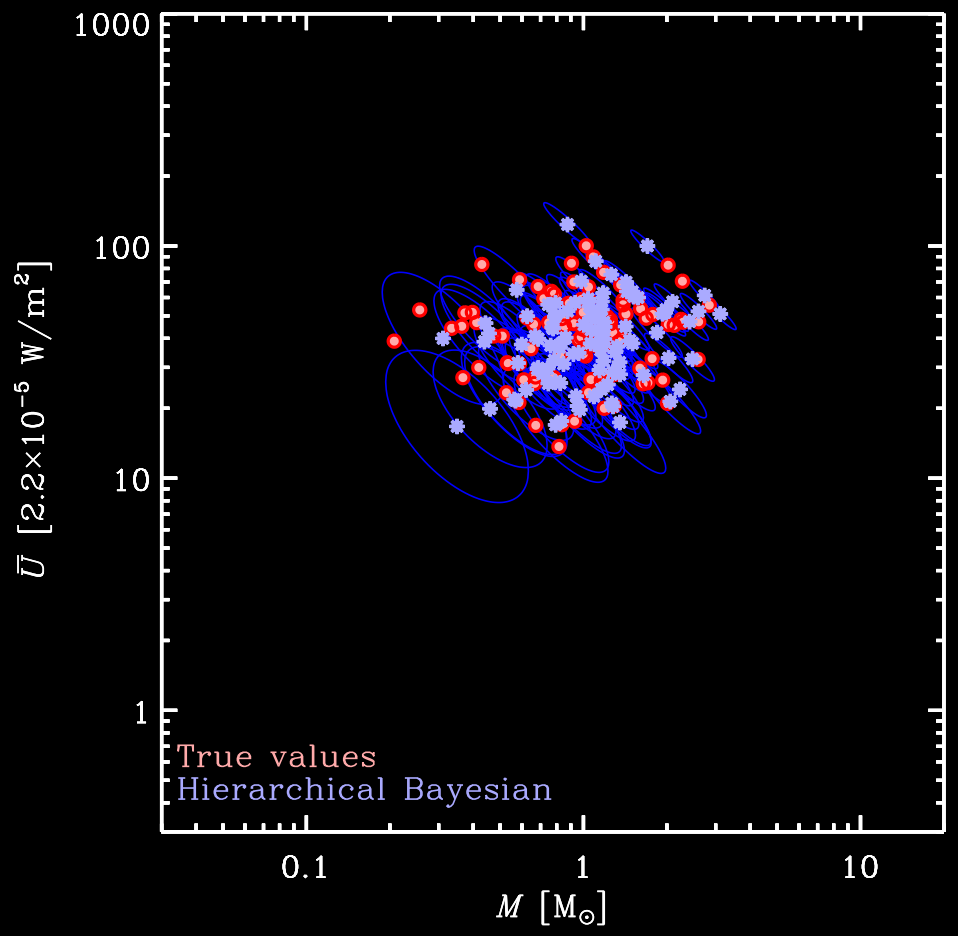

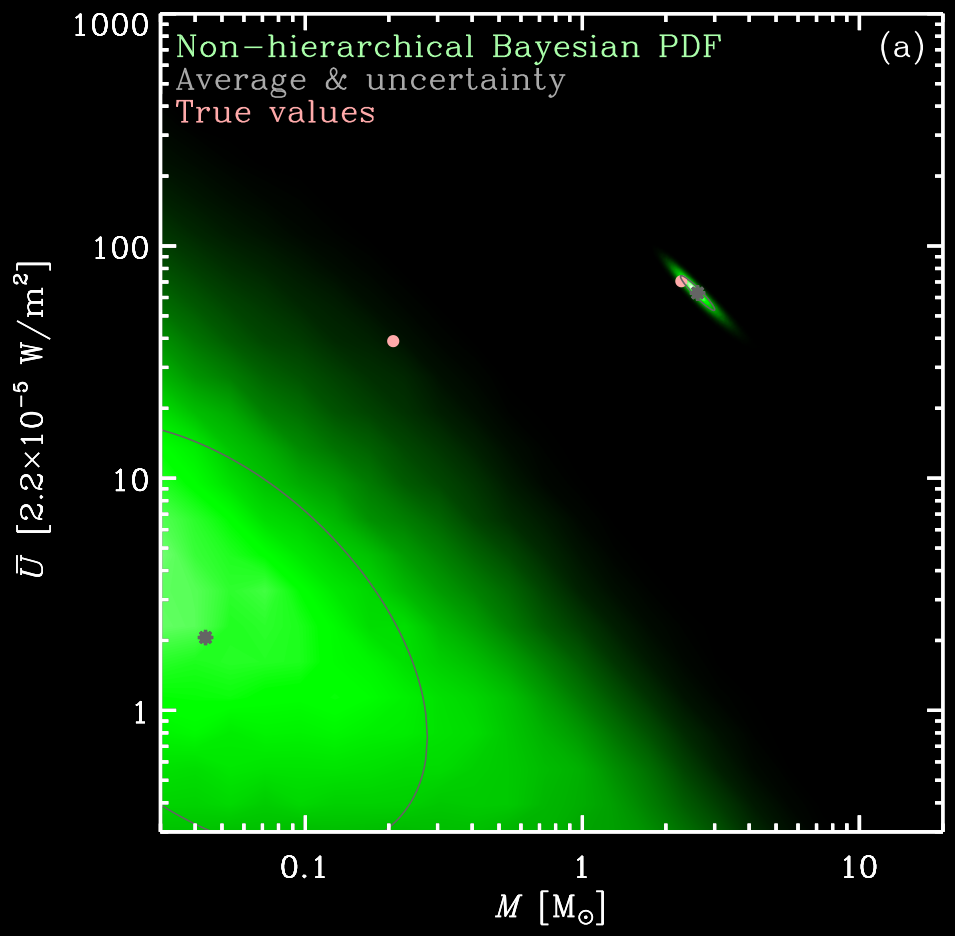

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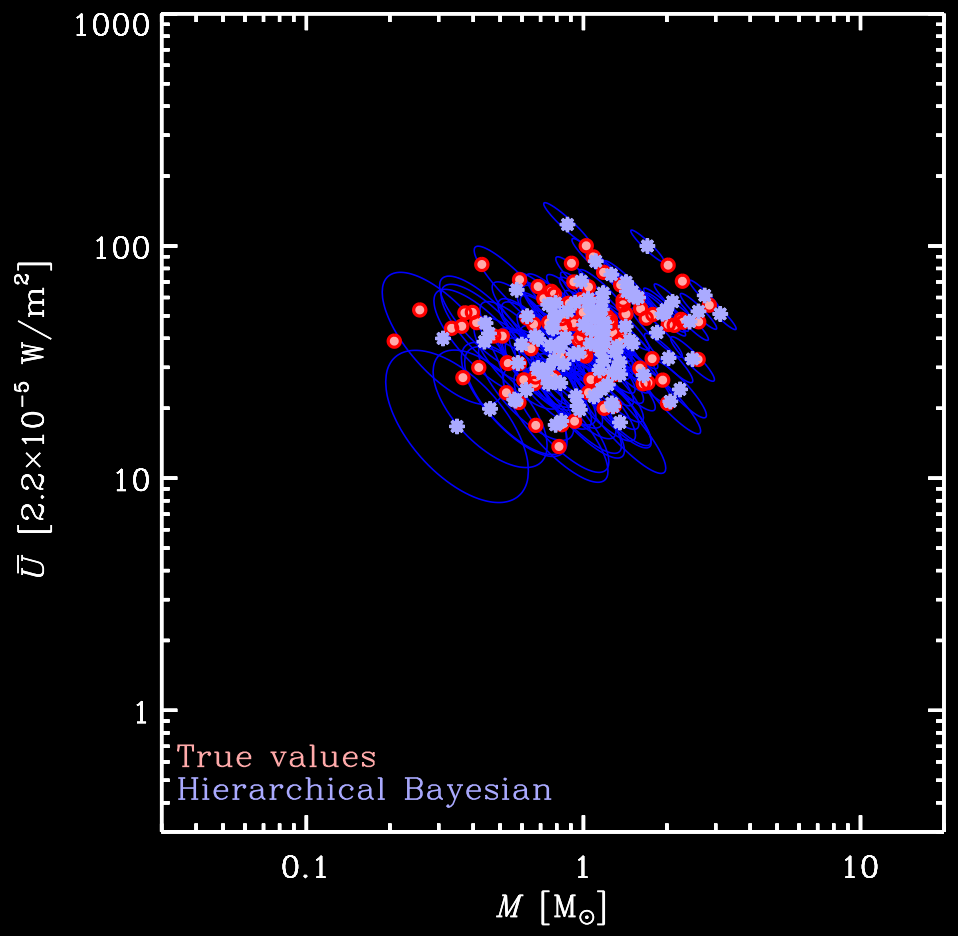

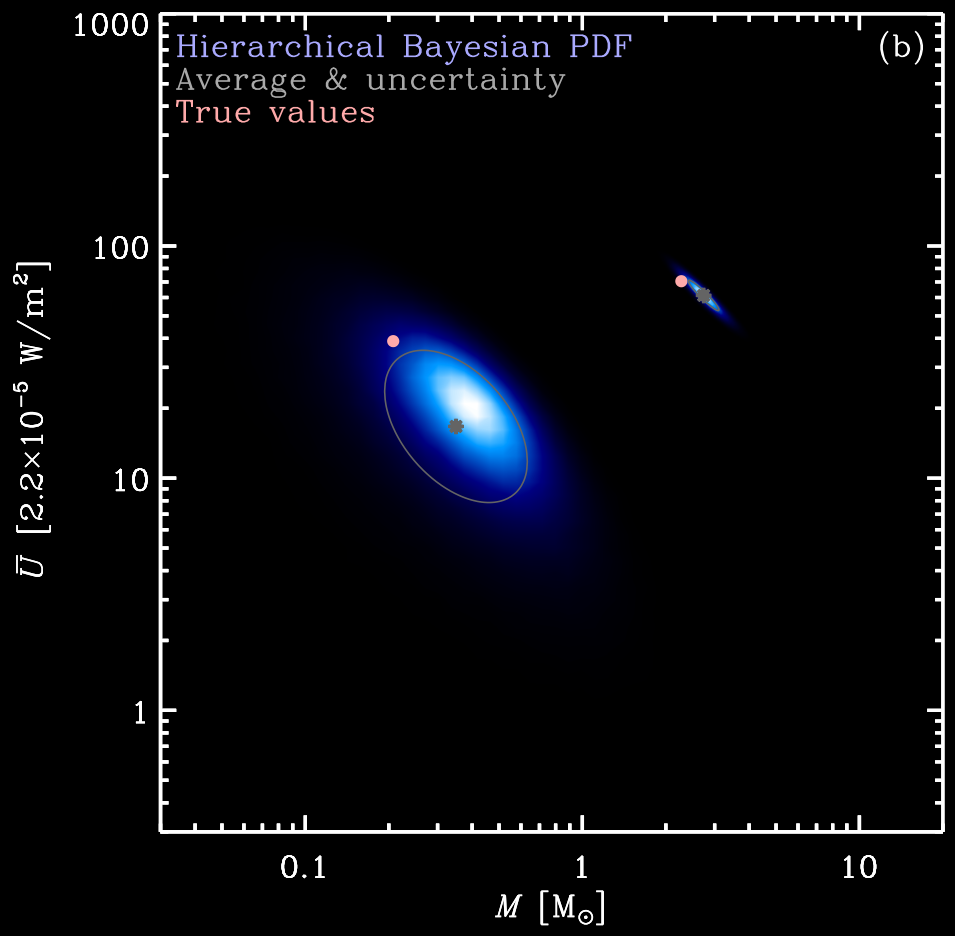

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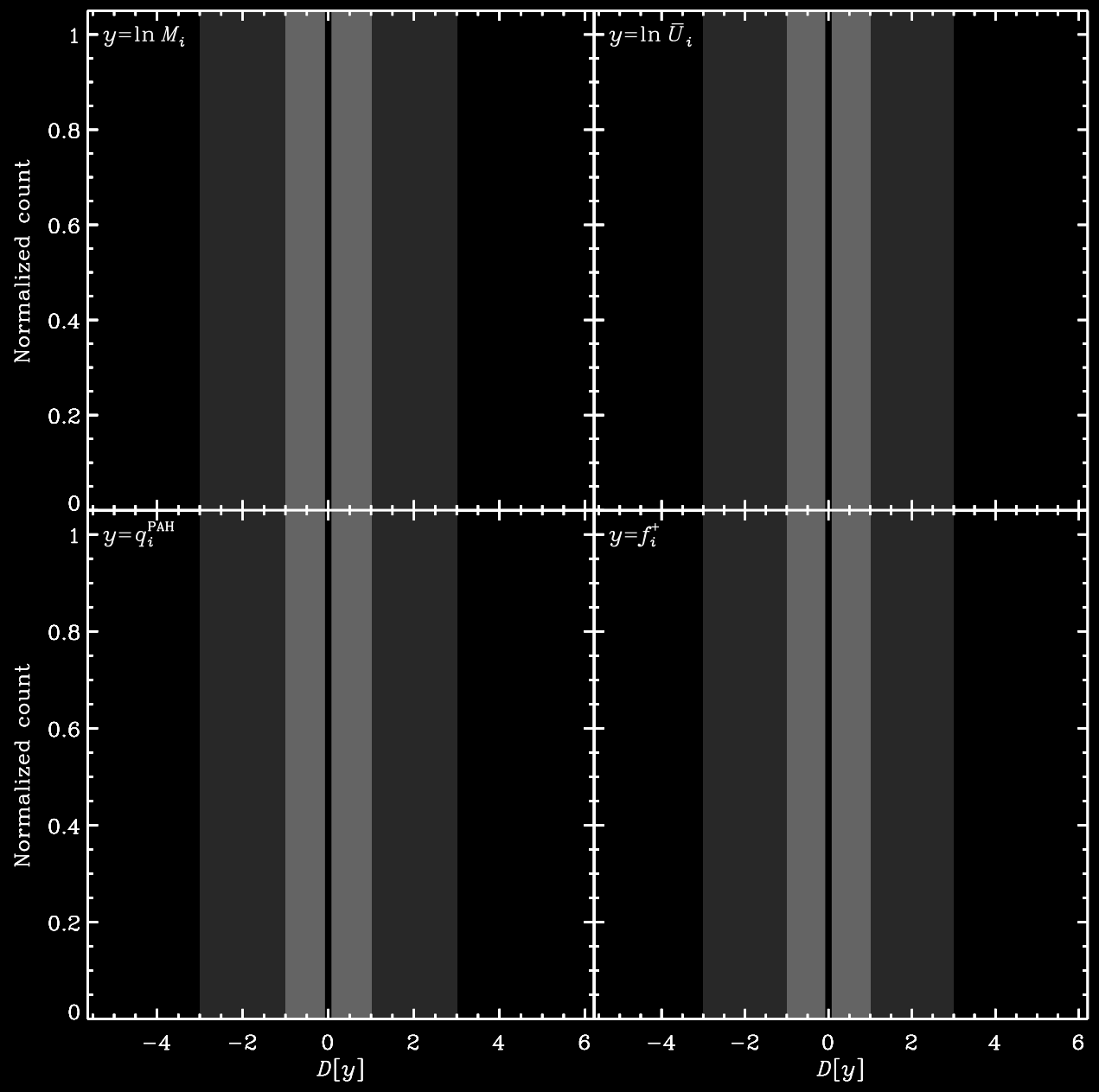

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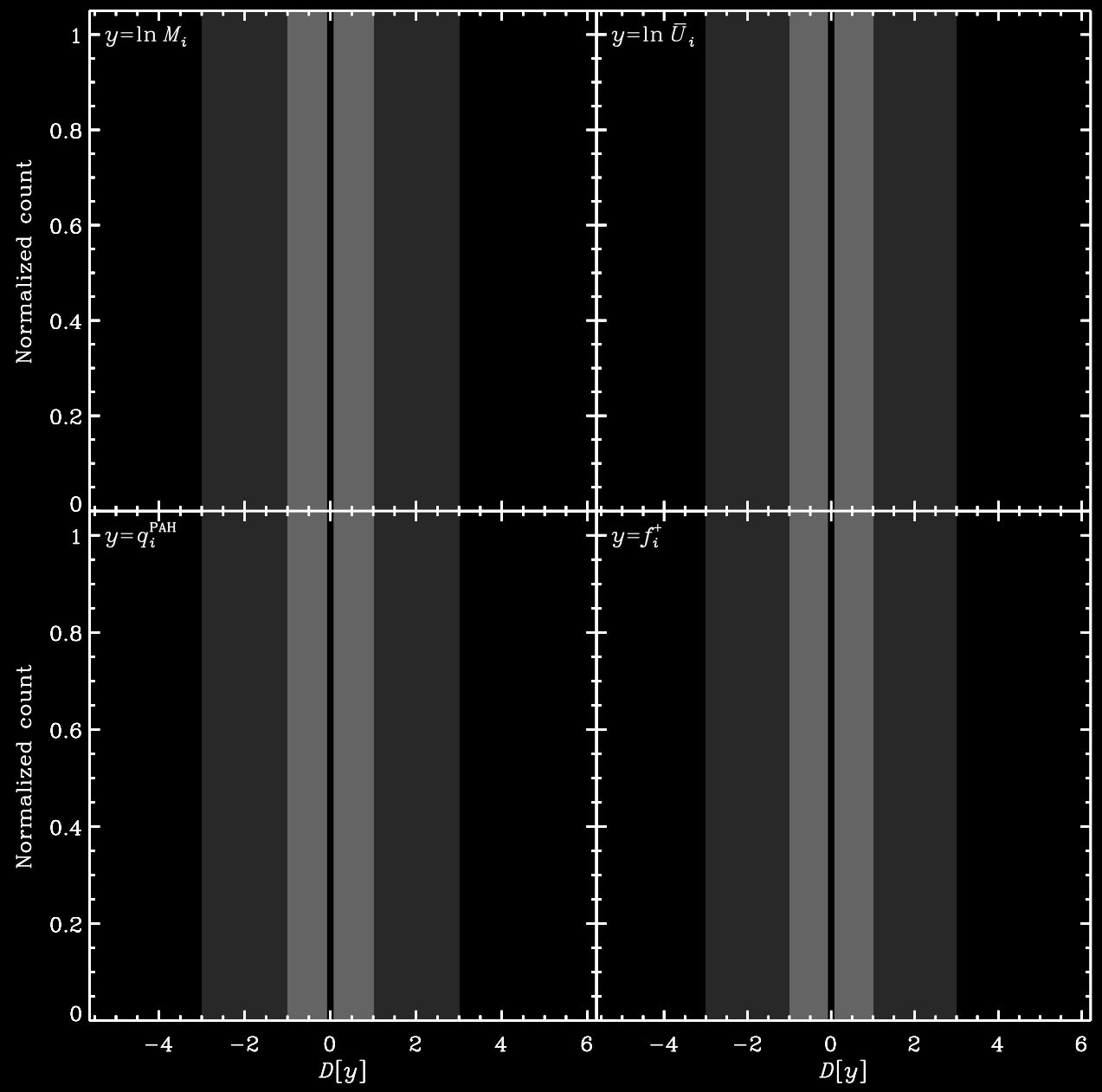

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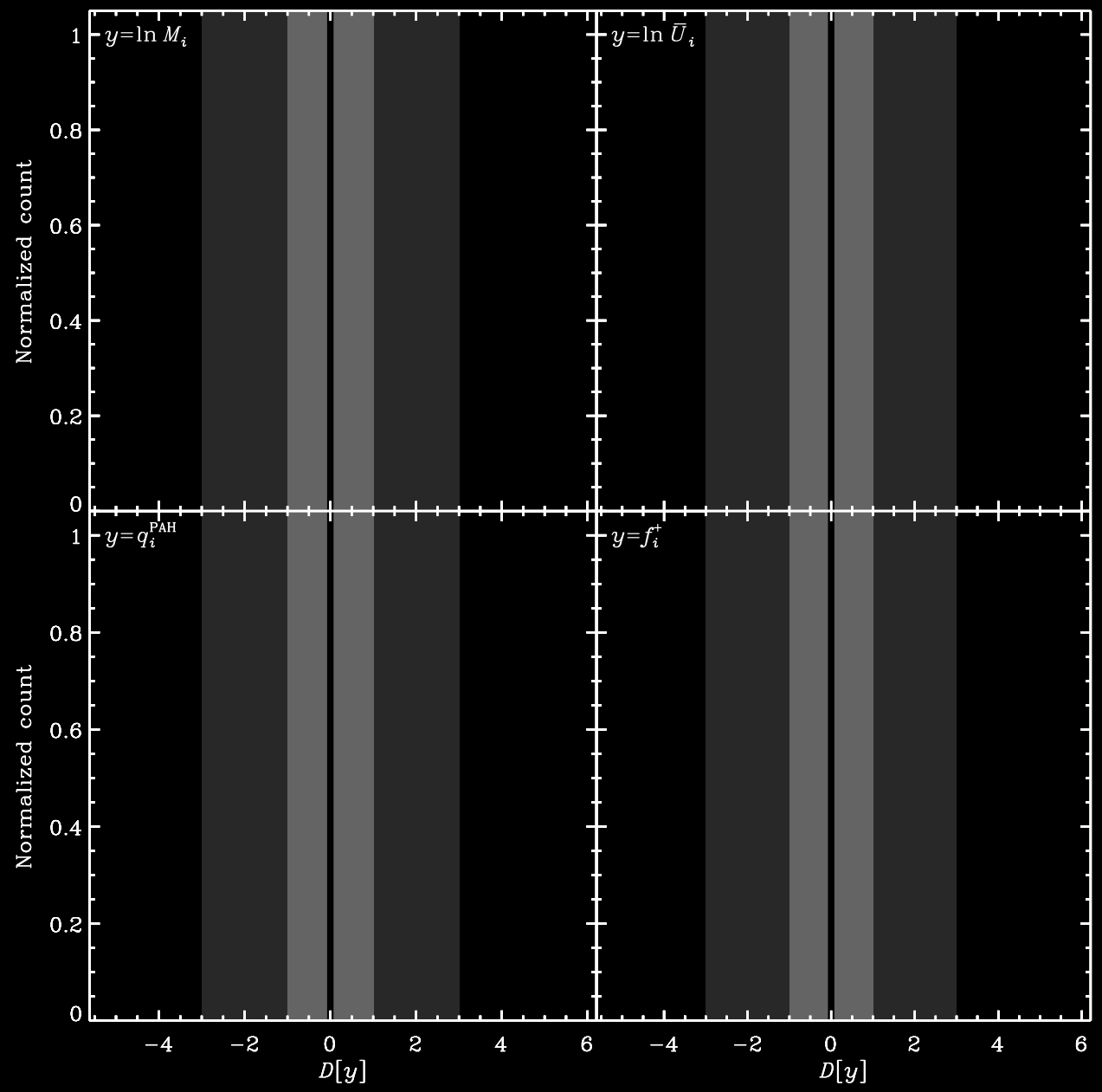

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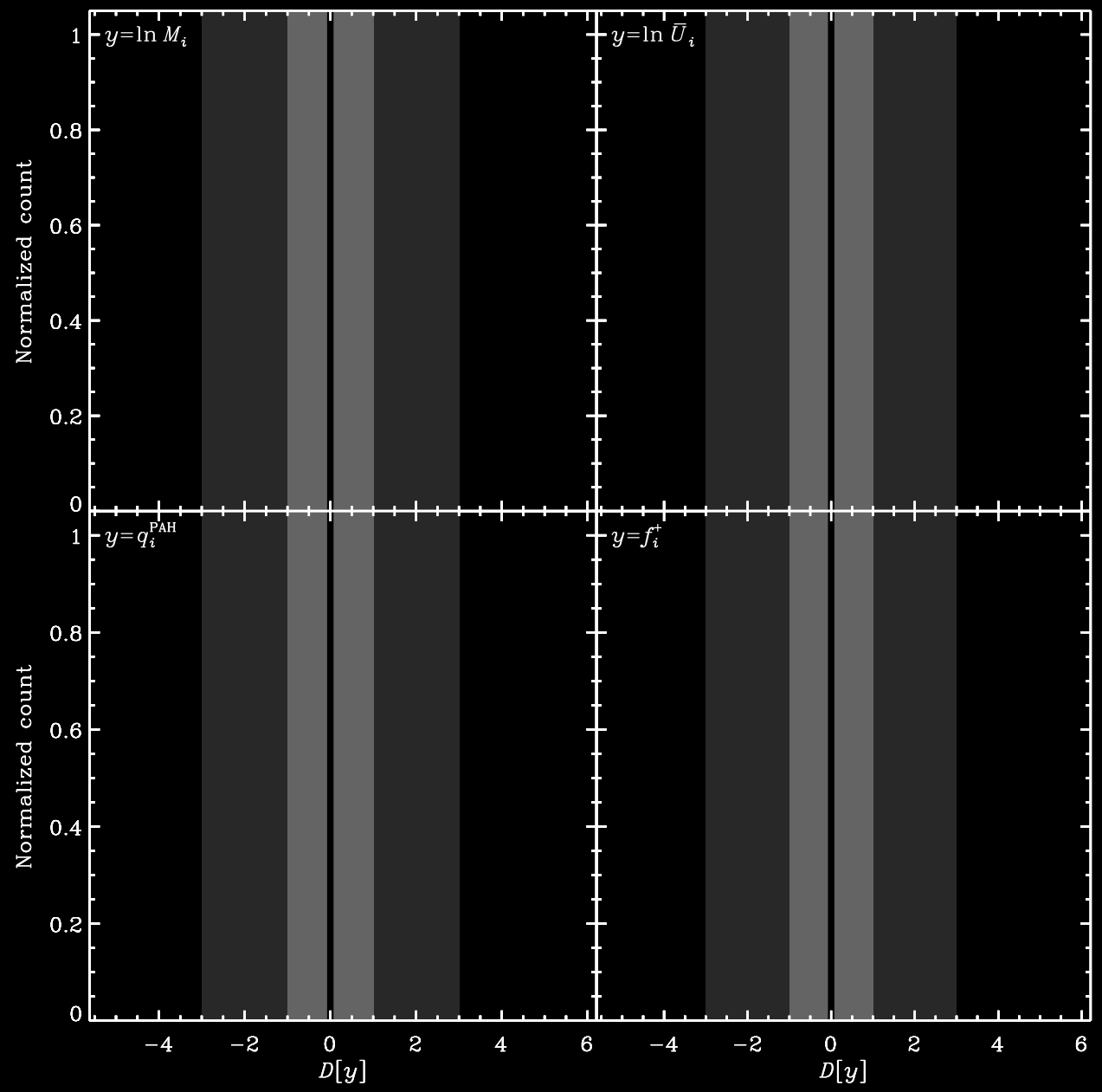

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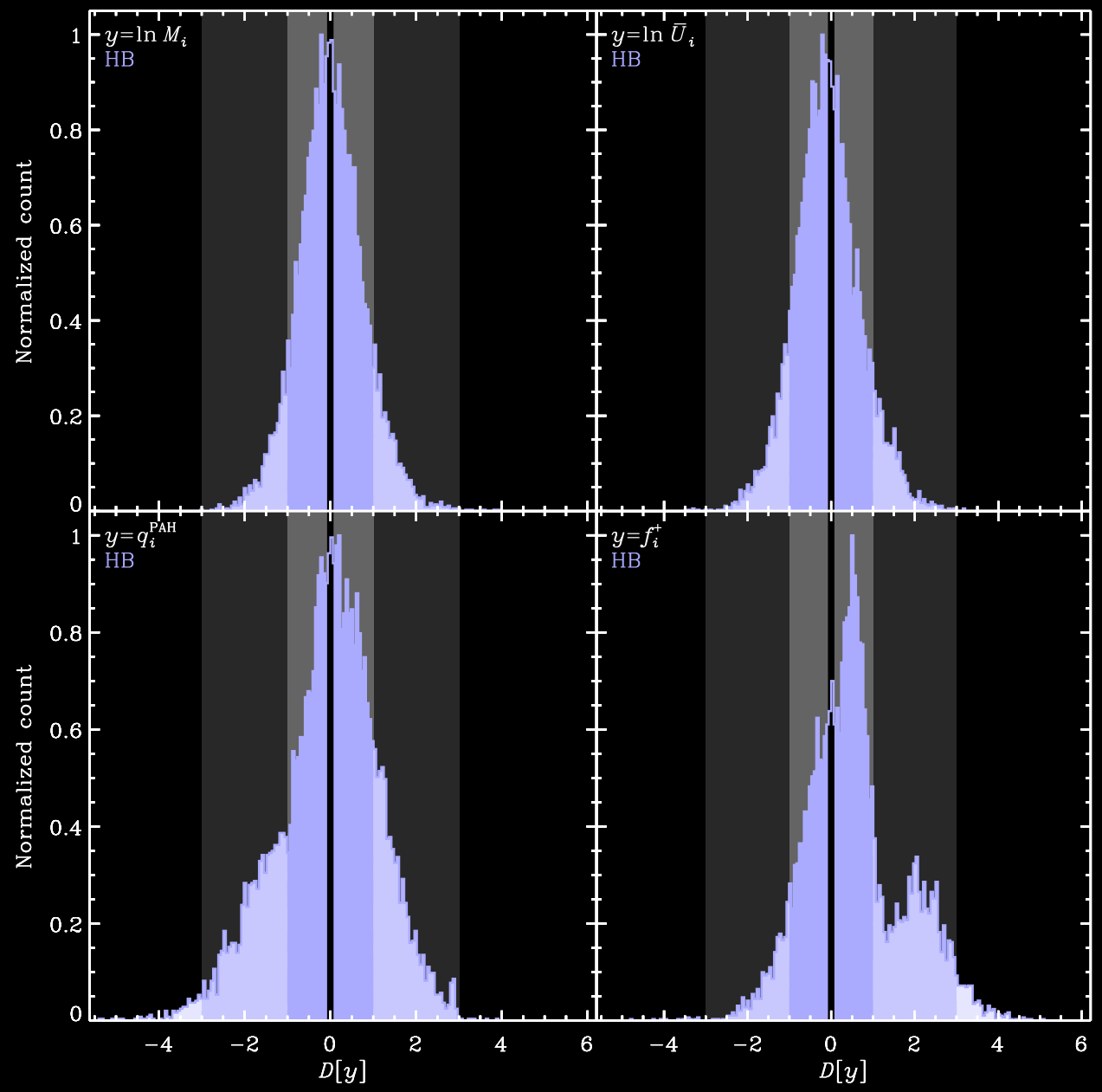

