Black bodies but not black boxes
Variations on fitting dust SEDs

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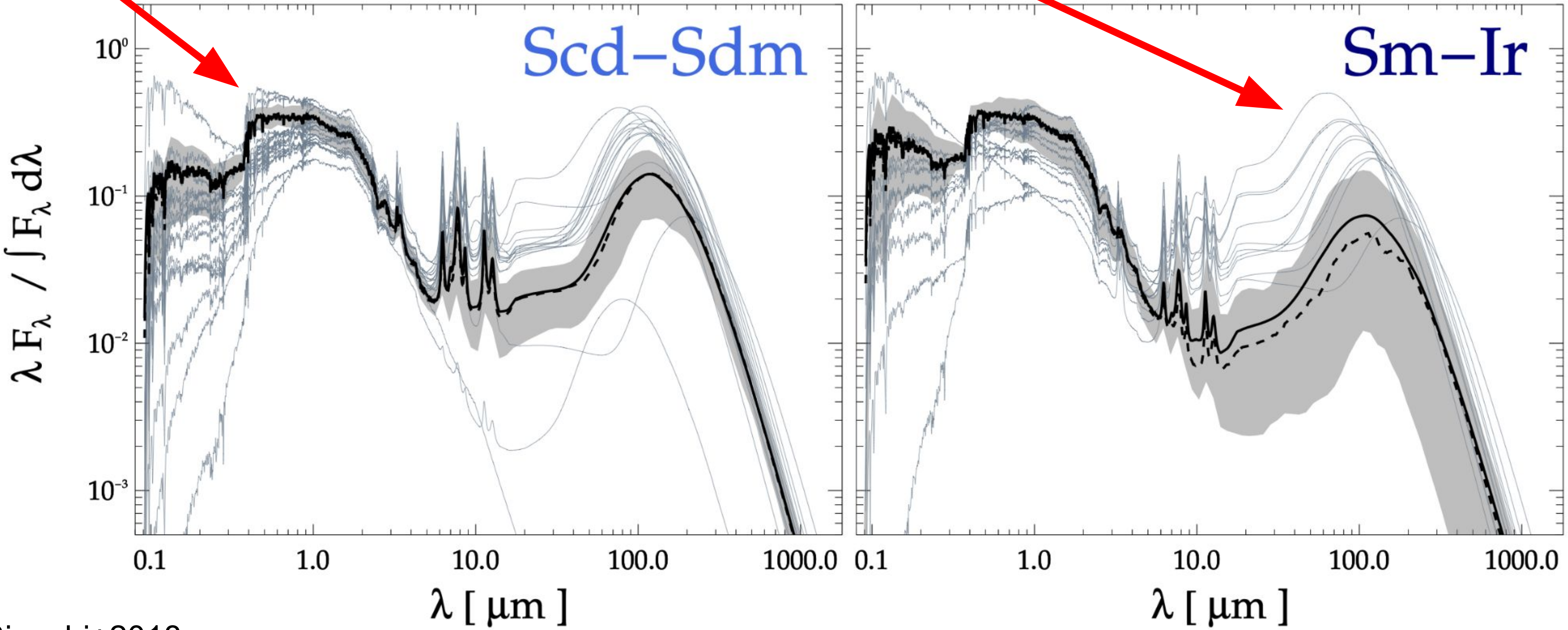
<u>Supervisors:</u> Annie Hughes *and* Frédéric Galliano

Credit: GLIMPSE survey

Motivation

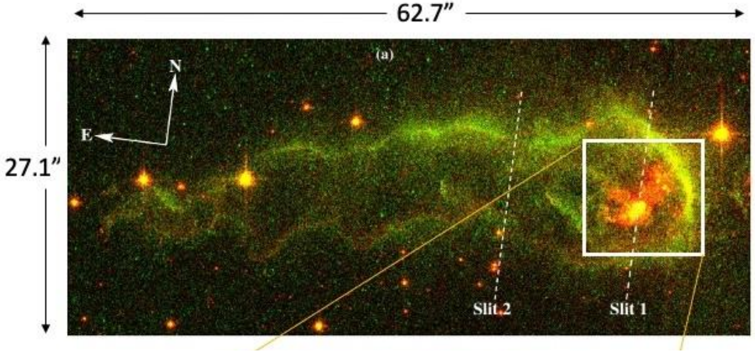
Starlight gets absorbed and re-emitted in the FIR



