ISSI AtomicHelioStatistics Collaboration

Can we deal with Atomic Data Uncertainties?*

Vinay Kashyap

ISSI AtomicHelioStatistics Collaboration

Can we deal with Atomic Data Uncertainties?*

Vinay Kashyap

*Beware of Betteridge's Law

ISSIAHS Collaboration

International Space Science Institute — Atomic, Heliophysics, and Statistics

To incorporate atomic data uncertainties and statistical uncertainties in estimates of parameters that define coronal structure.

Harry Warren (NRL; PI), *Adam Foster* (CfA), Chloe Guennou (Columbia), *Connor Ballance* (Queen's Univ), *David Stenning* (Imperial), *David van Dyk* (Imperial), Fabio Reale (OAPA, Palermo), Frederic Auchere (Inst. Astr. Spatiale), *Giulio Del Zanna* (Cambridge), Inigo Arregui (Inst. Astr. de Canarias), *Jessi Cisweski* (Yale), Mark Weber (CfA), *Nathan Stein* (Spotify), *Randall Smith* (CfA), Veronique Delouille (Royal Obs. Belgium), Vinay Kashyap (CfA), and *Xixi Yu* (Imperial)

Atomic Data Uncertainties

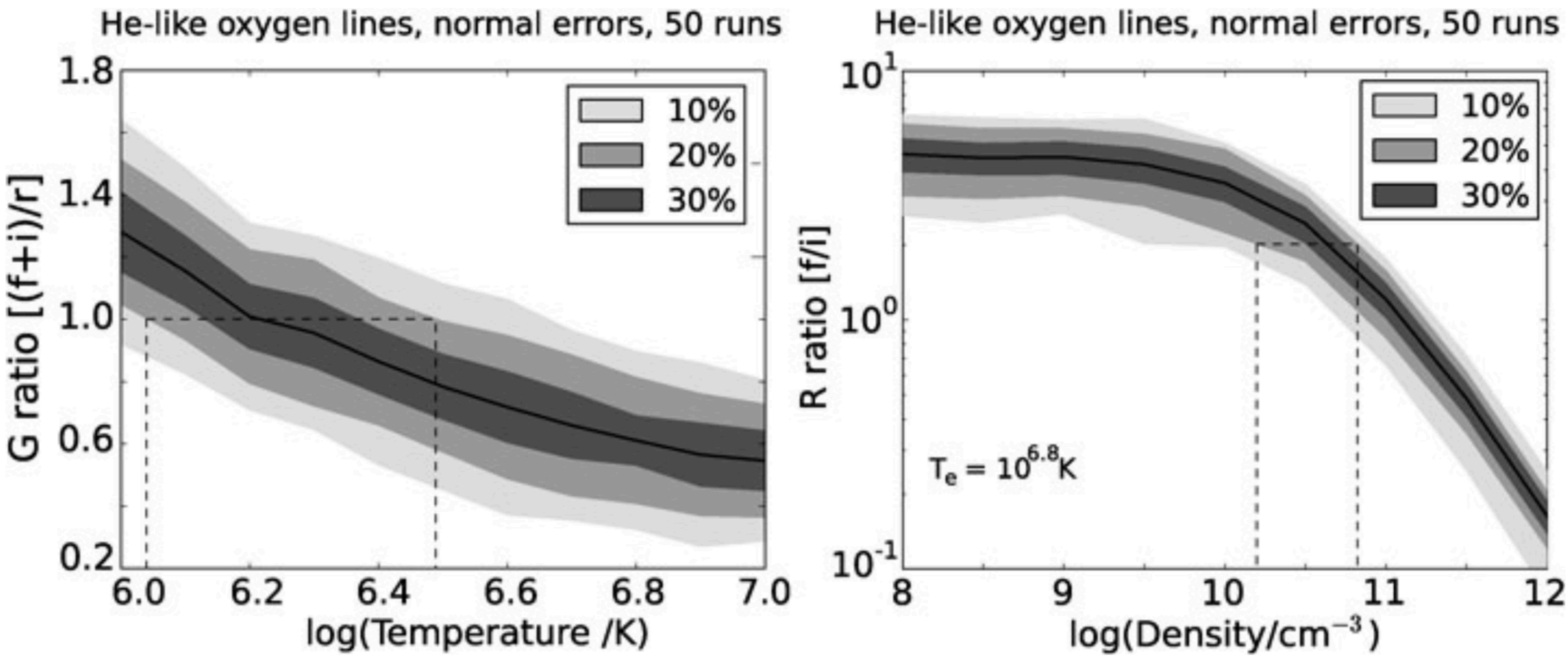


Fig. 9 The effect of normally distributed uncertainties of 10, 20 and 30% on the O VII $G(T_e)$ and $R(N_e)$ ratios. *Highlighted* is the effect of a 20% uncertainty in collision strengths: when $G = 1.0$, the temperature lies in the range $1.1 \times 10^6 < T_e < 3.2 \times 10^6$, while for $R = 2.0$ the density range is $1.5 \times 10^{10} < N_e < 7.1 \times 10^{10}$

Foster et al. 2010, SpSciRev 157, 135-154

Toy Problem

Toy Problem

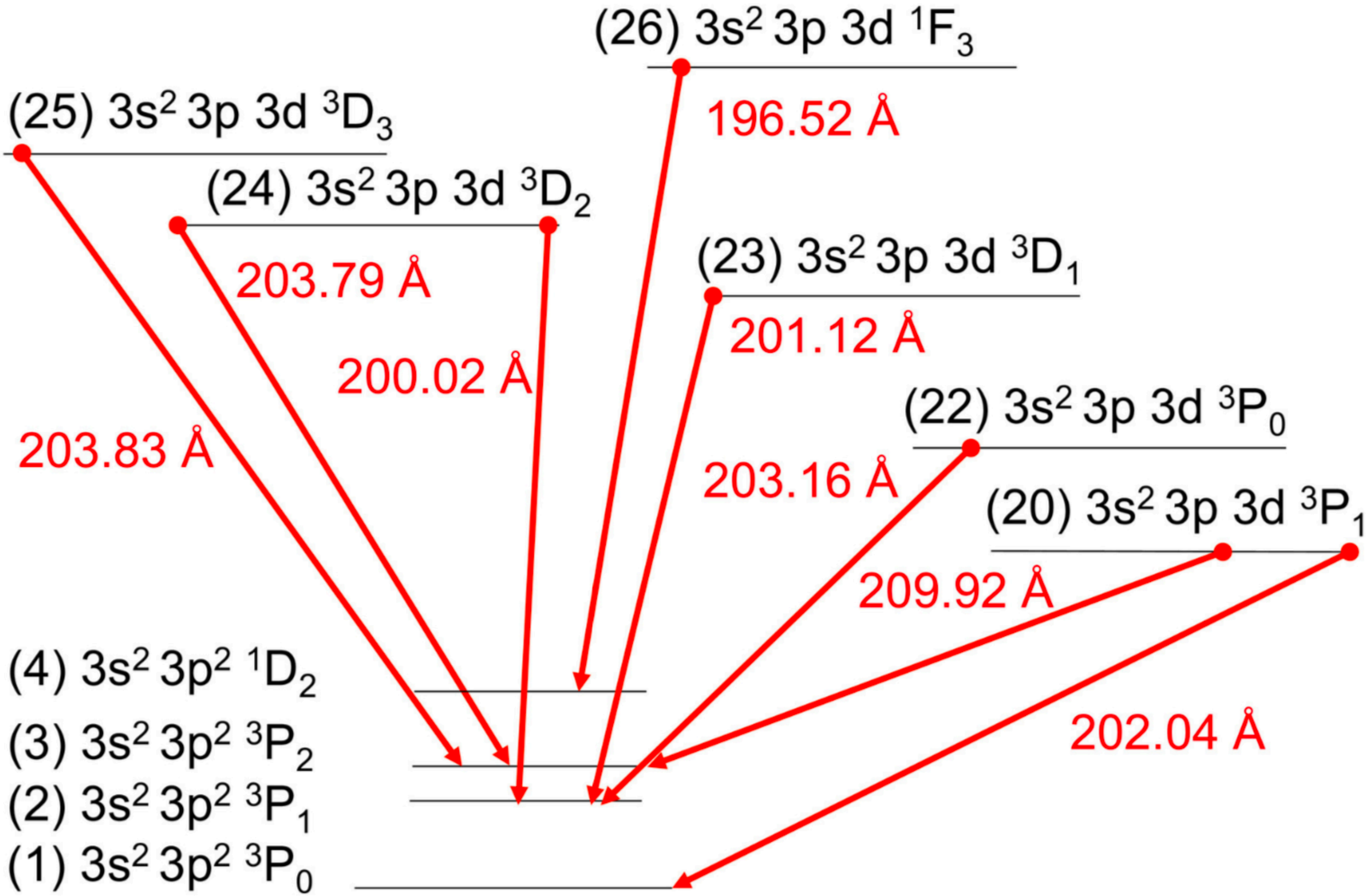
- Ultimate goal is to compute DEM($n_e(T_e)$,T_e,Z)