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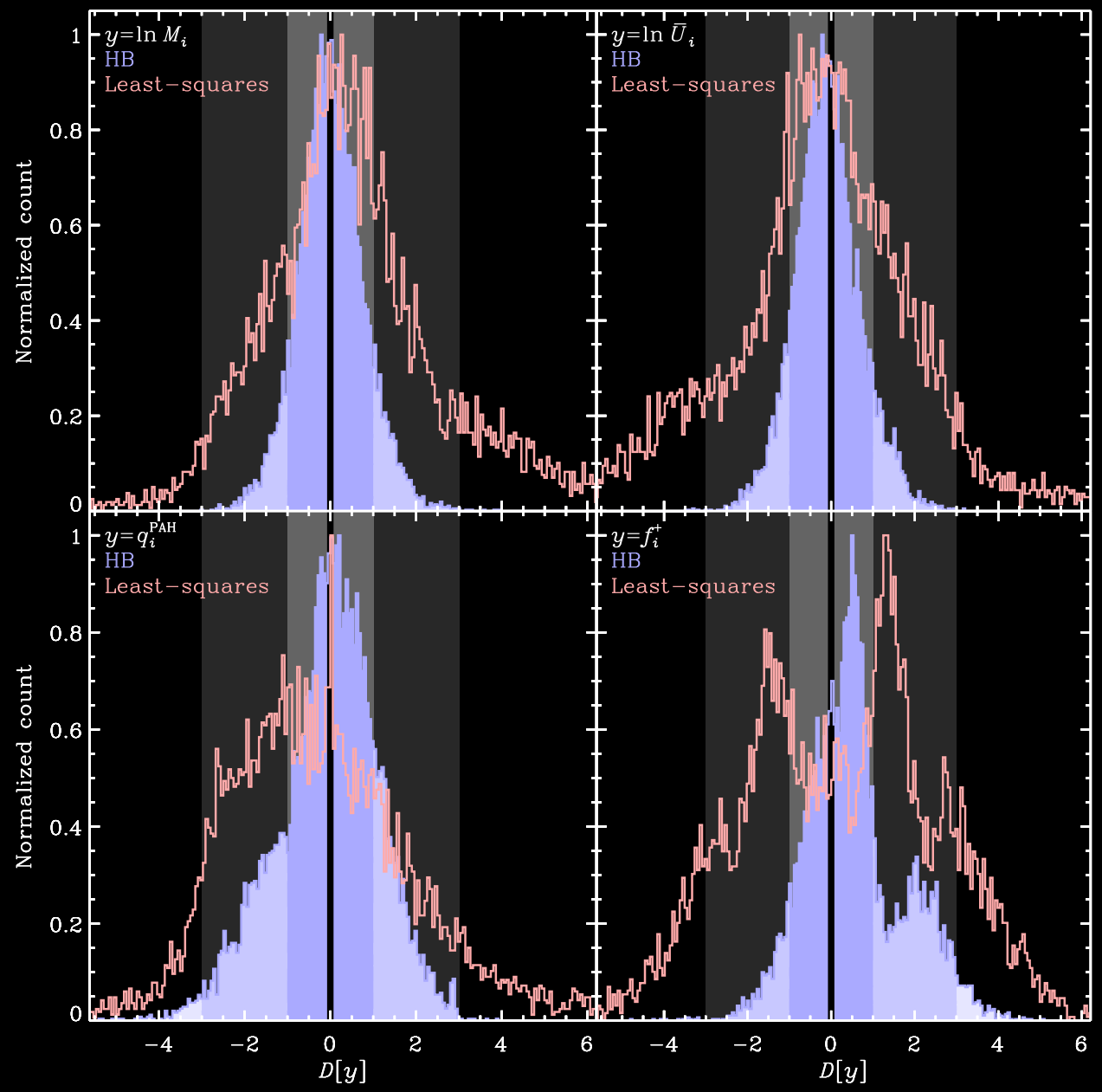

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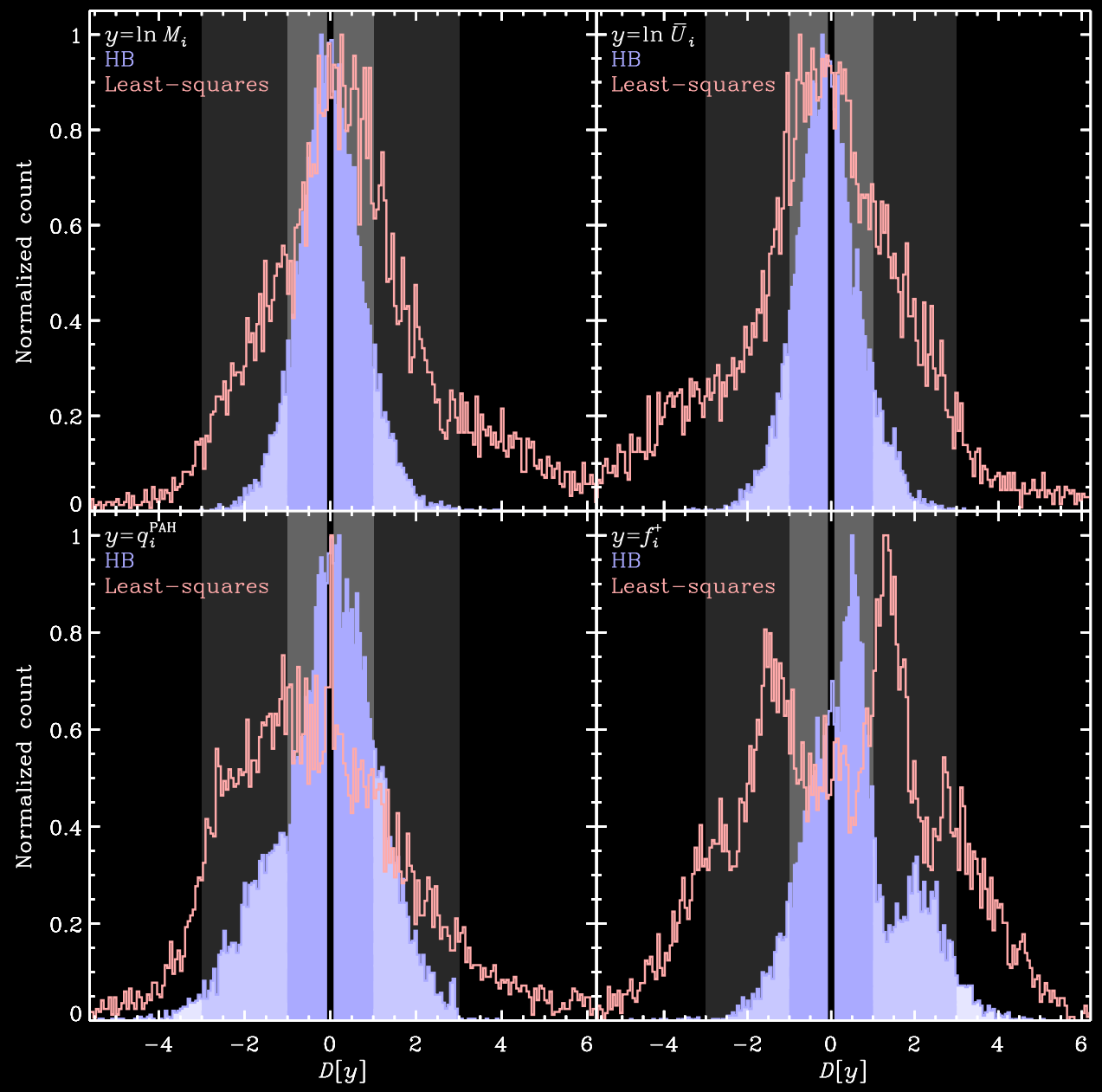

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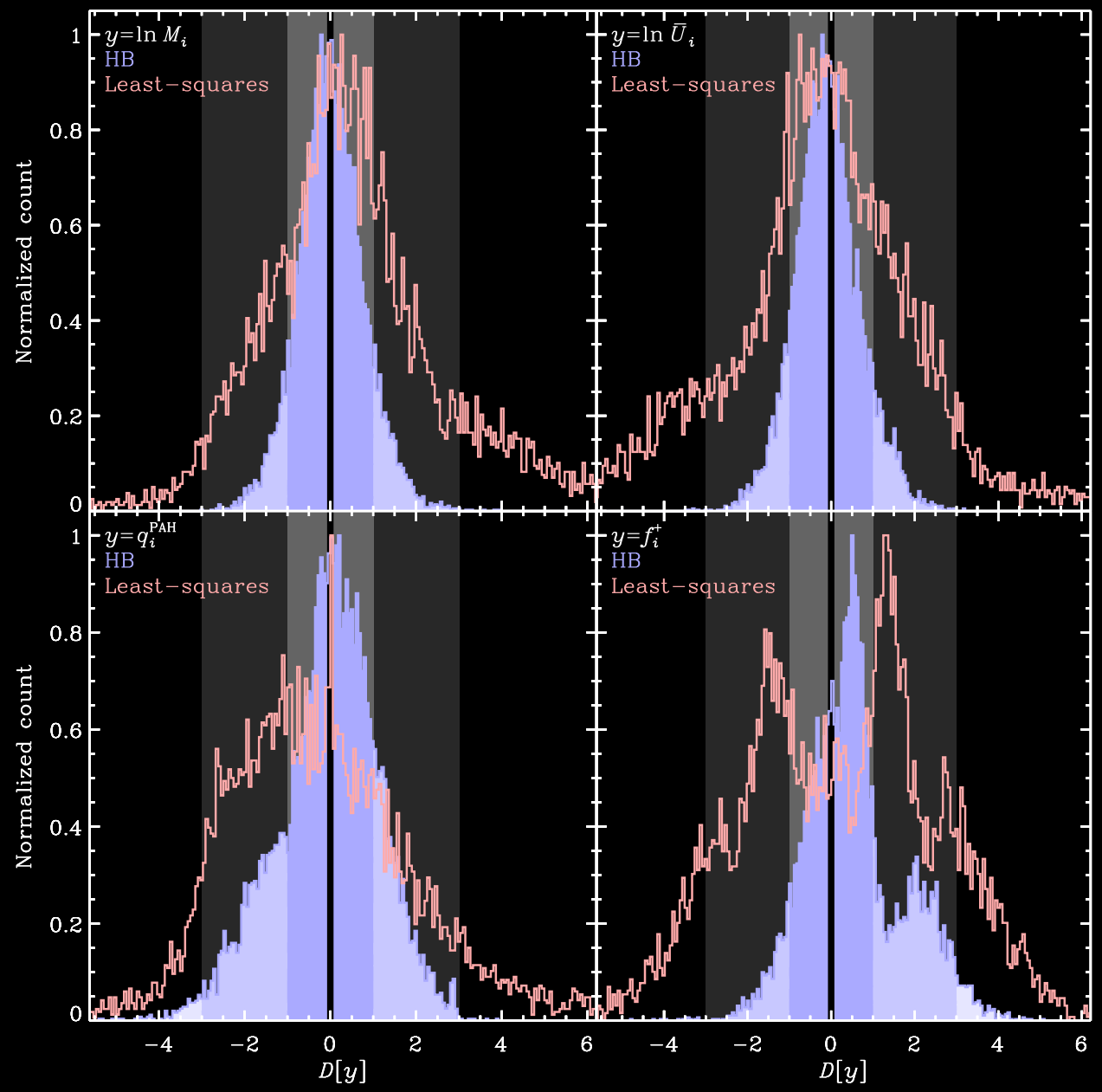

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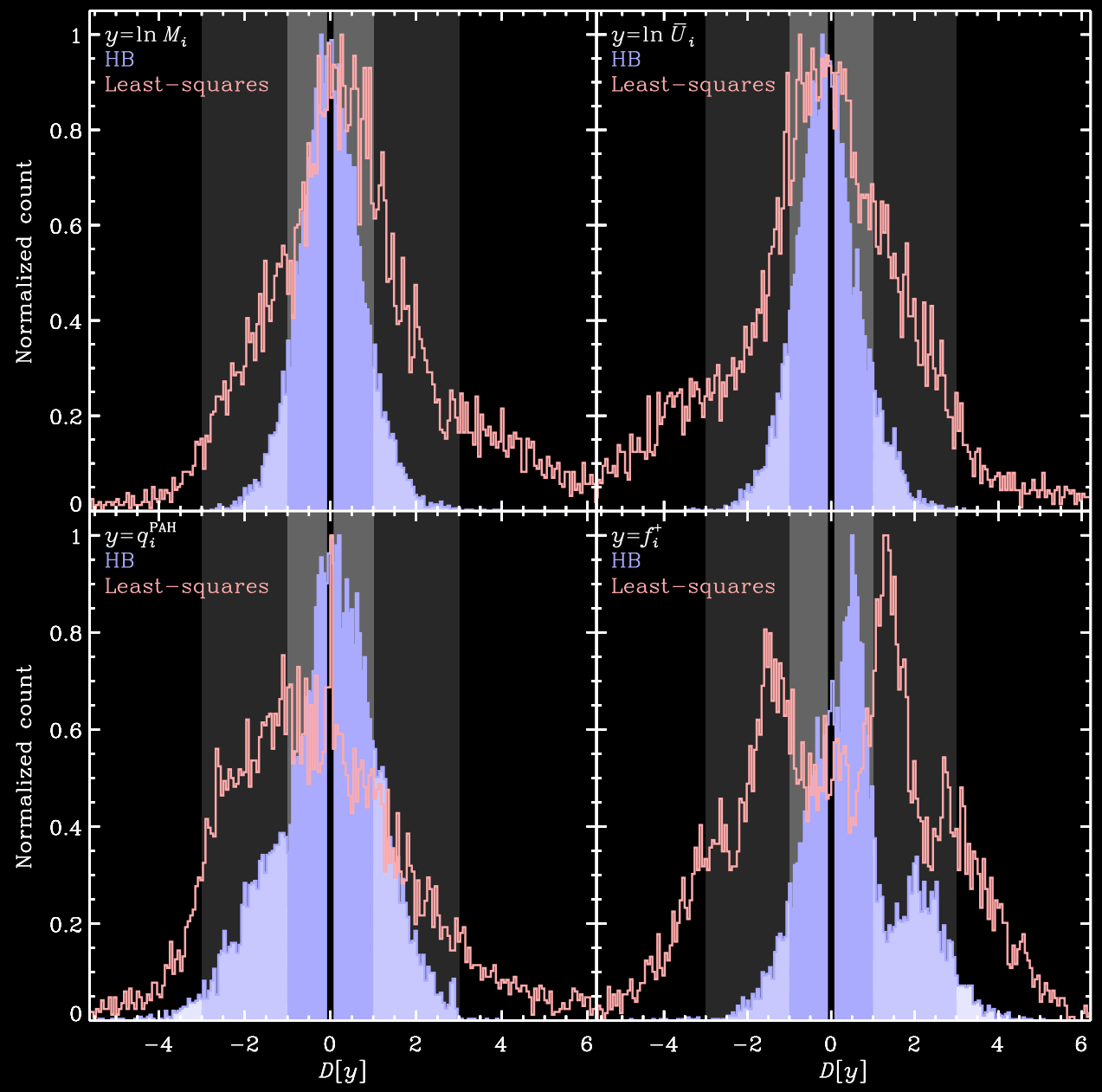

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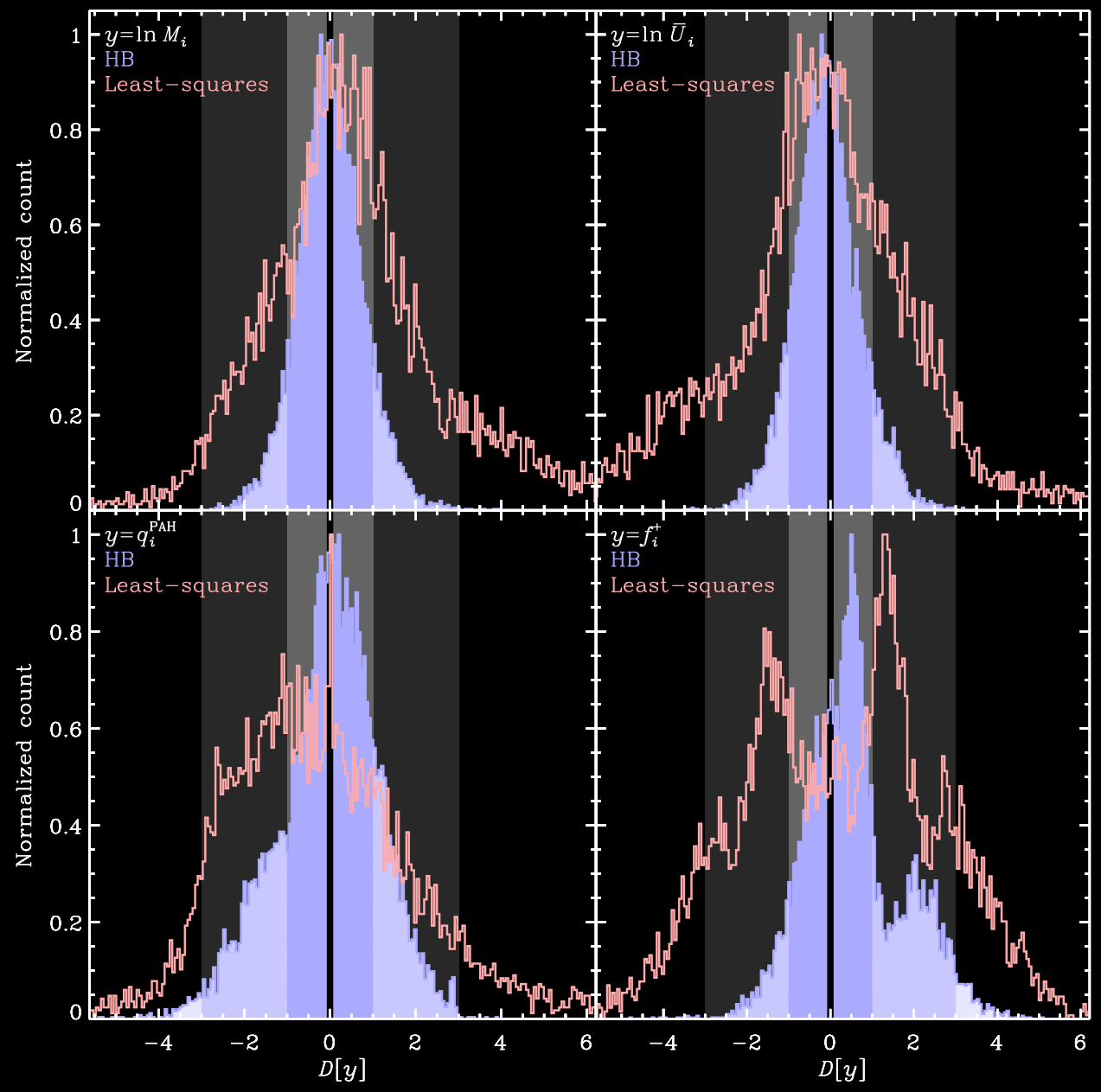

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4. Systematically better than χ^2.

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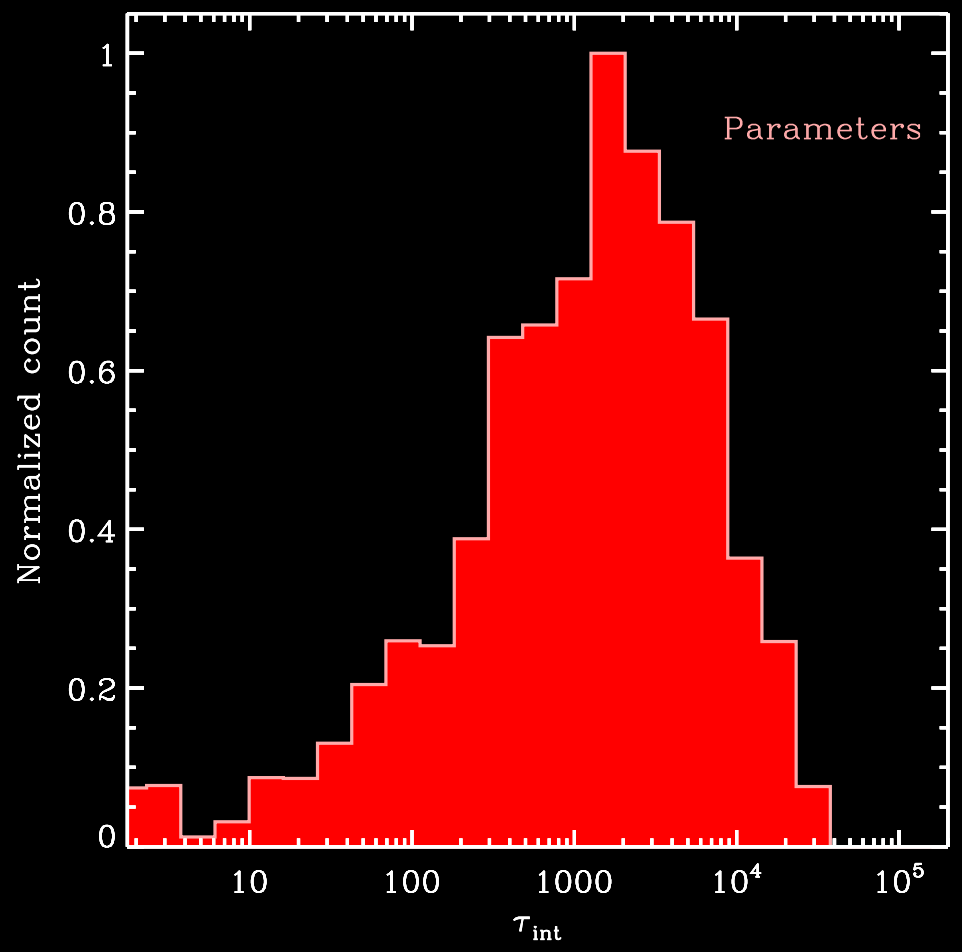

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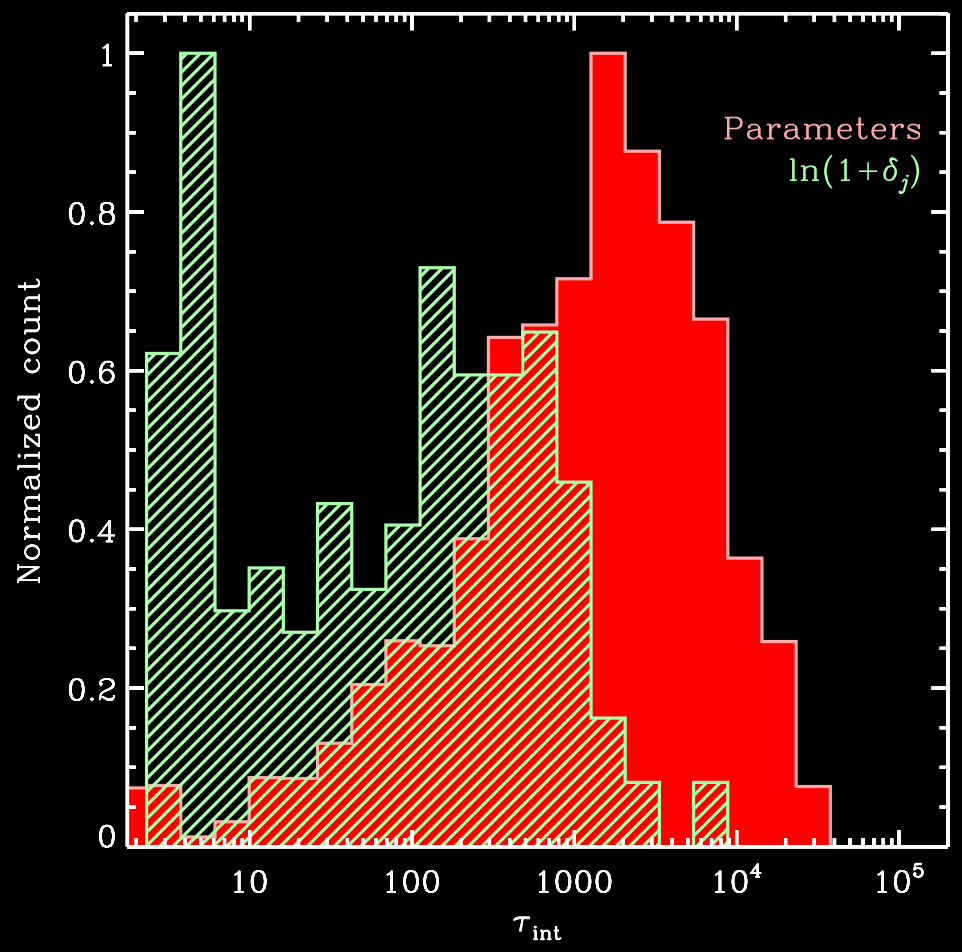

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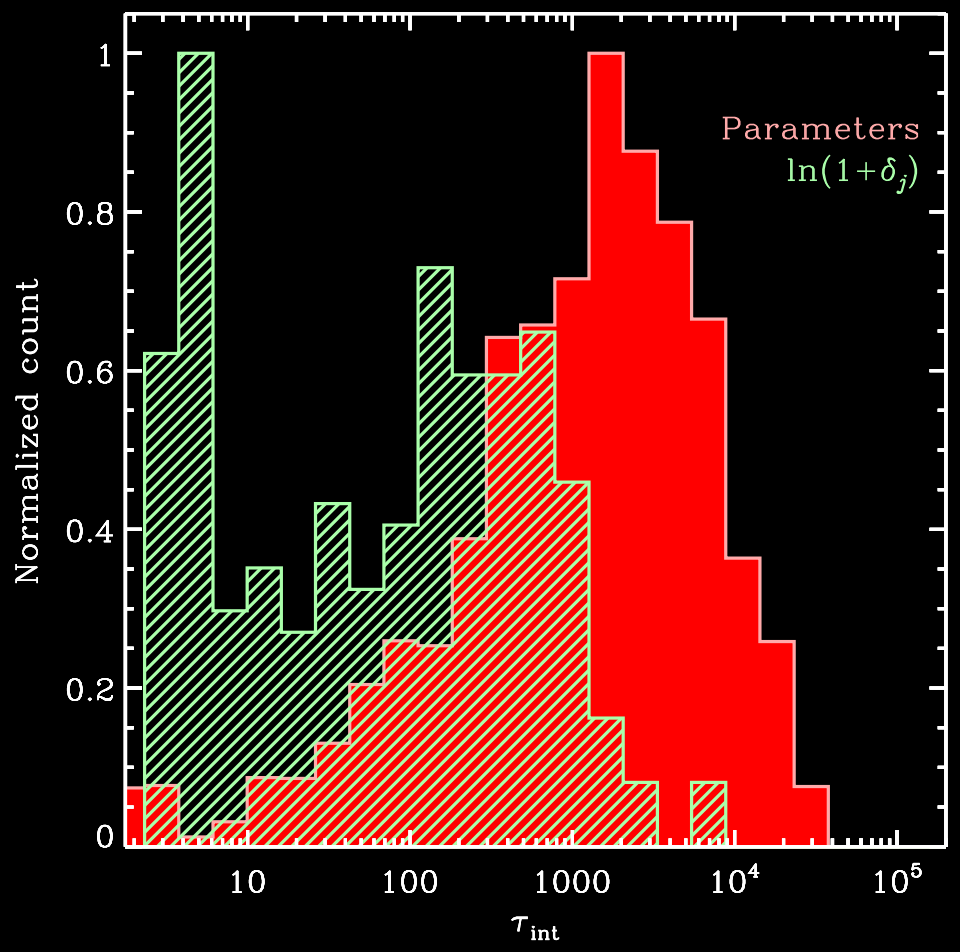

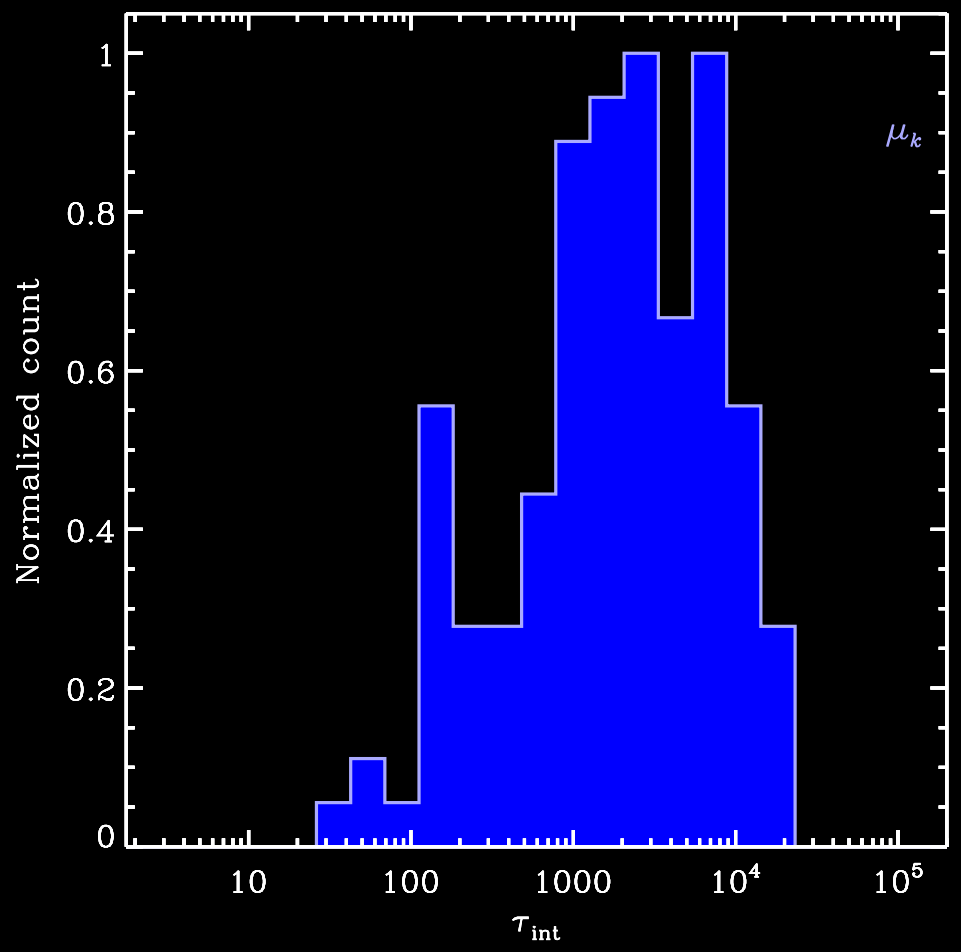

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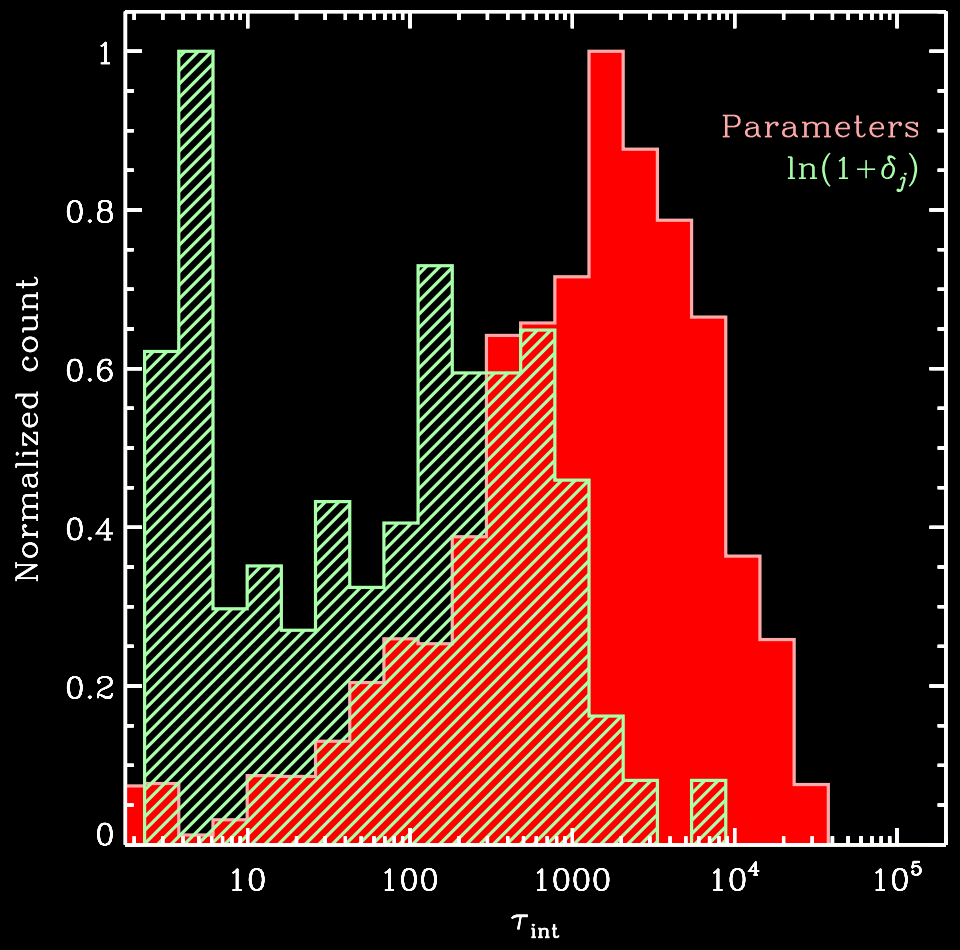