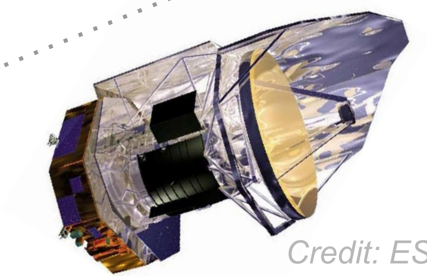
Bianchi+2018

Motivation

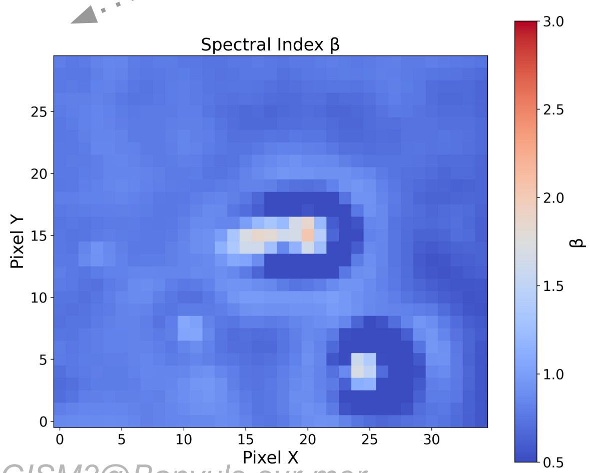
Allows to infer physical properties

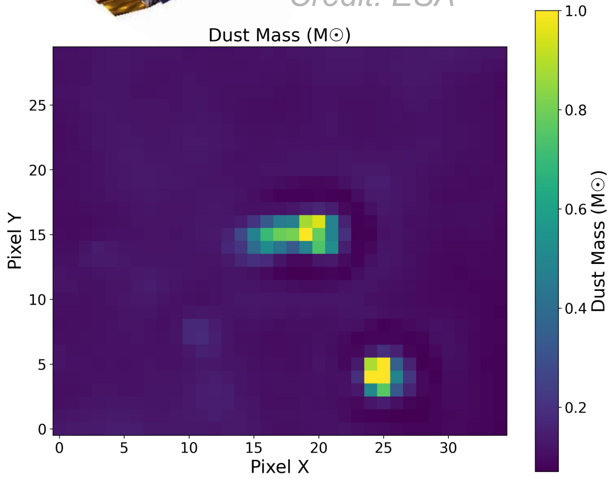


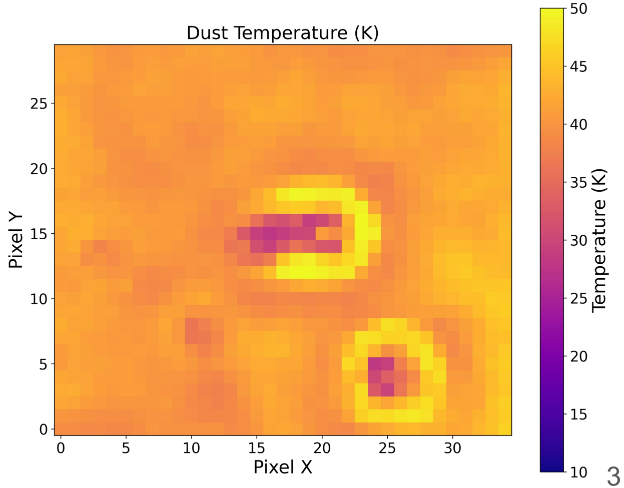
‘Proplyd’, Sahai+2012



Credit: ESA







Modified black body model

Modified black body

$L_v(\lambda)$ = $M_{dust} \times 4\pi\kappa_0\left(\frac{\lambda_0}{\lambda}\right)^\beta \times B_v(\lambda, T)$

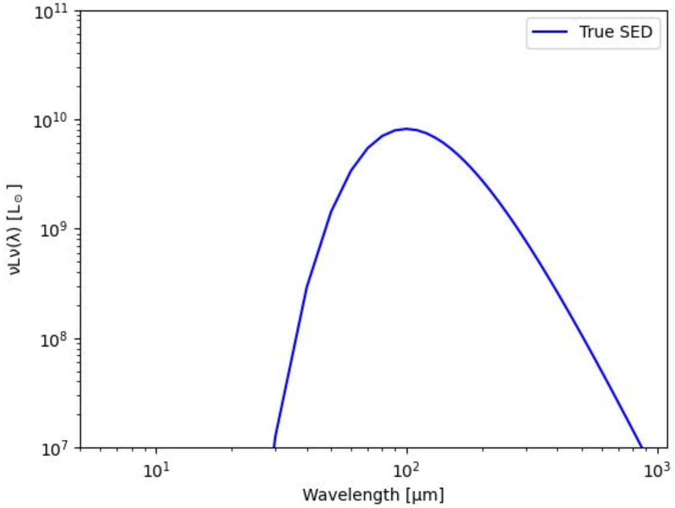
$B_v(\lambda, T) = \frac{2hc}{\lambda^3}\frac{1}{e^{\frac{hc}{\lambda kT}}-1}$

the opacity as a power-law

$\kappa_{abs}(\lambda) = \kappa_0\left(\frac{\lambda_0}{\lambda}\right)^\beta$

e.g.

κ_0 = 0.64 m^2/kg, $\beta = 1.79$, $M_{dust} = 10^7 M_\odot$, T_{dust}= 25 K



Modified black body model

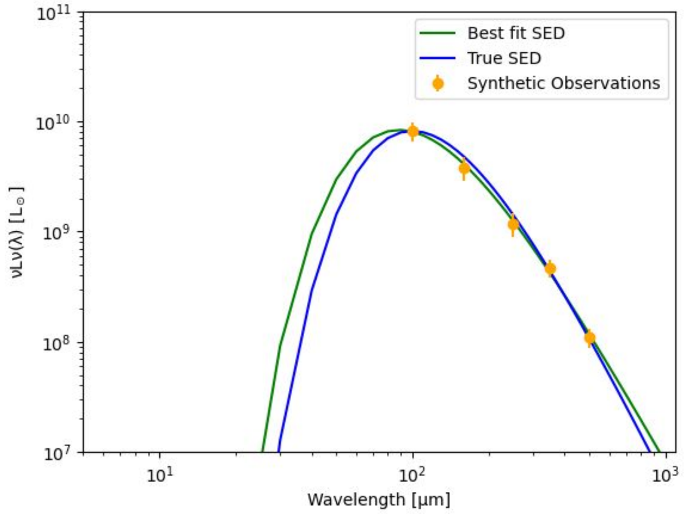
data point:

