Machine learning to improve scaling relations in cluster cosmology

(Jay) Digvijay Wadekar

IAS

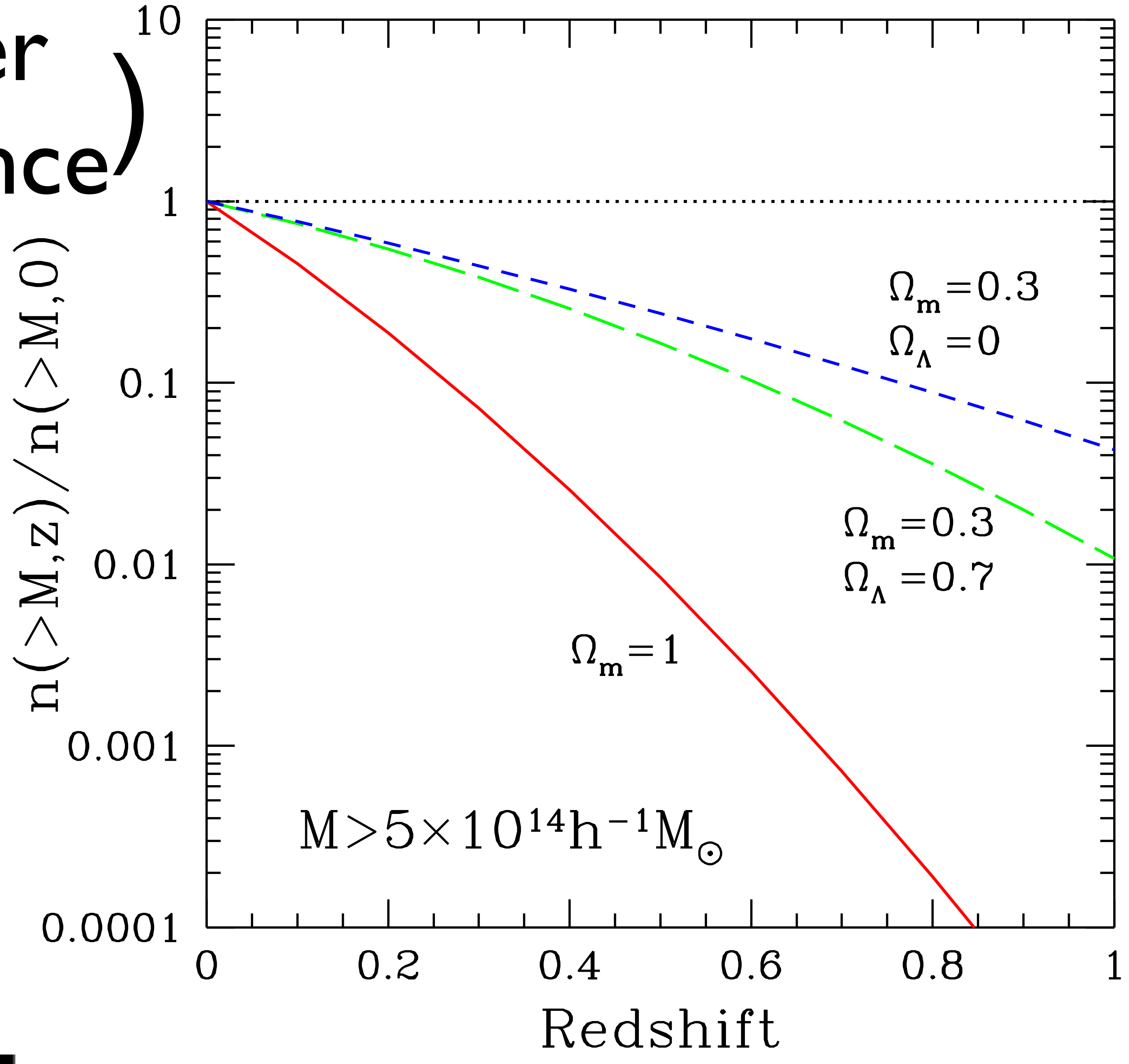
with

L. Thiele, J.C. Hill, F. Villaescusa-Navarro, D. Spergel, M. Cranmer, S. Pandey, N. Battaglia, S. Ho, D. Angles-Alcazar, L. Hernquist