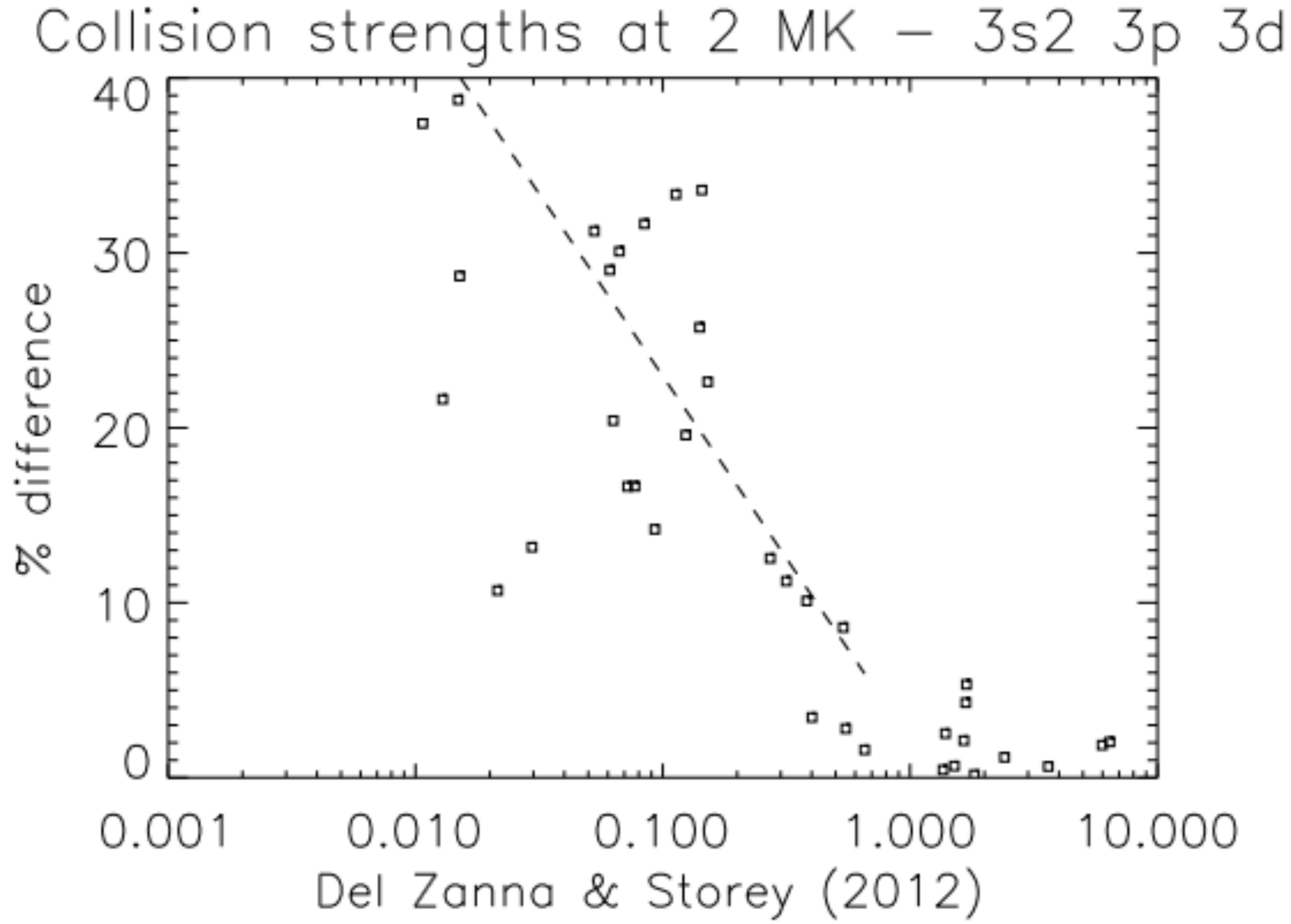
Toy Problem

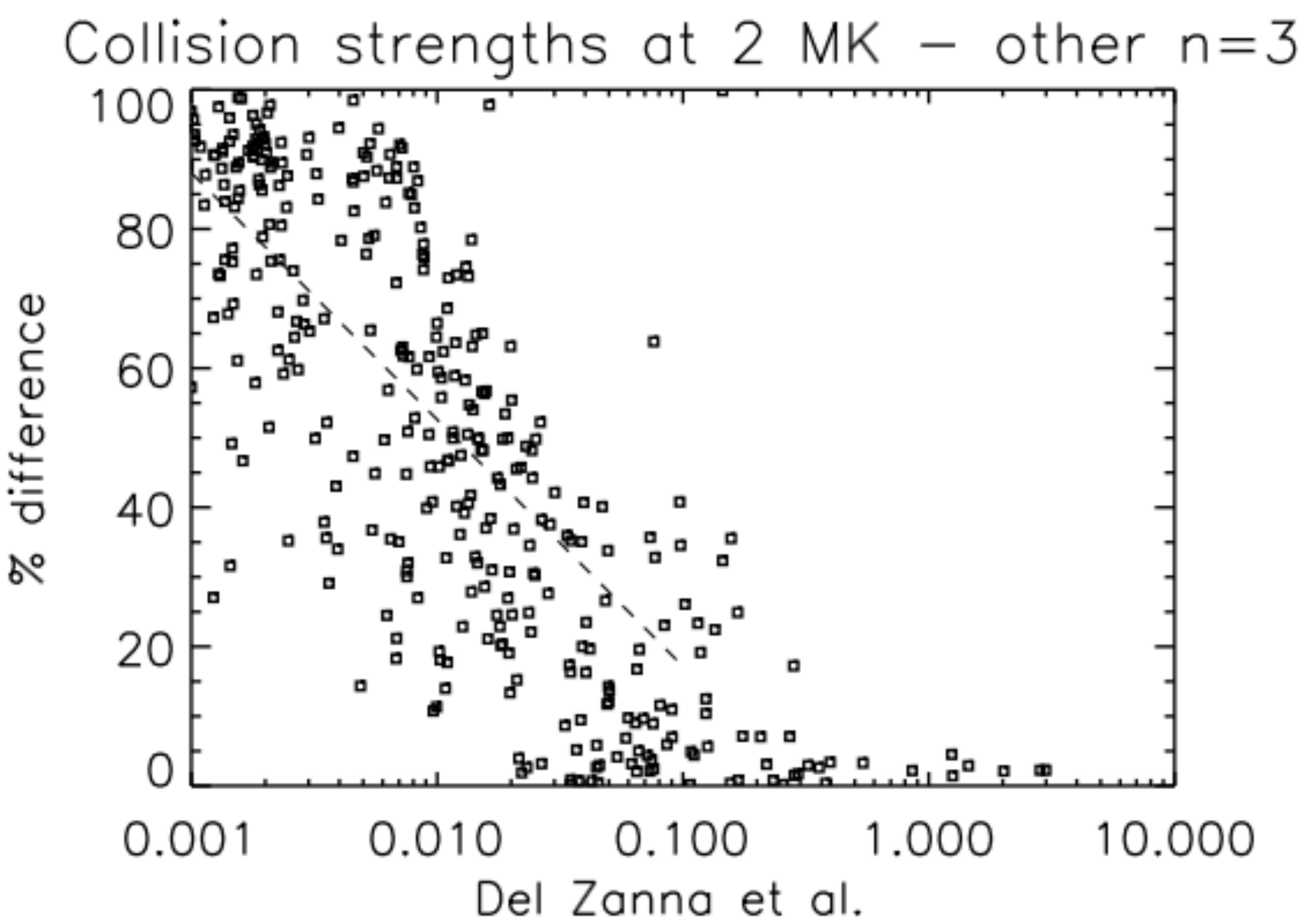
- Ultimate goal is to compute DEM($n_e(T_e)$,T_e,Z)
- Simplified toy problem — compute n_e from density-sensitive Fe XIII lines

$$\mathrm{Flux}_\lambda = \varepsilon_\lambda(n_e, T_e)\, n_e^2\, ds \equiv \varepsilon_\lambda(n_e)\, n_e^2\, ds$$

$$\lambda = \{196.525, 200.021, 201.121, 202.044, 203.165, 203.826, 209.916\}\ \text{Å}$$


(26) 3s2 3p 3d 1F3
196.52 Å
(25) 3s2 3p 3d 3D3
(24) 3s2 3p 3d 3D2
203.79 Å
(23) 3s2 3p 3d 3D1
201.12 Å
200.02 Å
(22) 3s2 3p 3d 3P0
203.83 Å
203.16 Å
(20) 3s2 3p 3d 3P1
209.92 Å
(4) 3s2 3p2 1D2
202.04 Å
(3) 3s2 3p2 3P2
(2) 3s2 3p2 3P1
(1) 3s2 3p2 3P0