100 µm, 160 µm, 250 µm, 350 µm, 500 µm

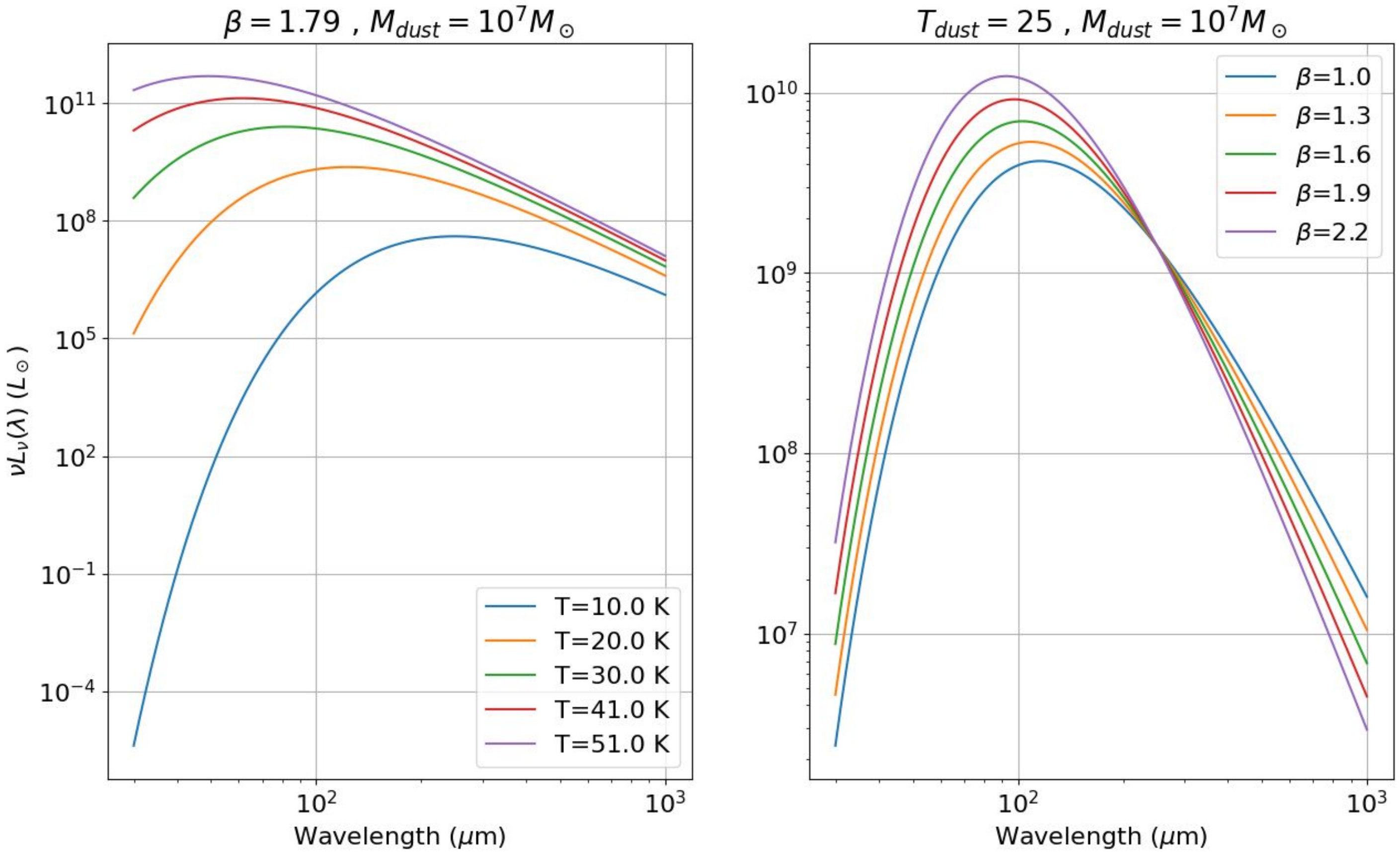
with gaussain noise added S/N = 5

Assume a multivariate Gaussian distribution of parameters, assuming no correlations:

$$\langle \log M_{\rm dust} \rangle = 7,\ \sigma(\log M_{\rm dust}) = 0.2;$$
$$\langle \log T_{\rm dust} \rangle = \log 25,\ \sigma(\log T_{\rm dust}) = 0.1;$$
$$\langle \beta \rangle = 1.79,\ \sigma(\beta) = 0.1.$$