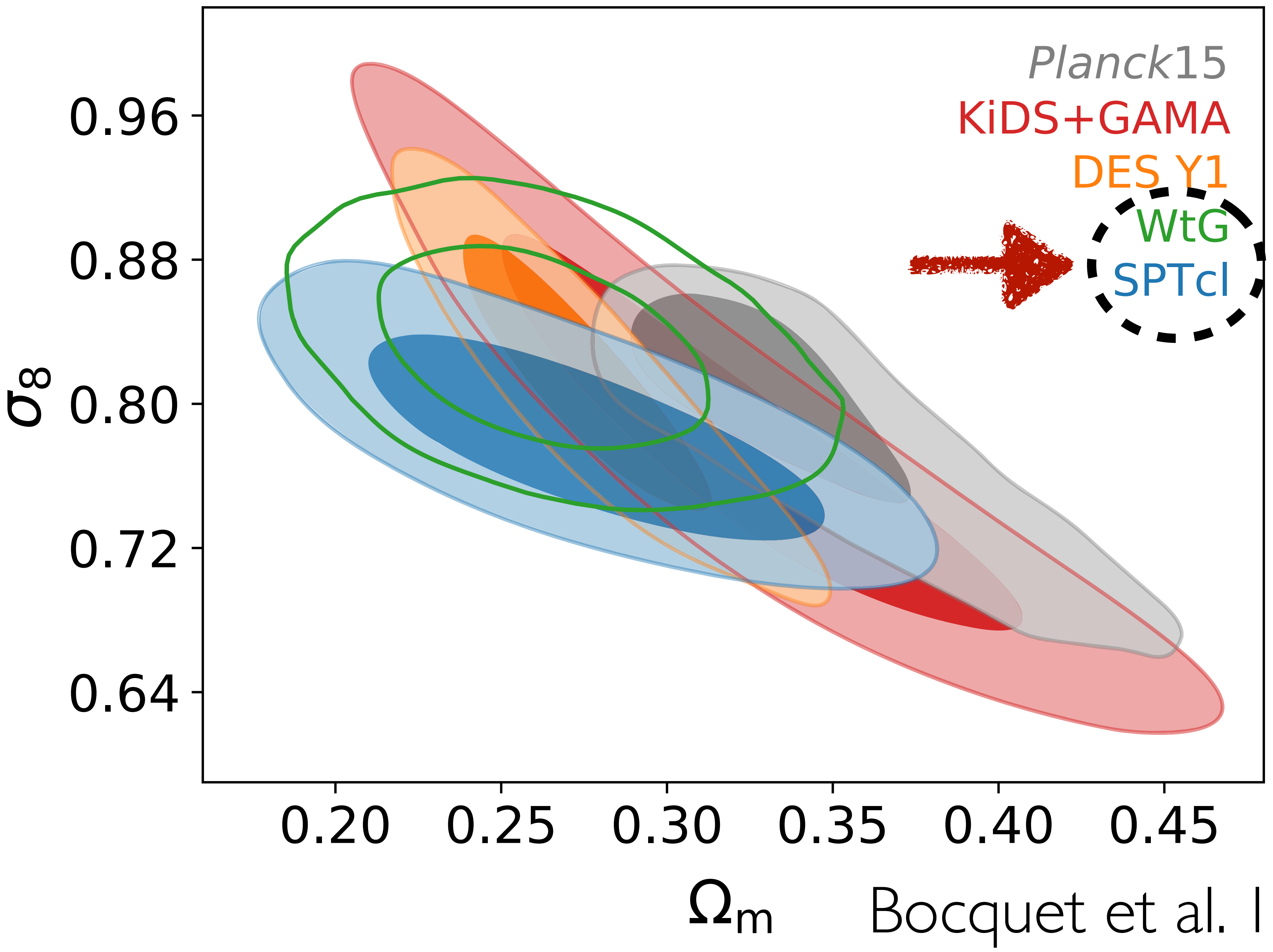
arXiv:2201.01305 & in prep.