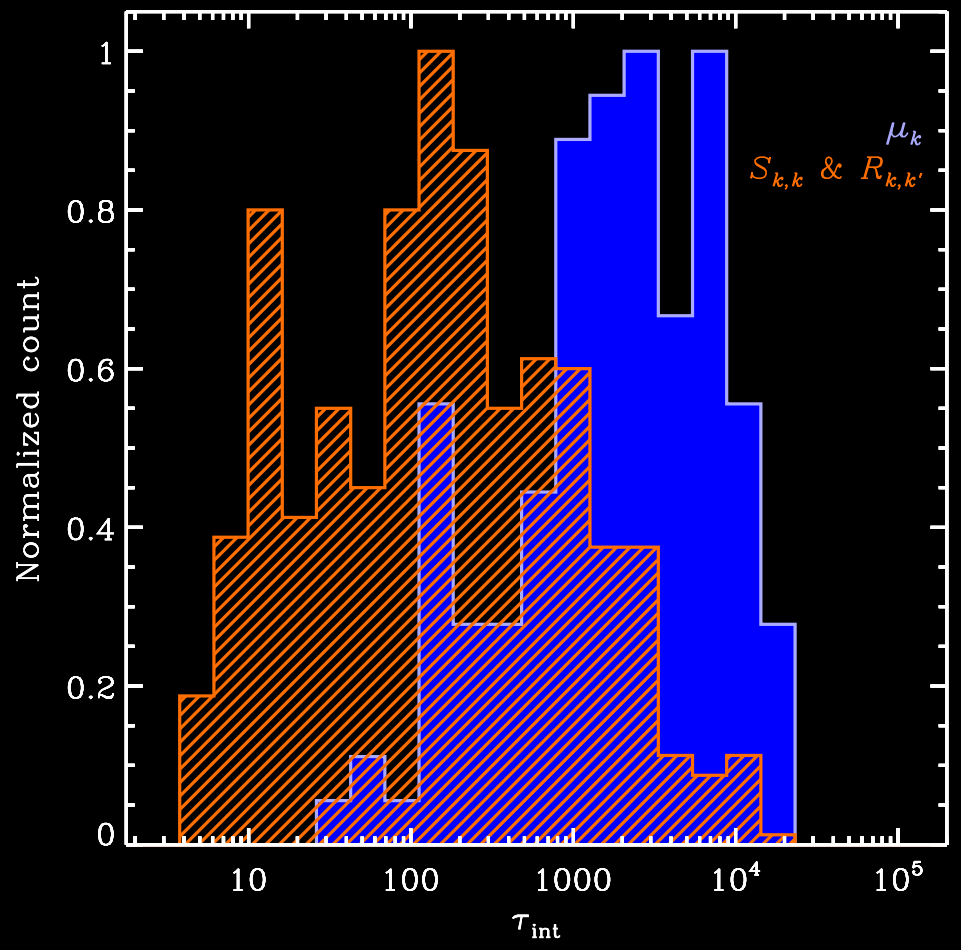

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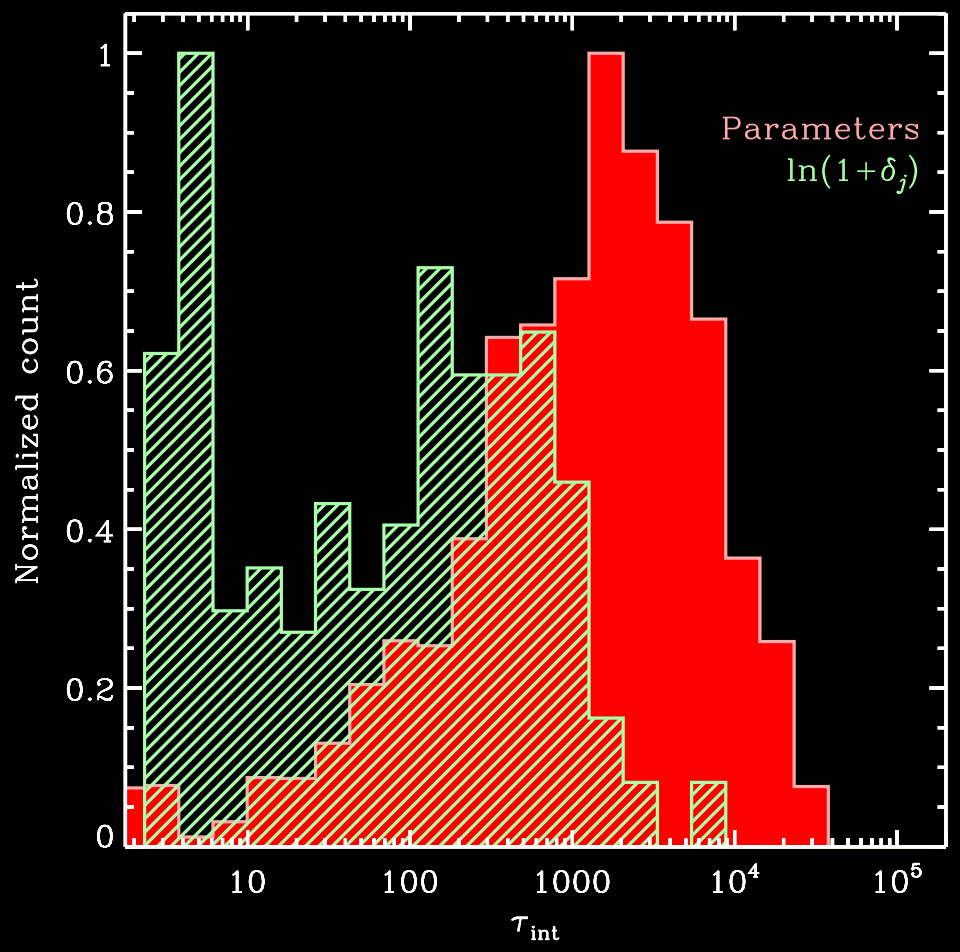

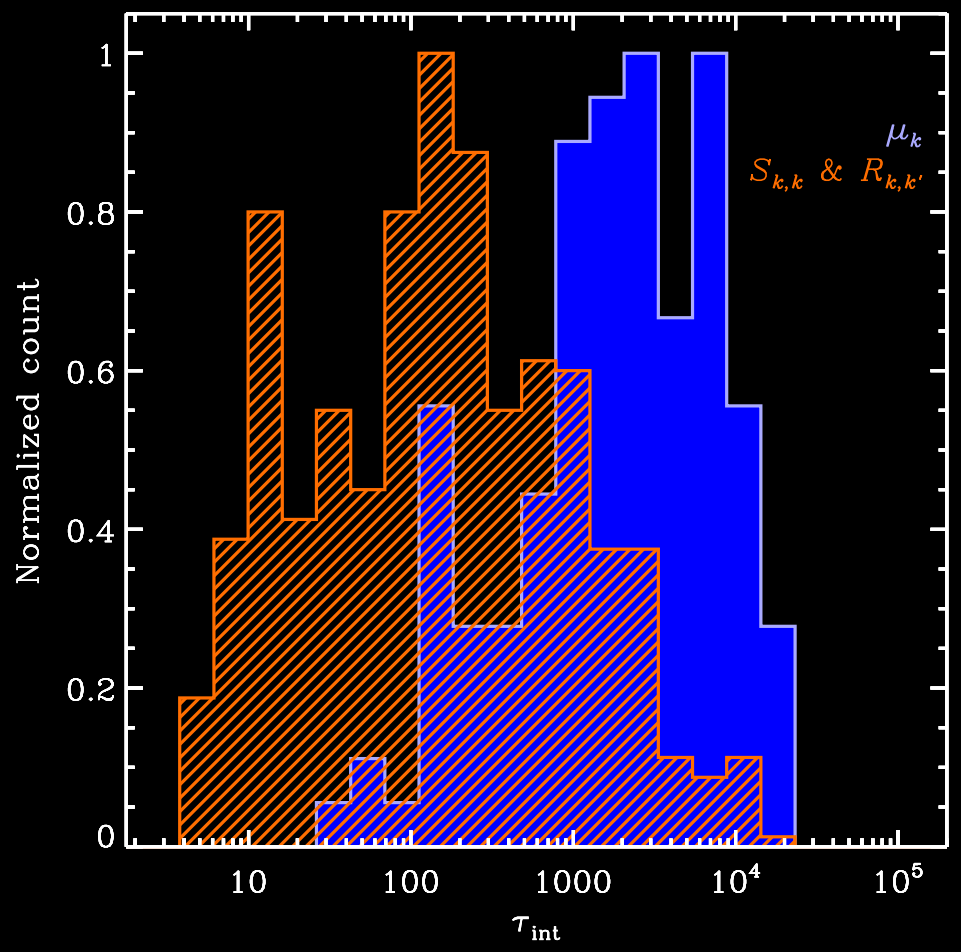

$\Rightarrow$ most parameters have $\tau_{\rm int} \lesssim 10^4 \Rightarrow N_{\rm MCMC} \lesssim 10^6$.

Presence of Intrinsic Correlations

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Efficiency to recover correlation coefficients:

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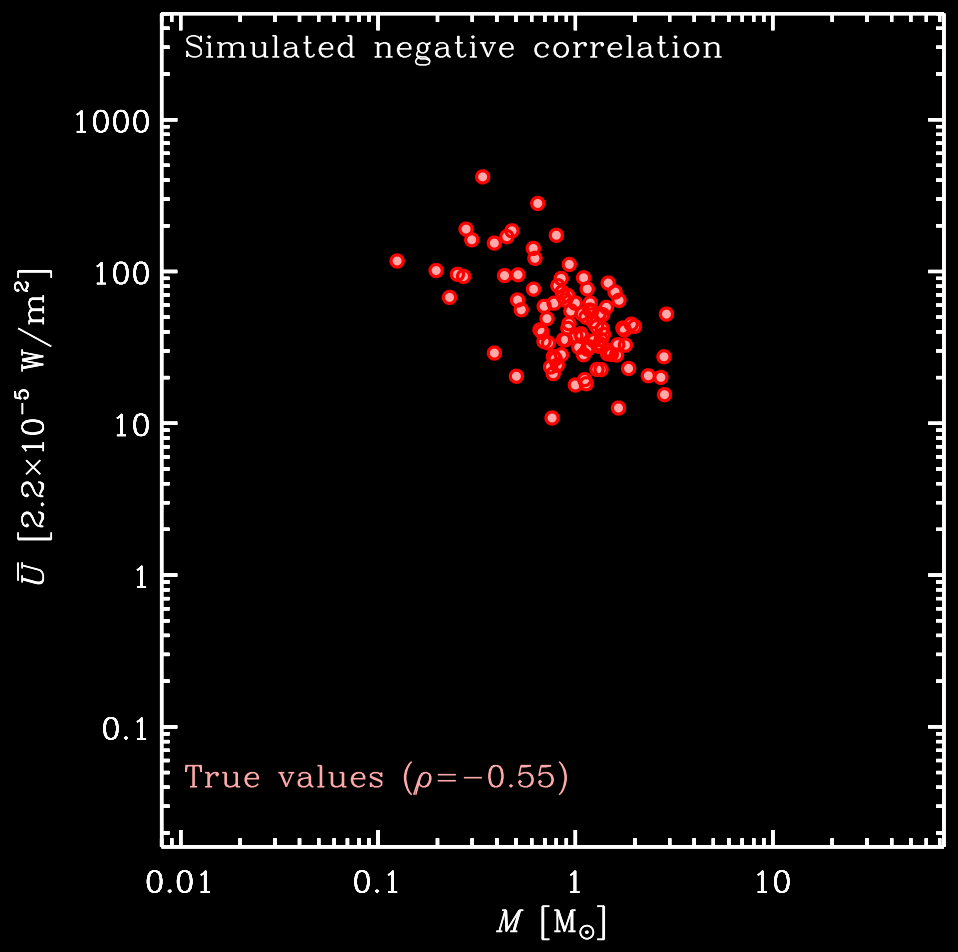

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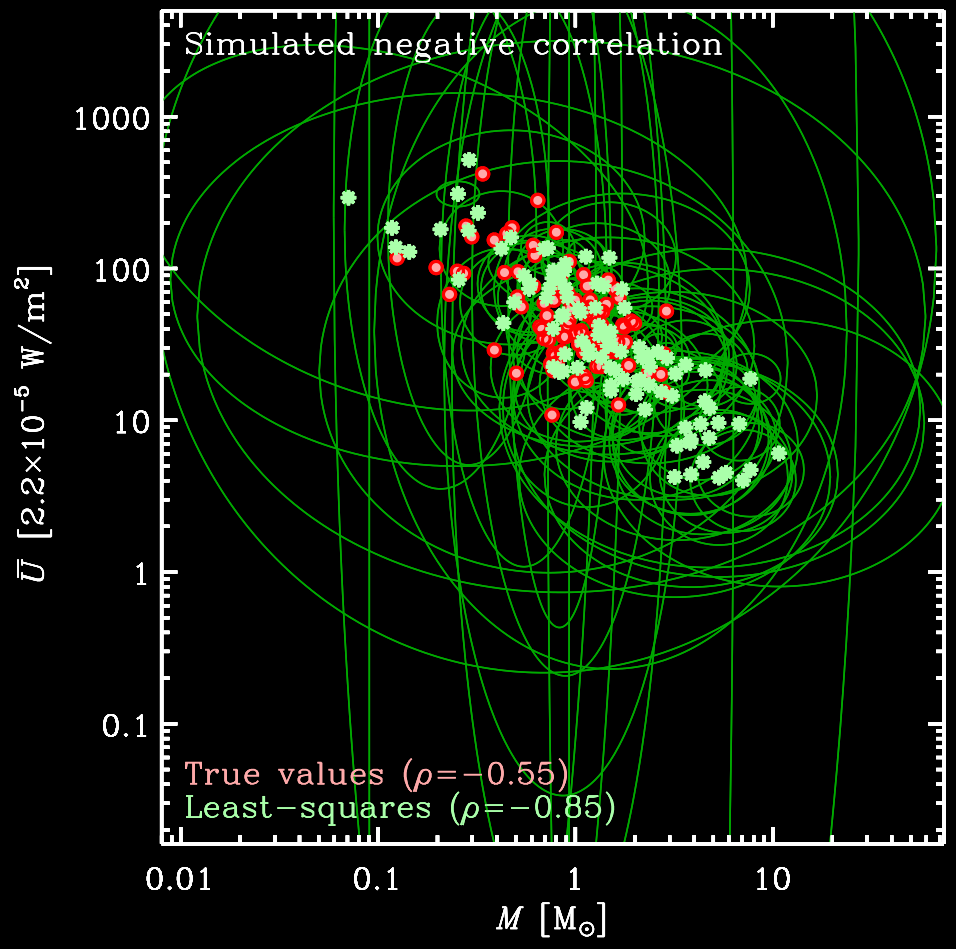

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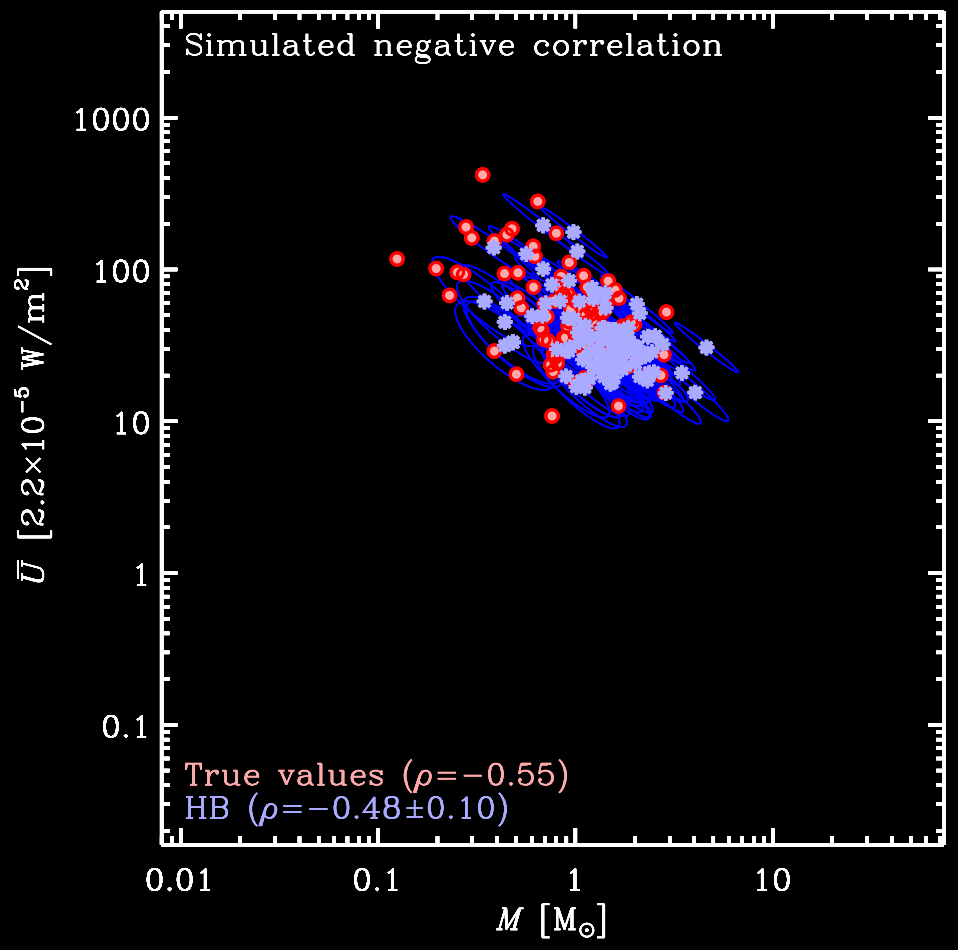

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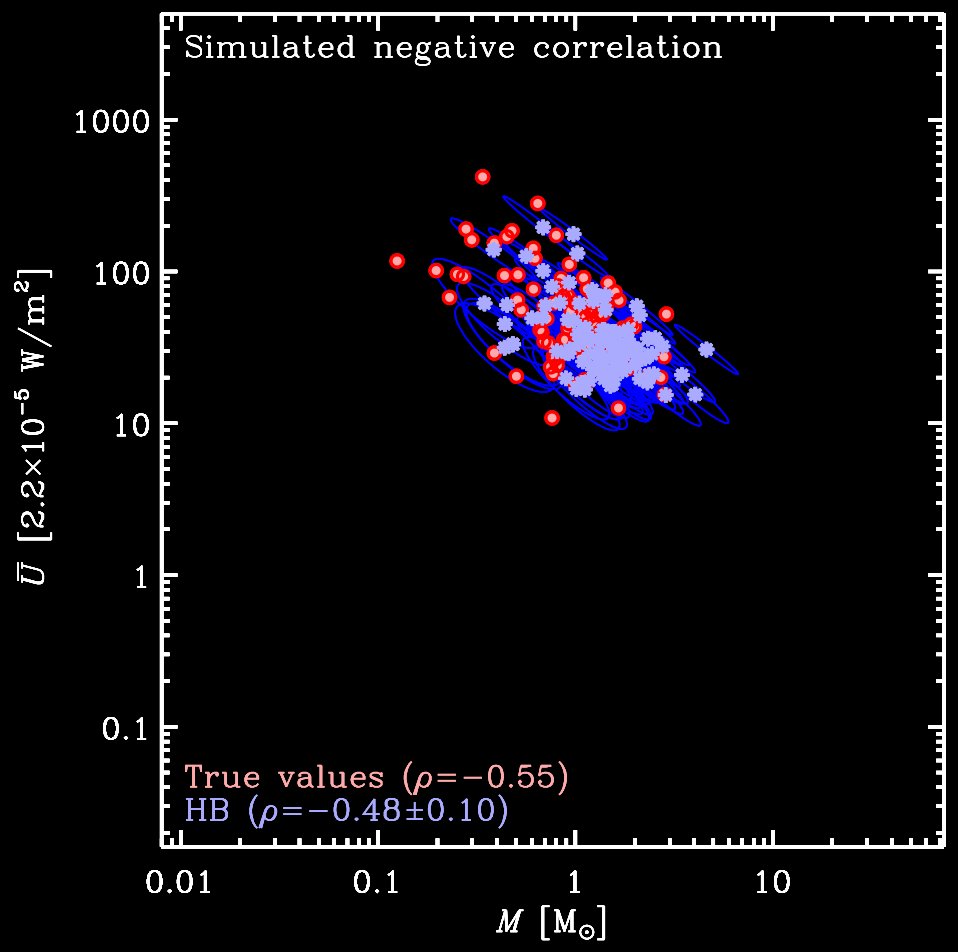

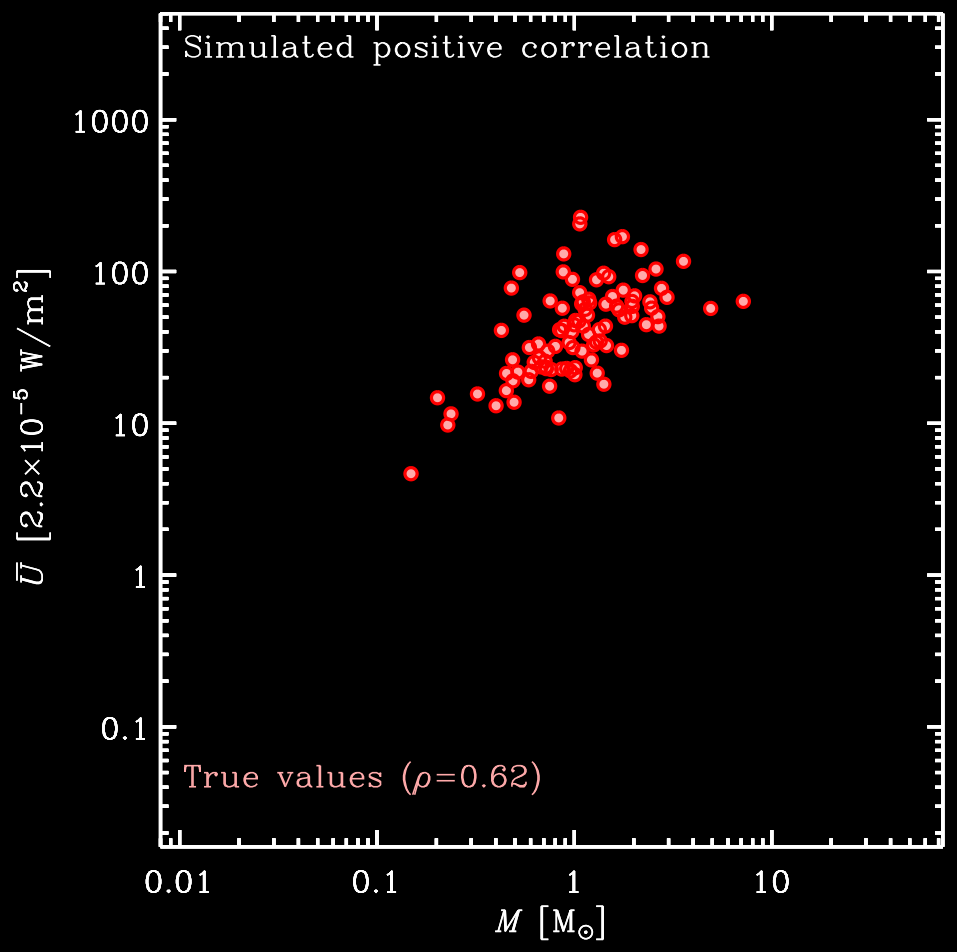

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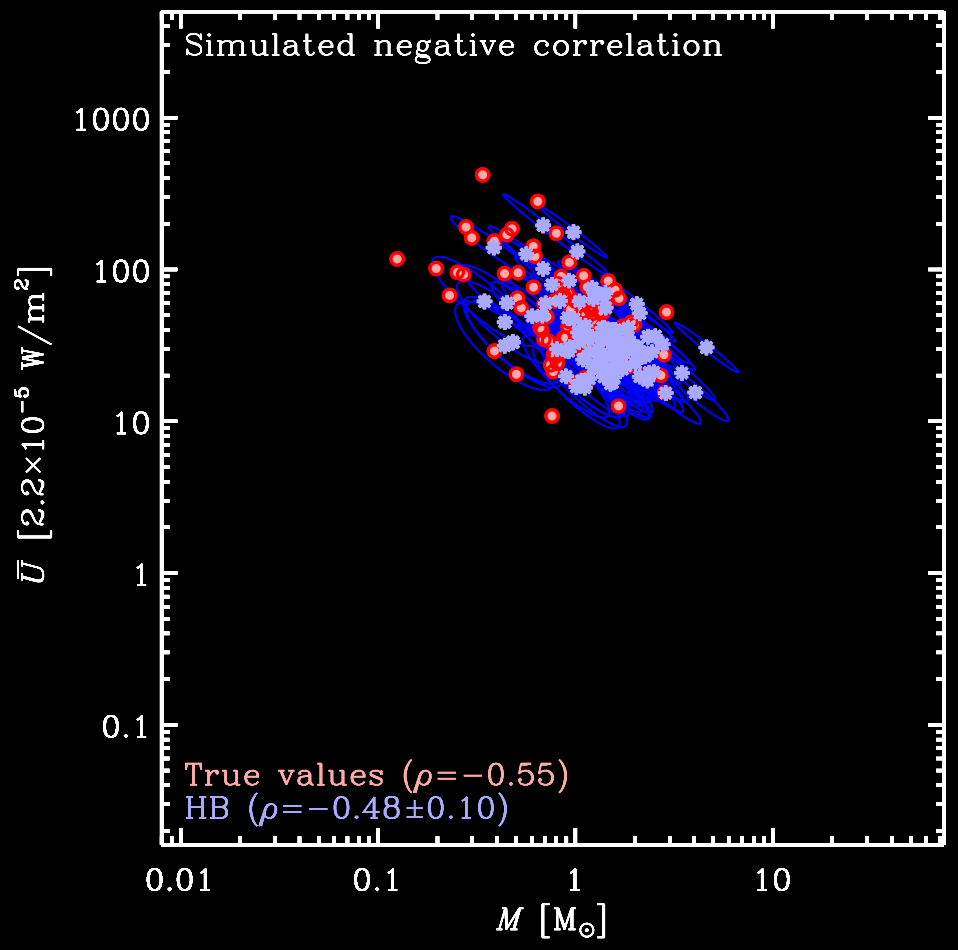

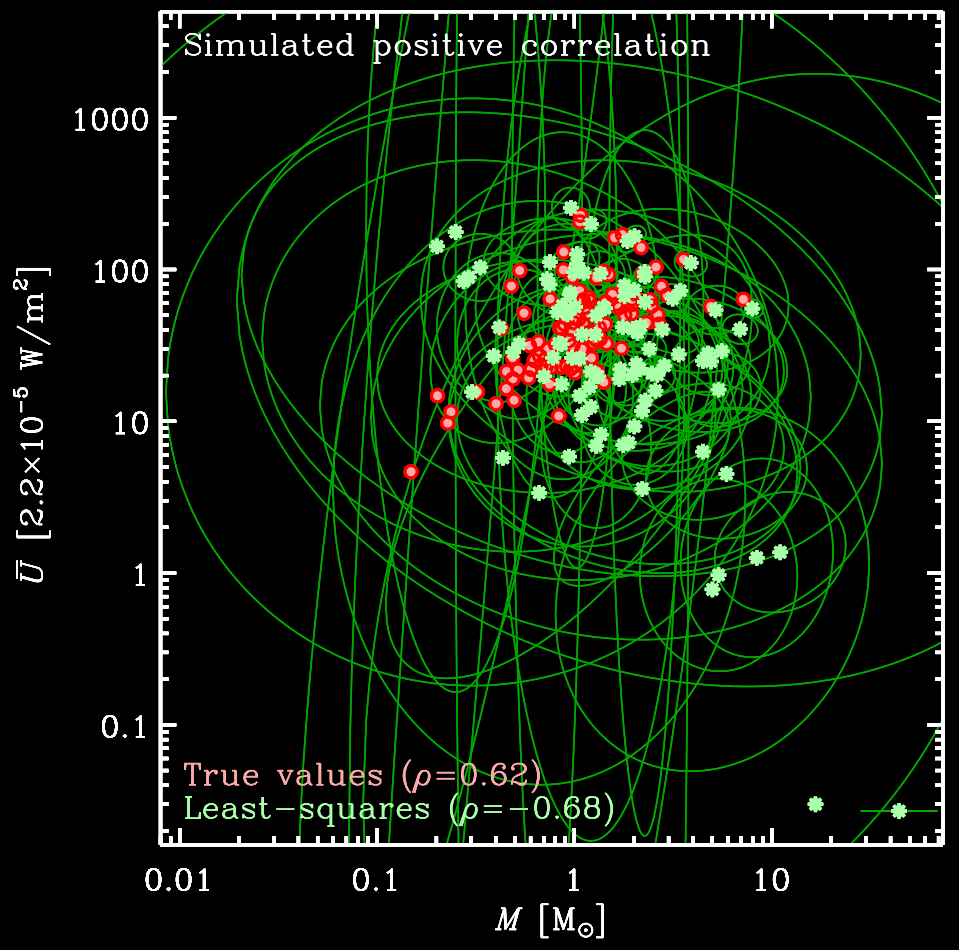

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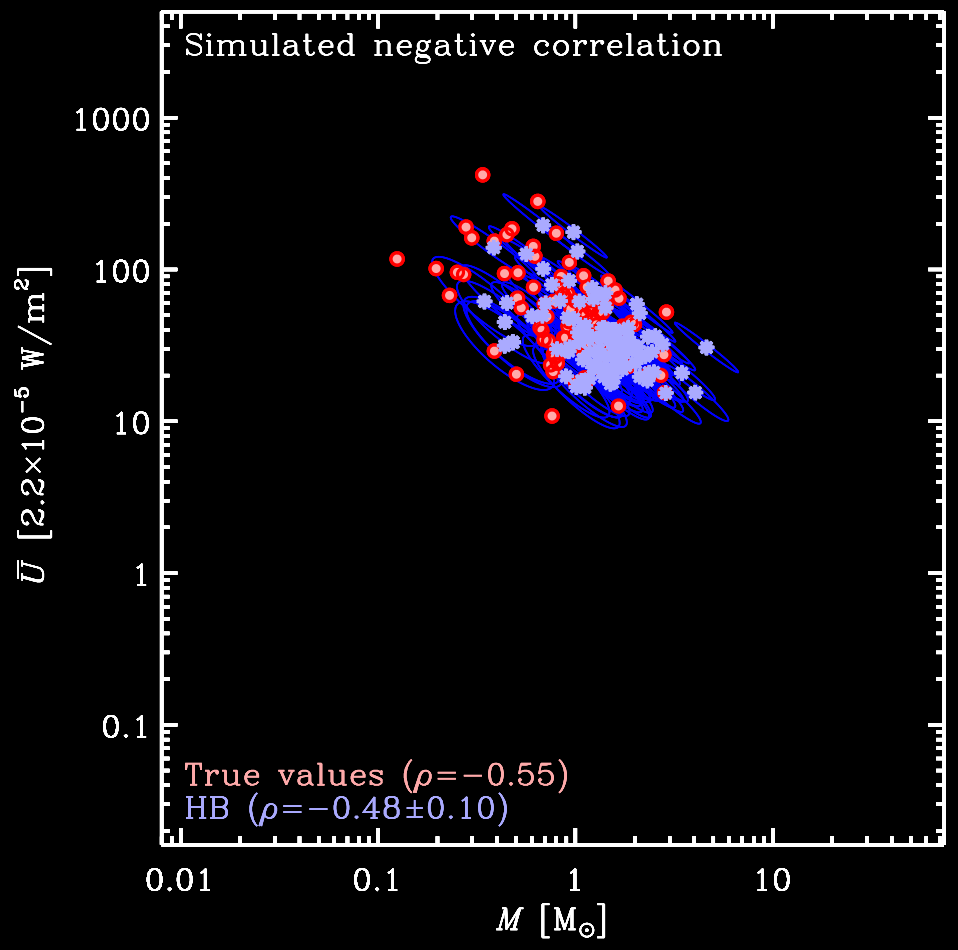