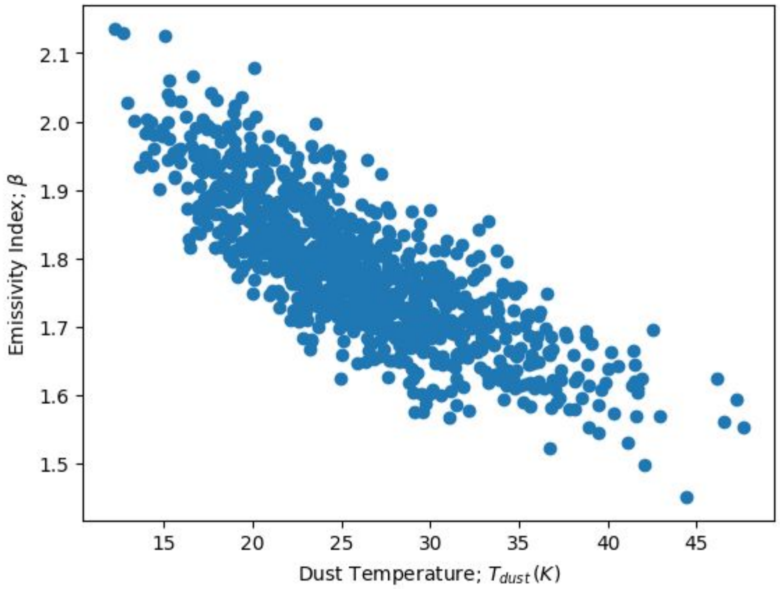
Modified black body model



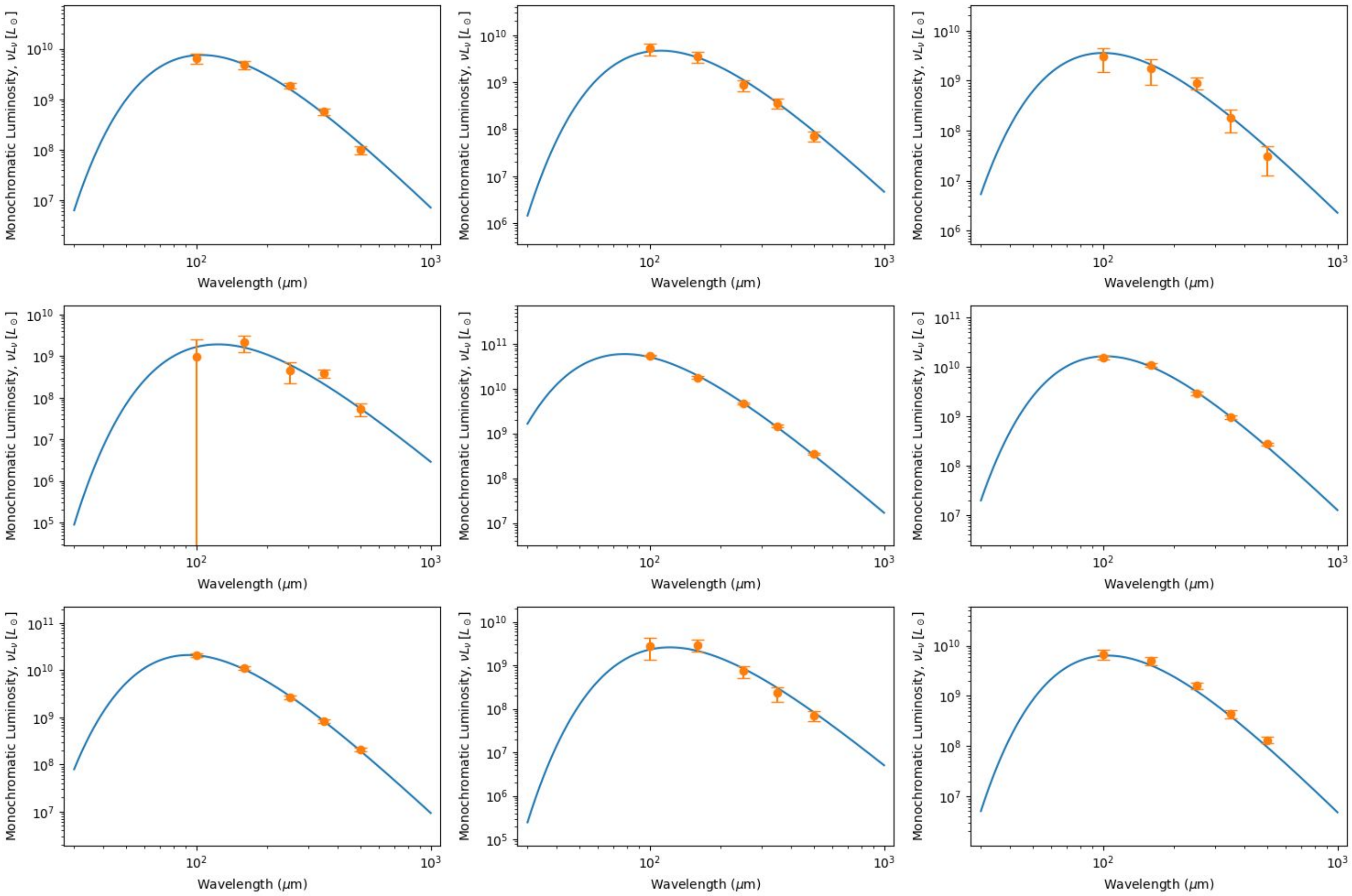
The effect of correlated parameters

assuming correlations between the parameters:

$$\begin{aligned}\rho(\log M_{\mathrm{dust}}, \log T_{\mathrm{dust}}) &= -0.5\\ \rho(\log T_{\mathrm{dust}}, \beta) &= -0.8\\ \rho(\log M_{\mathrm{dust}}, \beta) &= 0\end{aligned}$$