Mass estimation of galaxy clusters is important for cosmology

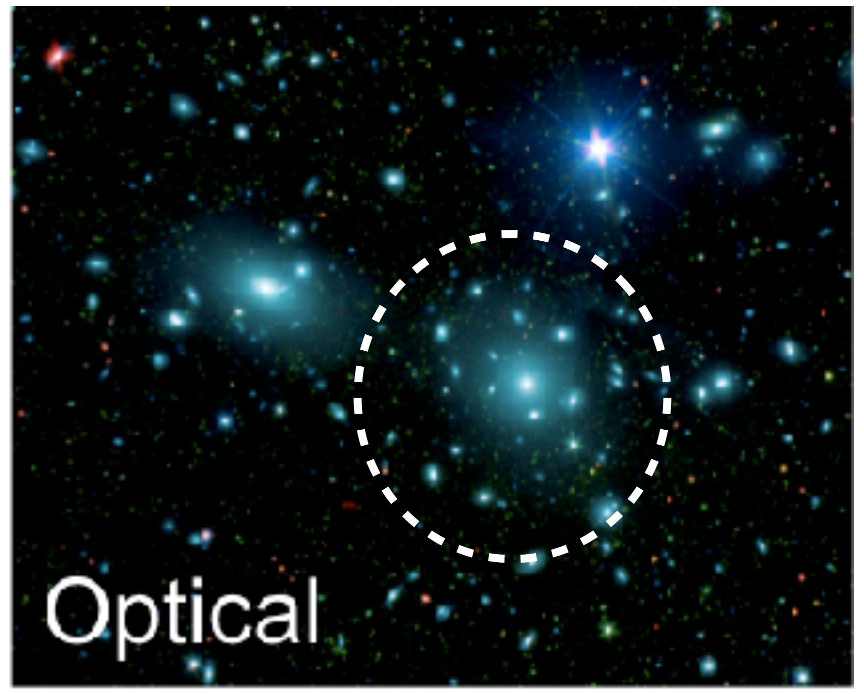
(Cluster abundance)