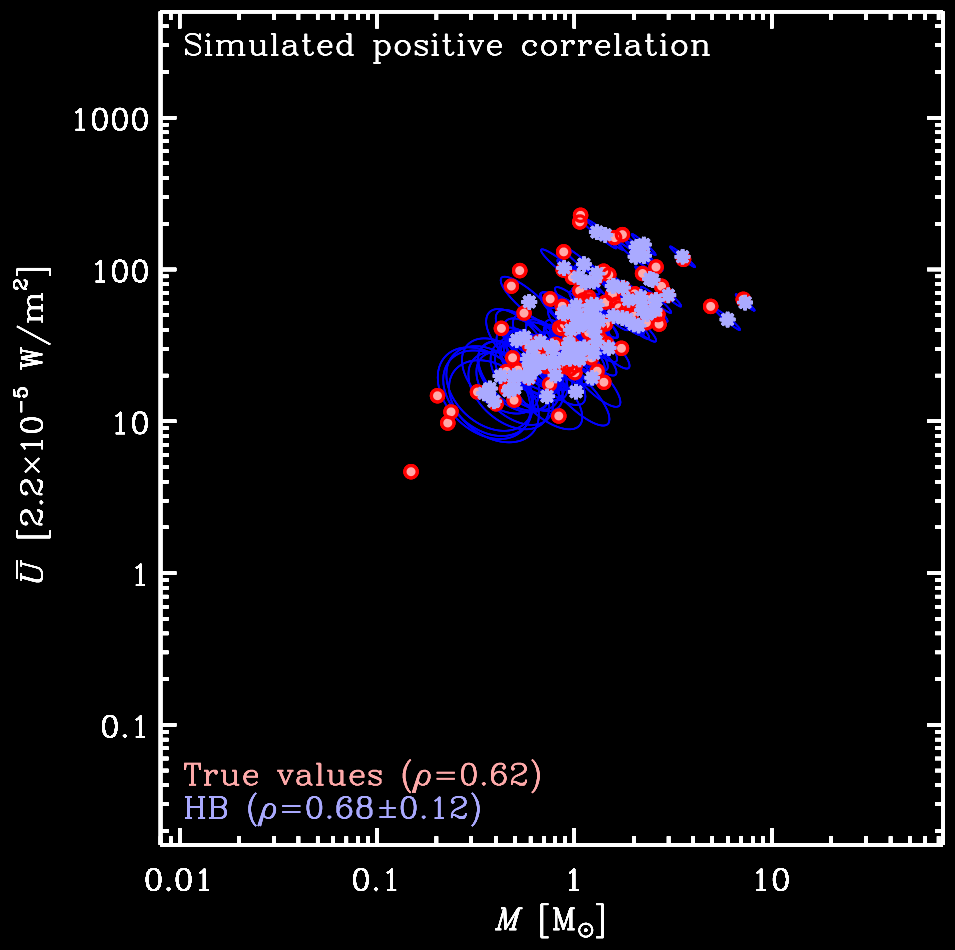

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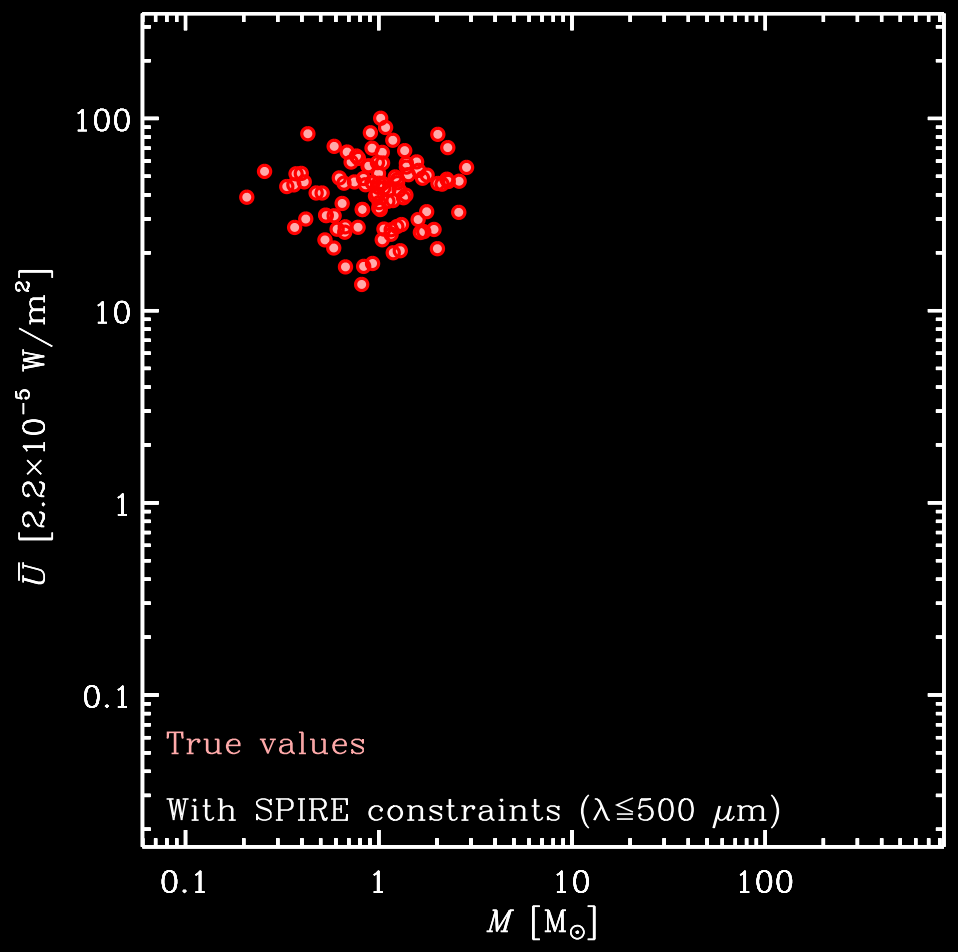

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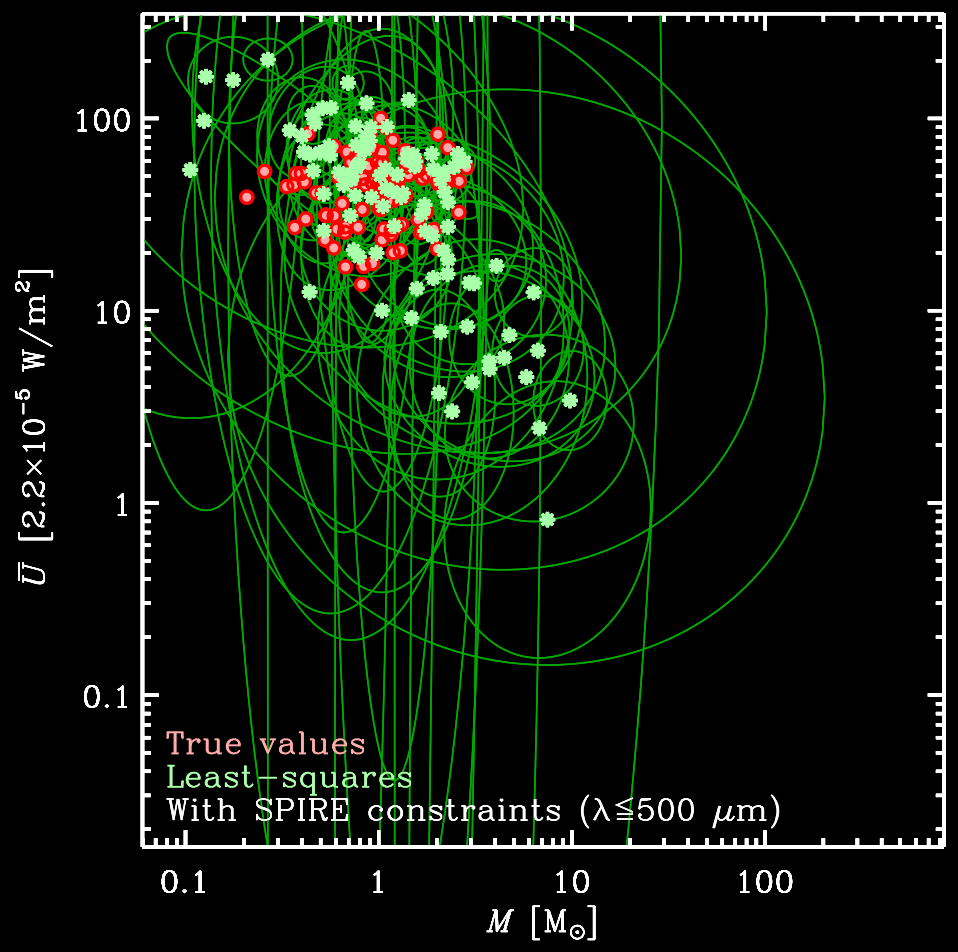

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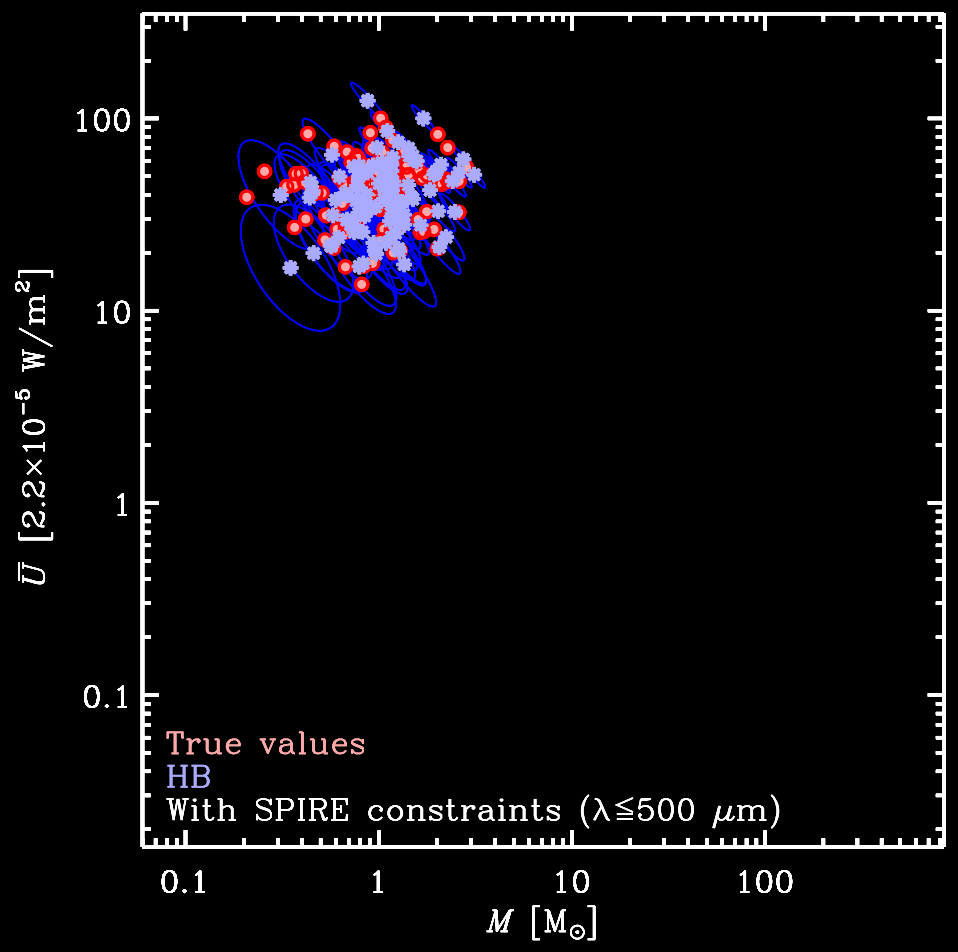

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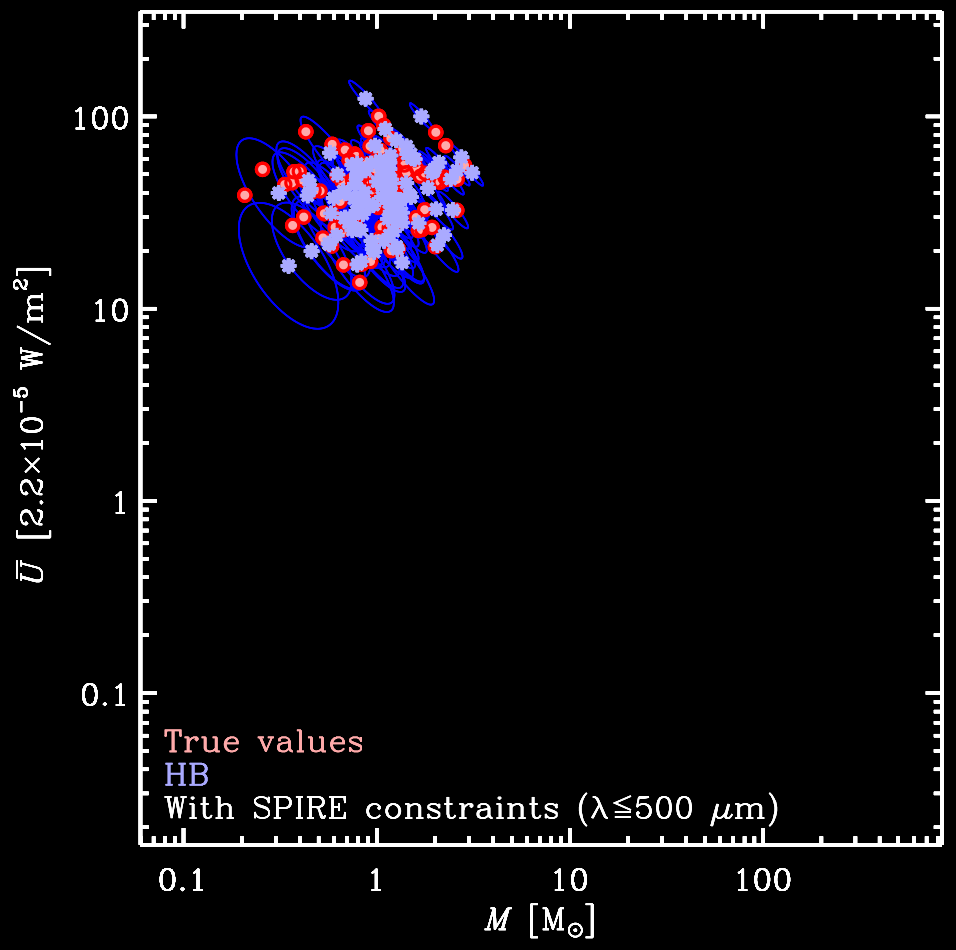

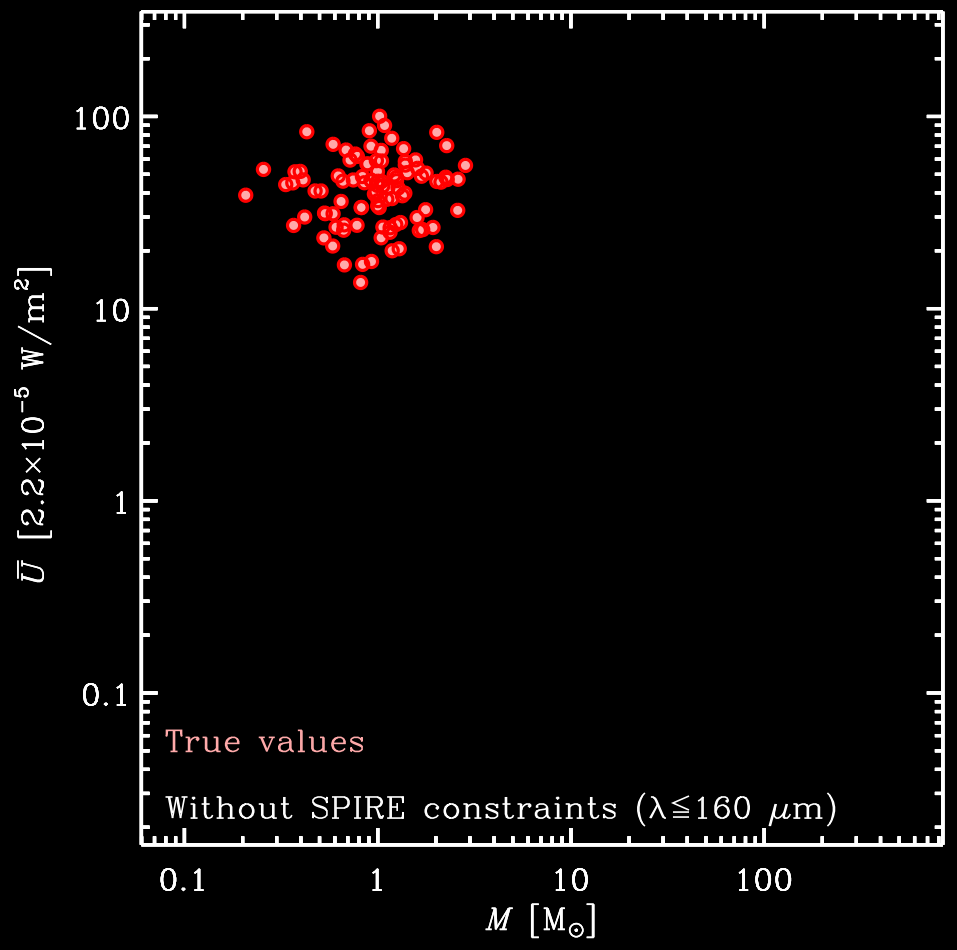

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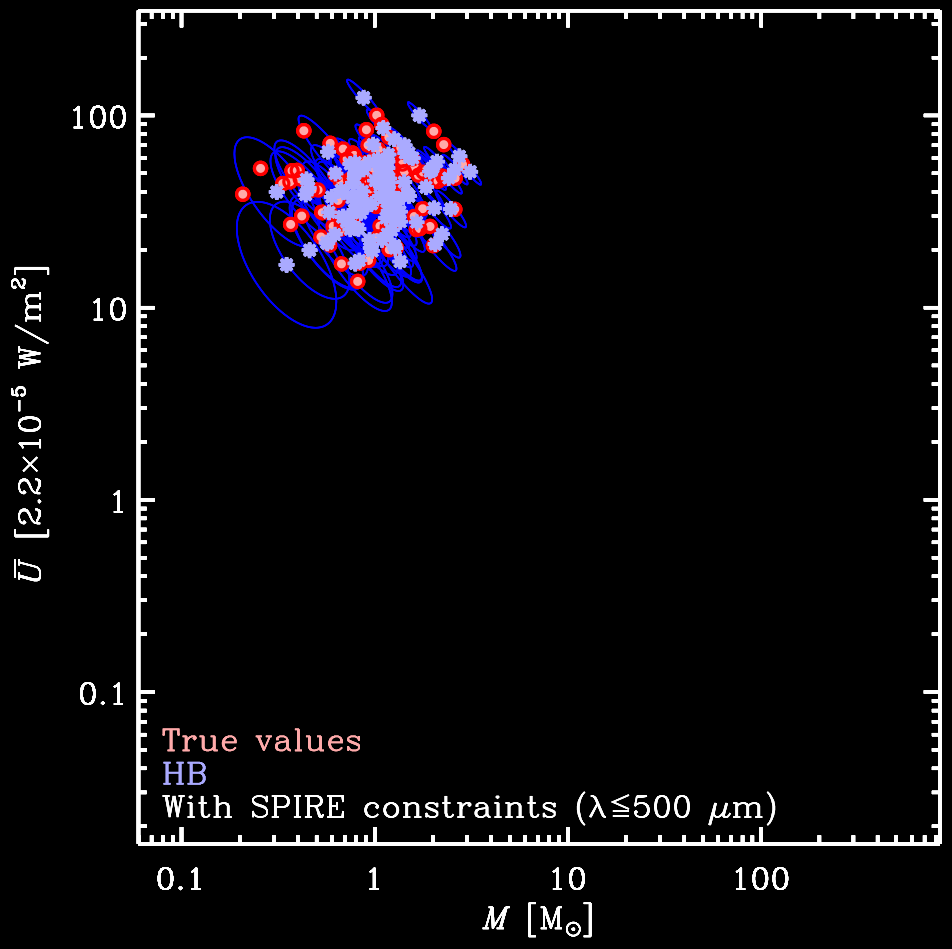

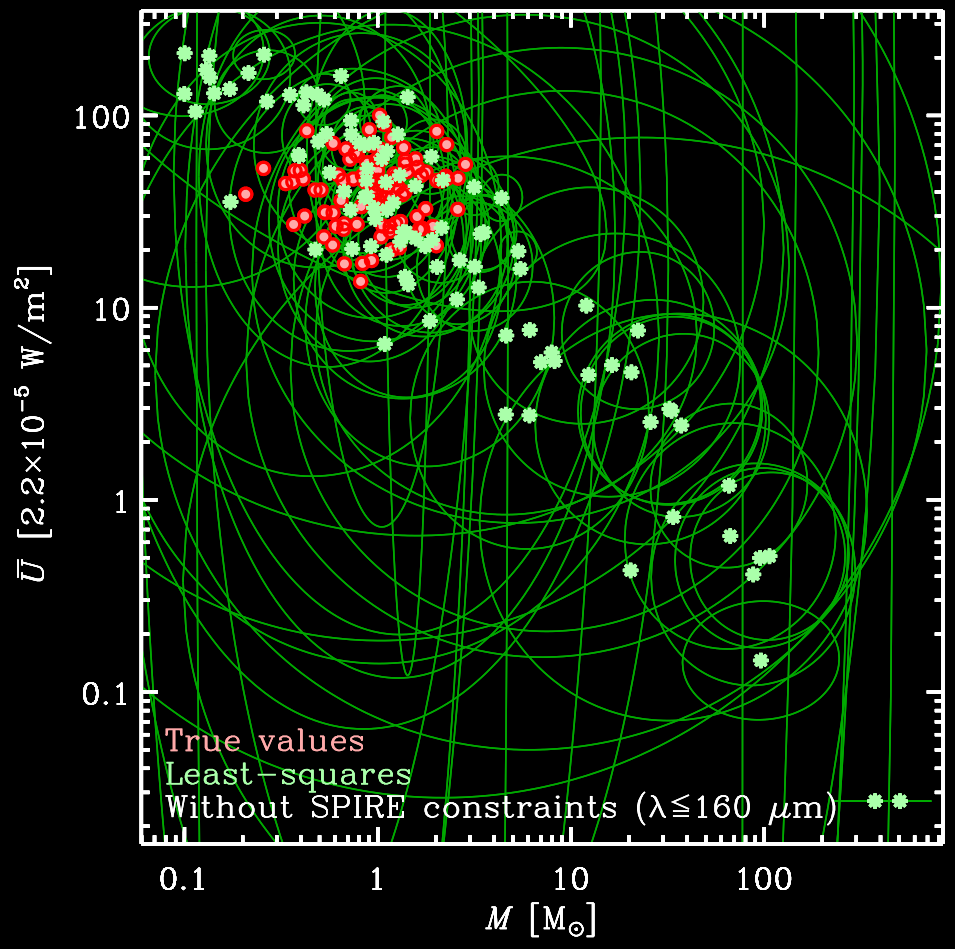

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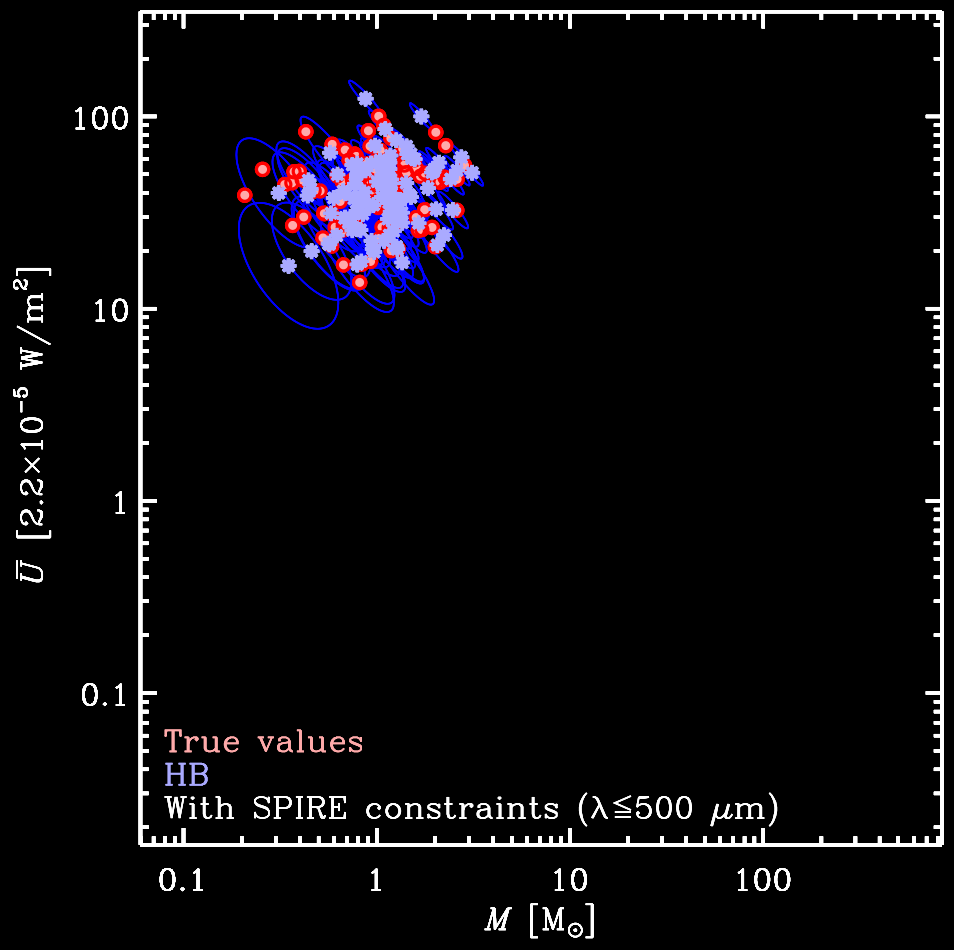

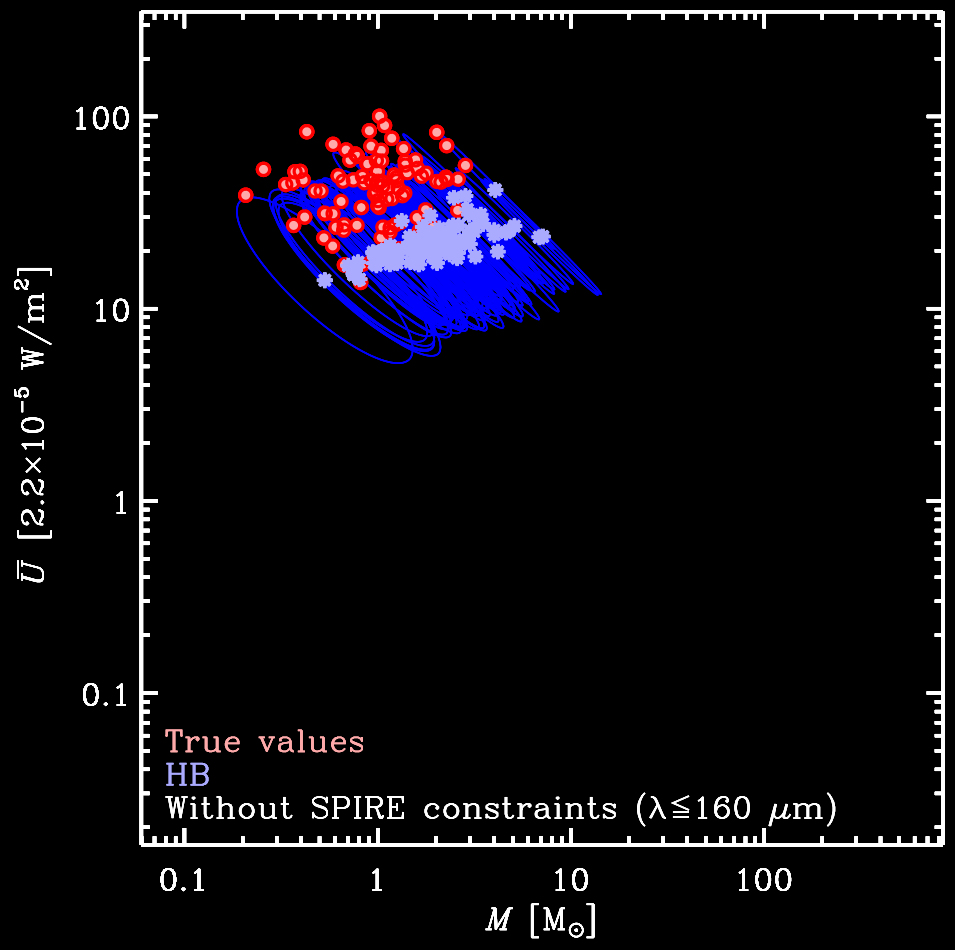

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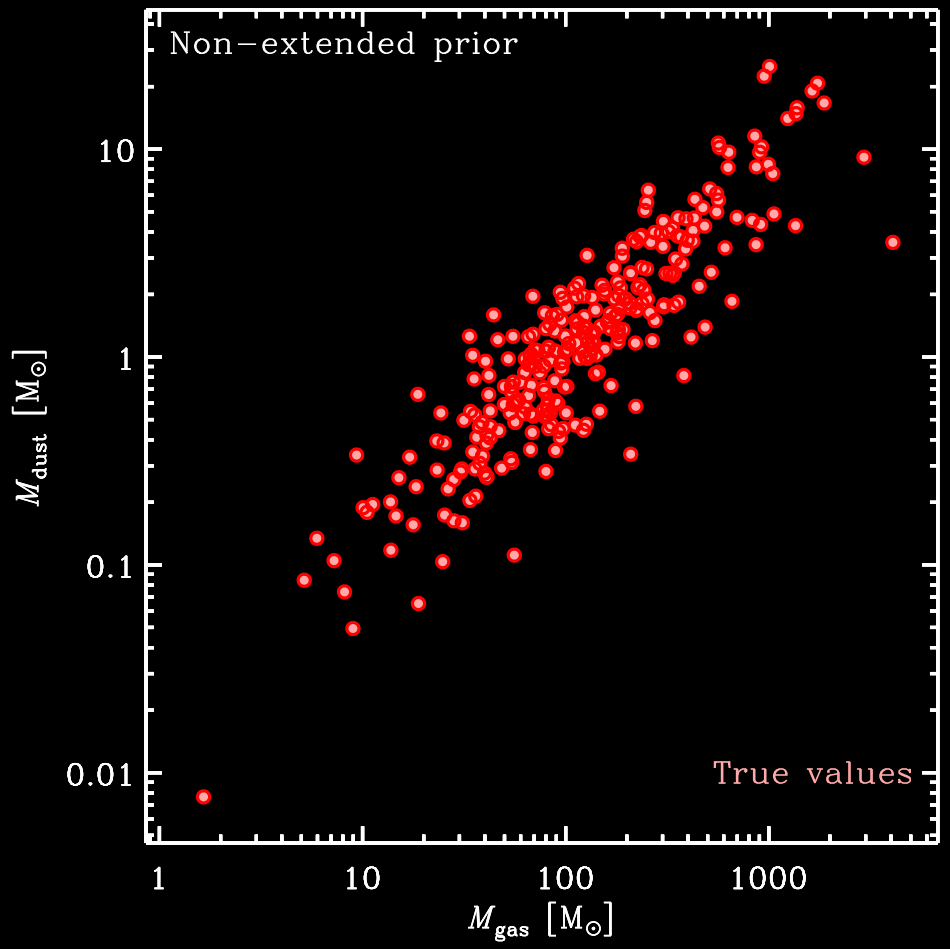