(Optimized) least-squares fitting



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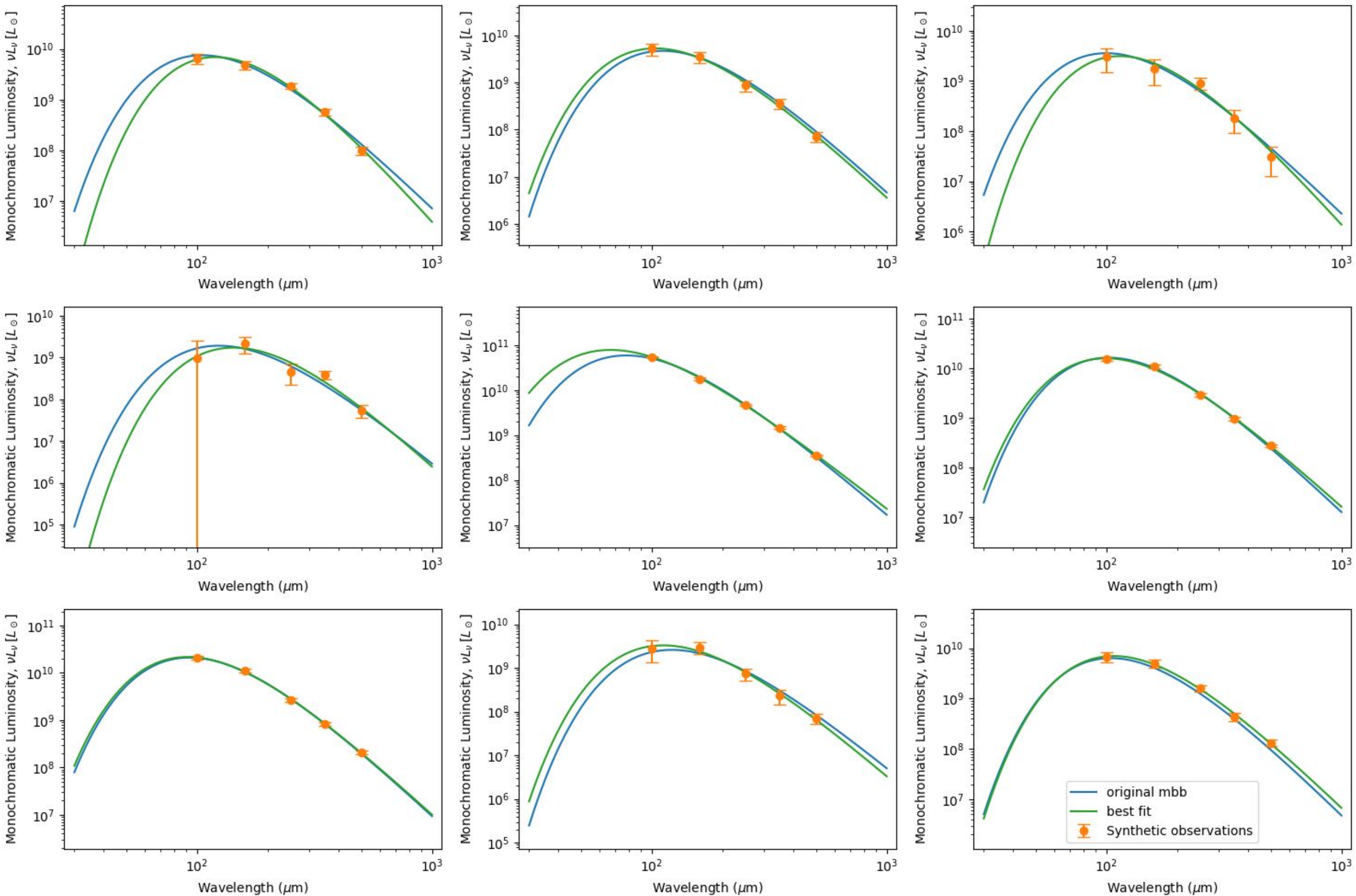
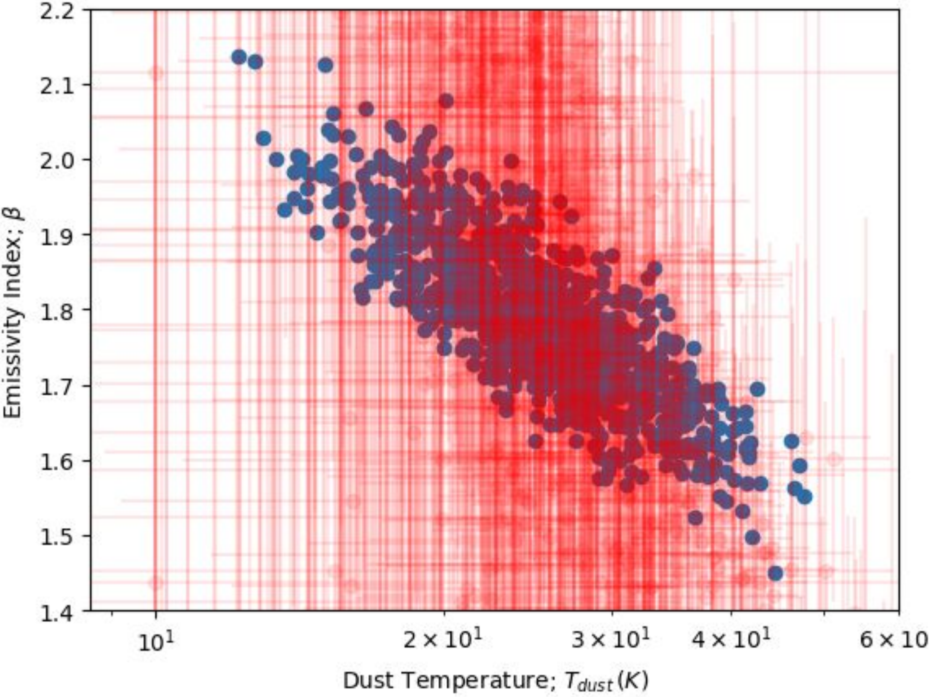
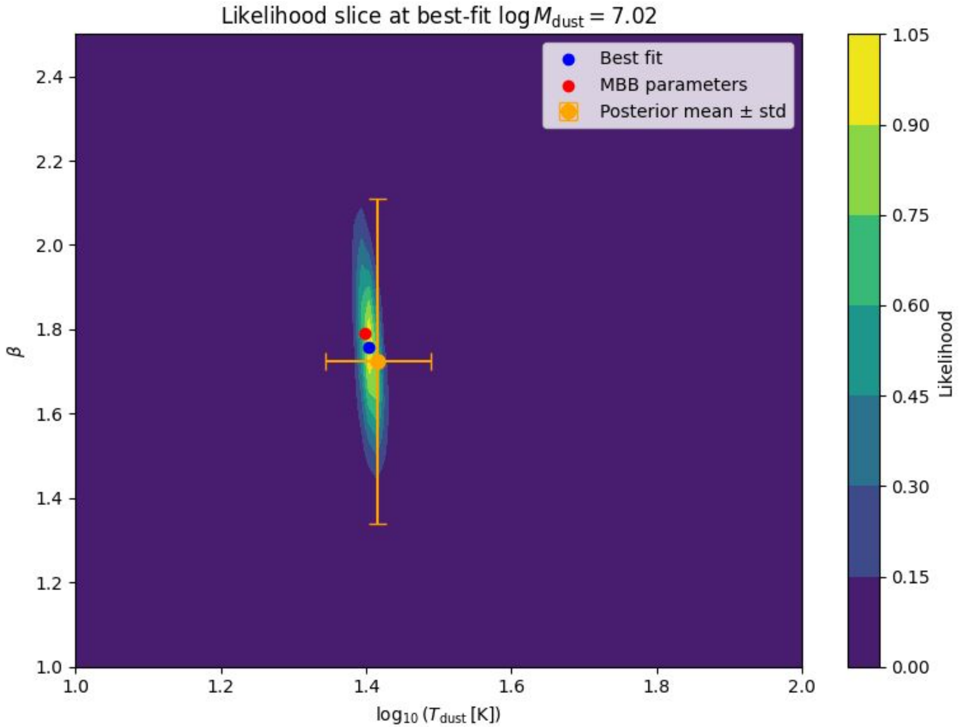
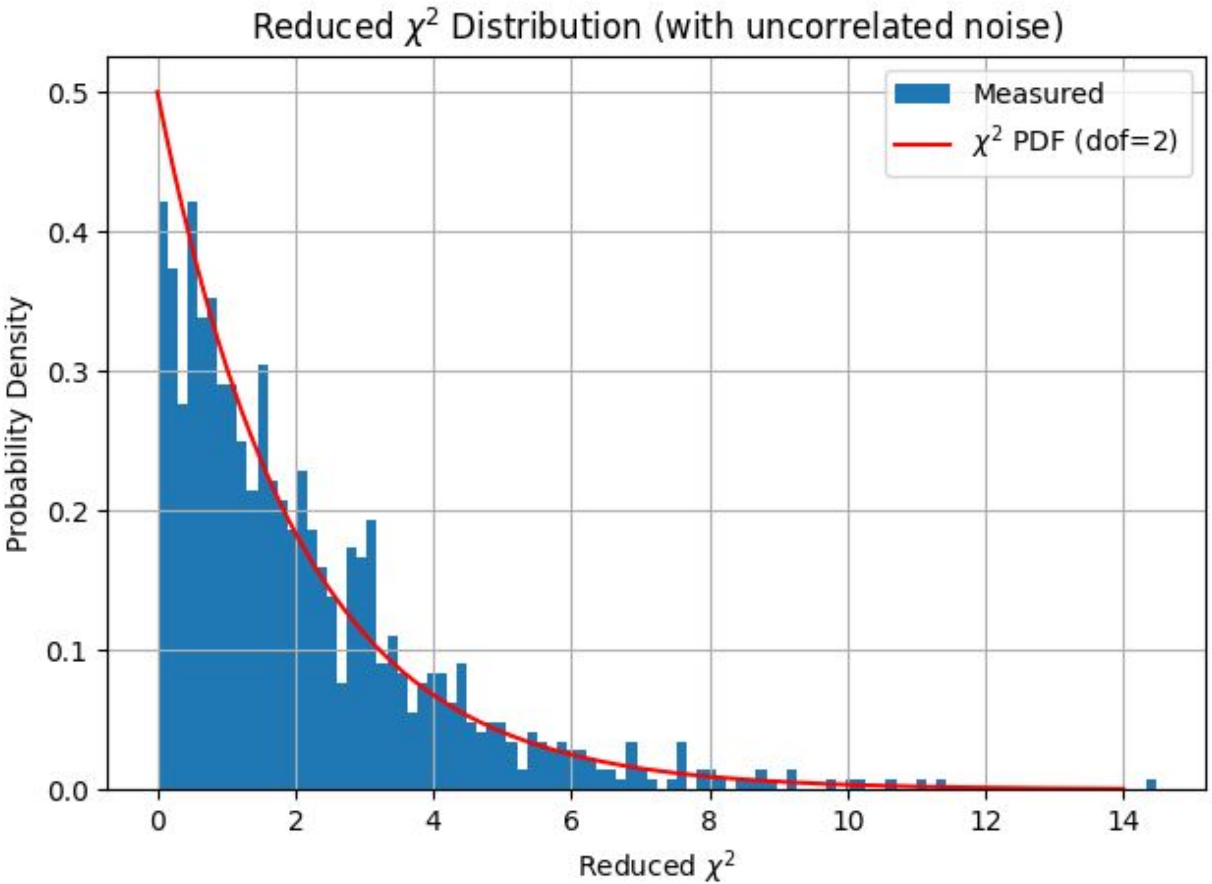