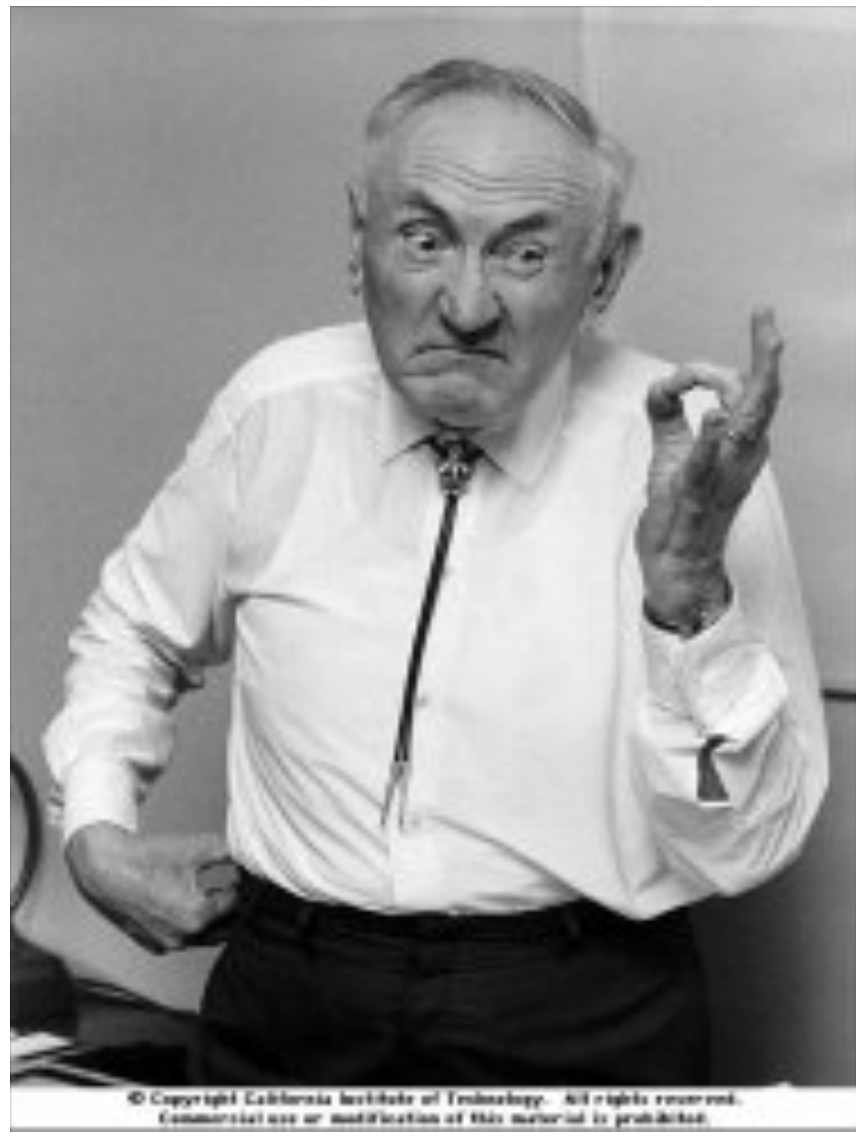
Rosati et al. 02



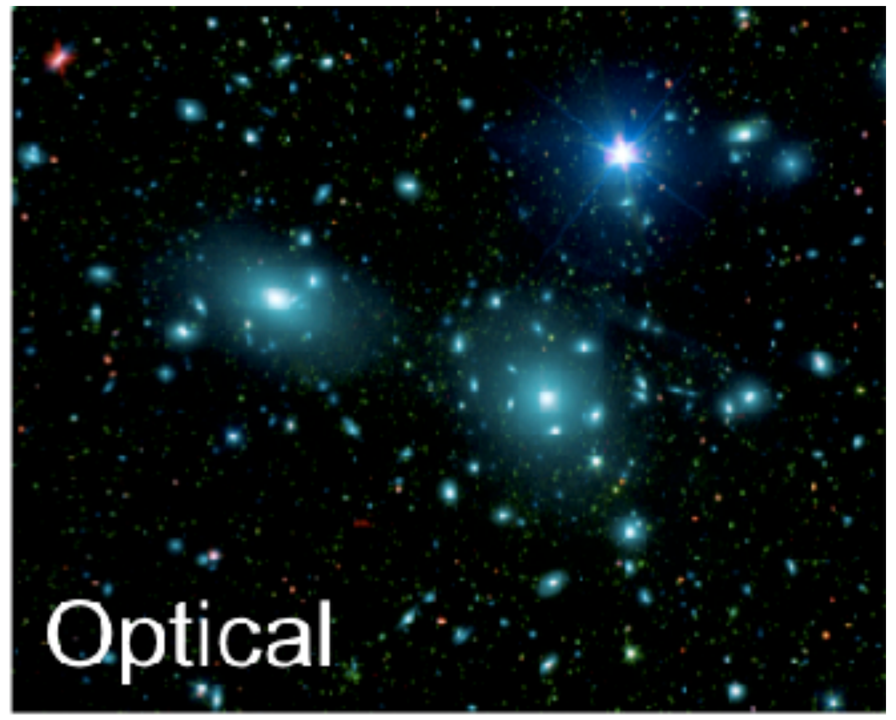