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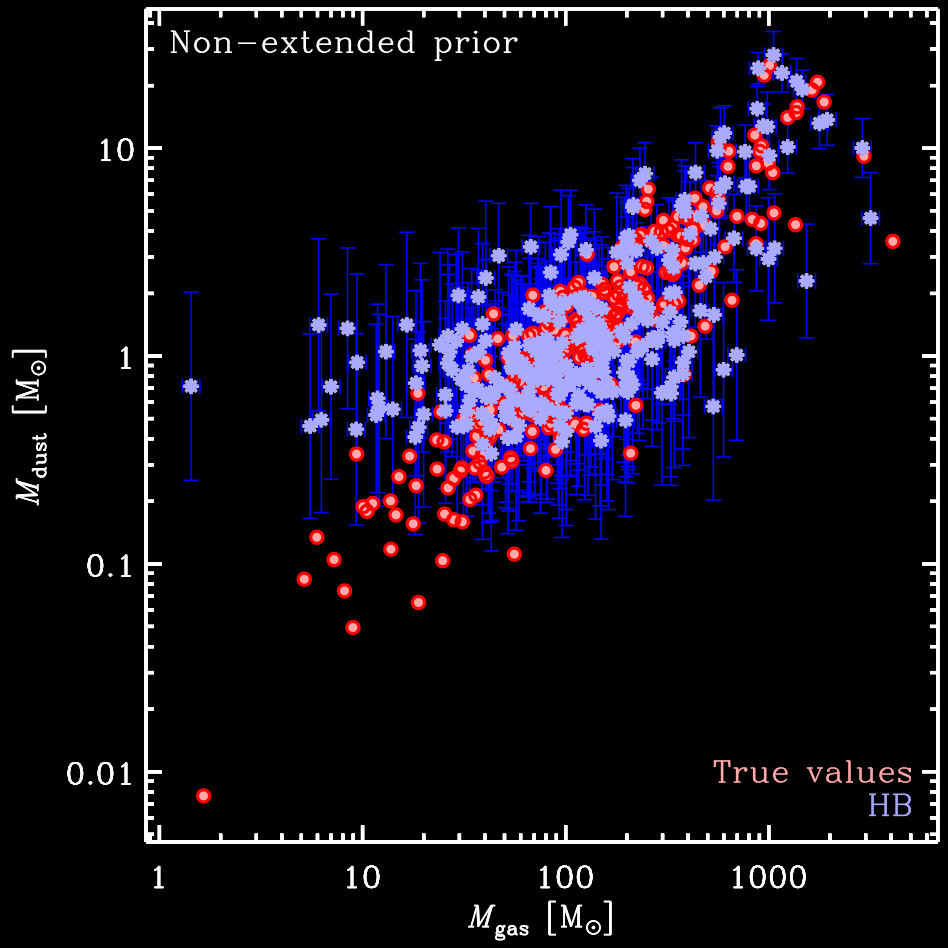

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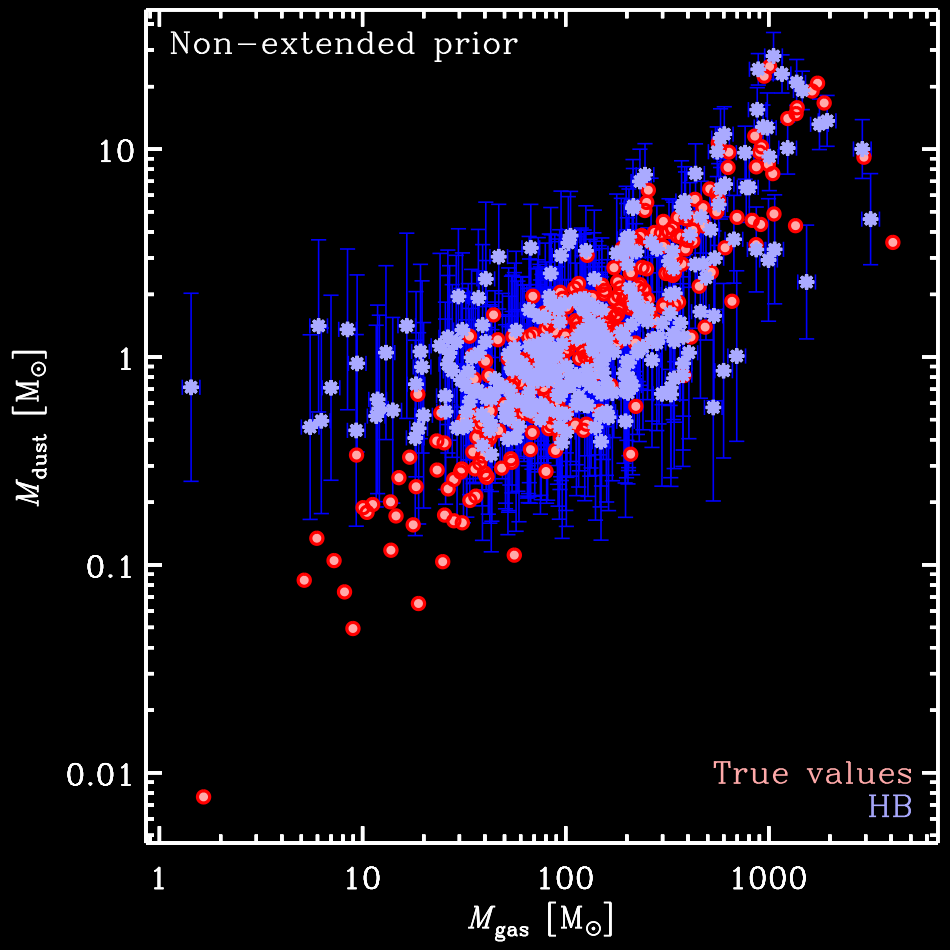

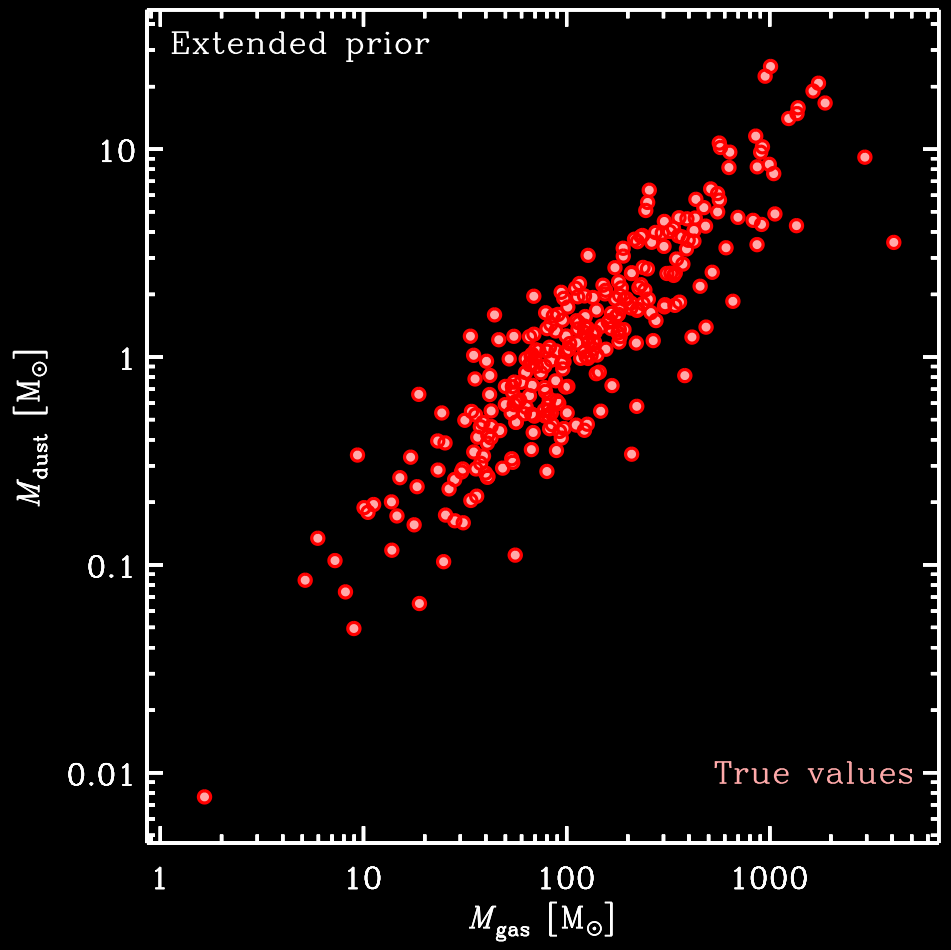

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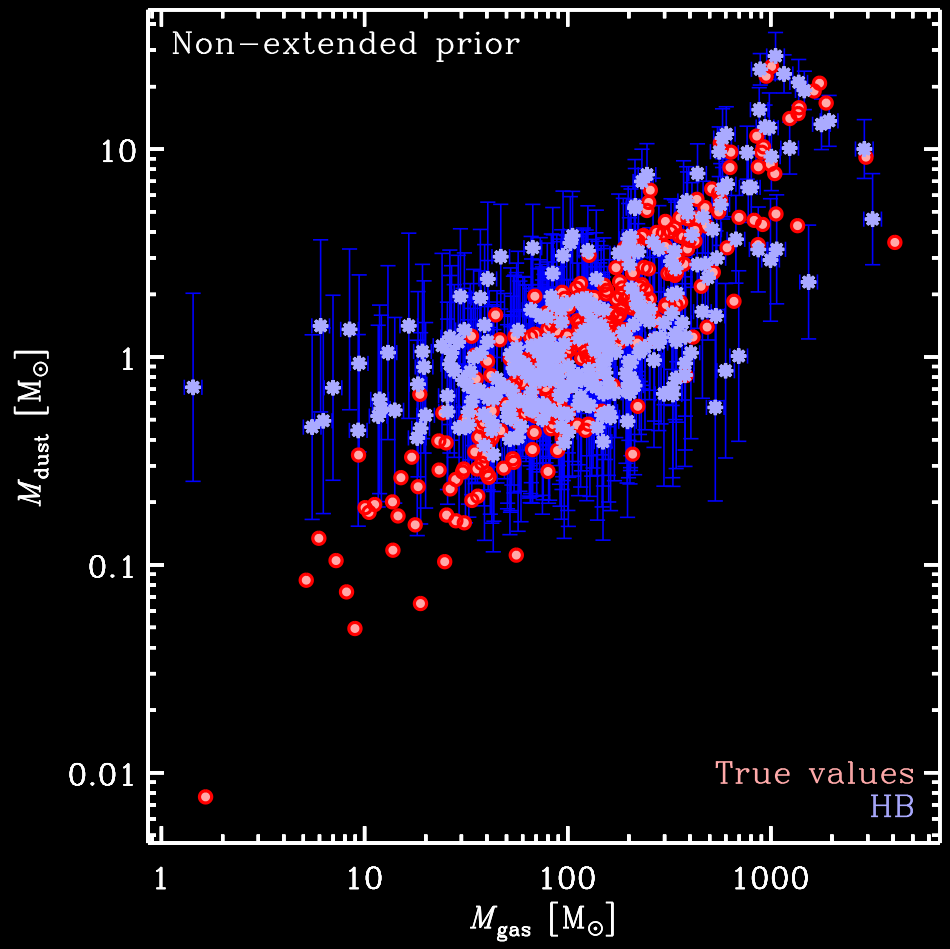

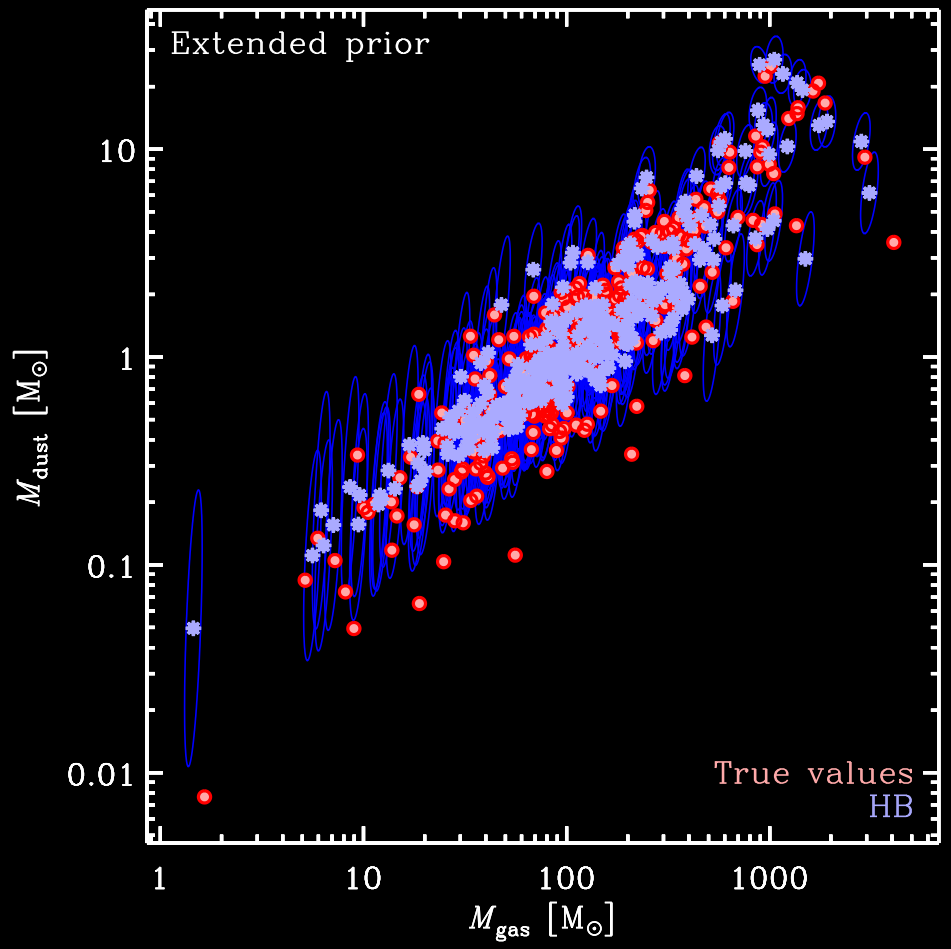

Outline of the Talk

The Anomalous Microwave Emissions (AME)

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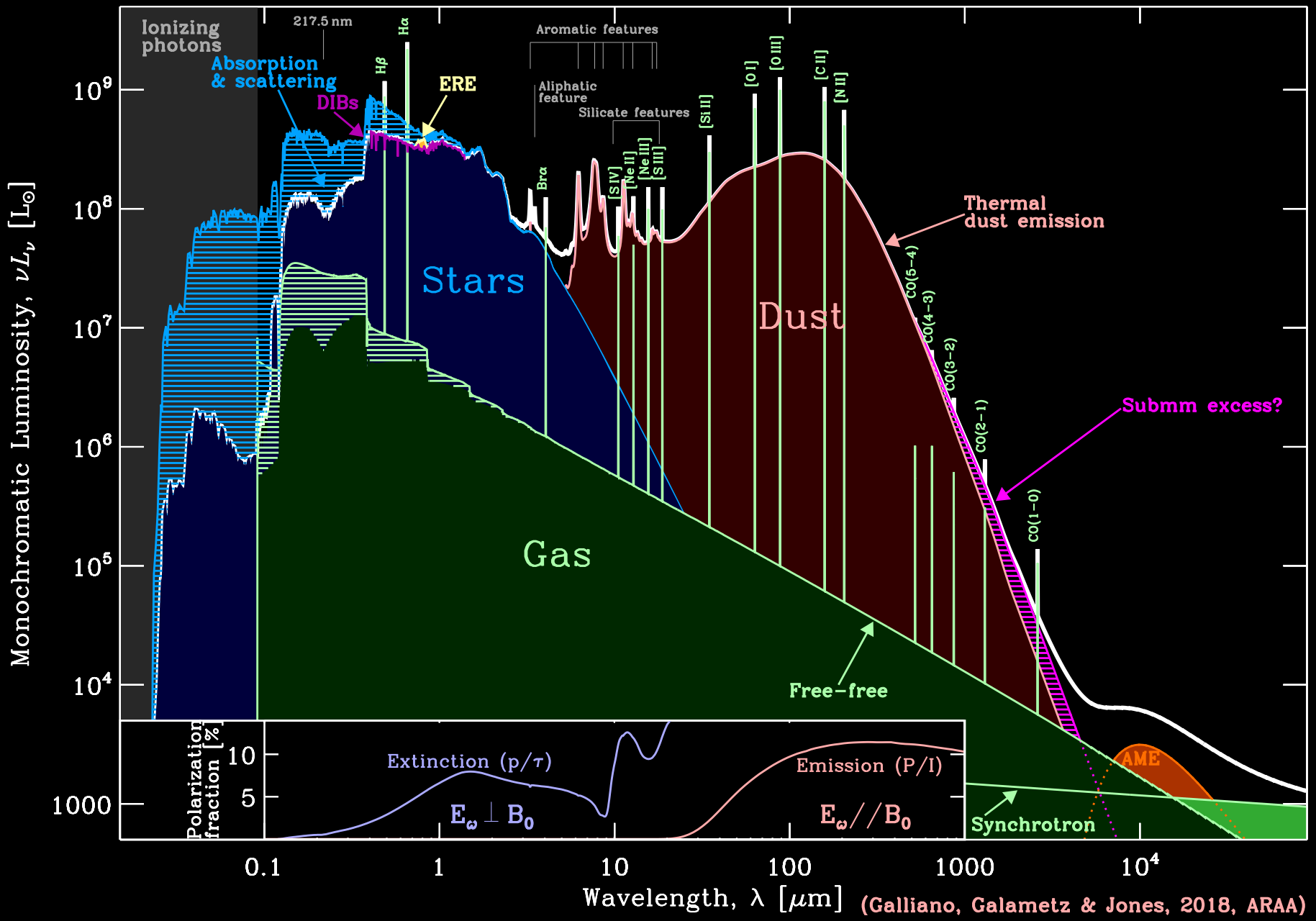

(Galliano, Galametz & Jones, 2018, ARAA)

Spinning Grains in λ-Orionis

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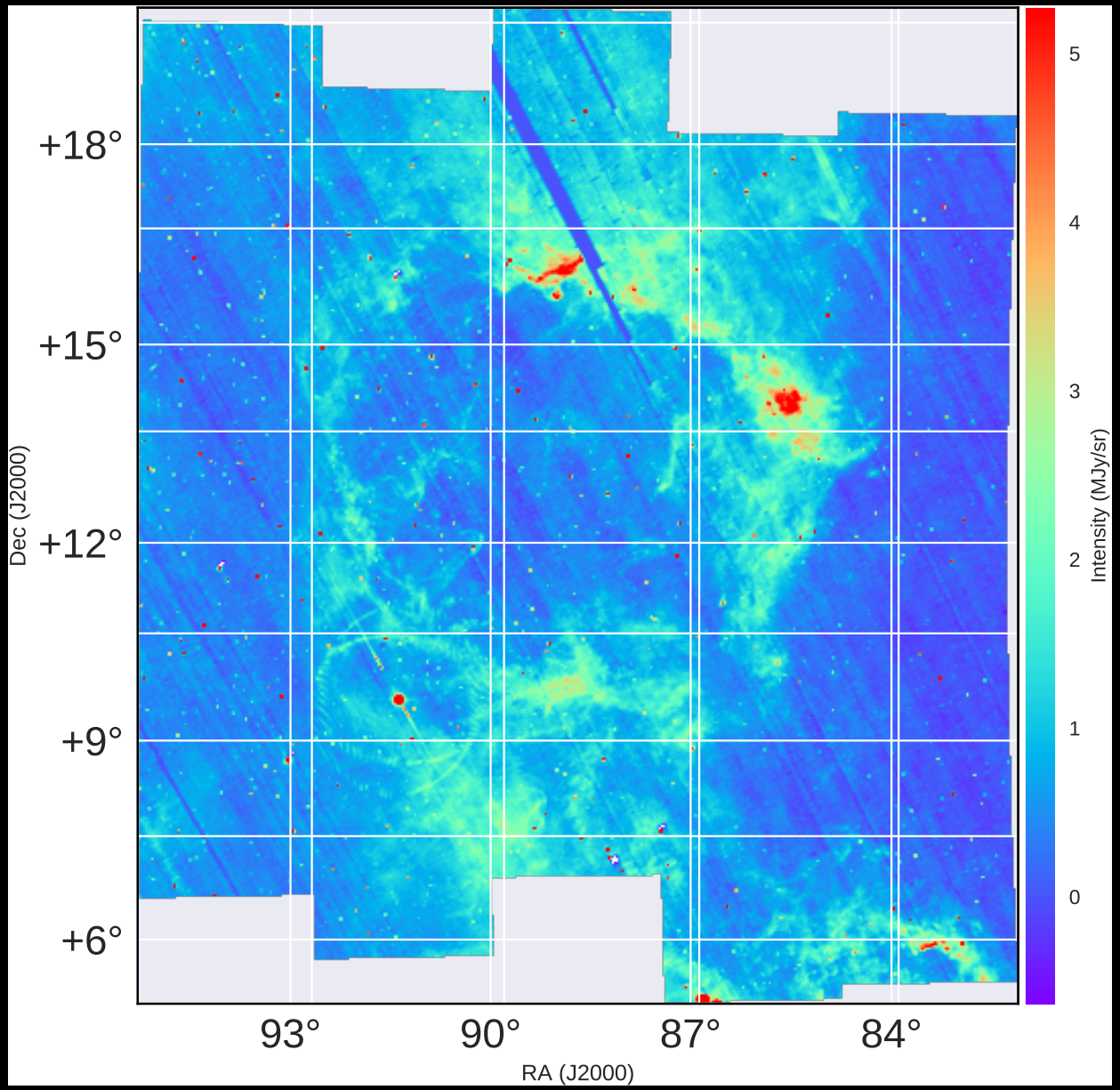

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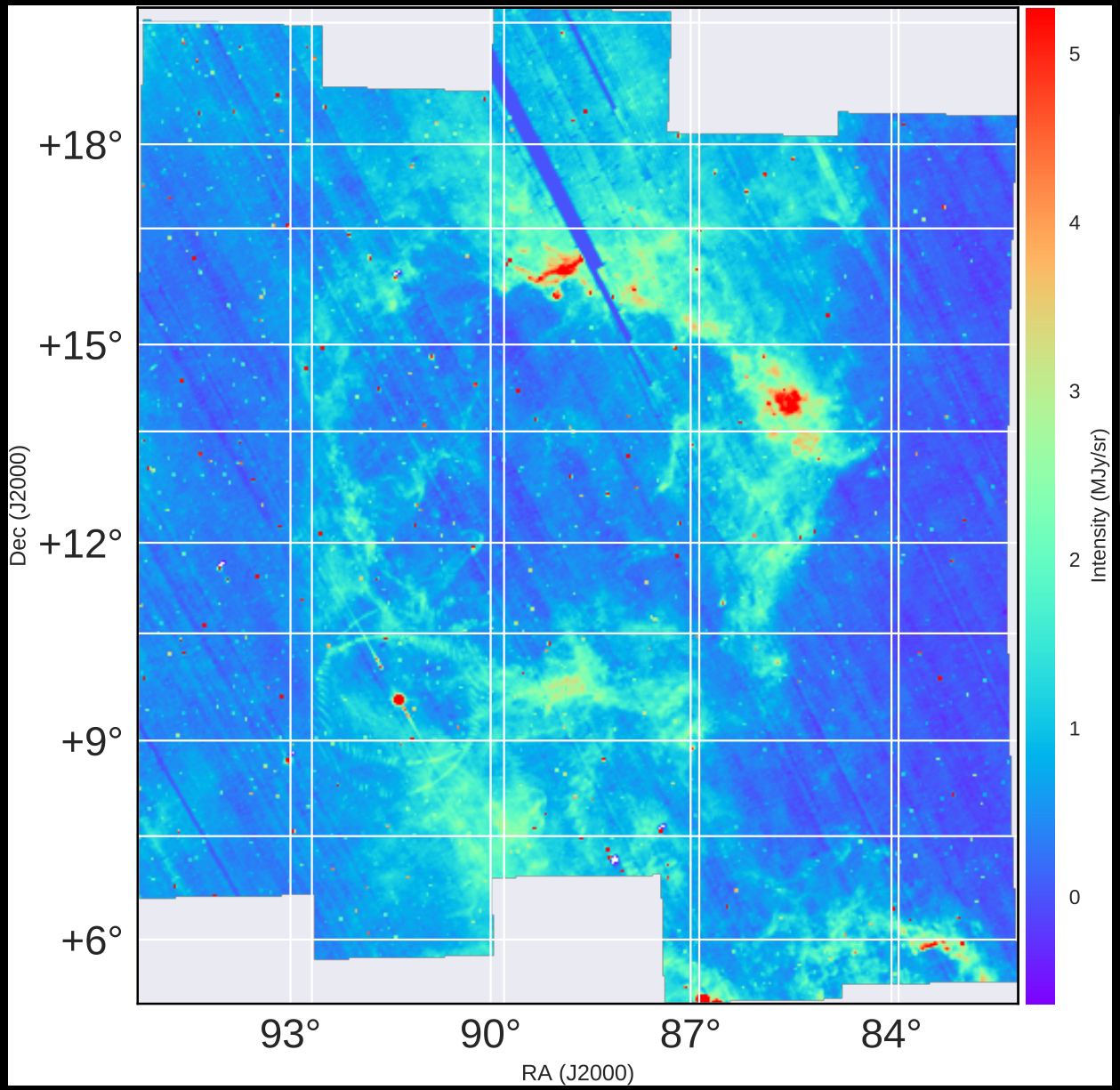

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Dust SED: AKARI & DIRBE photometry (9 to 500 μm).