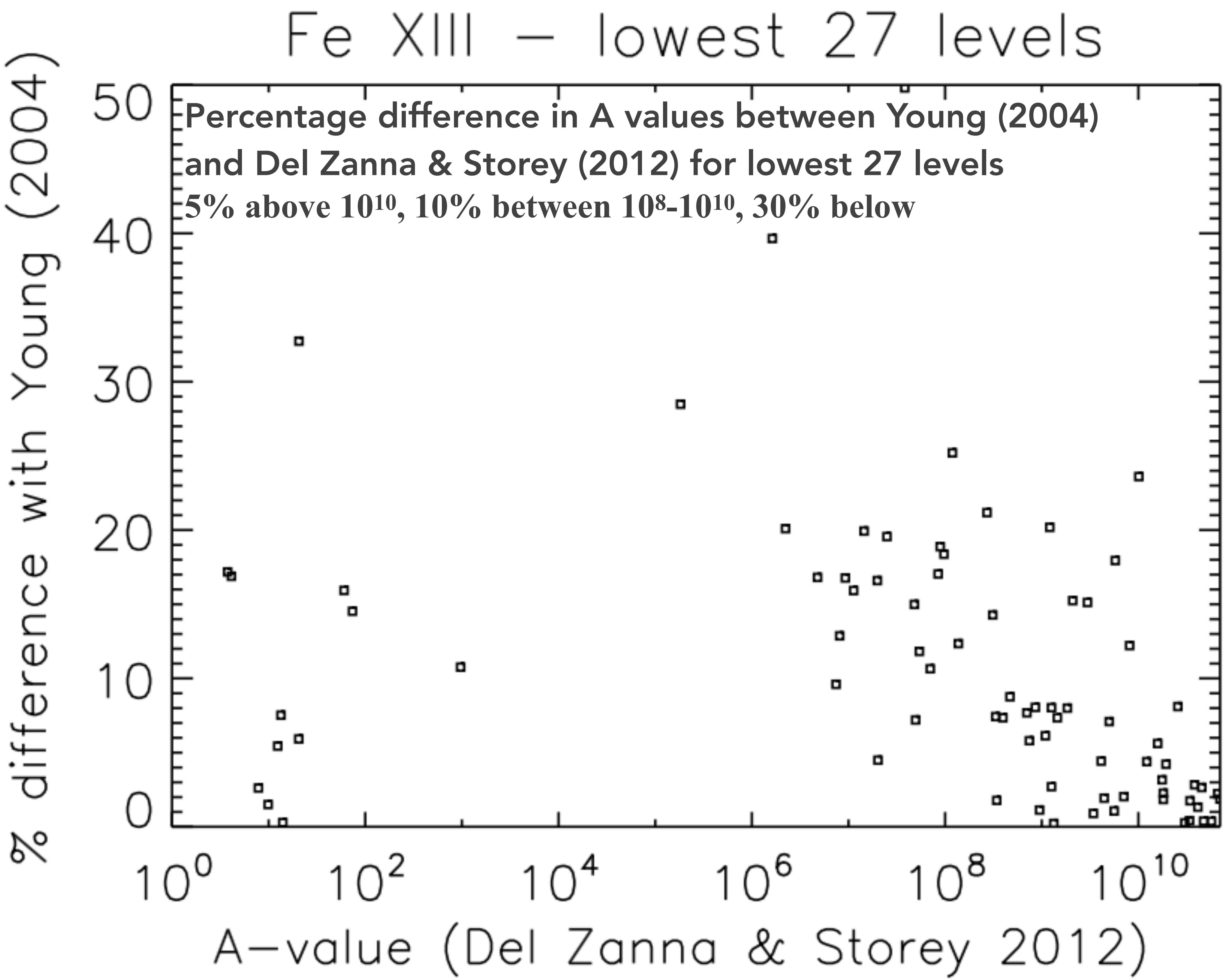


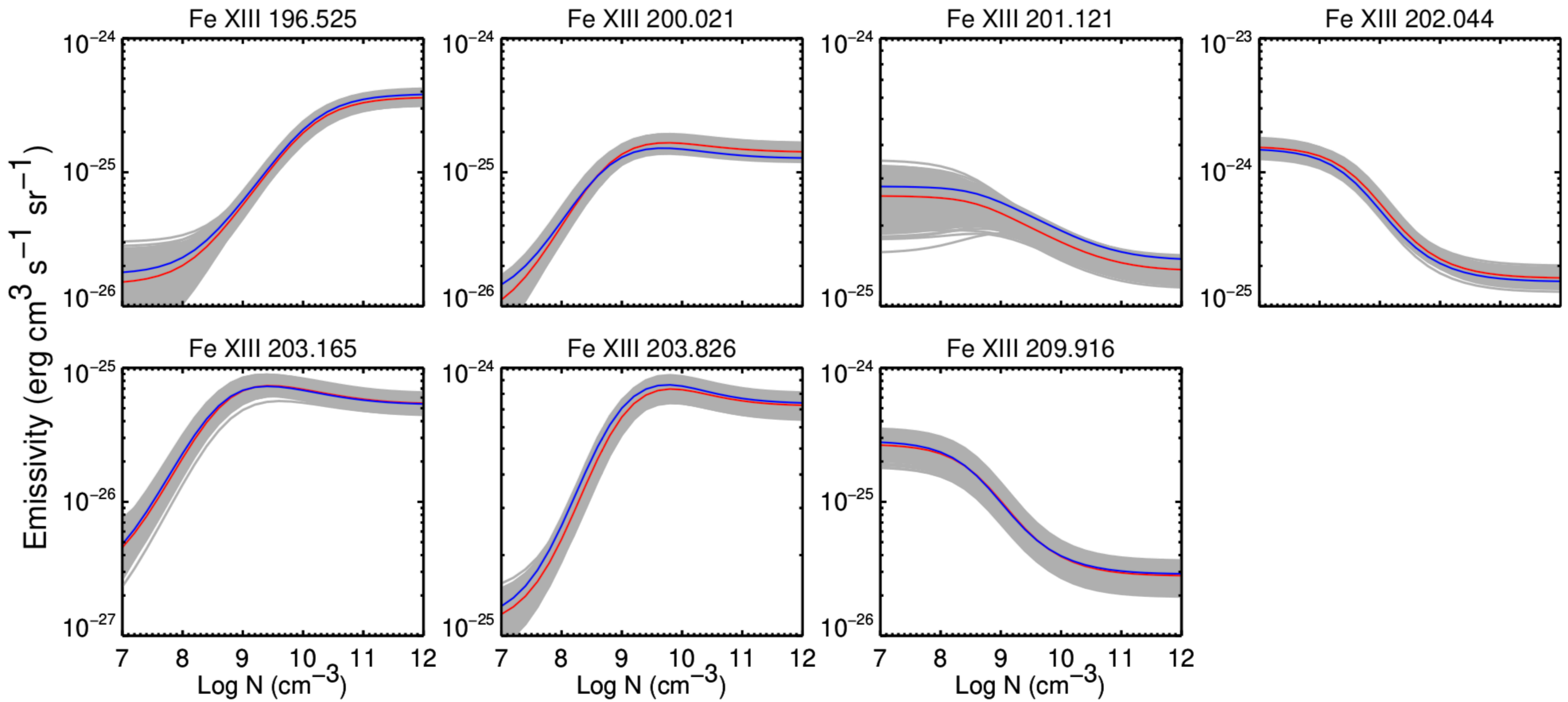
Estimated uncertainty in collision strengths for transitions to different levels, based on comparison between different calculations.

Percentage difference between Storey & Zeippen (2010) vs Del Zanna & Storey (2012) for 3p 3d (top) and other n=3 (bottom) levels

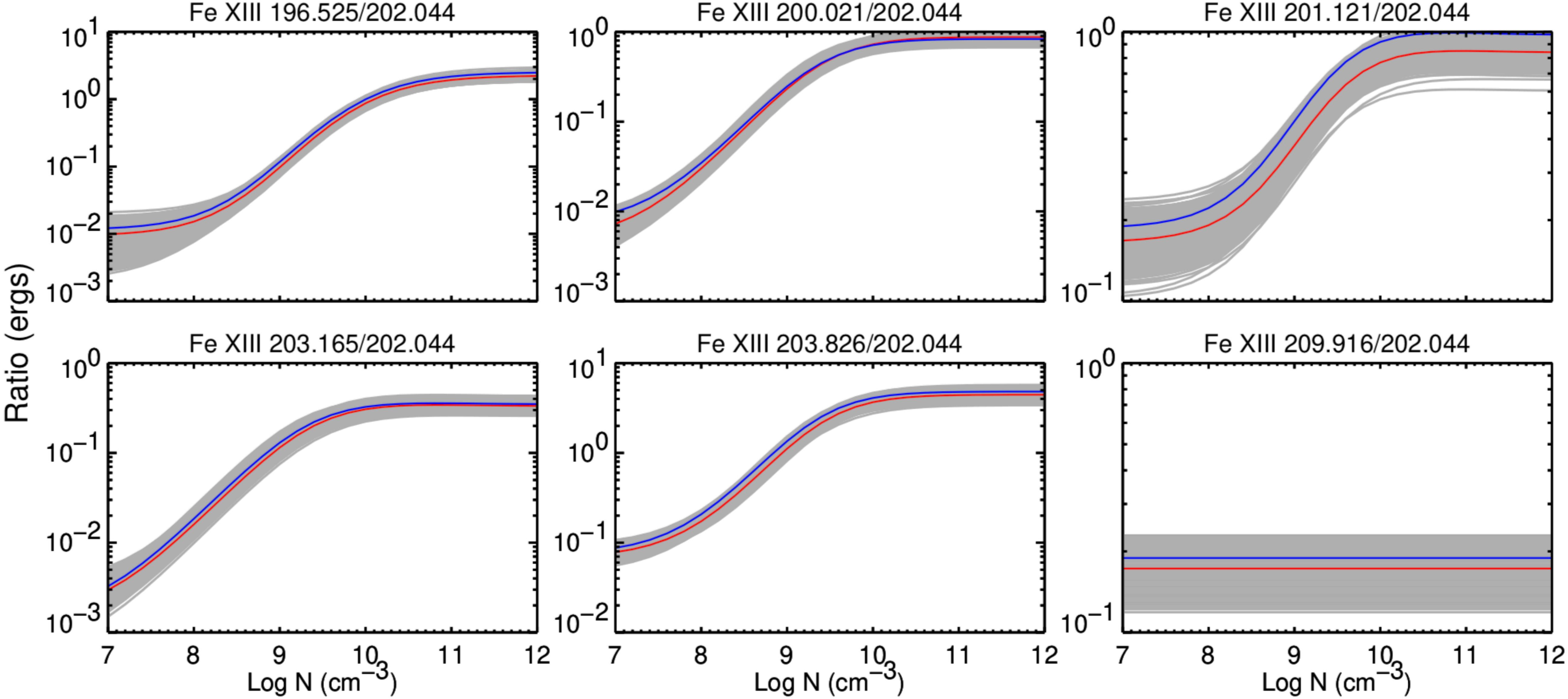
For 3p3d levels, 5% for collision strengths >1, linear dashed line up to 50% below