Bocquet et al. 19

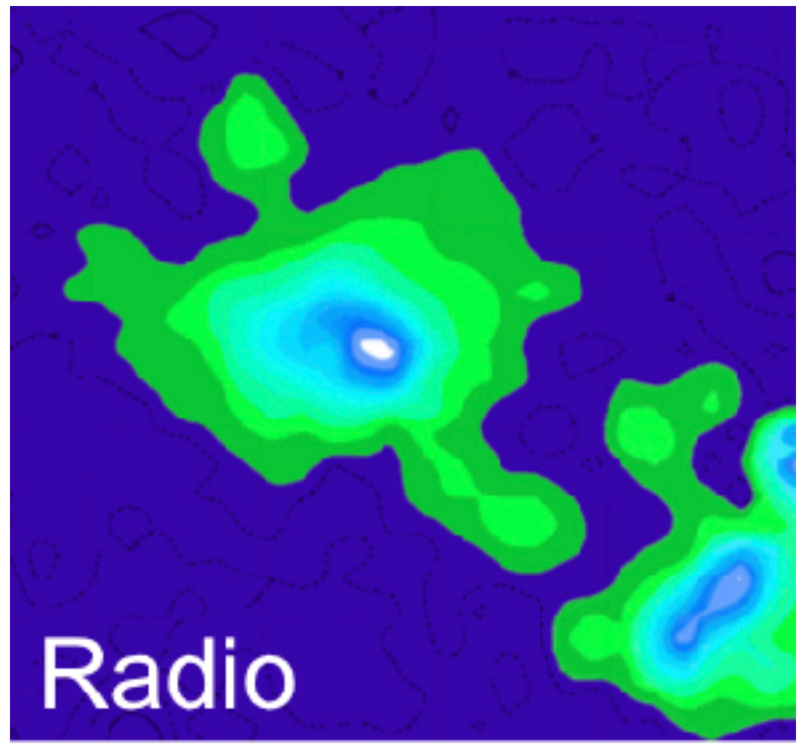


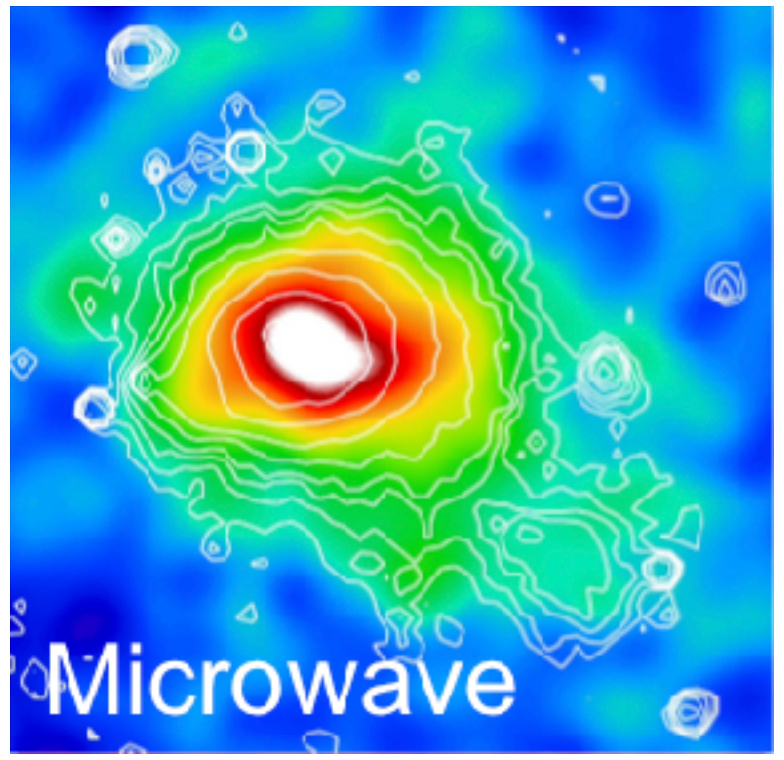
“dunkle materie”