The distribution of fitted parameters





The reduced χ^2 distribution



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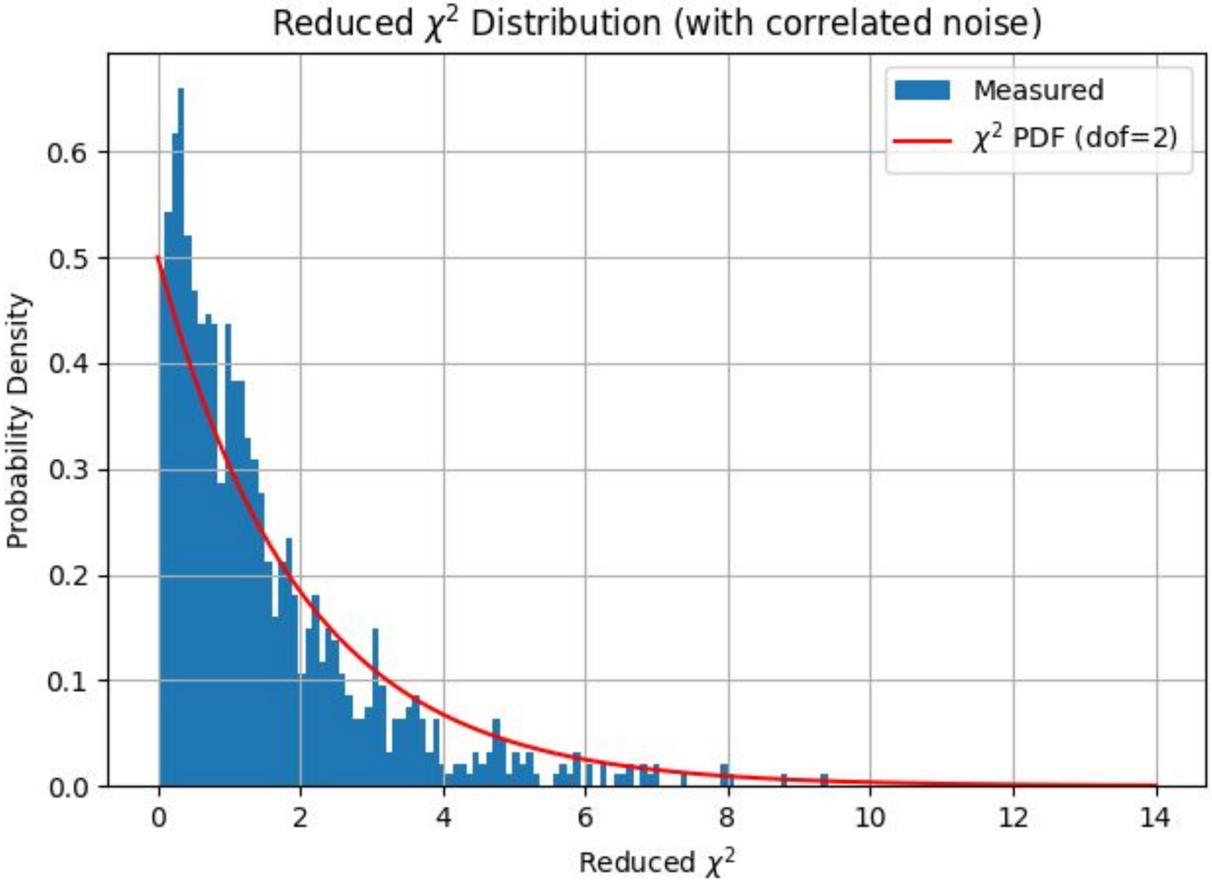


DustEM (physical ISM dust models)