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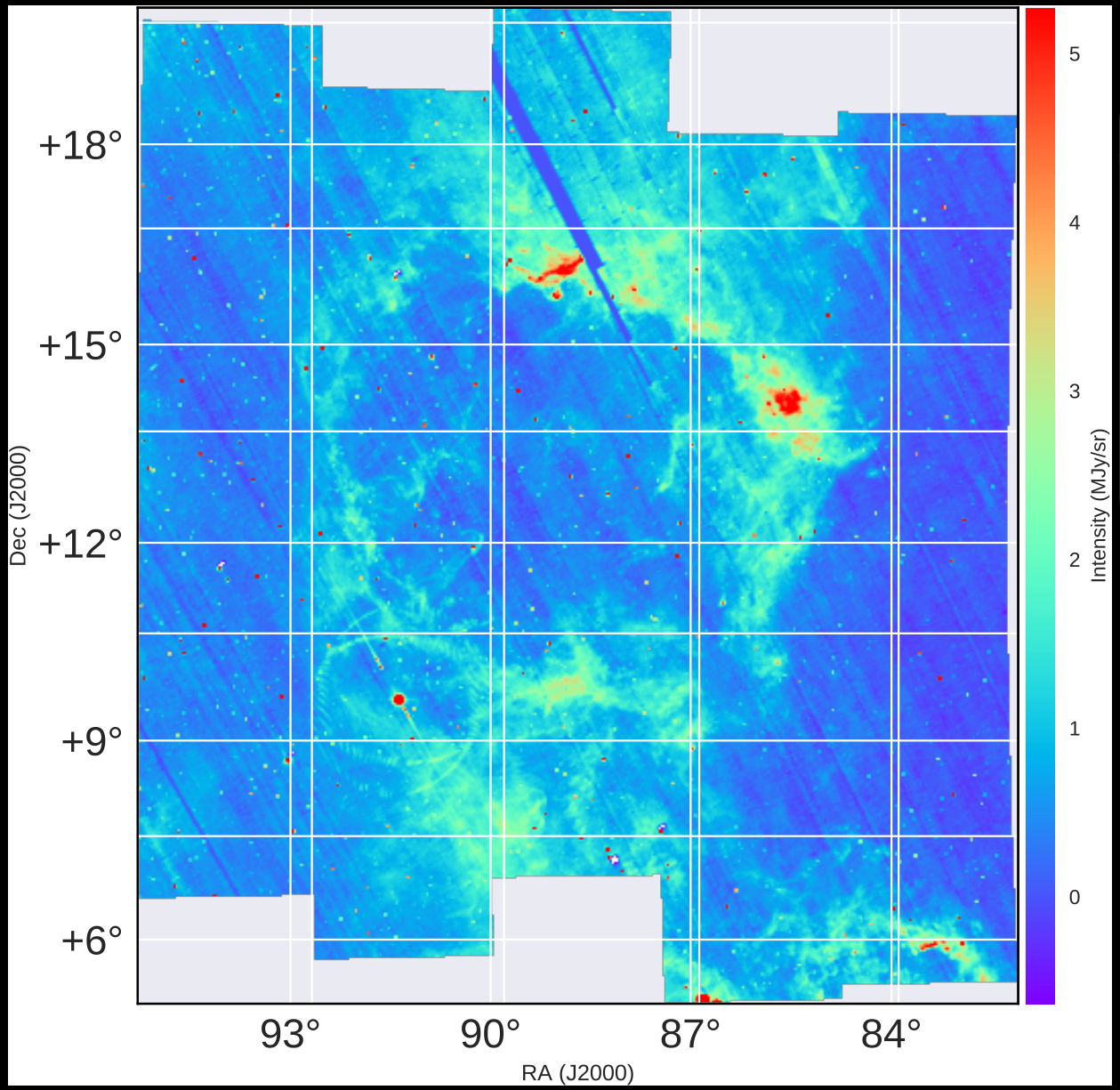

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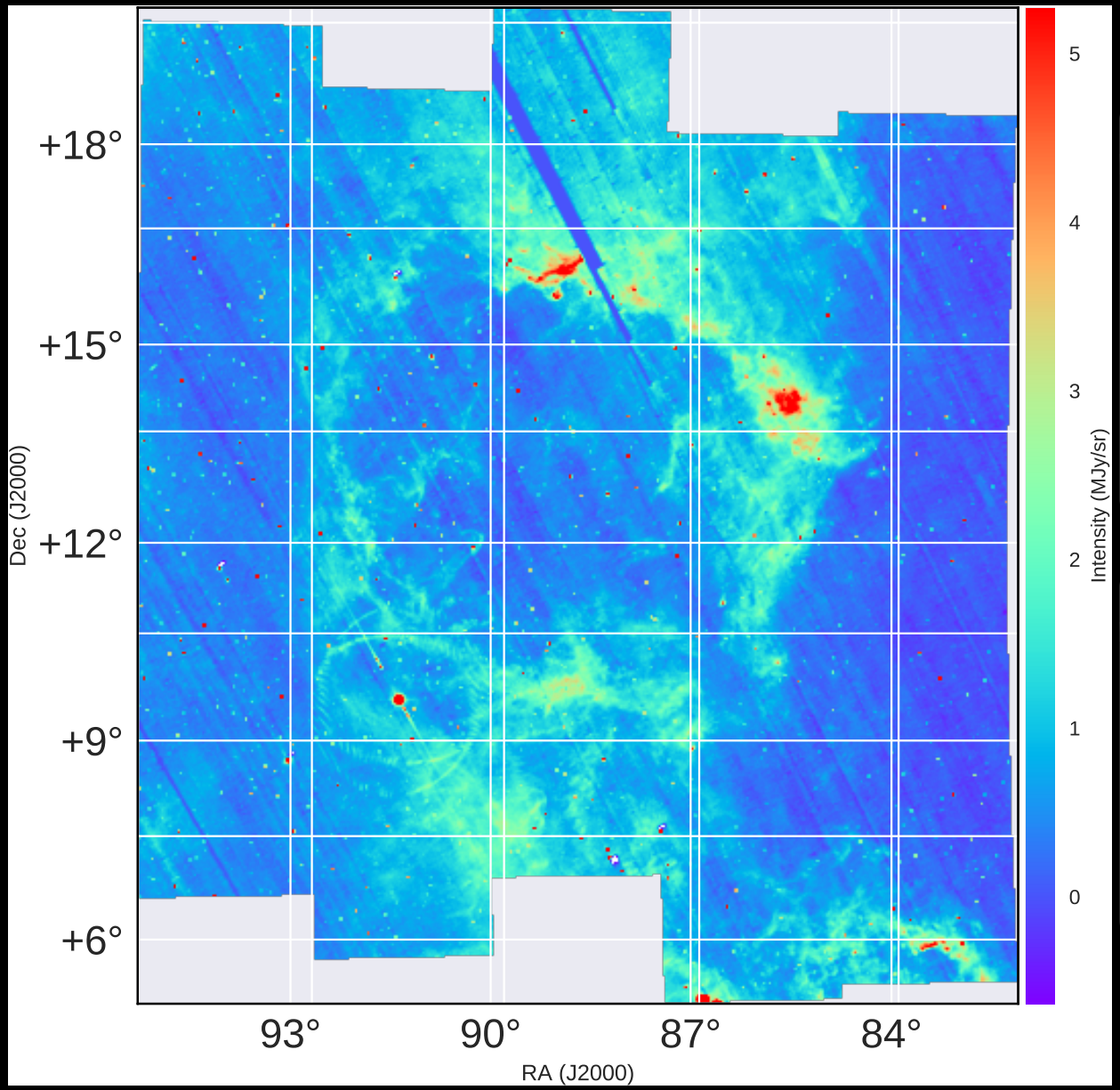

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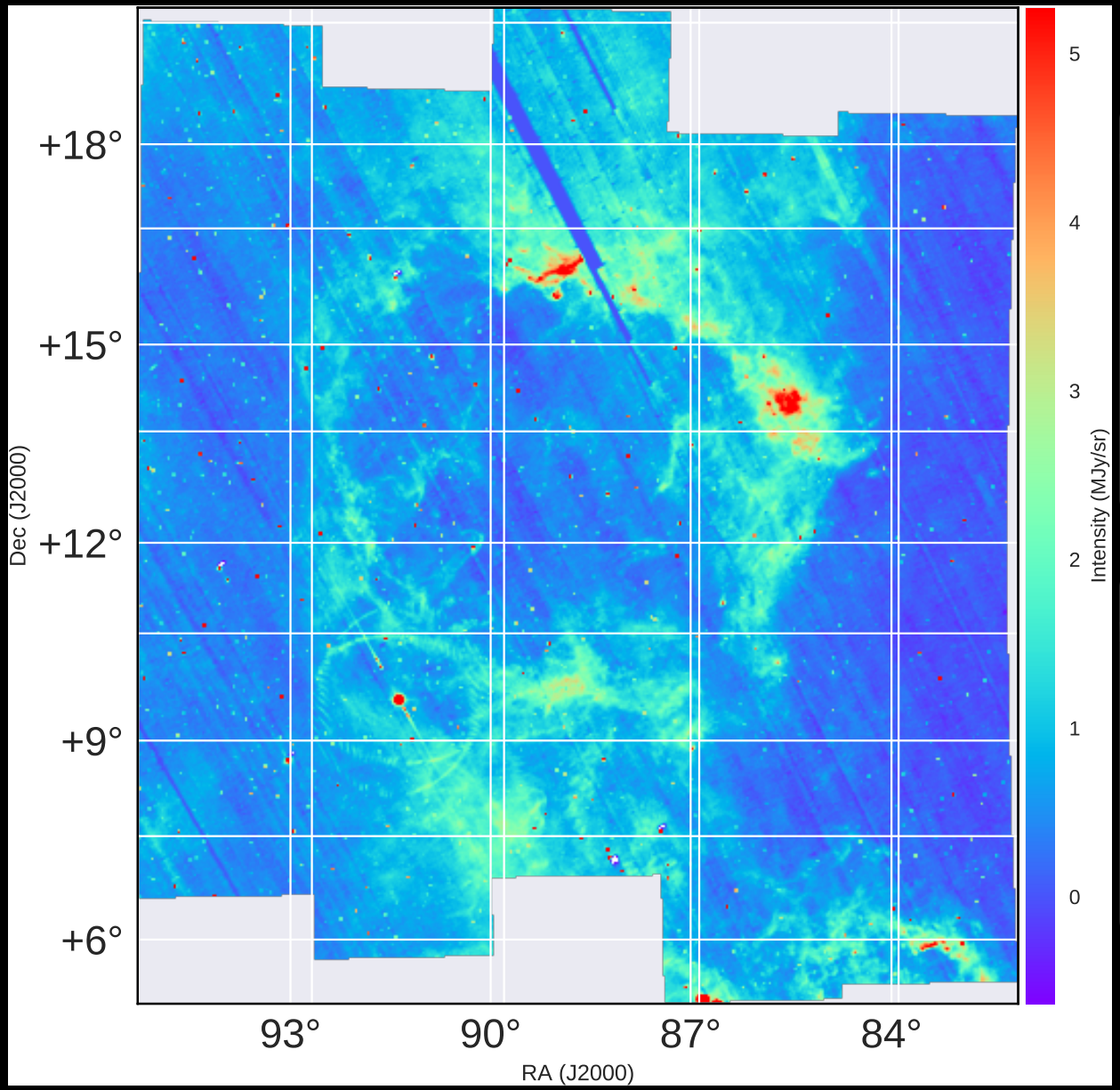

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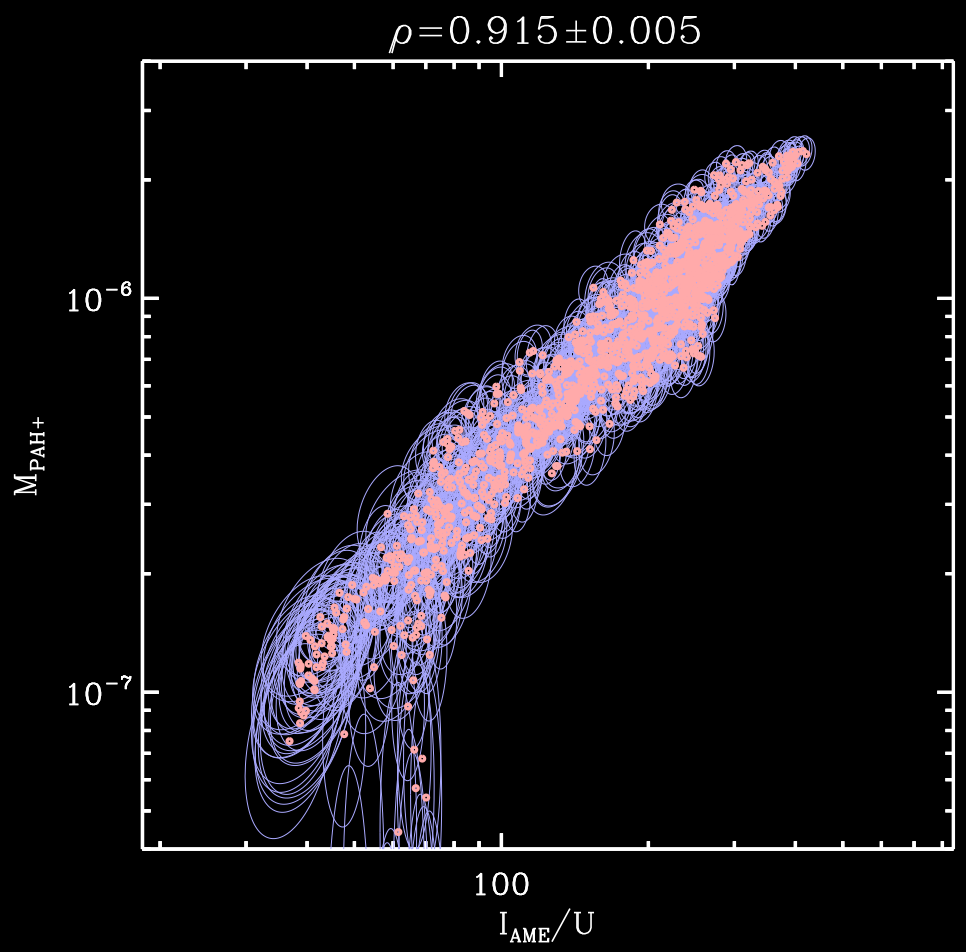

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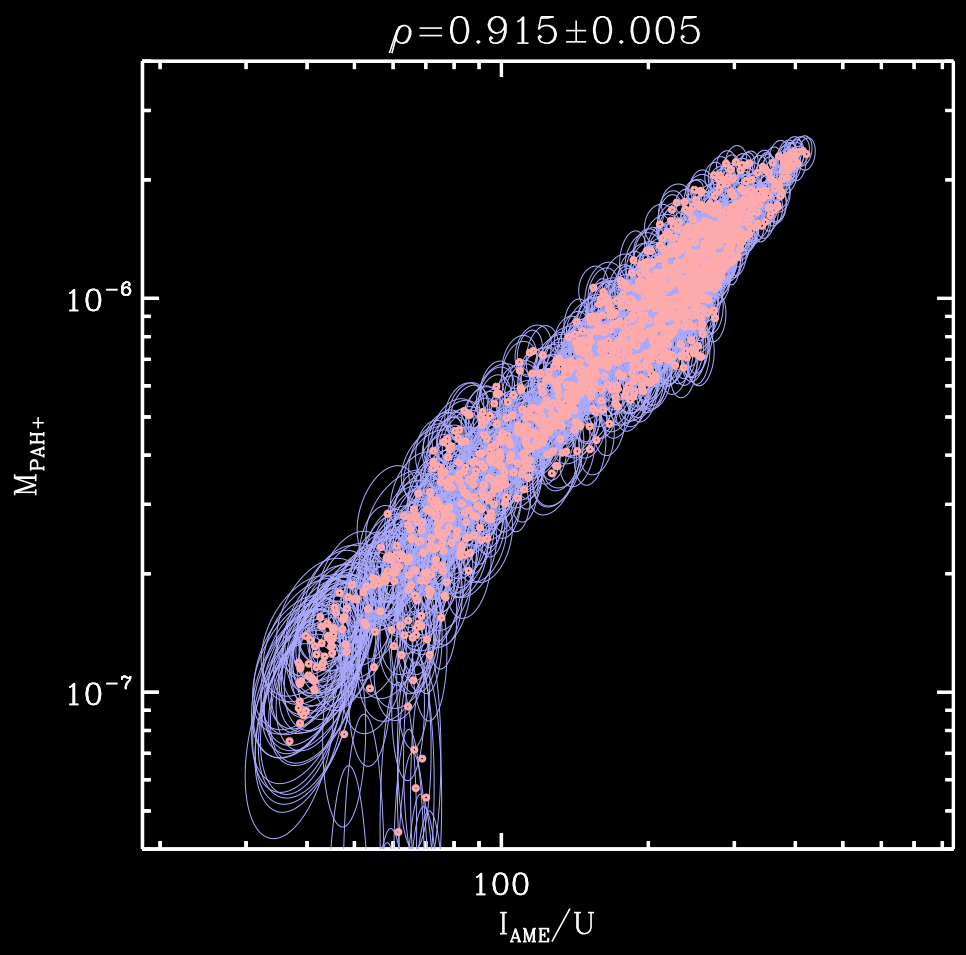

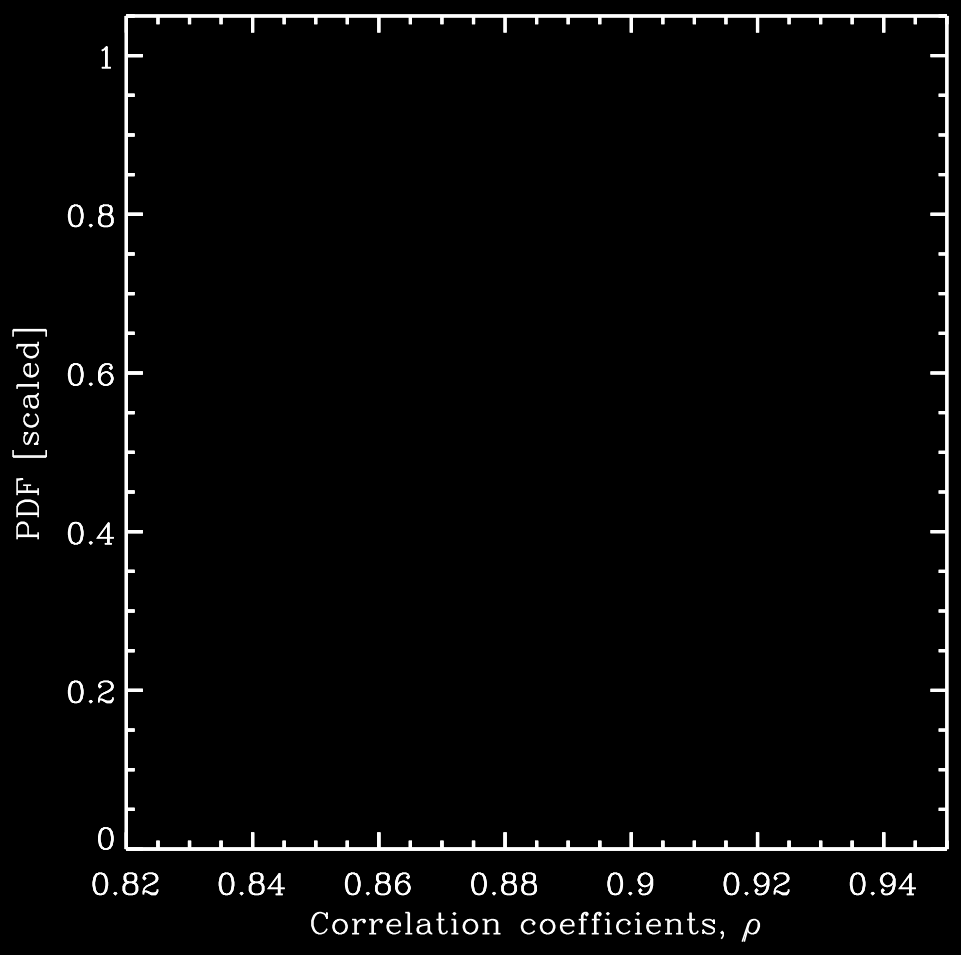

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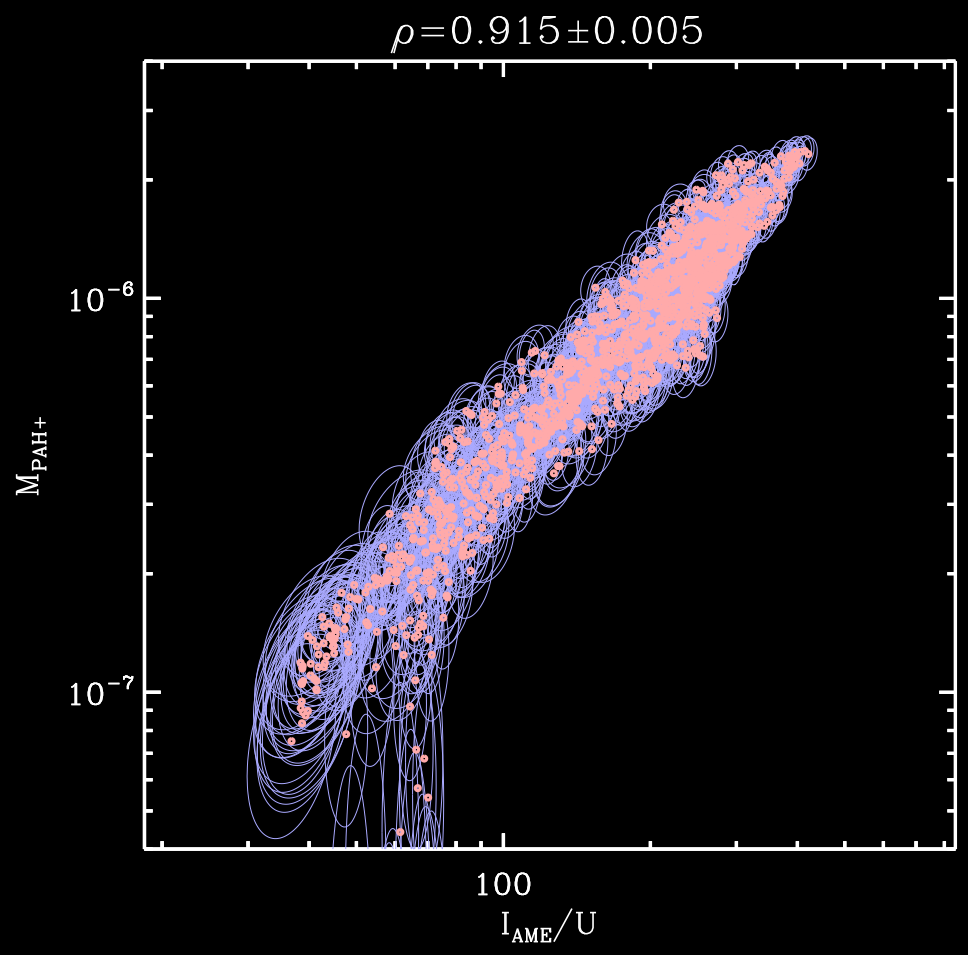

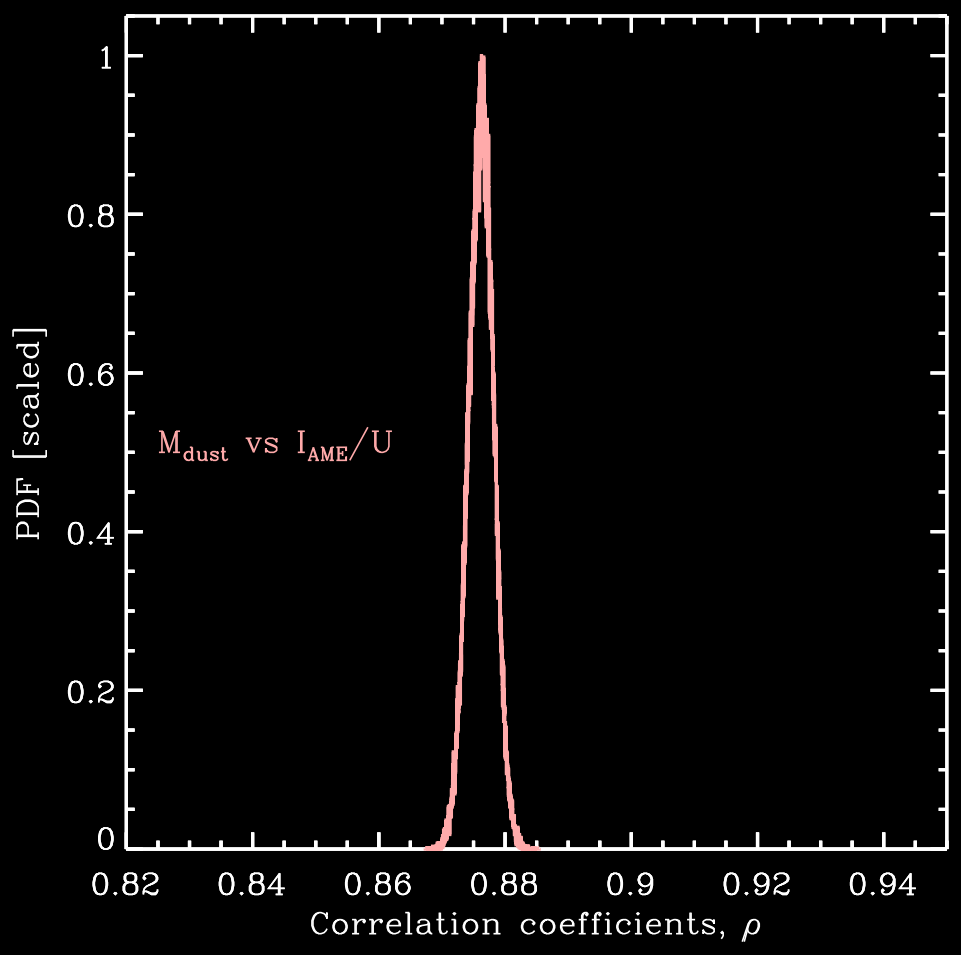

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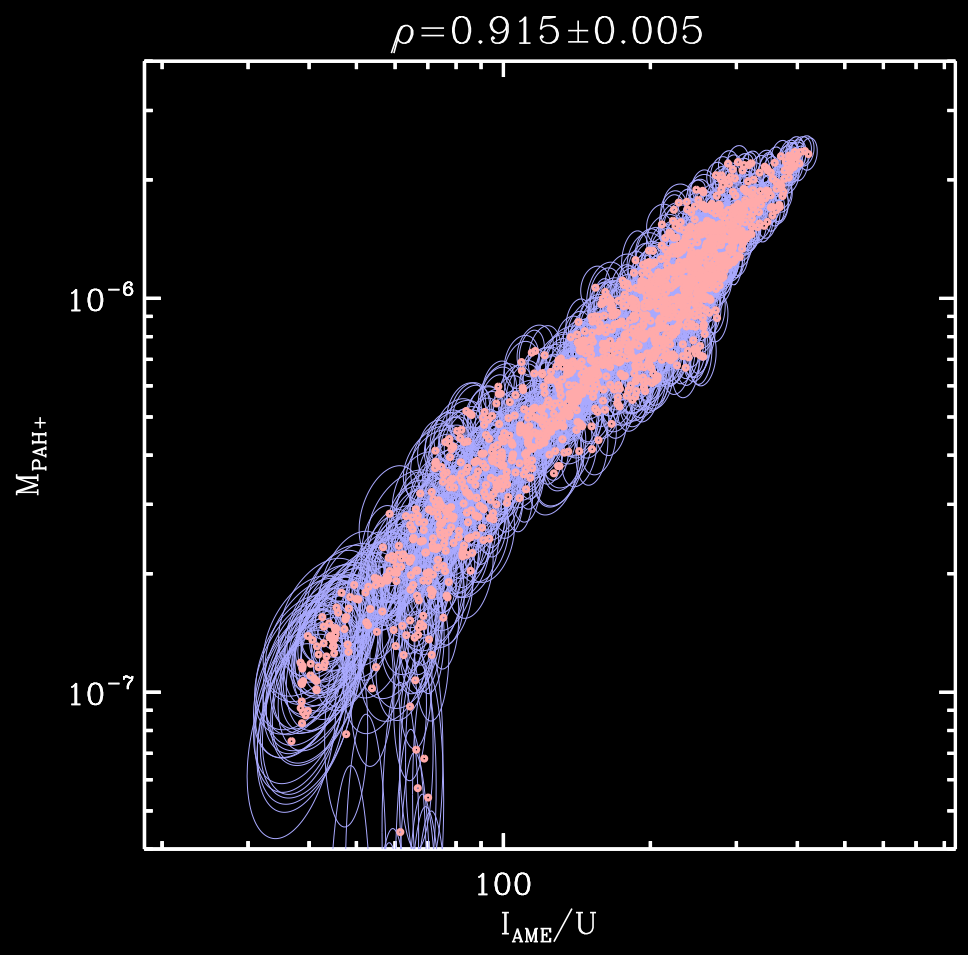

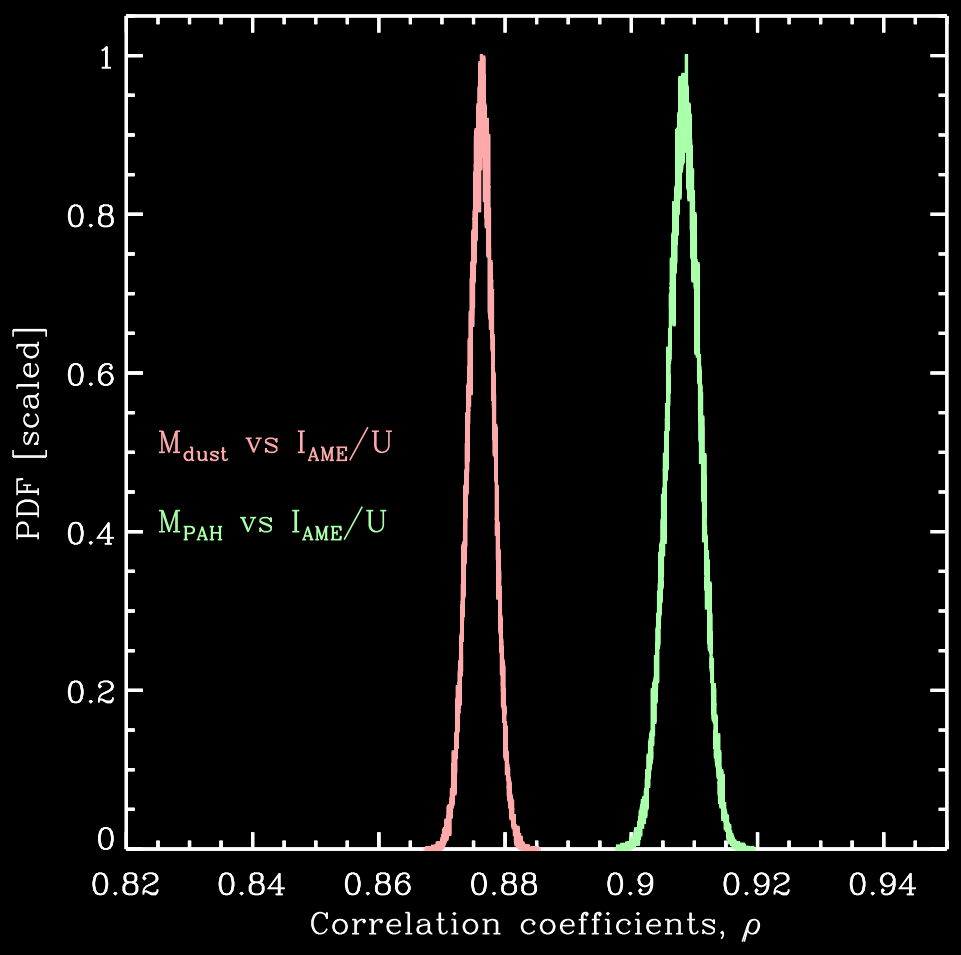

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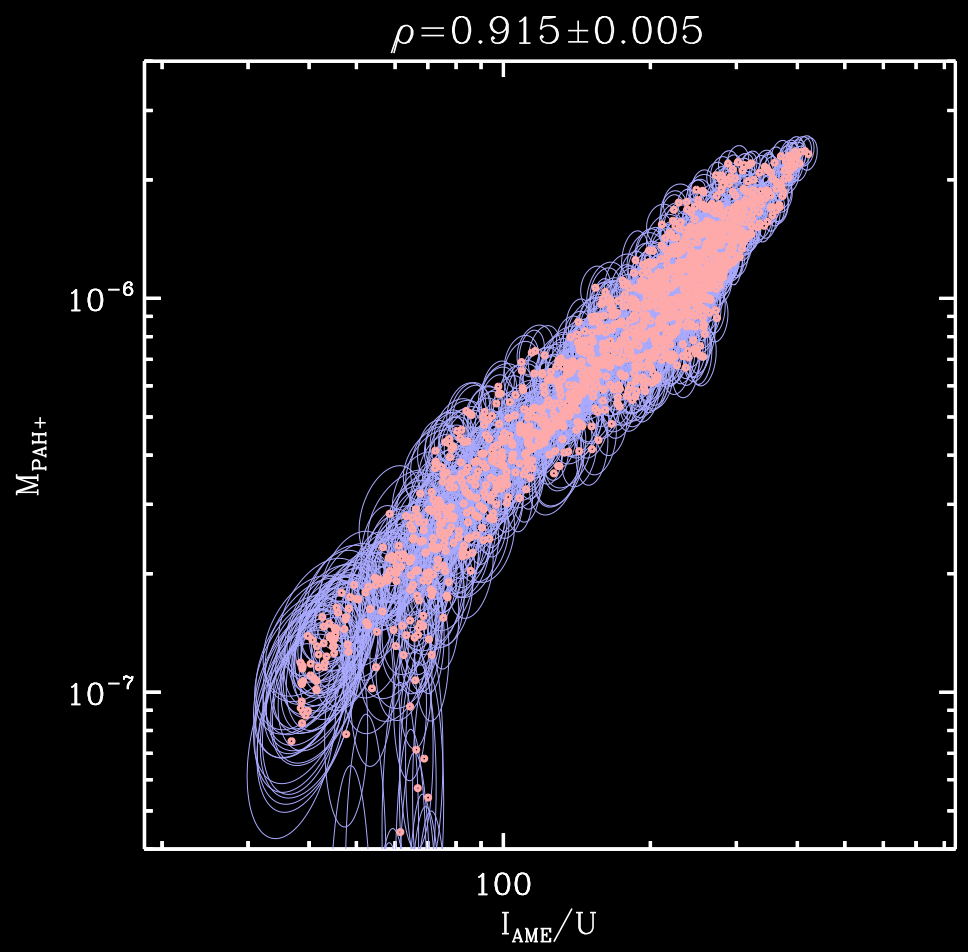