For other n=3 levels, 10% above 0.1, linear dashed line below

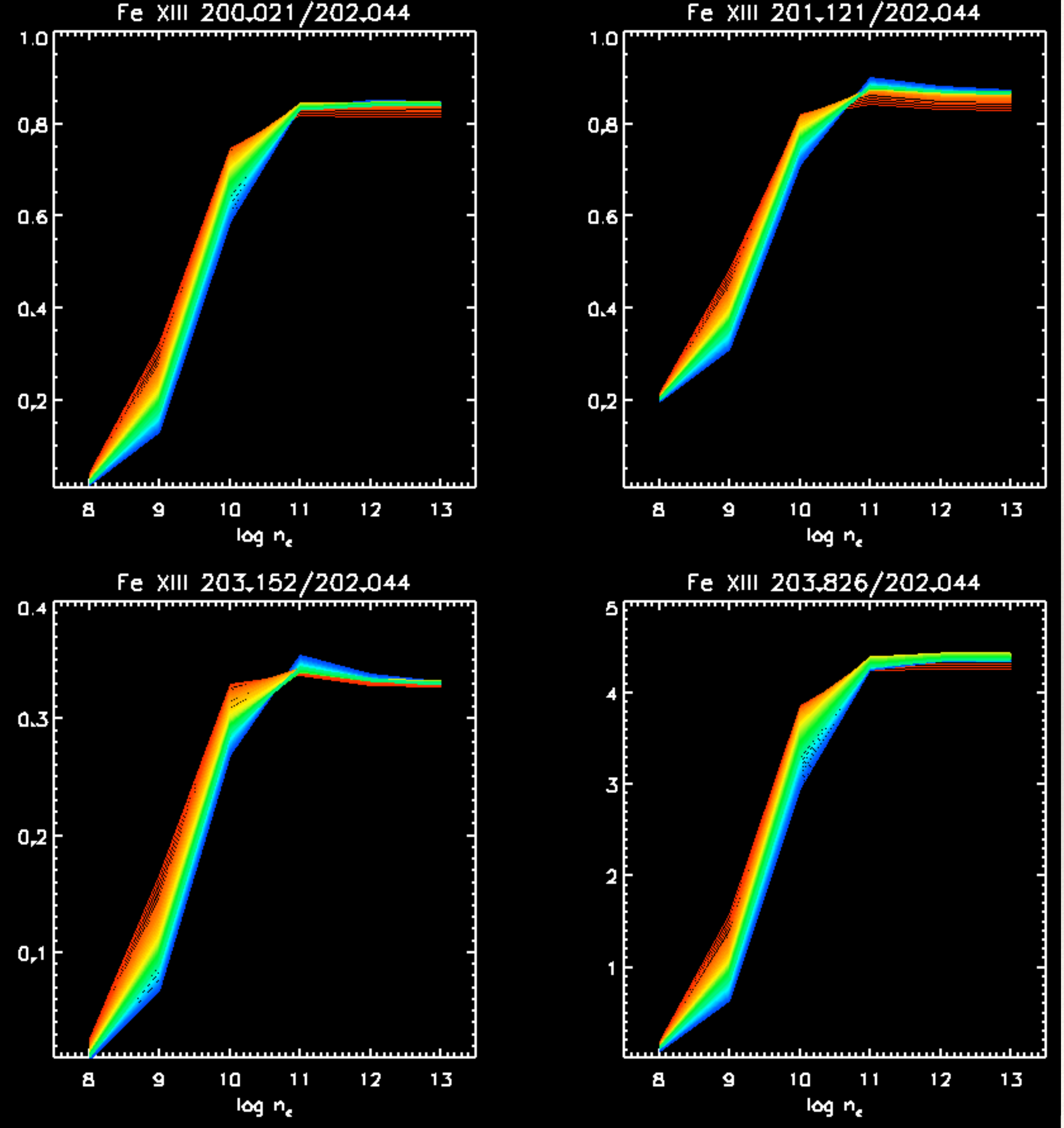

Fe XIII – lowest 27 levels
Percentage difference in A values between Young (2004)
and Del Zanna & Storey (2012) for lowest 27 levels
5% above 10^10, 10% between 10^8-10^10, 30% below
% difference with Young (2004)
A–value (Del Zanna & Storey 2012)
0
10
20
30
40
50
10^0
10^2
10^4
10^6
10^8
10^10



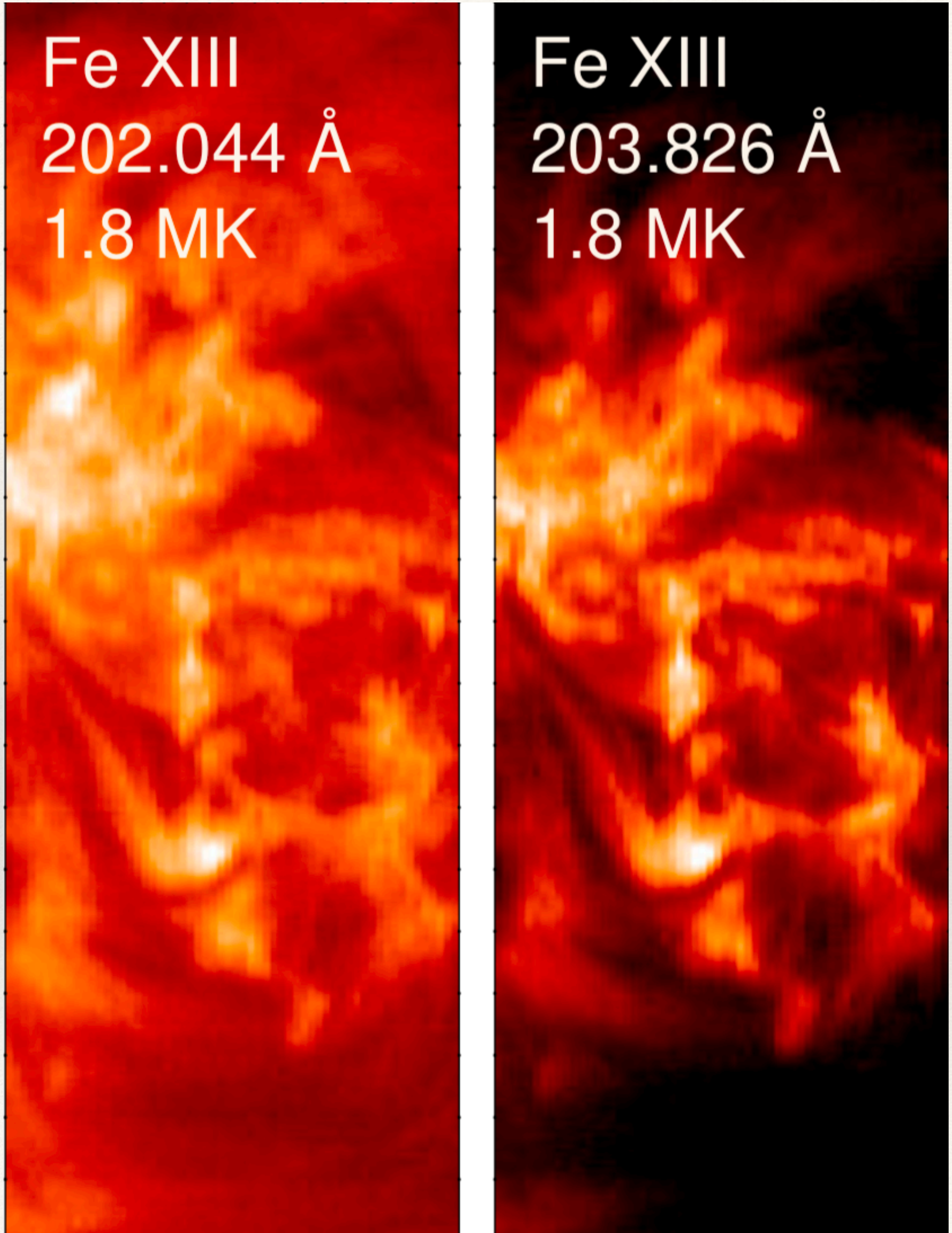
1000 emissivities generated by imputing uncertainties on collision strengths and transition probabilities of Fe XIII levels in Chianti, and generating new emissivities by propagating these uncertainties through level population estimates. Red curve is default Chianti. Blue curve is #471 (foreshadowing!)



Ratios of sampled emissivities relative to 202.044 Å line

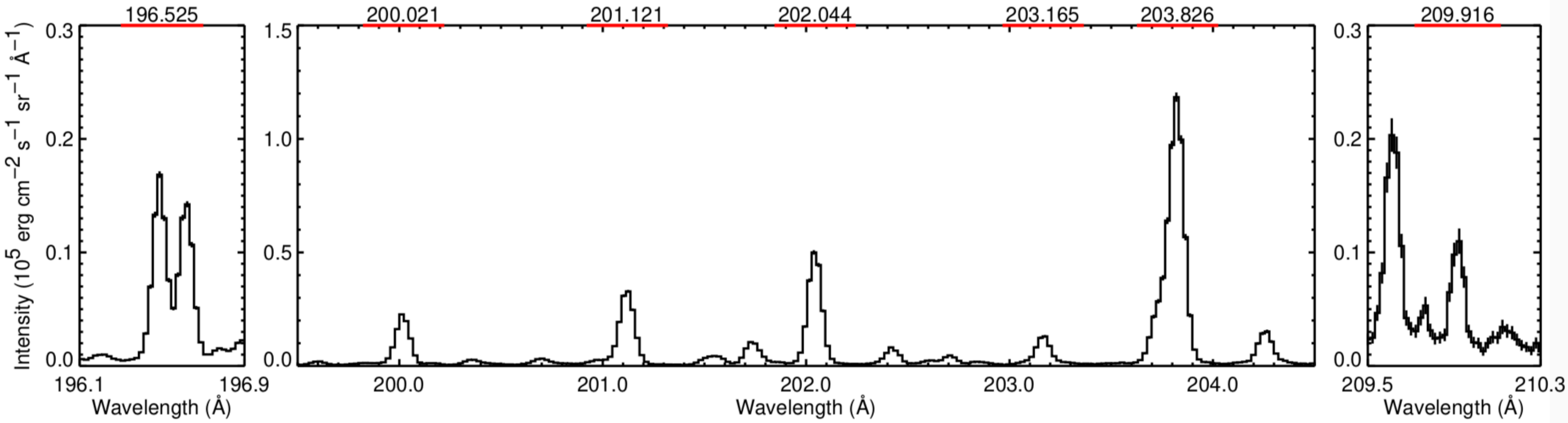


Temperature sensitivity of the density sensitivity for several Fe XIII line ratios, for default Chianti. Red is 1 MK, blue is 10 MK.