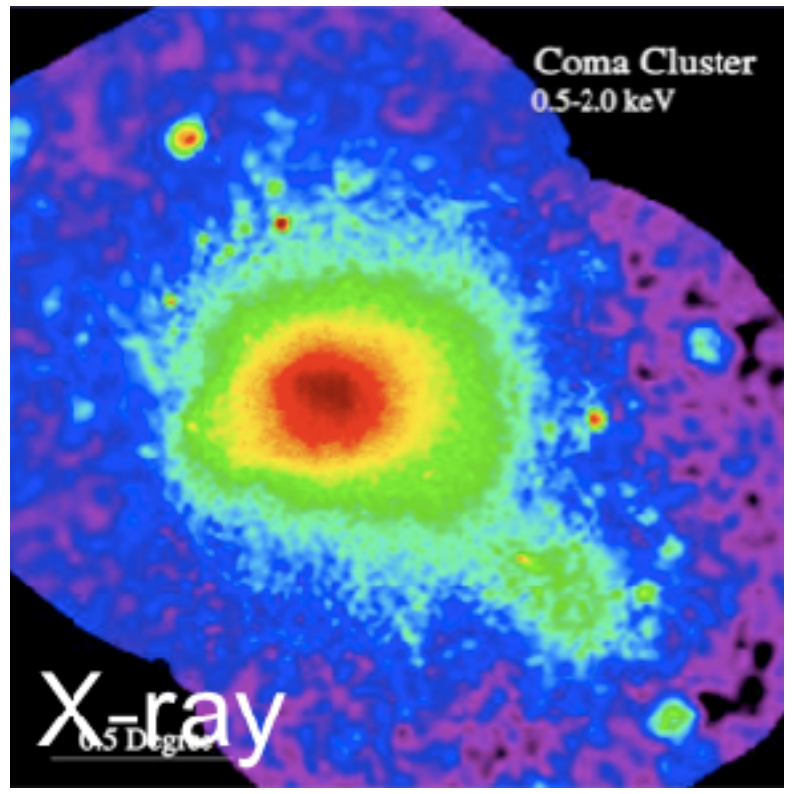


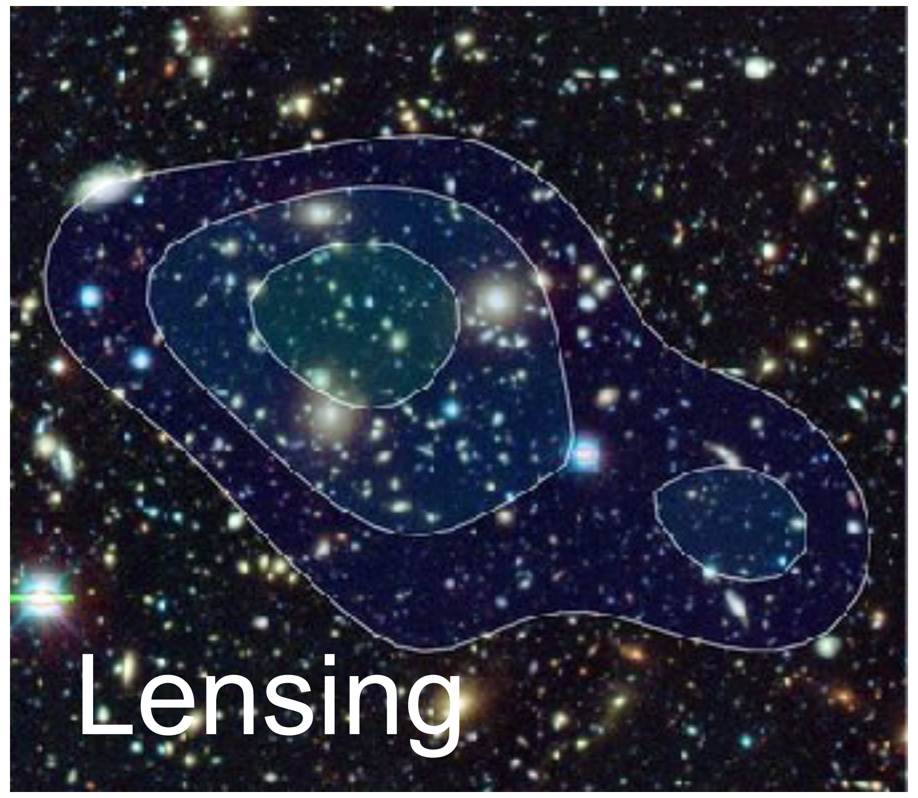
Traditional approaches for cluster mass estimation