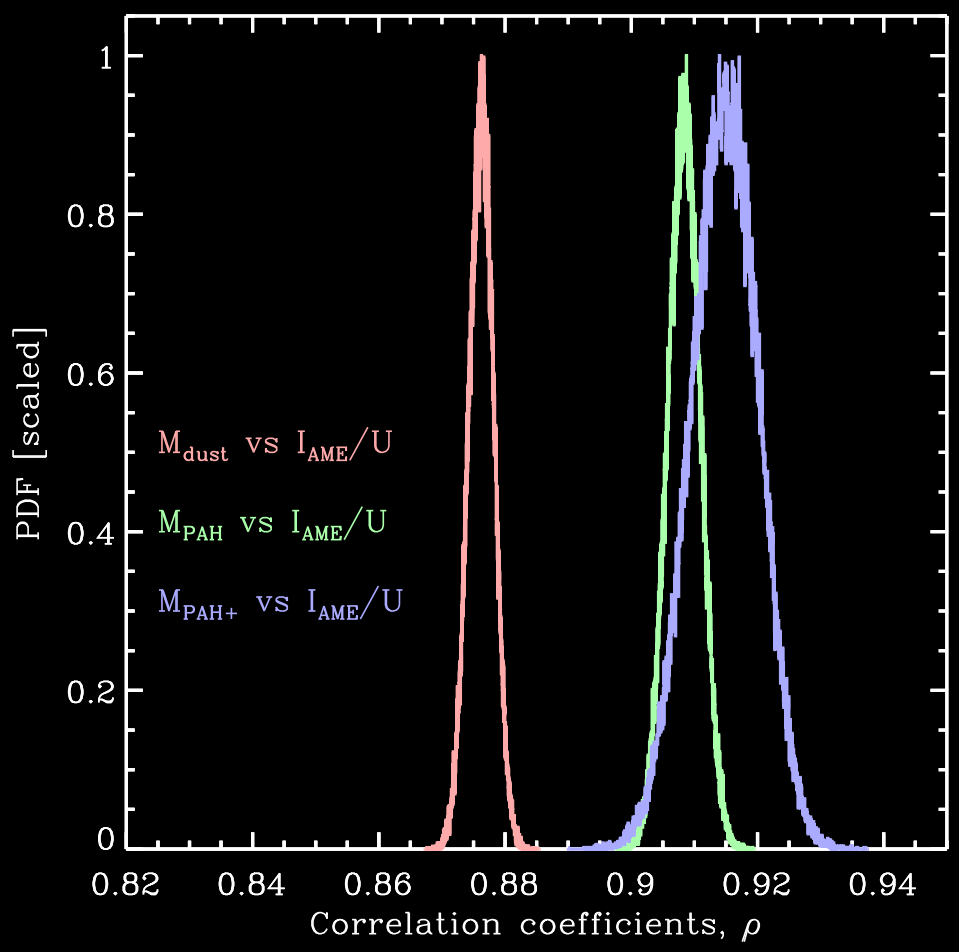

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- $p(\rho_{\text{dust}} < \rho_{\text{PAH}}) = 1.000$
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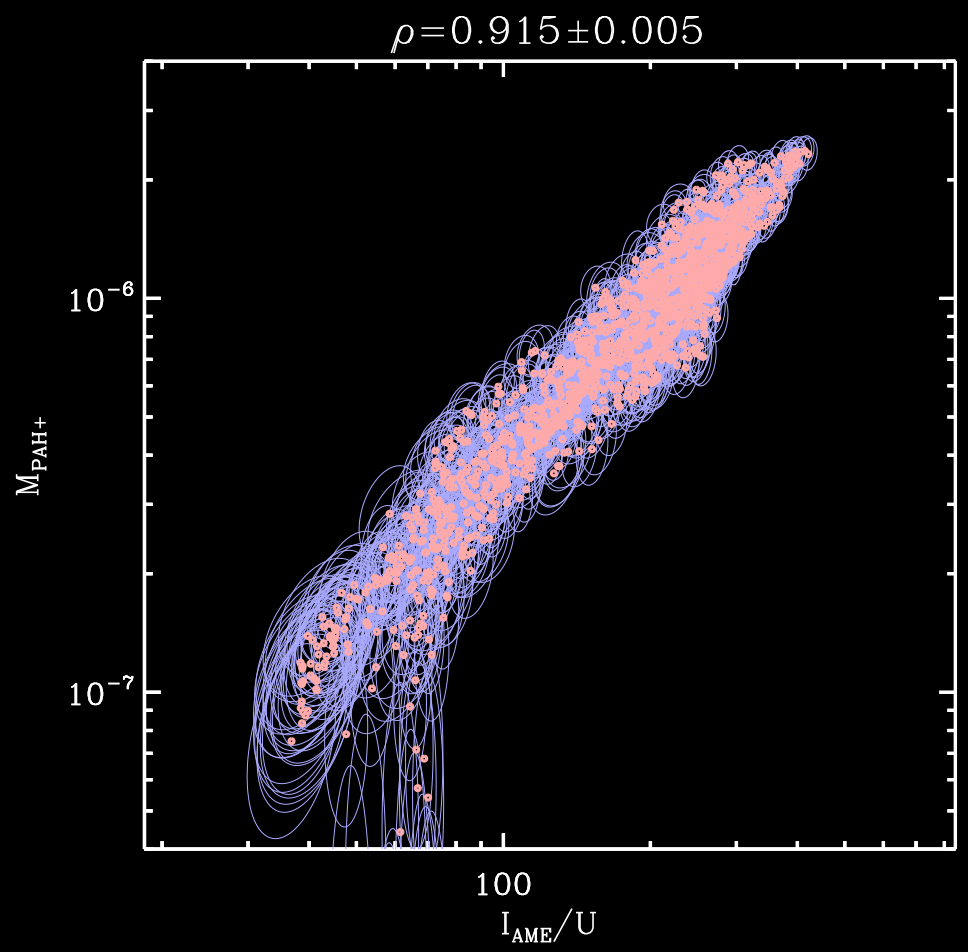

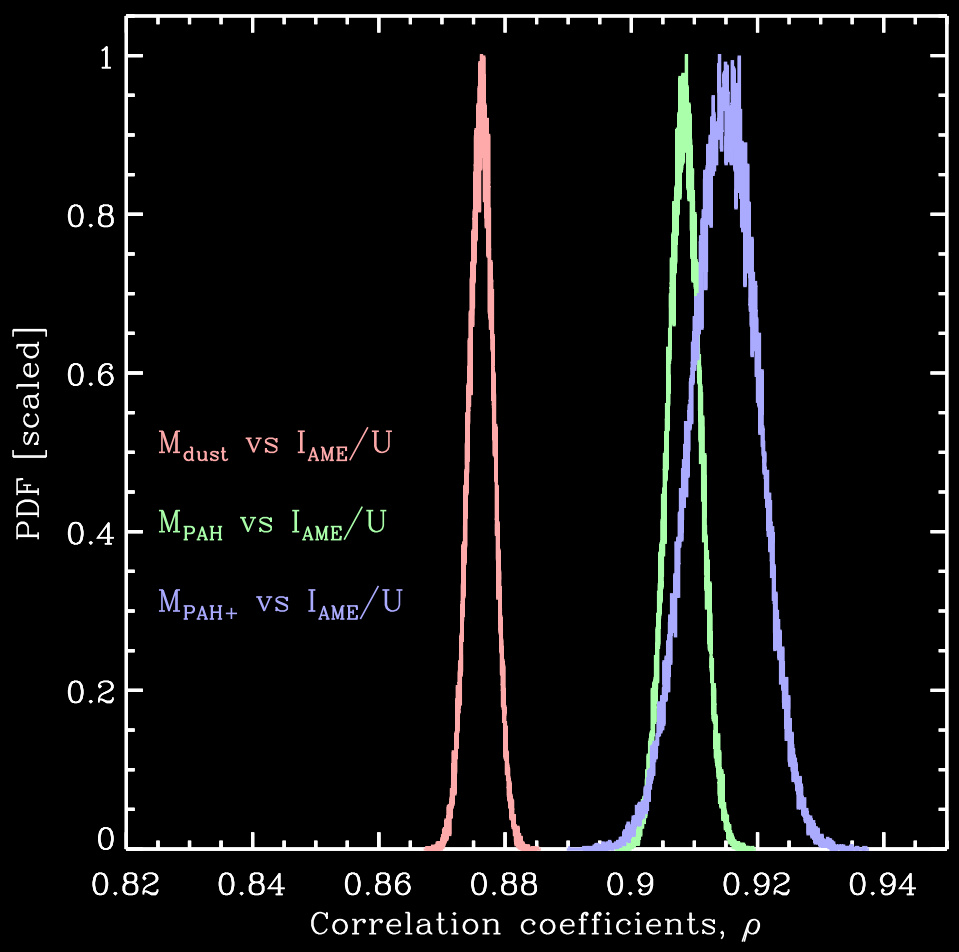

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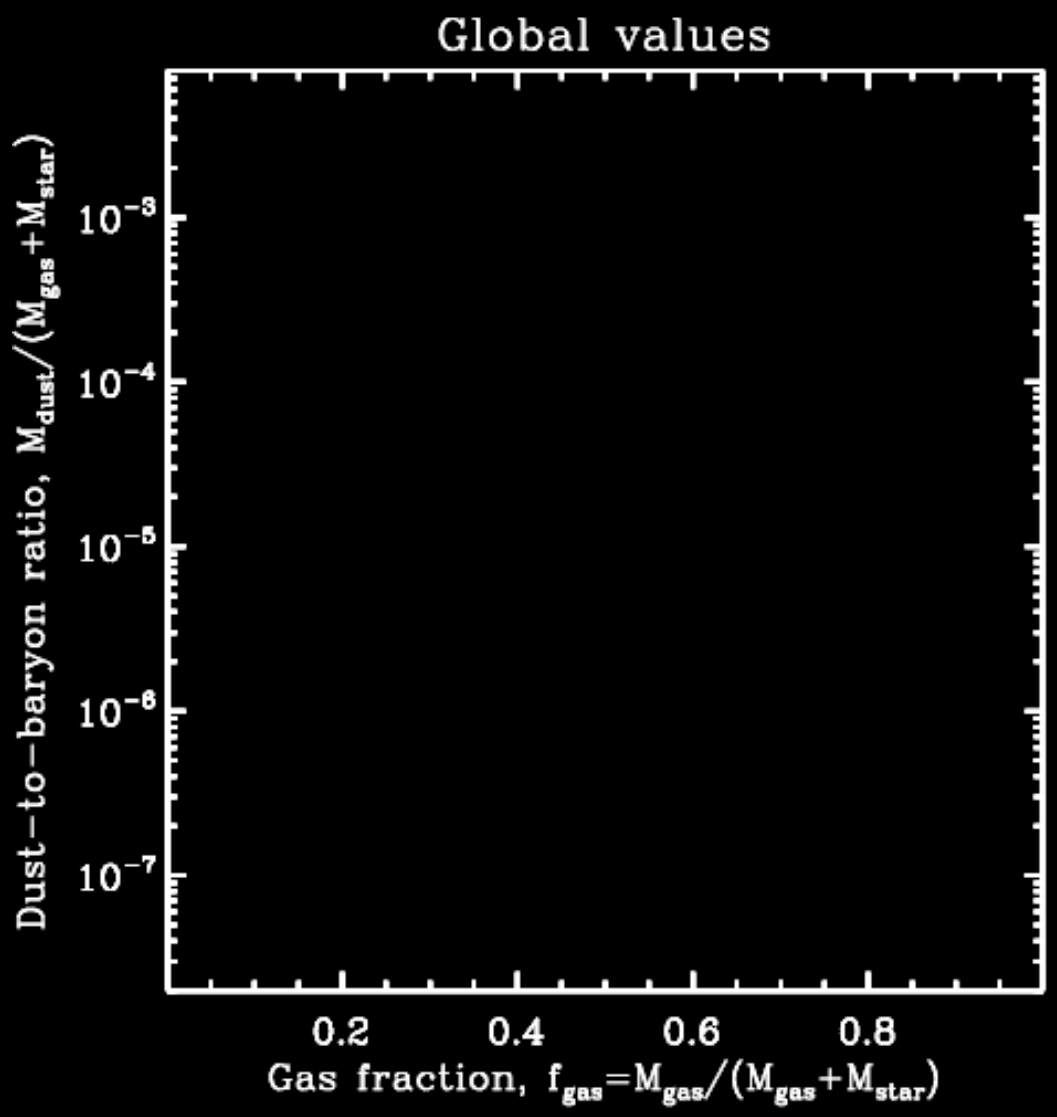
- $p(\rho_{\text{dust}} < \rho_{\text{PAH+}}) = 1.000$
- $p(\rho_{\text{PAH}} < \rho_{\text{PAH+}}) = 0.934 \Rightarrow$ better correlation with PAH$^+$.

Dust Mass Build-Up & Astration in Galaxies



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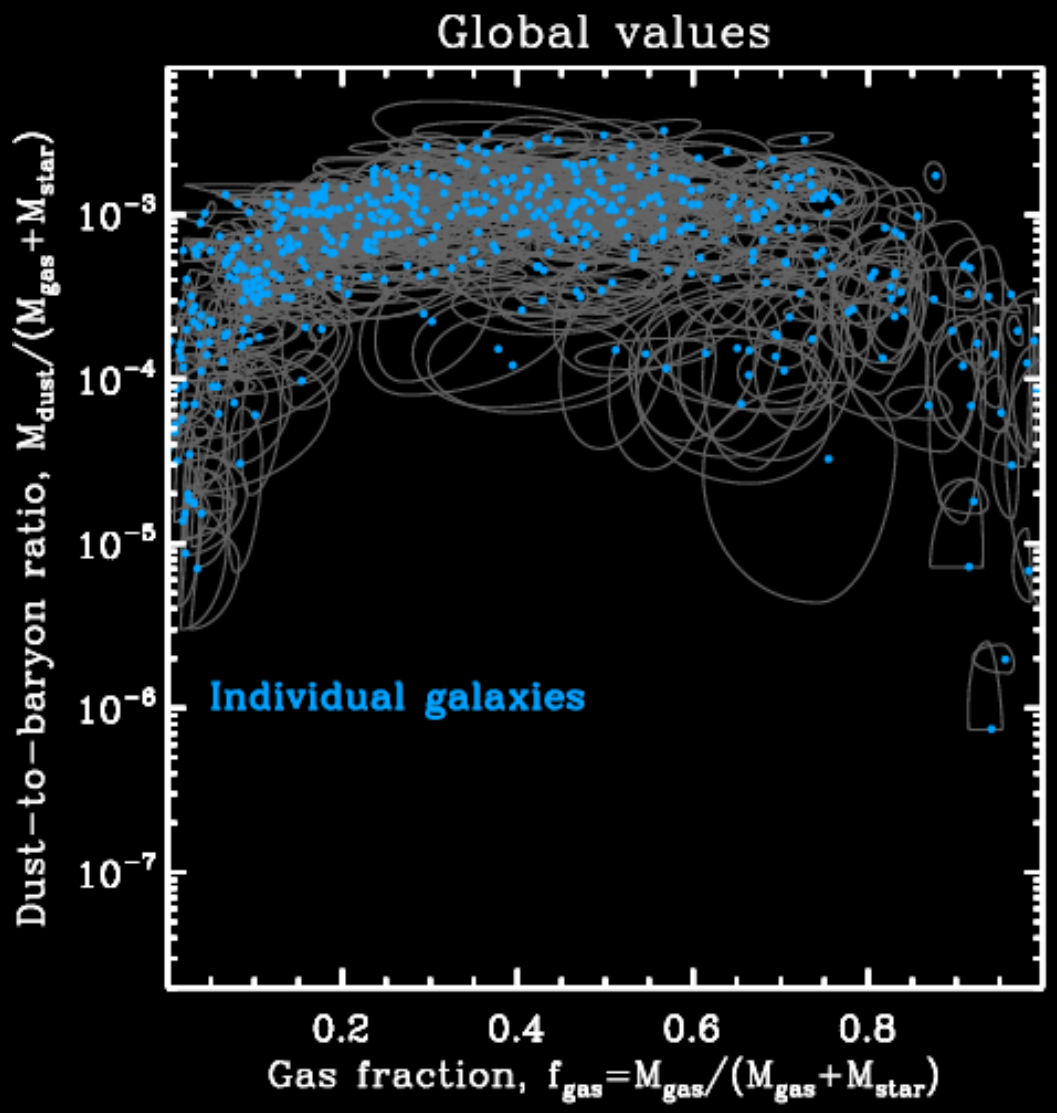

DustPedia sample (Galliano *et al.*, *in prep.*)

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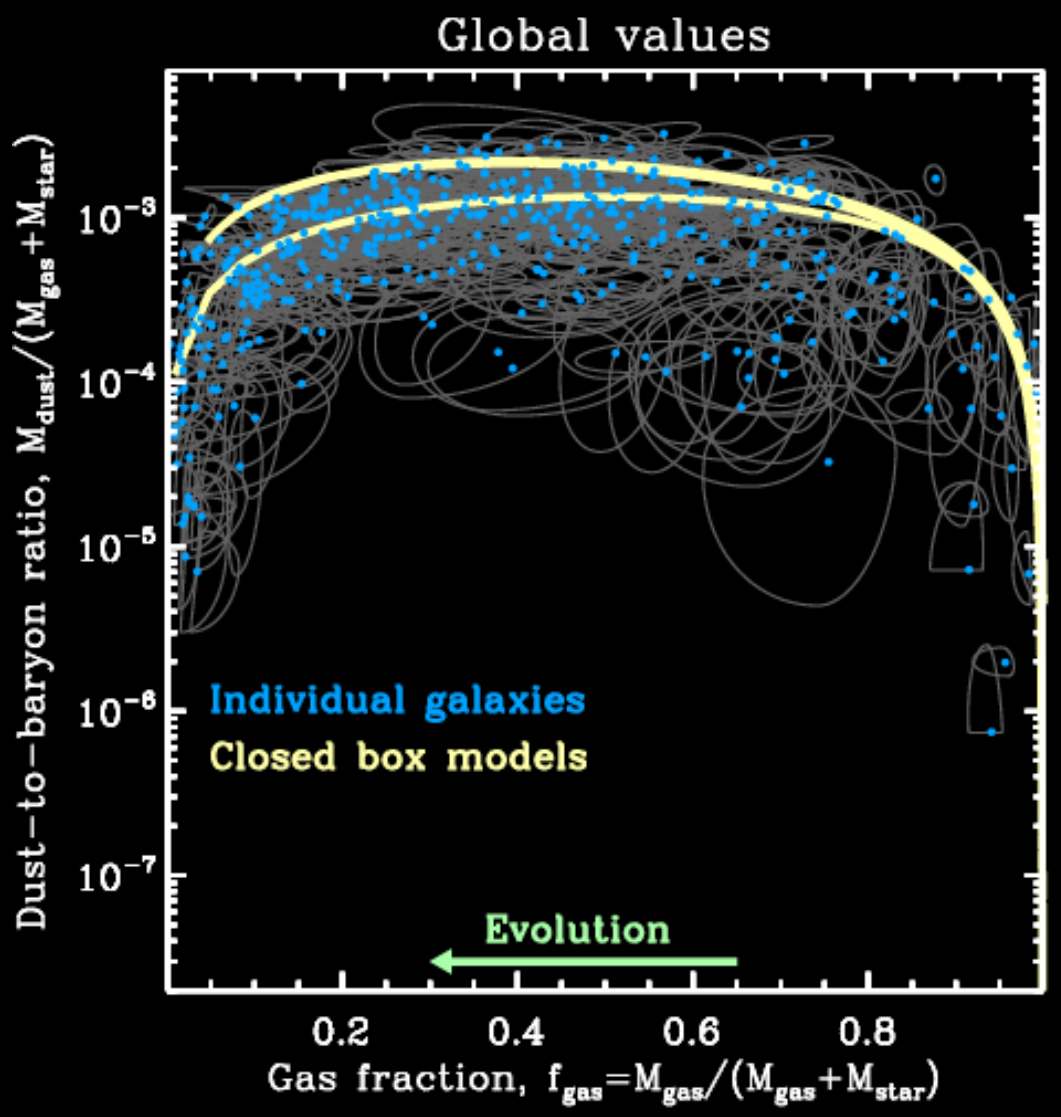

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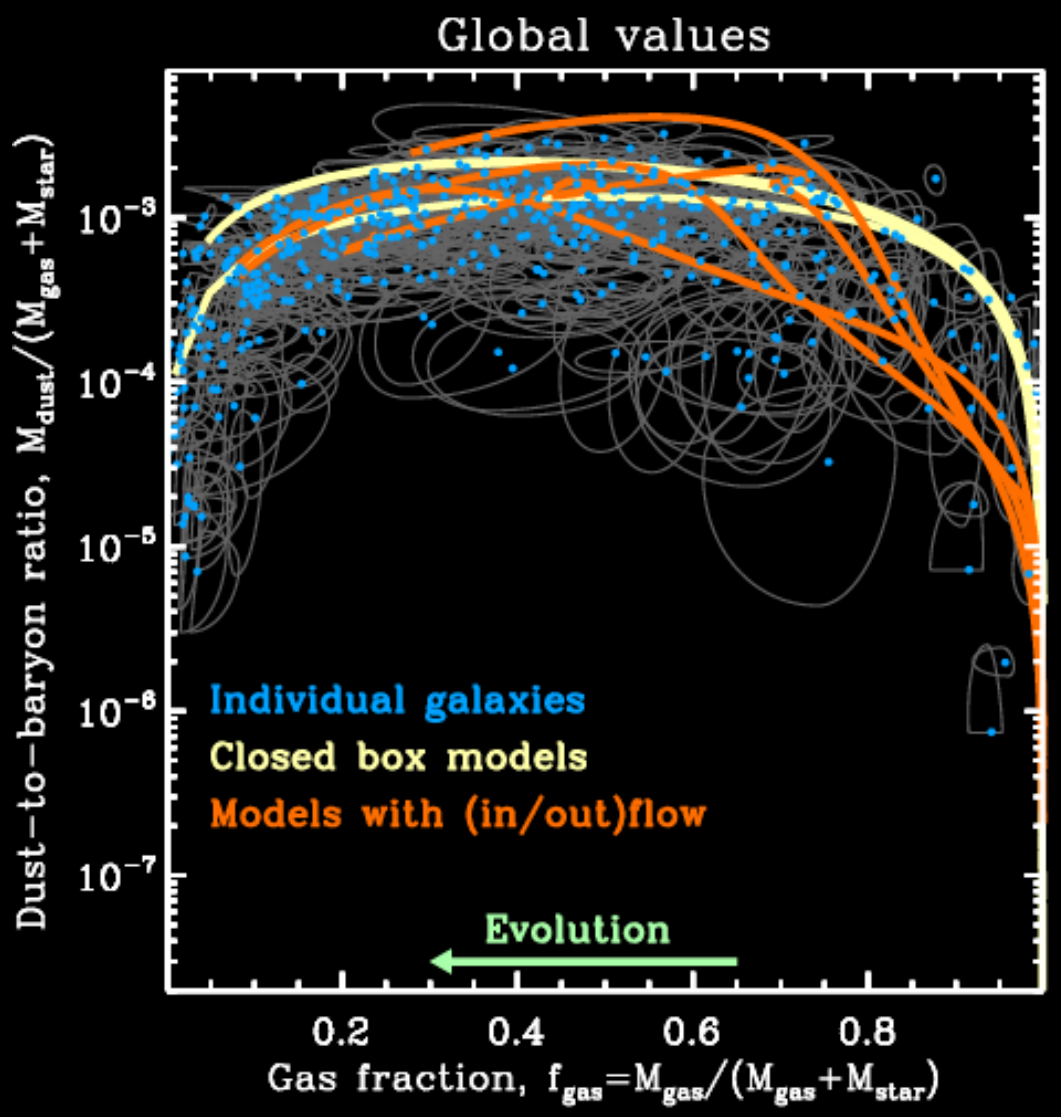

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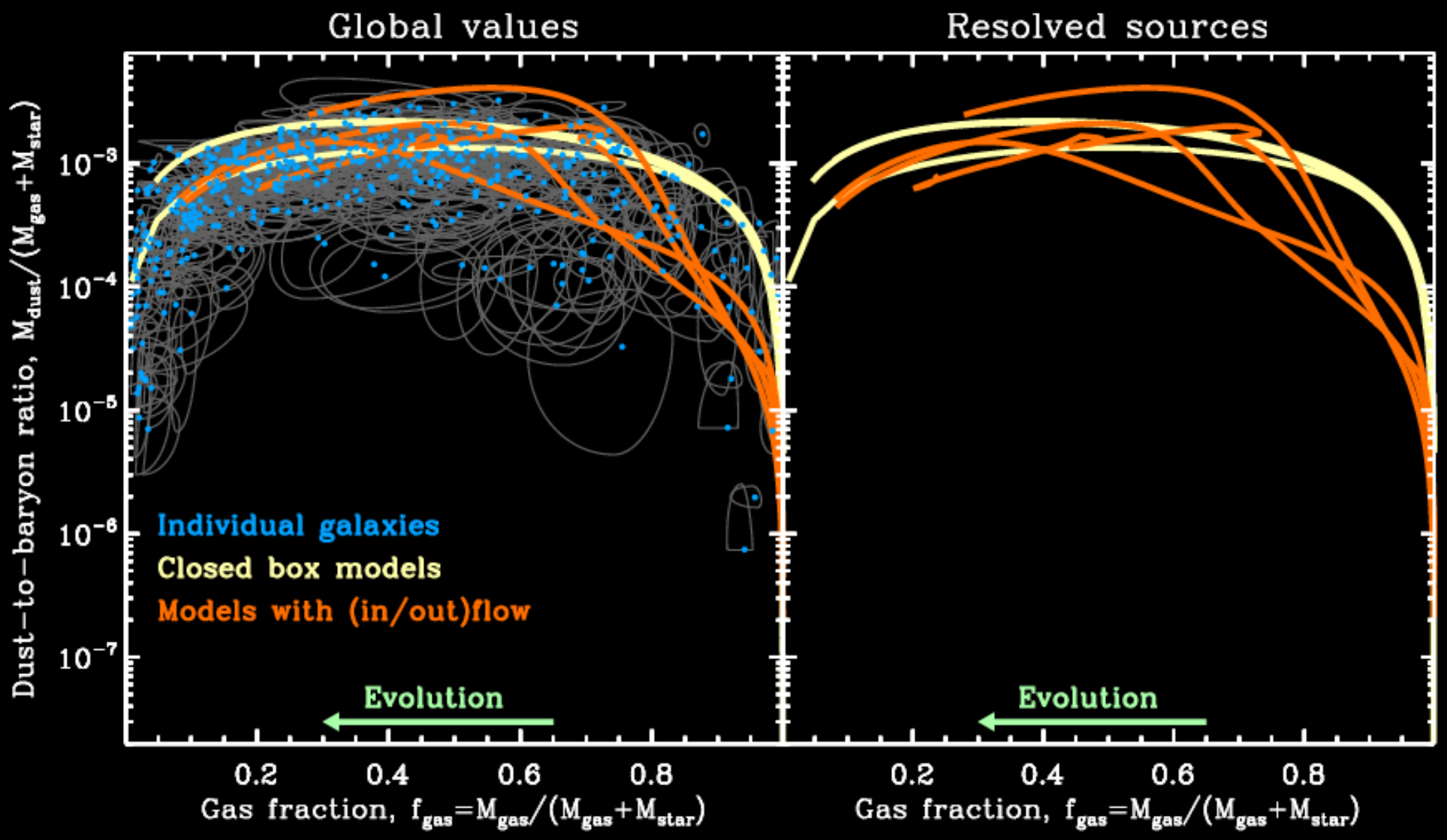

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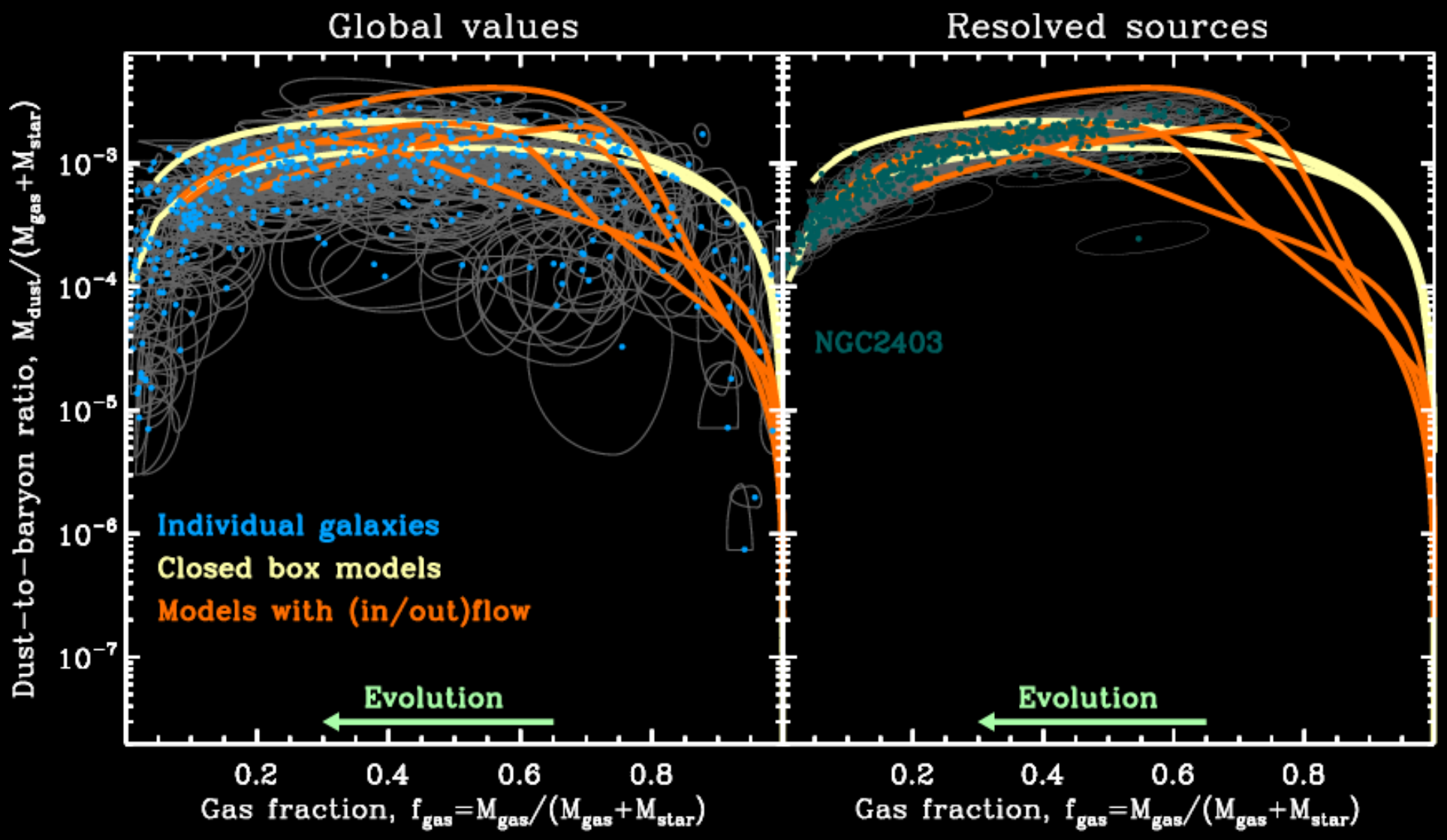