EIS raster of AR 11785
from 8 Jul 2013
from which 1000 pixels were
chosen randomly for analysis

Fe XIII: Example spectrum



Statistical Analysis

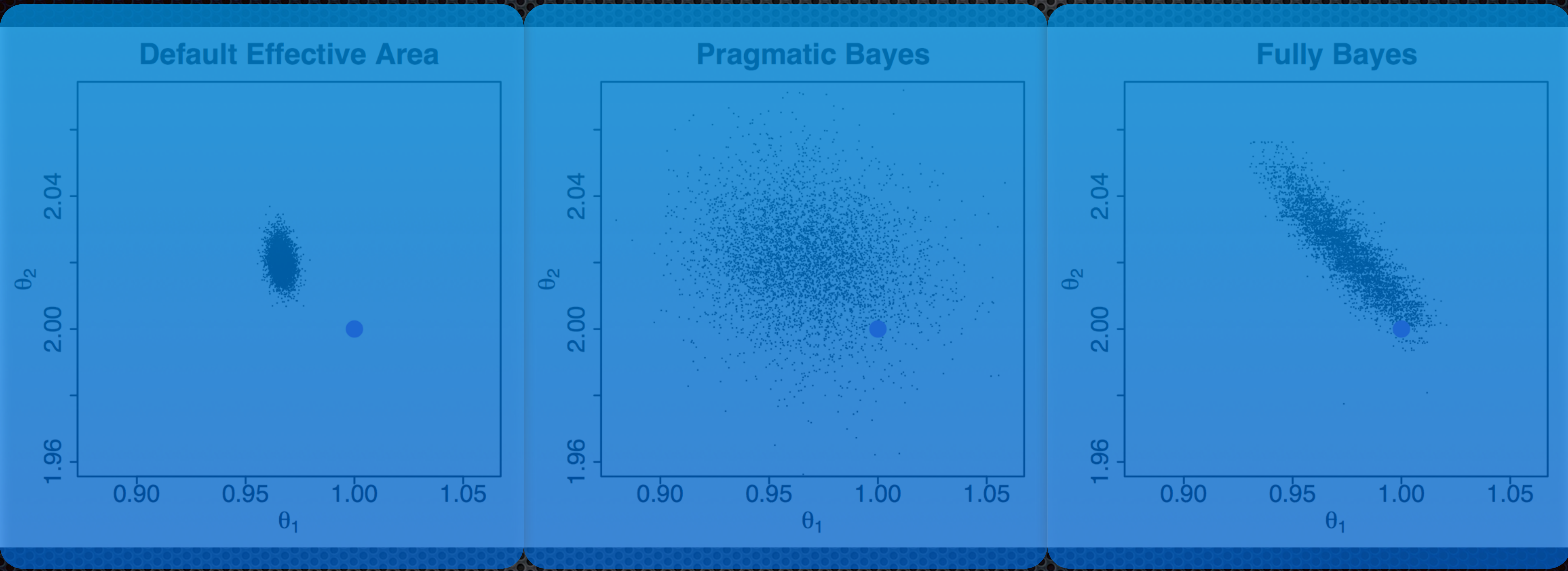
- Bayesian analysis, following the same track as Lee et al. 2011 (ApJ 731, 126) and Xu et al. 2014 (ApJ 794, 97)

pyBLoCXS / Calibration

Yaming Yu / Taeyoung Park / Hyunsook Lee / Jin Xu / Shandong Min

fitting to simulated data

$$f(\varepsilon;\theta) = \theta_3\, \varepsilon^{-\theta_1}\, e^{-\theta_2\, \sigma(\varepsilon)}$$

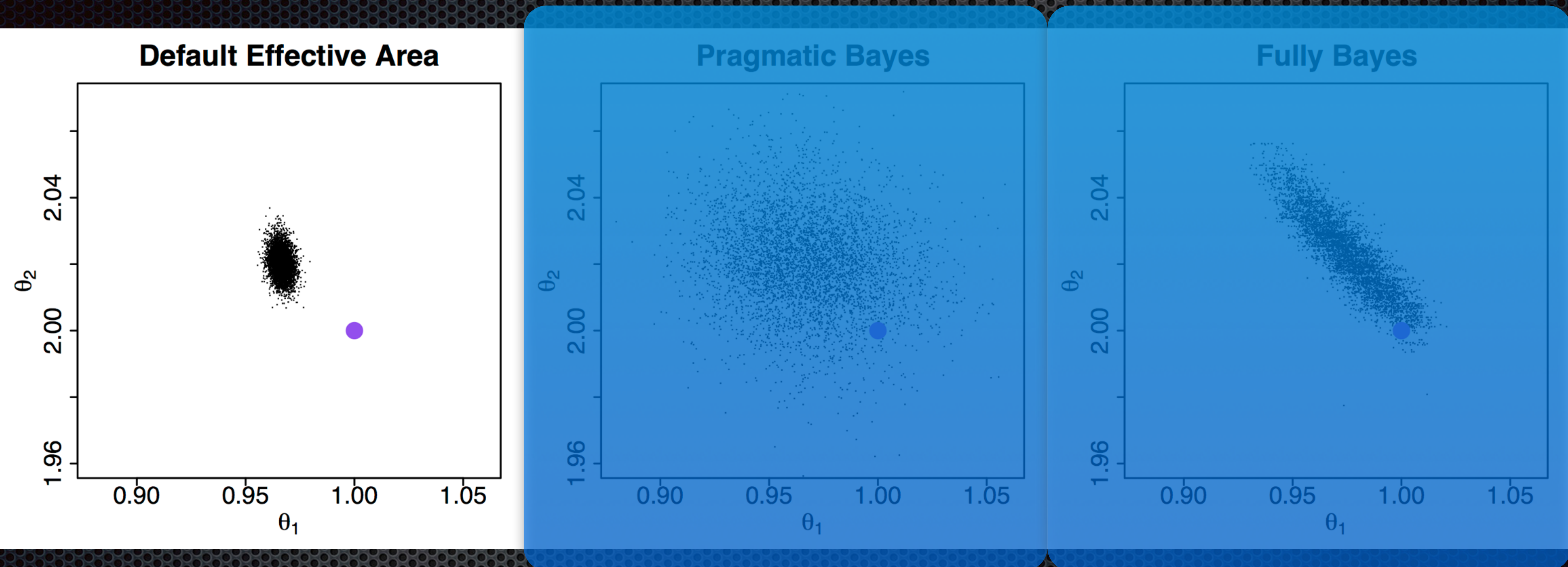


pyBLoCXS / Calibration

Yaming Yu / Taeyoung Park / Hyunsook Lee / Jin Xu / Shandong Min

fitting to simulated data

$$f(\varepsilon;\theta) = \theta_3\, \varepsilon^{-\theta_1}\, e^{-\theta_2\, \sigma(\varepsilon)}$$



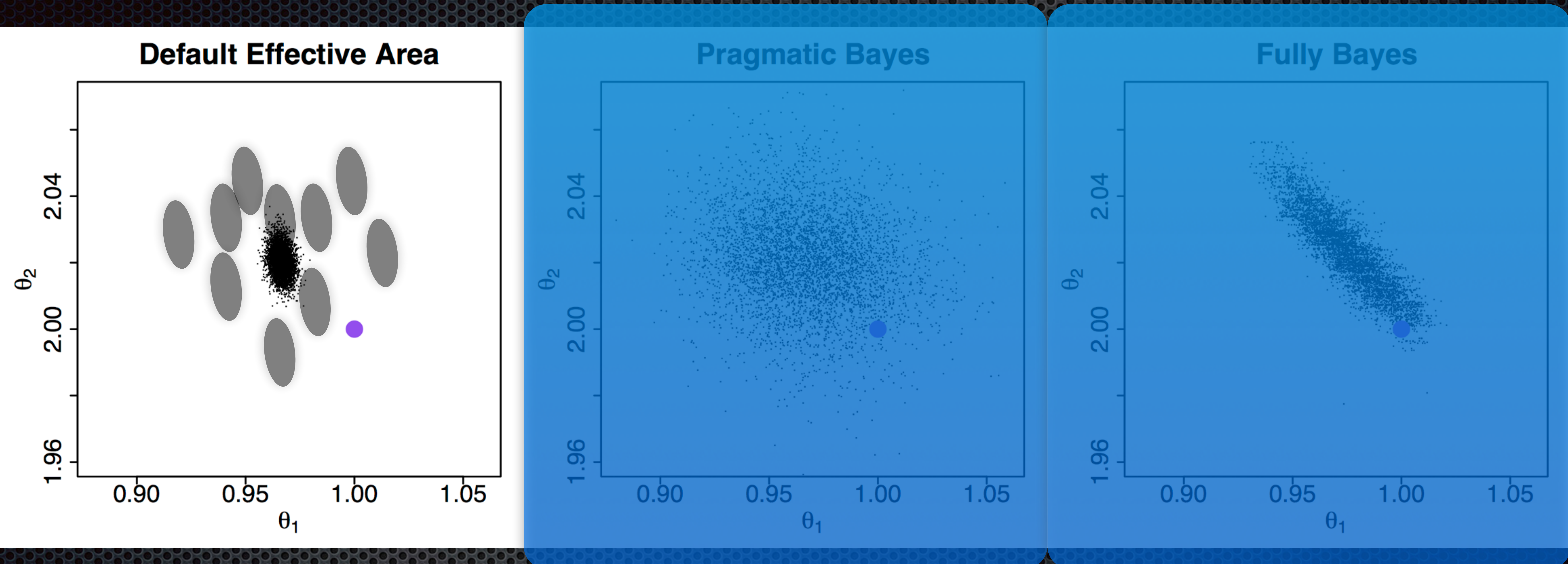
$p(\theta|D,A_0)$

pyBLoCXS / Calibration

Yaming Yu / Taeyoung Park / Hyunsook Lee / Jin Xu / Shandong Min

fitting to simulated data

$$f(\varepsilon;\theta) = \theta_3\, \varepsilon^{-\theta_1}\, e^{-\theta_2\, \sigma(\varepsilon)}$$