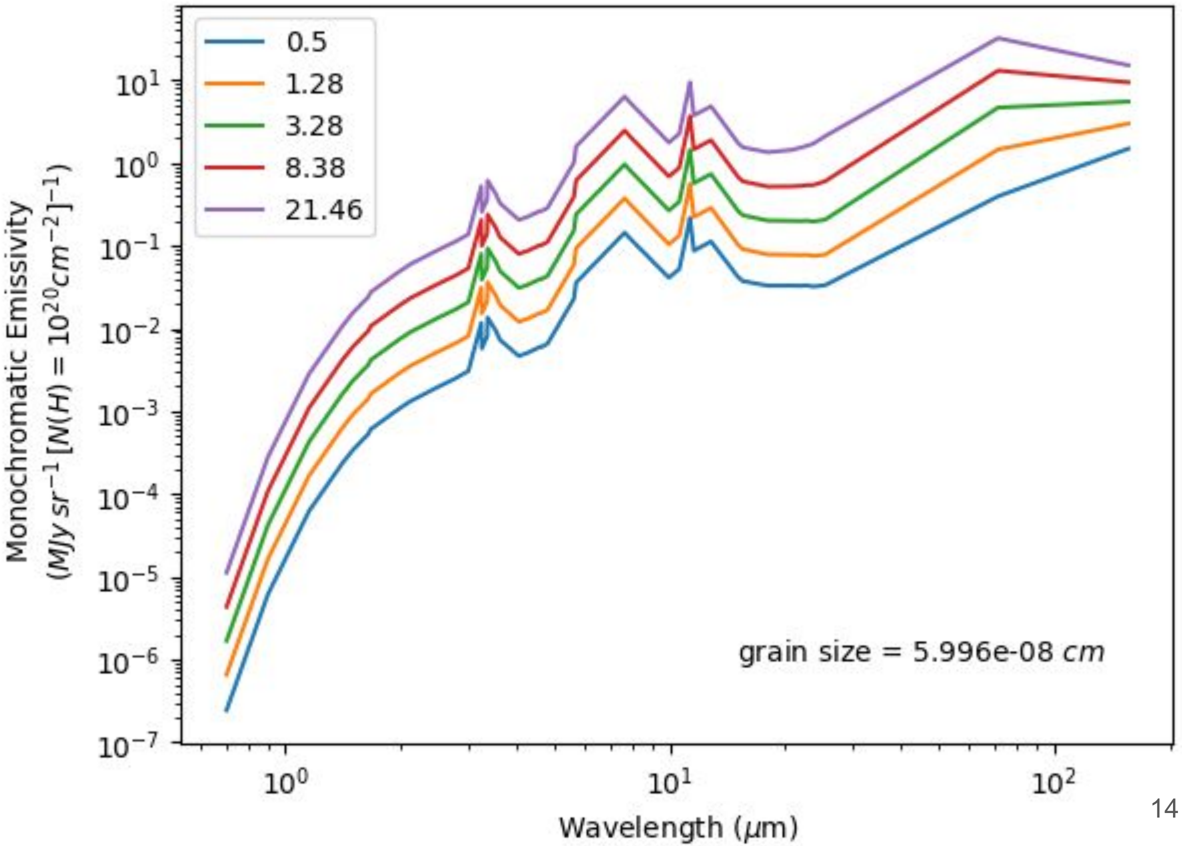
Parameters

1. multiple radiation fields (intensity/hardness)
2. multiple dust grain types (size distributions/abundances)
3. add other processes (free-free/synchrotron)

DustEM (physical ISM dust models)

Some examples
minimum grain size
vs.
radiation field
strength

(change radiation
field strength)



DustEM (physical ISM dust models)

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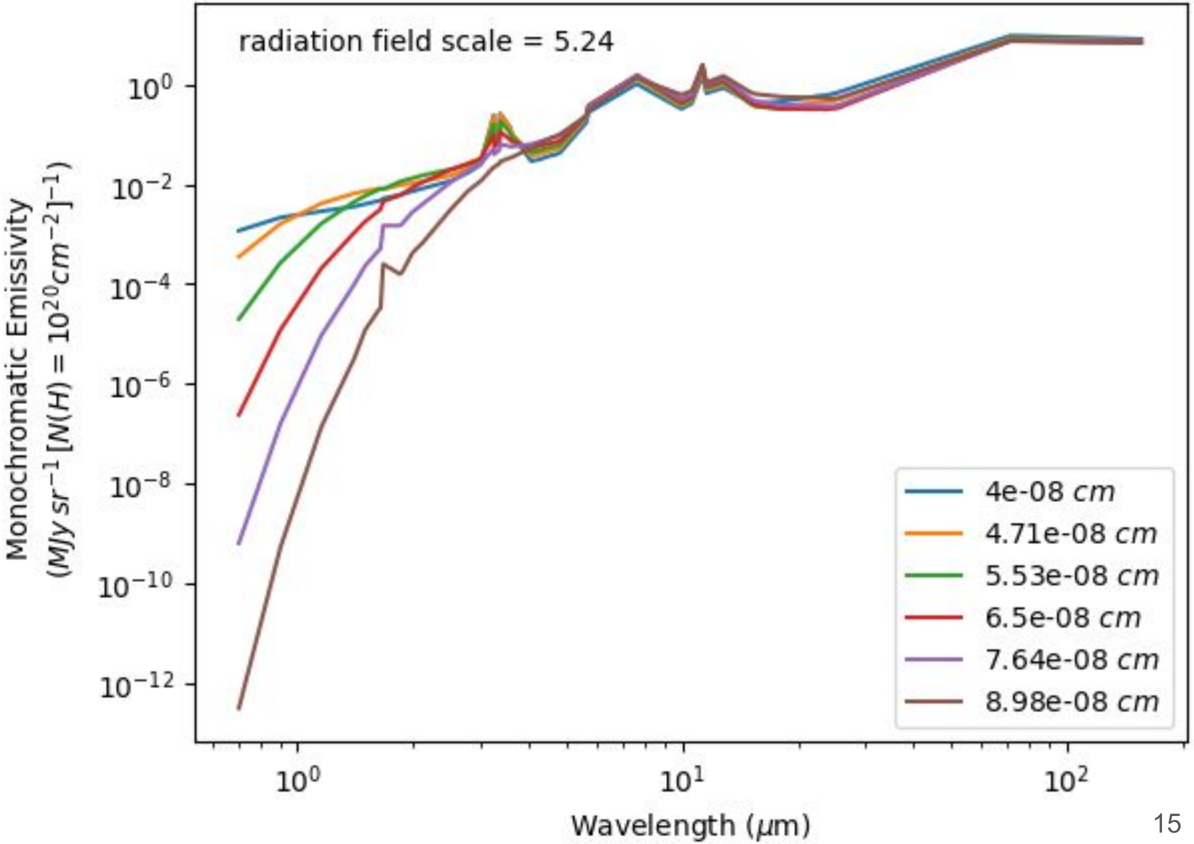
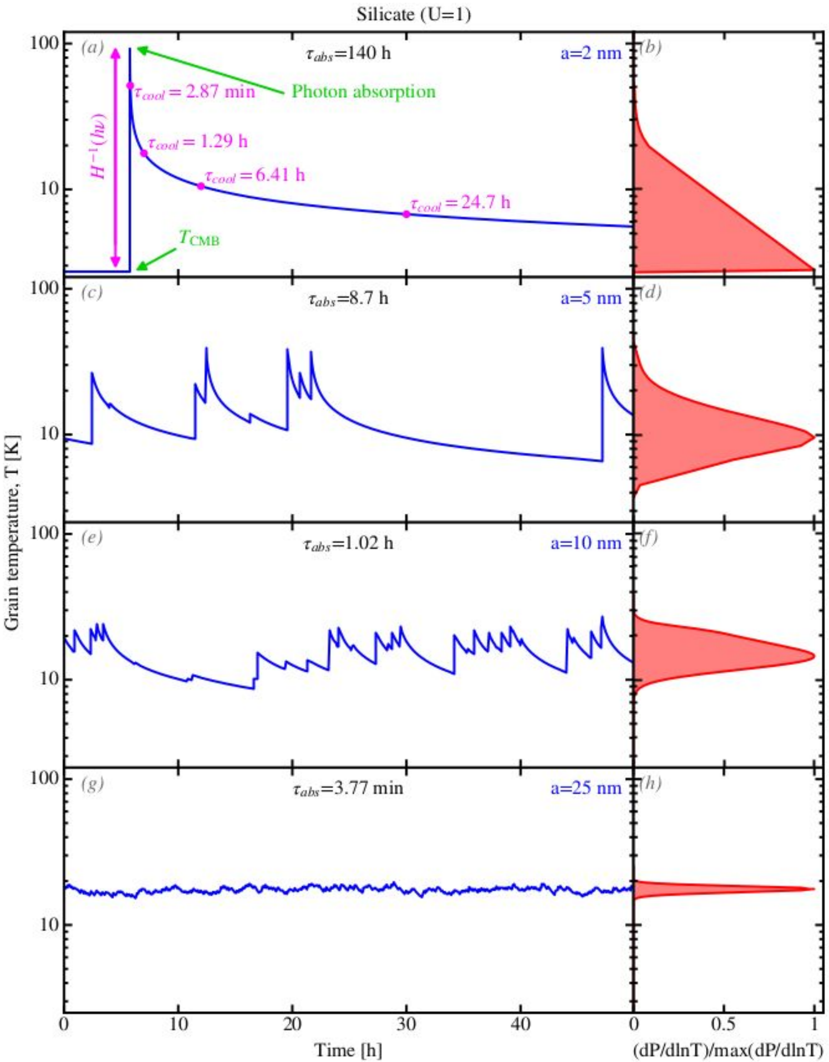


DustEM (physical ISM dust models)

Why the drop at high frequency?