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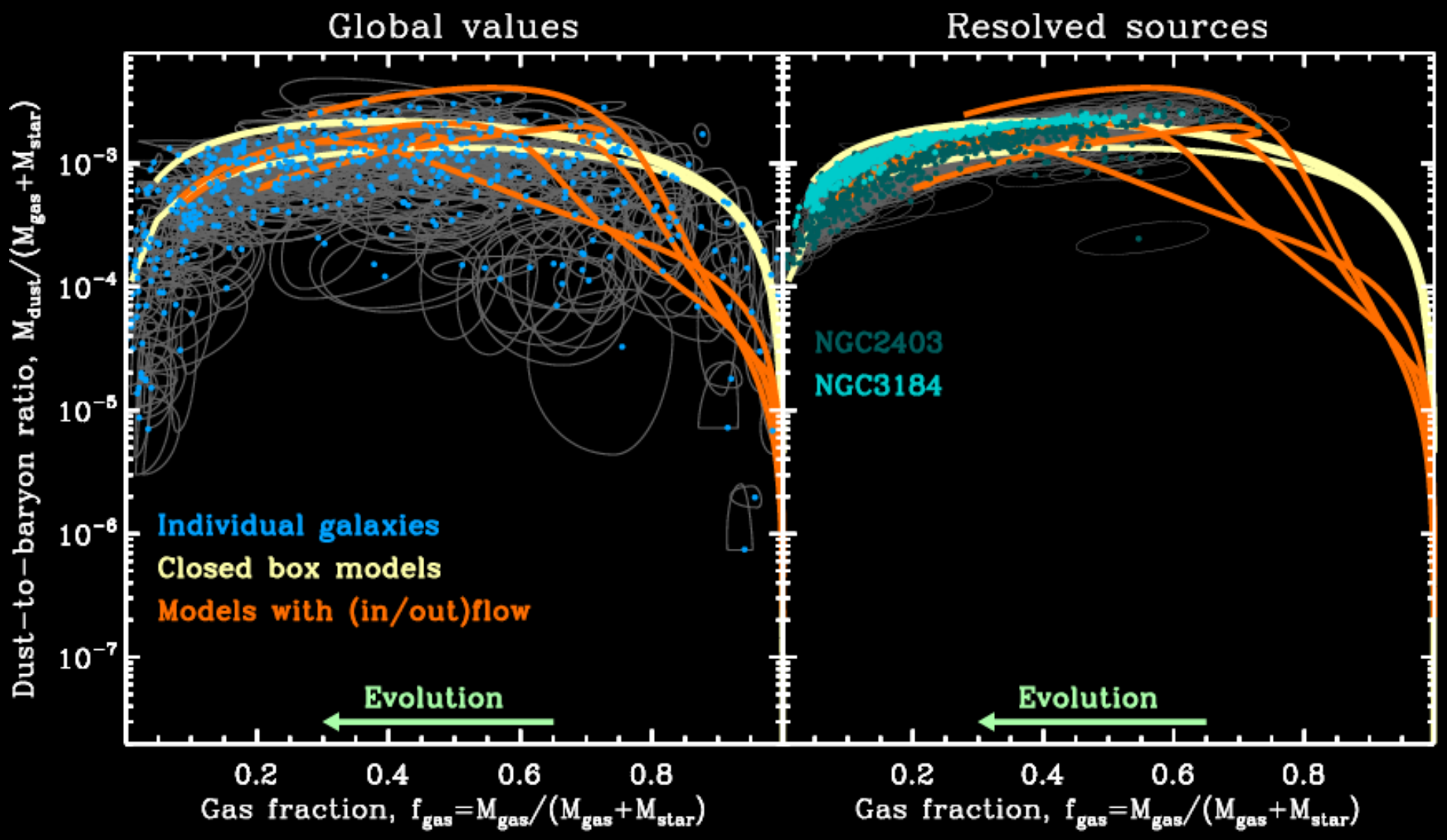

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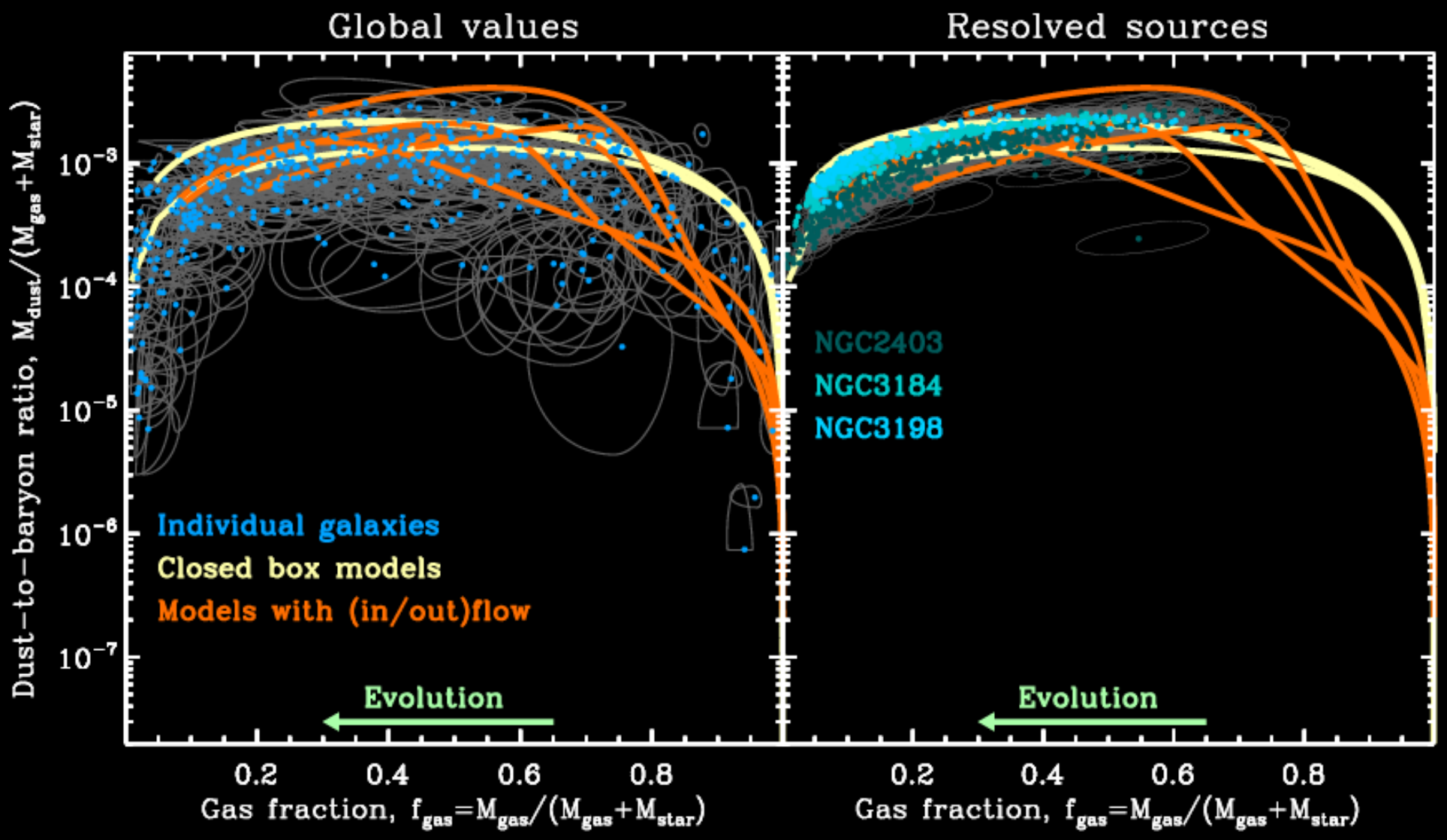

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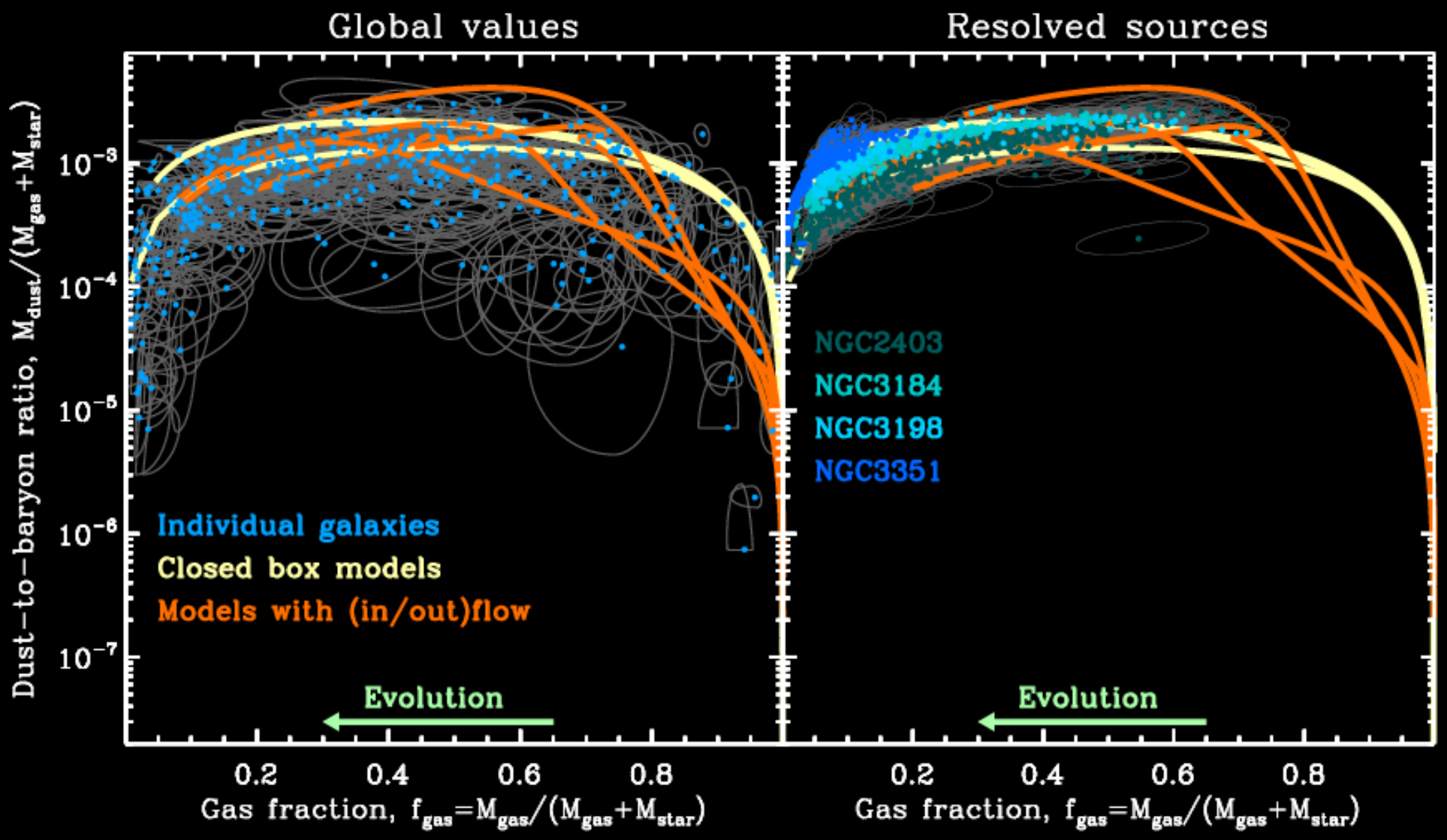
Dust Mass Build-Up & Astration in Galaxies



DustPedia sample (Galliano *et al.*, *in prep.*)
(Dust evolution tracks by De Vis *et al.*, 2017b)

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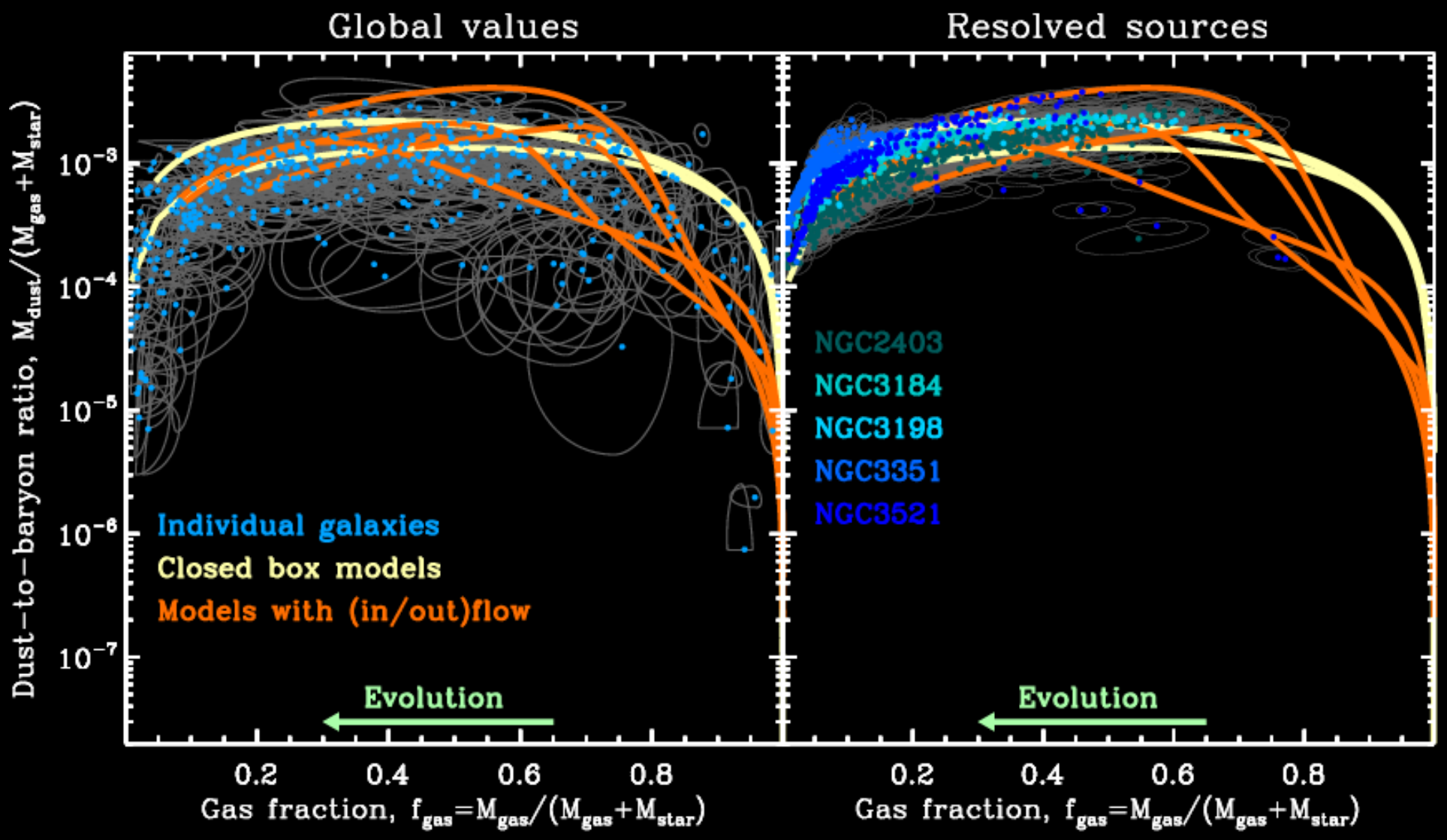

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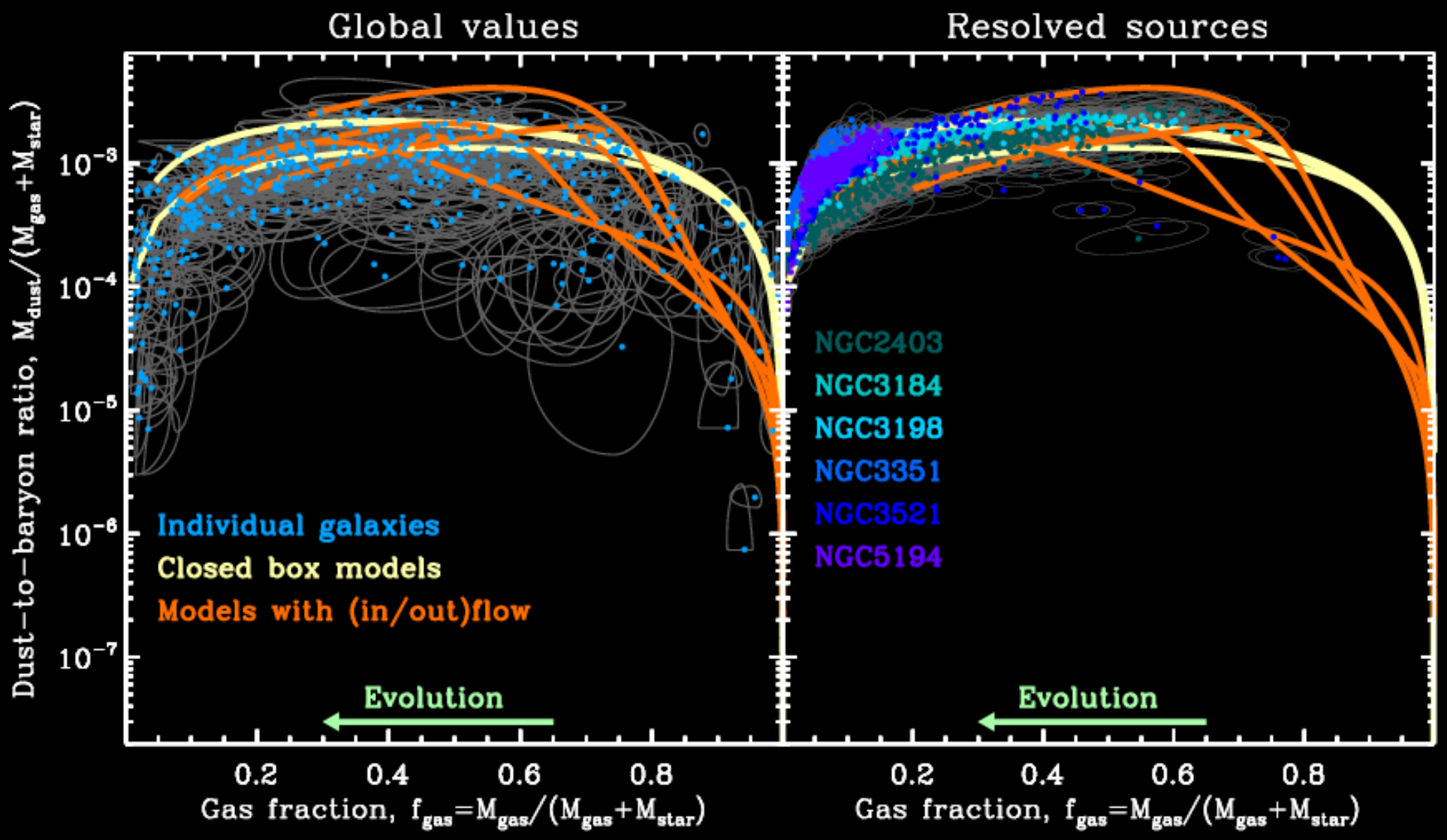

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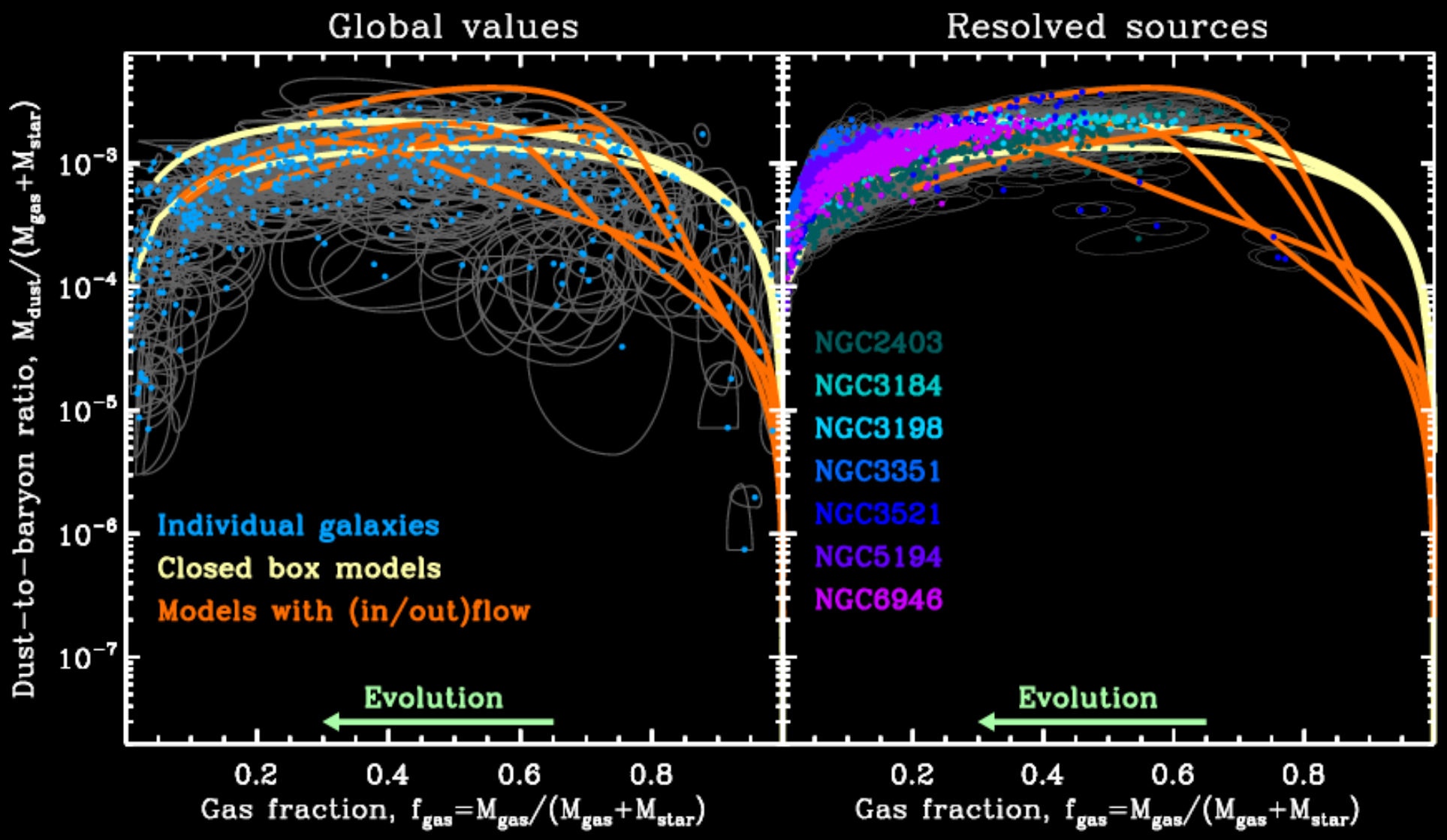

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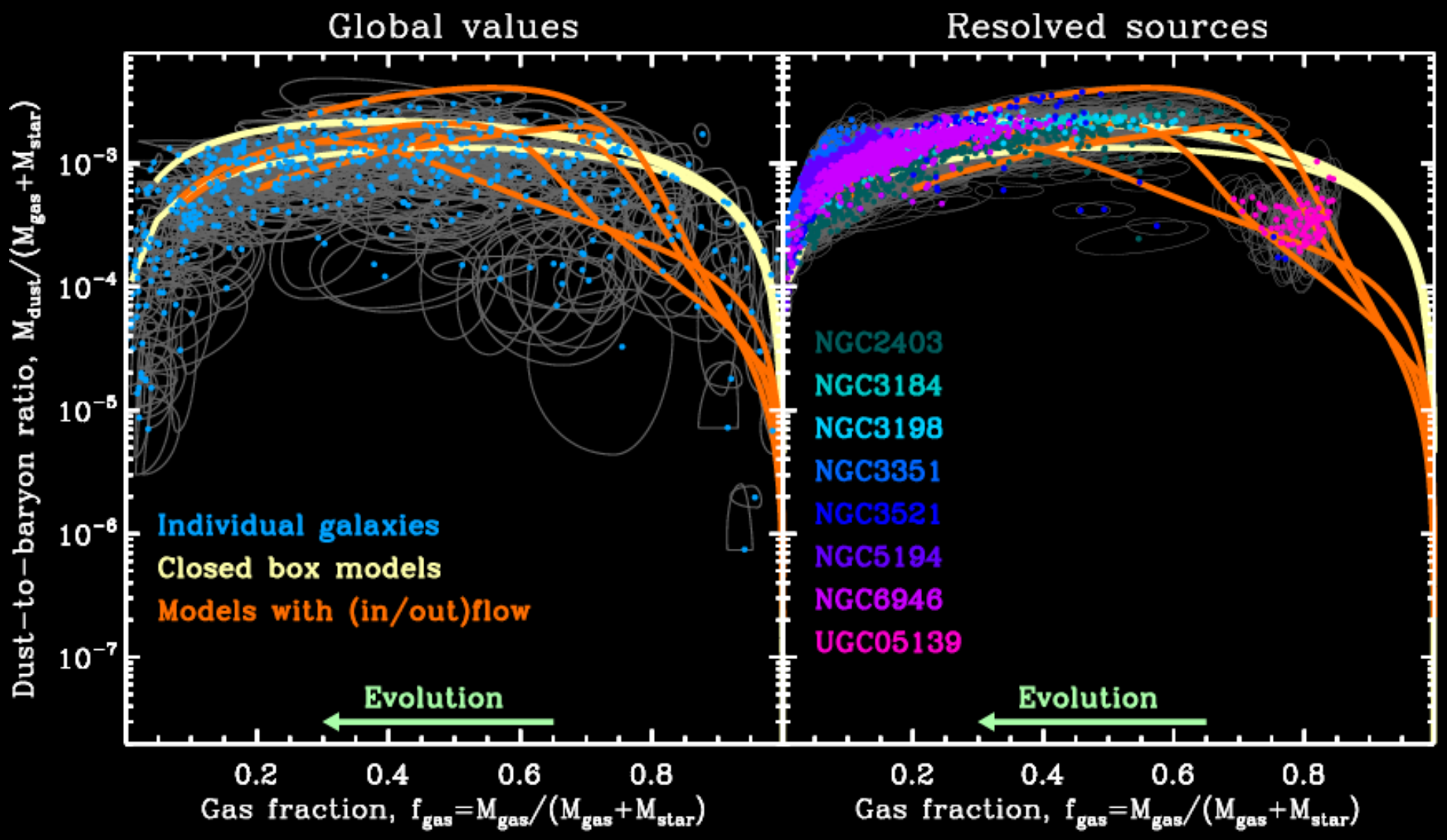

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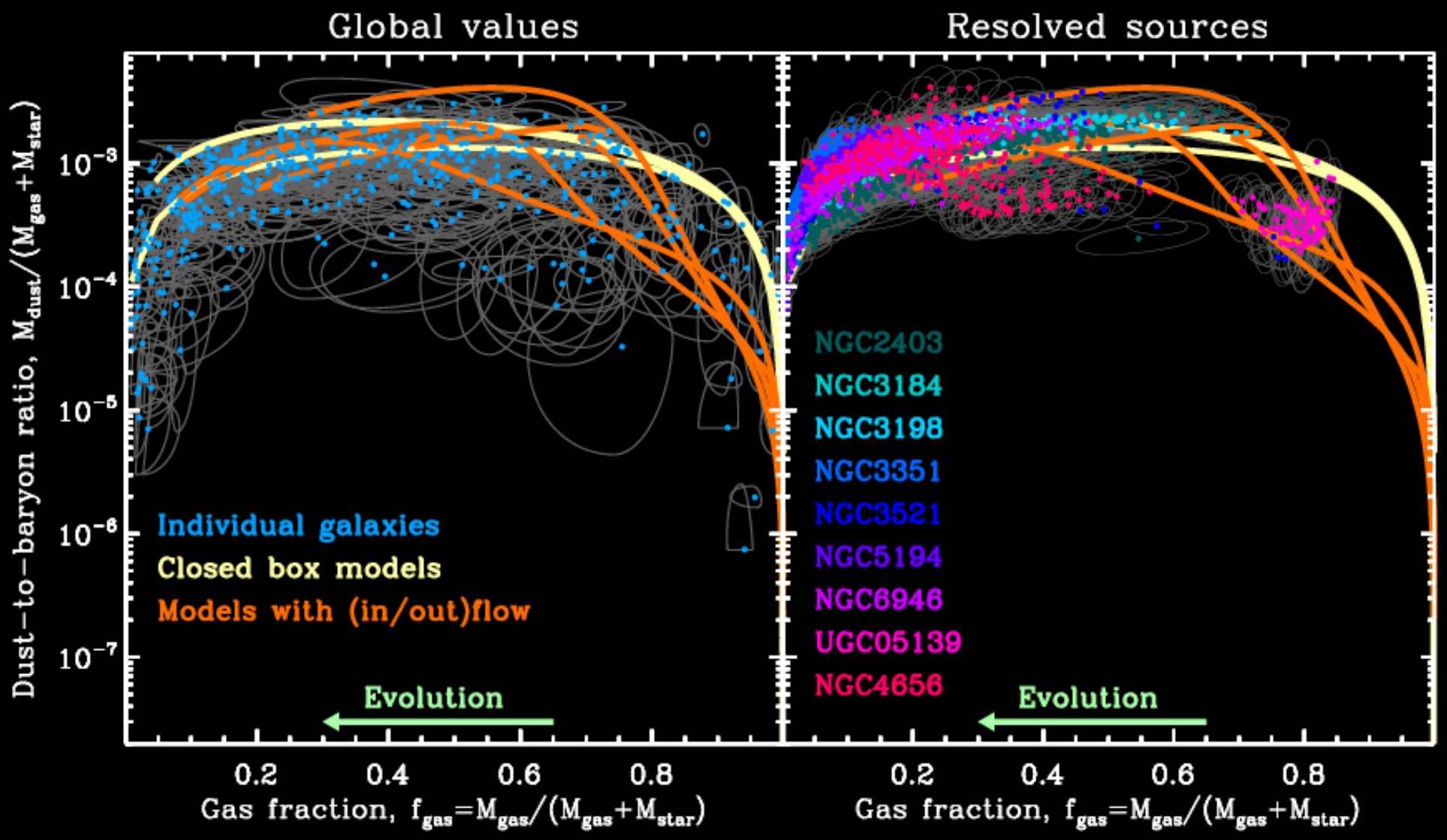

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Outline of the Talk

Conclusion & Prospectives

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Benchmarking Summary

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