$$p(\theta|D,A_0)$$

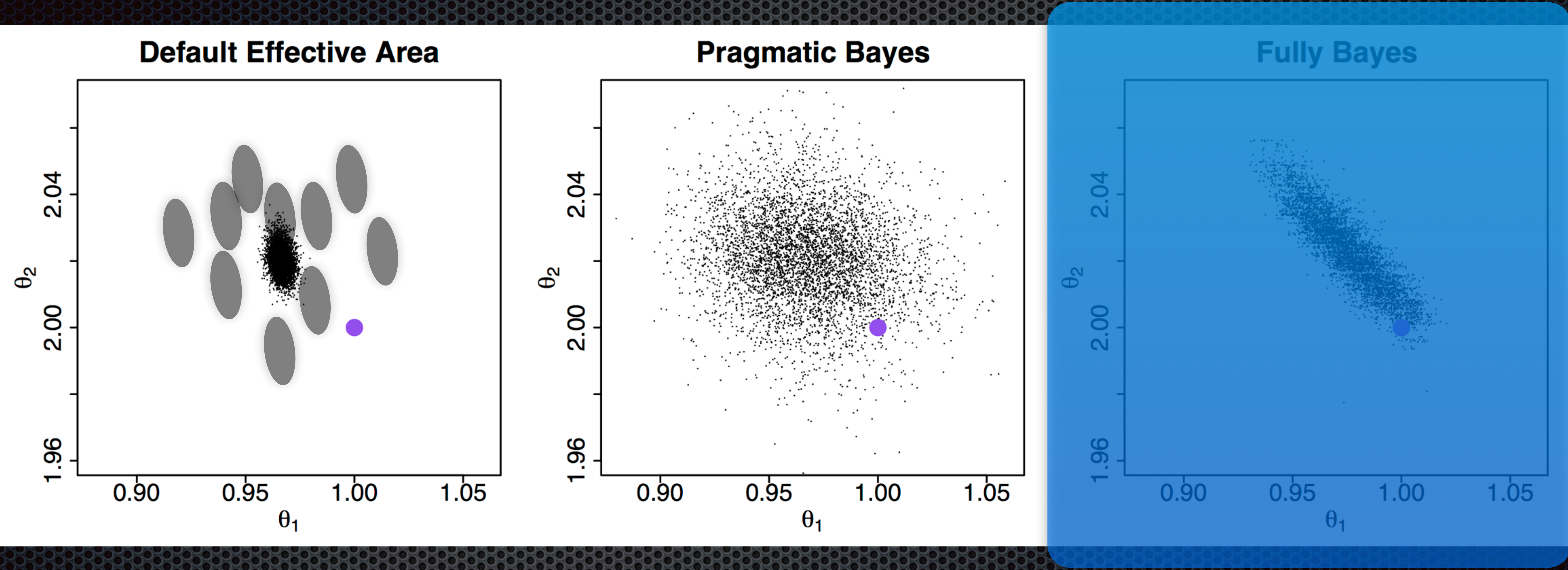
$$p(\theta|D,A_i)$$

pyBLoCXS / Calibration

Yaming Yu / Taeyoung Park / Hyunsook Lee / Jin Xu / Shandong Min

fitting to simulated data

$$f(\varepsilon;\theta) = \theta_3\, \varepsilon^{-\theta_1}\, e^{-\theta_2\, \sigma(\varepsilon)}$$



$p(\theta|D,A_0)$

$p(A)\ p(\theta|D,A)$

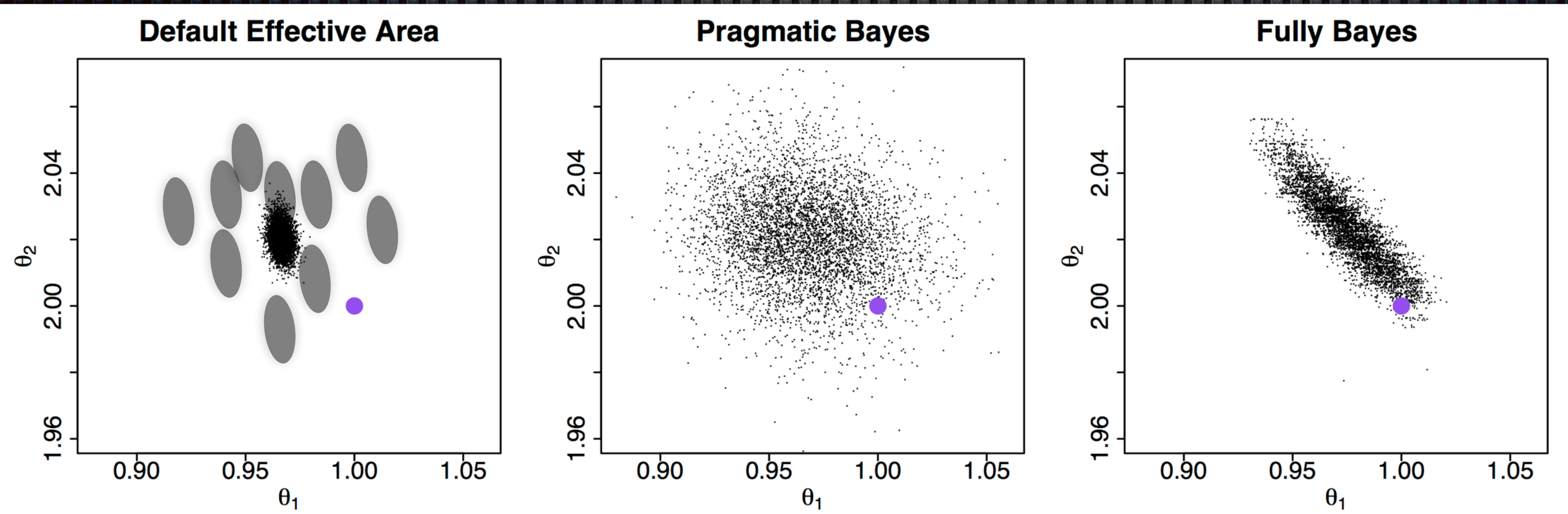
$p(\theta|D,A_i)$

pyBLoCXS / Calibration

Yaming Yu / Taeyoung Park / Hyunsook Lee / Jin Xu / Shandong Min

fitting to simulated data

$$f(\varepsilon;\theta) = \theta_3\, \varepsilon^{-\theta_1}\, e^{-\theta_2\, \sigma(\varepsilon)}$$