DustEM ... odels)

Why the drop a



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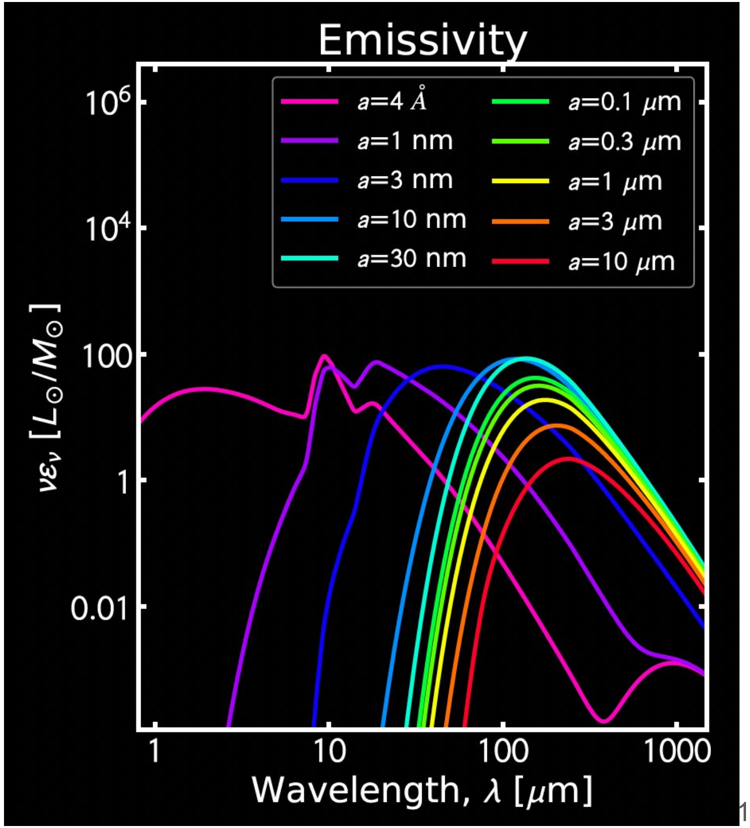
Why the drop at high frequency?



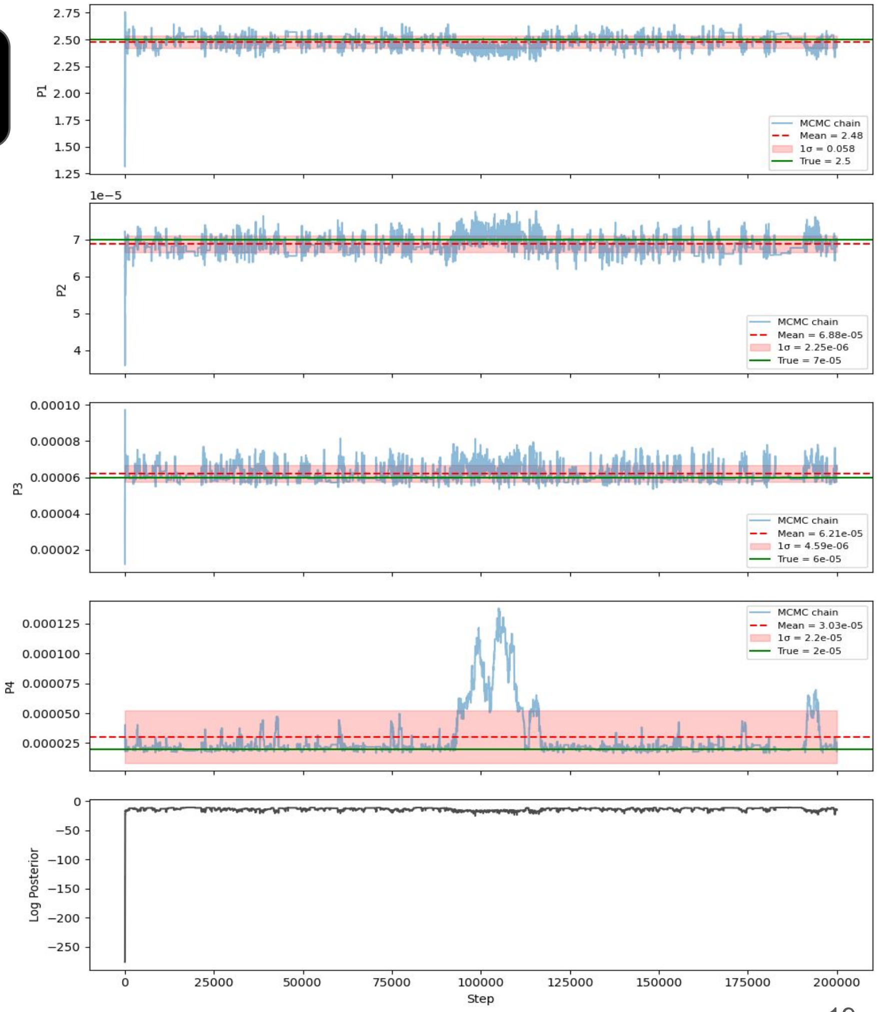
Solving with MCMC- Bayesian approach

Bayes theorem: $P(\theta|D) \propto P(D|\theta) * P(\theta)$

Tested on a MBB SED model before

Applications to Dust SED Models

- likelihood: from the interpolated SED model
- prior: uniform distribution
- sampler: Metropolis-Hastings



MCMC chains for Dust SED model parameters

Conclusions

- The MBB model can effectively describe the shape of the FIR dust slope.
- Degeneracies between model parameters can be easily explored in a Bayesian framework, given that one carefully accounts for the effect of noise.
- Radiation field and grain size can have a major effect on the shape of the SED.