$p(\theta|D,A_0)$

$p(\theta|D,A_i)$

$p(A)\ p(\theta|D,A)$

$p(A,\theta|D)$

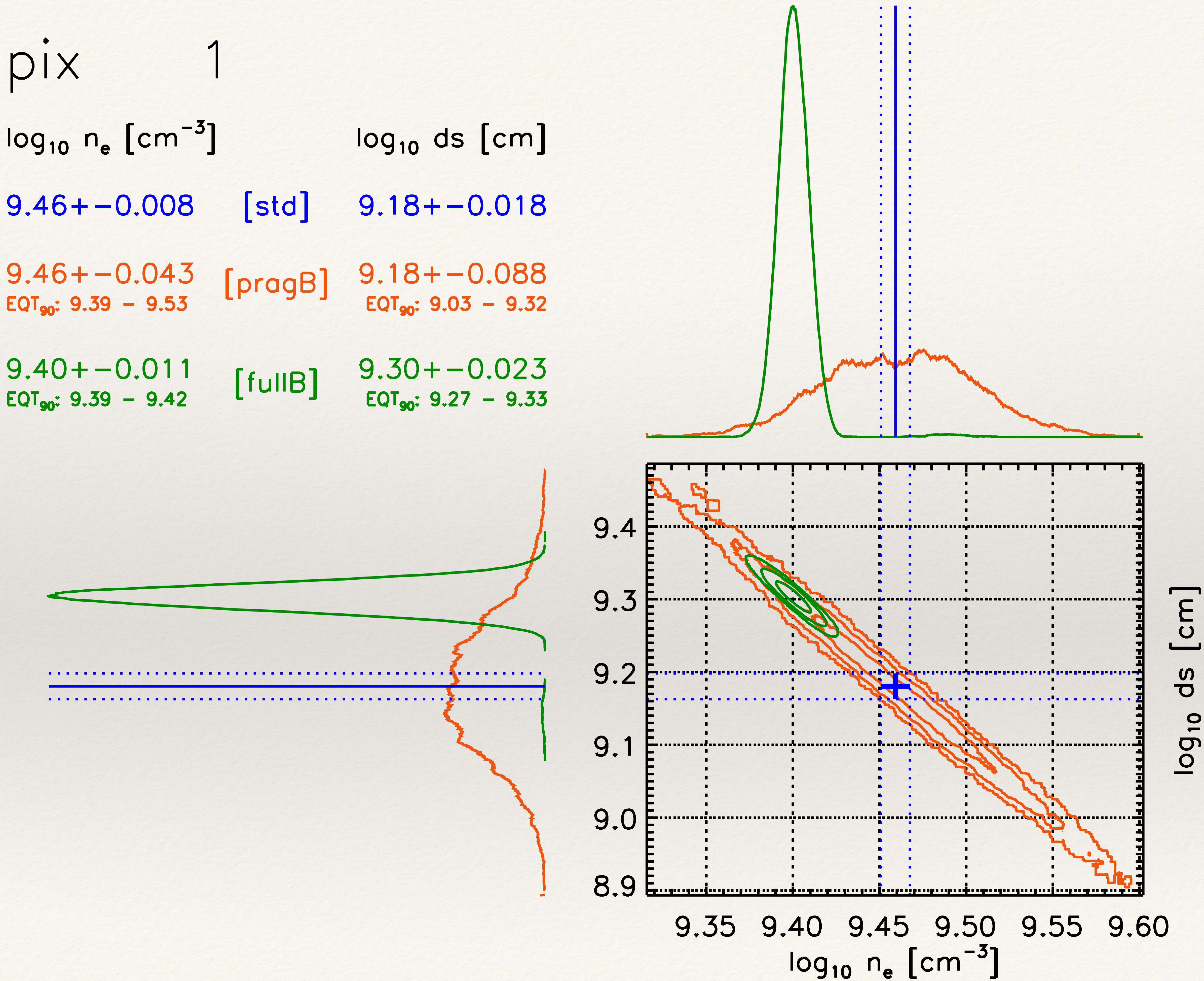
Statistical Analysis

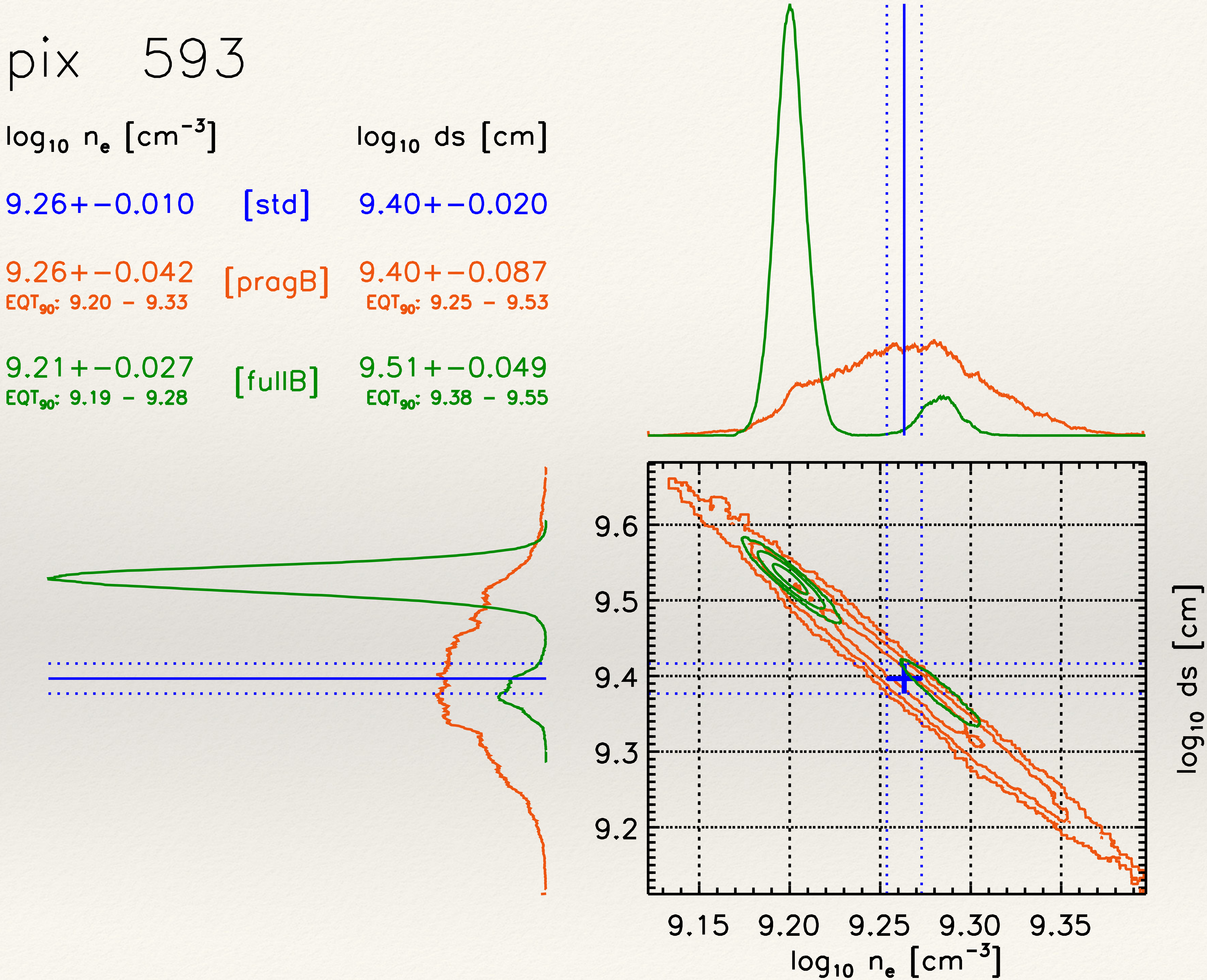
- Bayesian analysis, following the same track as Lee et al. 2011 (ApJ 731, 126) and Xu et al. 2014 (ApJ 794, 97)
- Pragmatic Bayes, which takes the sample of emissivities as given, and sees what effect it has on the parameter estimates and uncertainties

$$p(m,\theta|D) = p(\theta|D,m)\ p(m)$$

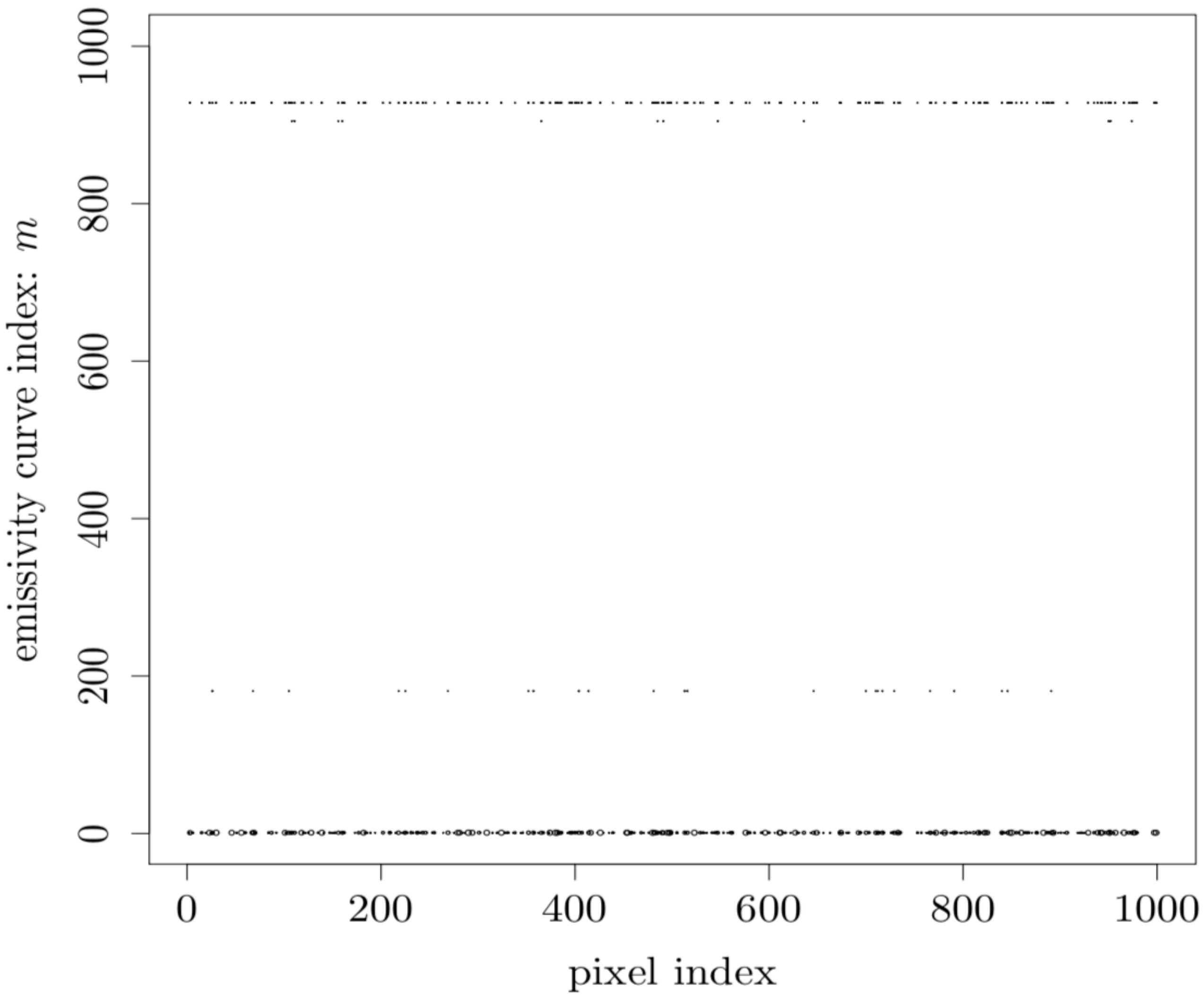
- Full Bayes, which "filters out" instances of emissivity samples that produce bad likelihoods hence additionally selects preferred emissivities

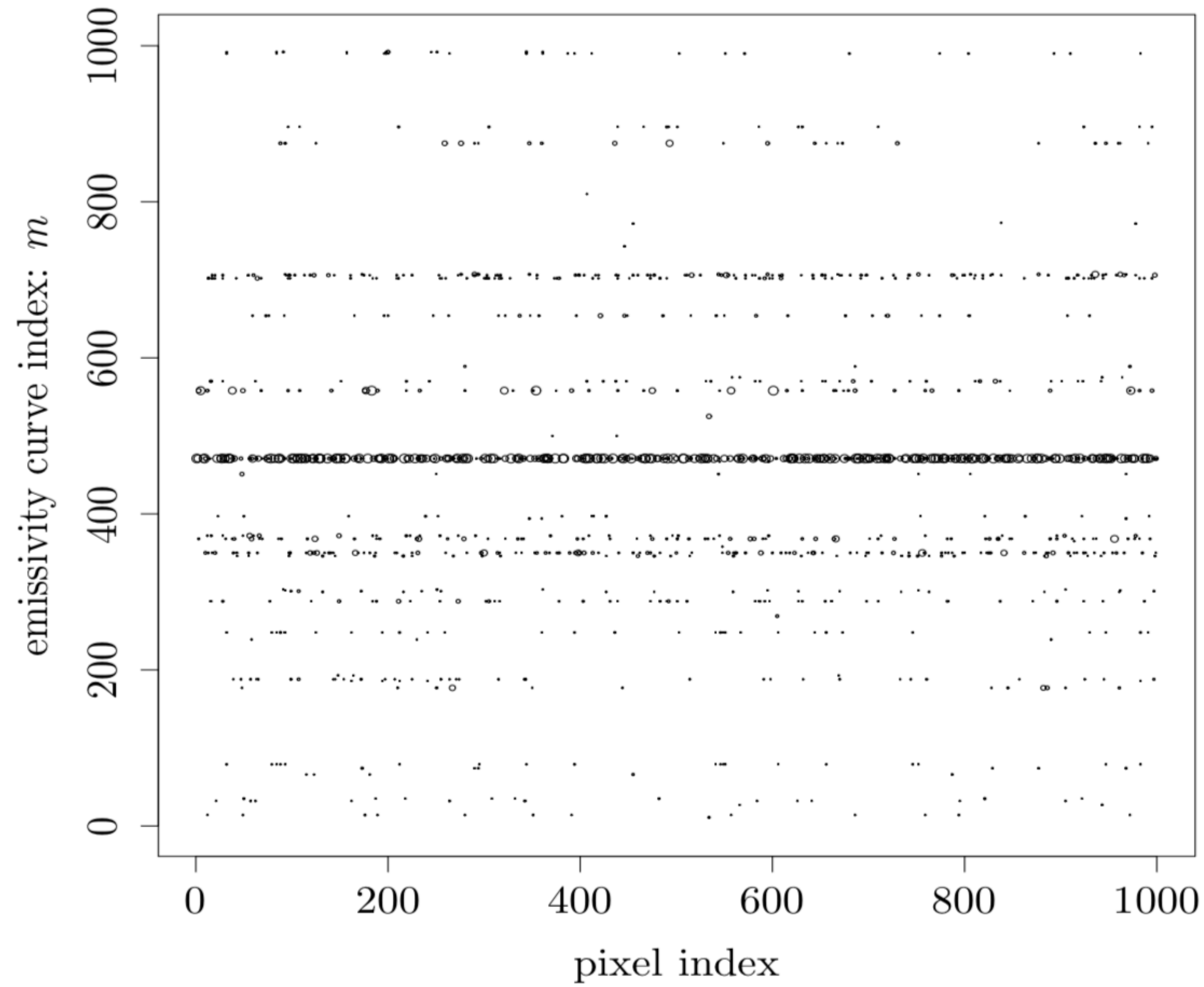
$$p(m,\theta|D) = p(\theta|D,m)\ p(m|D)$$


pix 1
log10 ne [cm-3]
log10 ds [cm]
9.46+-0.008
[std]
9.18+-0.018
9.46+-0.043
EQT90: 9.39 - 9.53
[pragB]
9.18+-0.088
EQT90: 9.03 - 9.32
9.40+-0.011
EQT90: 9.39 - 9.42
[fullB]
9.30+-0.023
EQT90: 9.27 - 9.33
9.4
9.3
9.2
9.1
9.0
8.9
9.35
9.40
9.45
9.50
9.55
9.60
log10 ne [cm-3]
log10 ds [cm]



pix 593
log10 ne [cm-3]
log10 ds [cm]
9.26+-0.010 [std] 9.40+-0.020
9.26+-0.042 [pragB] 9.40+-0.087
EQT90: 9.20 - 9.33
EQT90: 9.25 - 9.53
9.21+-0.027 [fullB] 9.51+-0.049
EQT90: 9.19 - 9.28
EQT90: 9.38 - 9.55
9.6
9.5
9.4
9.3
9.2
9.15
9.20
9.25
9.30
9.35
log10 ne [cm-3]
log10 ds [cm]





Best choice of generated emissivity; only those with >5% probability are shown.
Left: simulated from default Chianti — picks up #0, as it should
Right: pixels chosen from EIS raster — picks up #471 mostly, and #368 secondarily

Compare selected emissivities with default

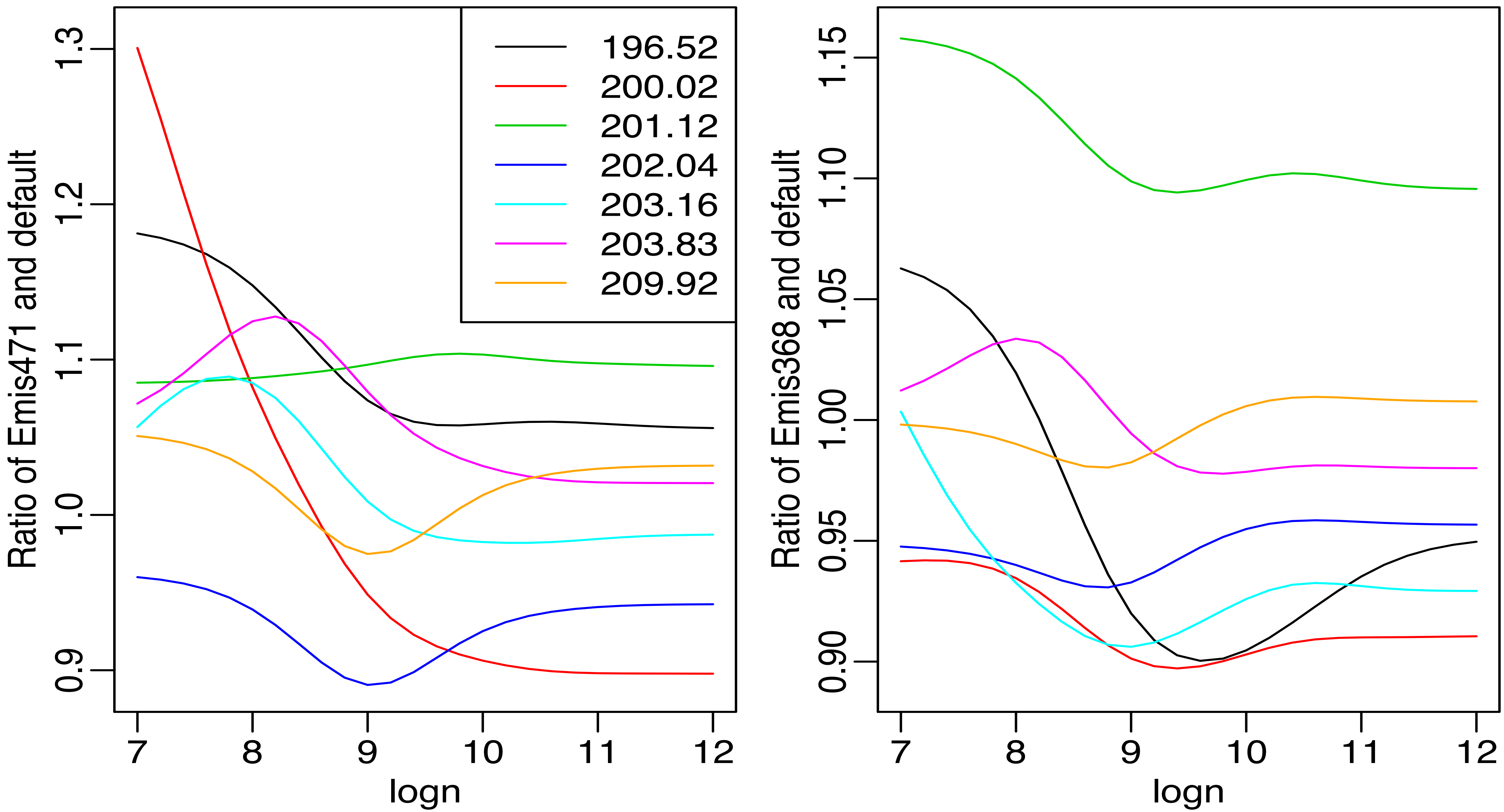
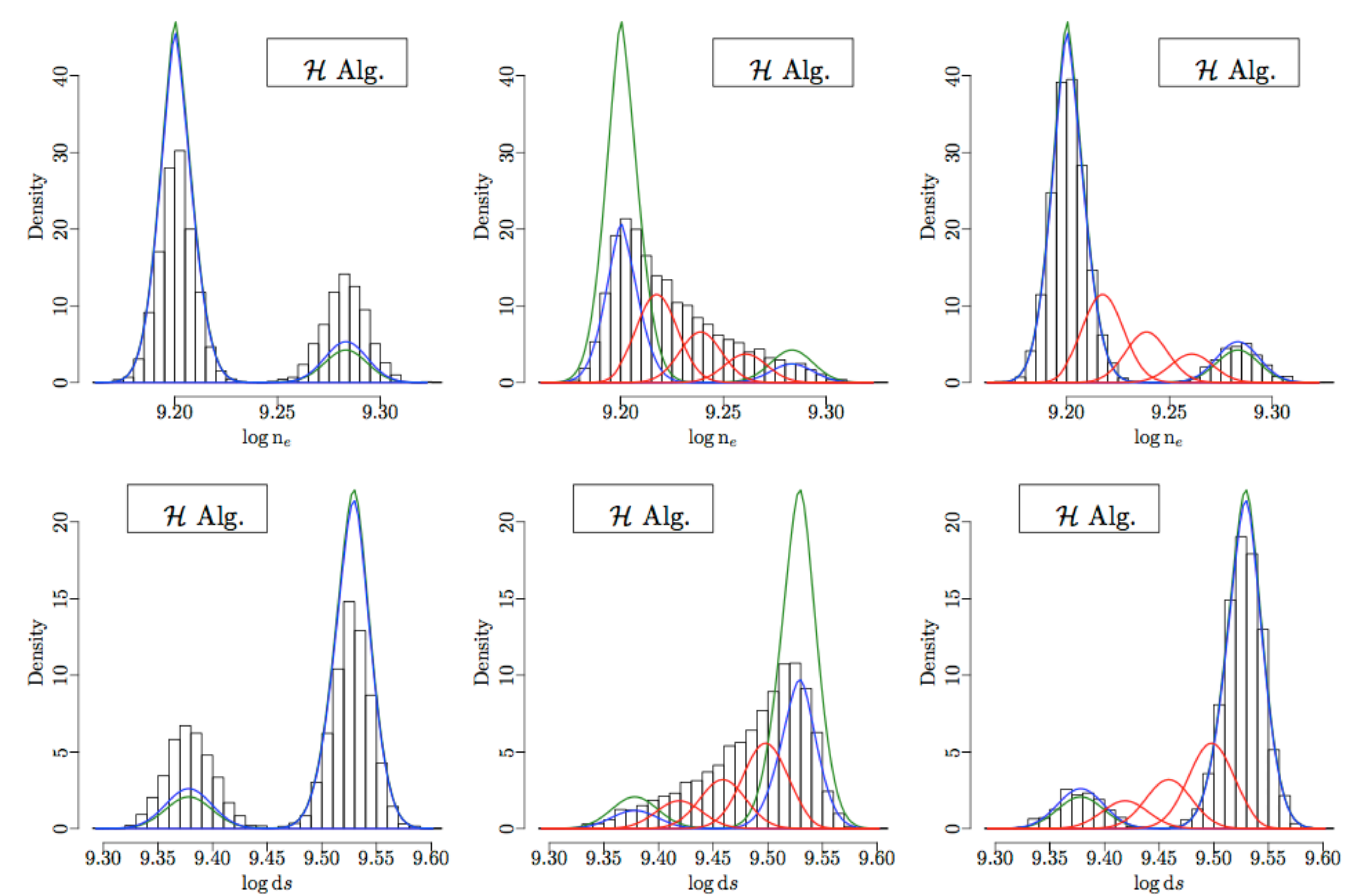


Figure: Plot of ratio of selected emissivities and default CHIANTI over 7 lines.

Next

- PCA to overcome sparsity
- Chandra Capella O VII+O VIII to extend to ion balance uncertainties, logT



When MCMC doesn't match sizes of different modes, trick it to traverse by imputing intermediate curves and then removing them. Aha! So PCA generated emissivity curves could solve sparsity problem?

Chandra : Capella