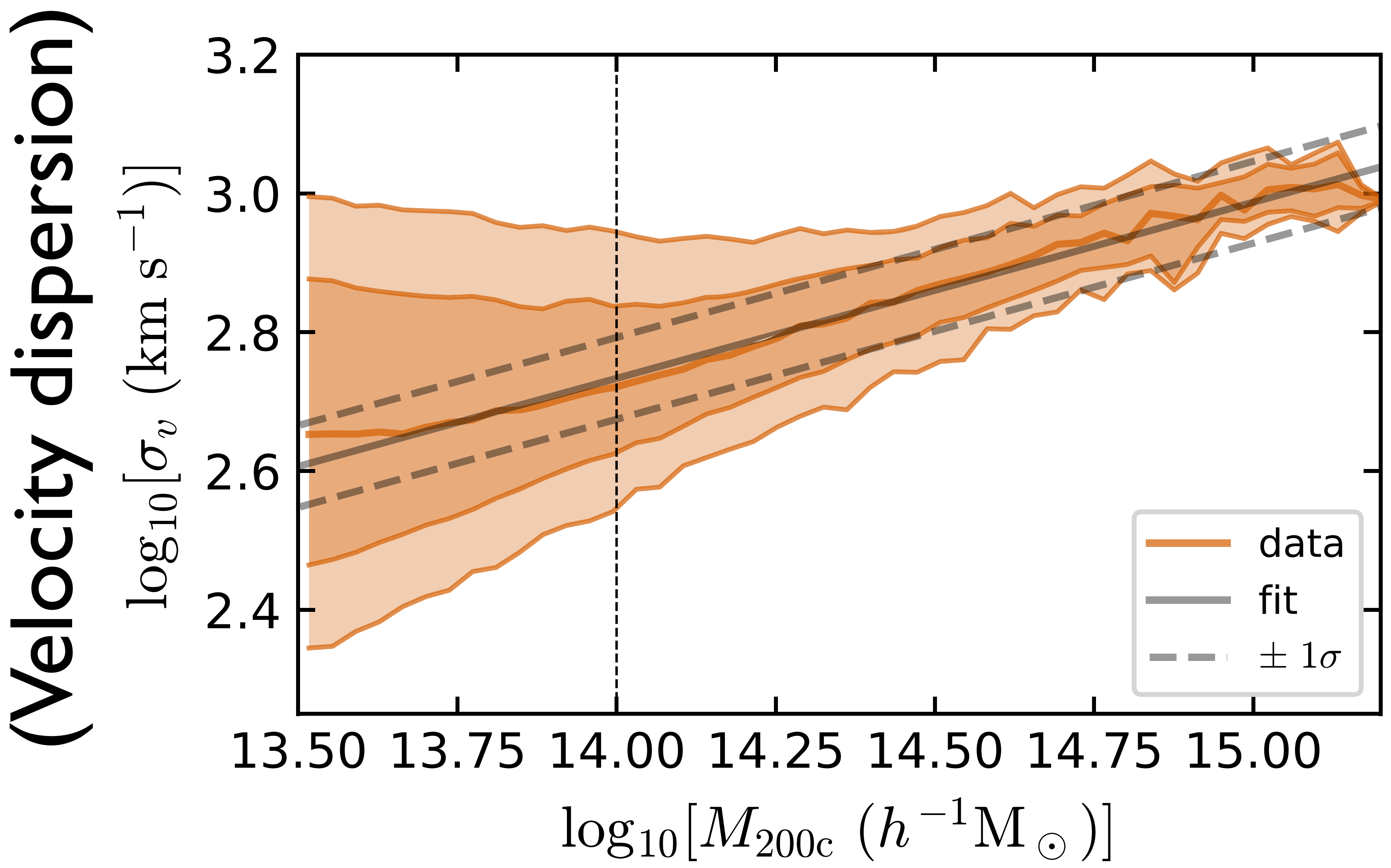


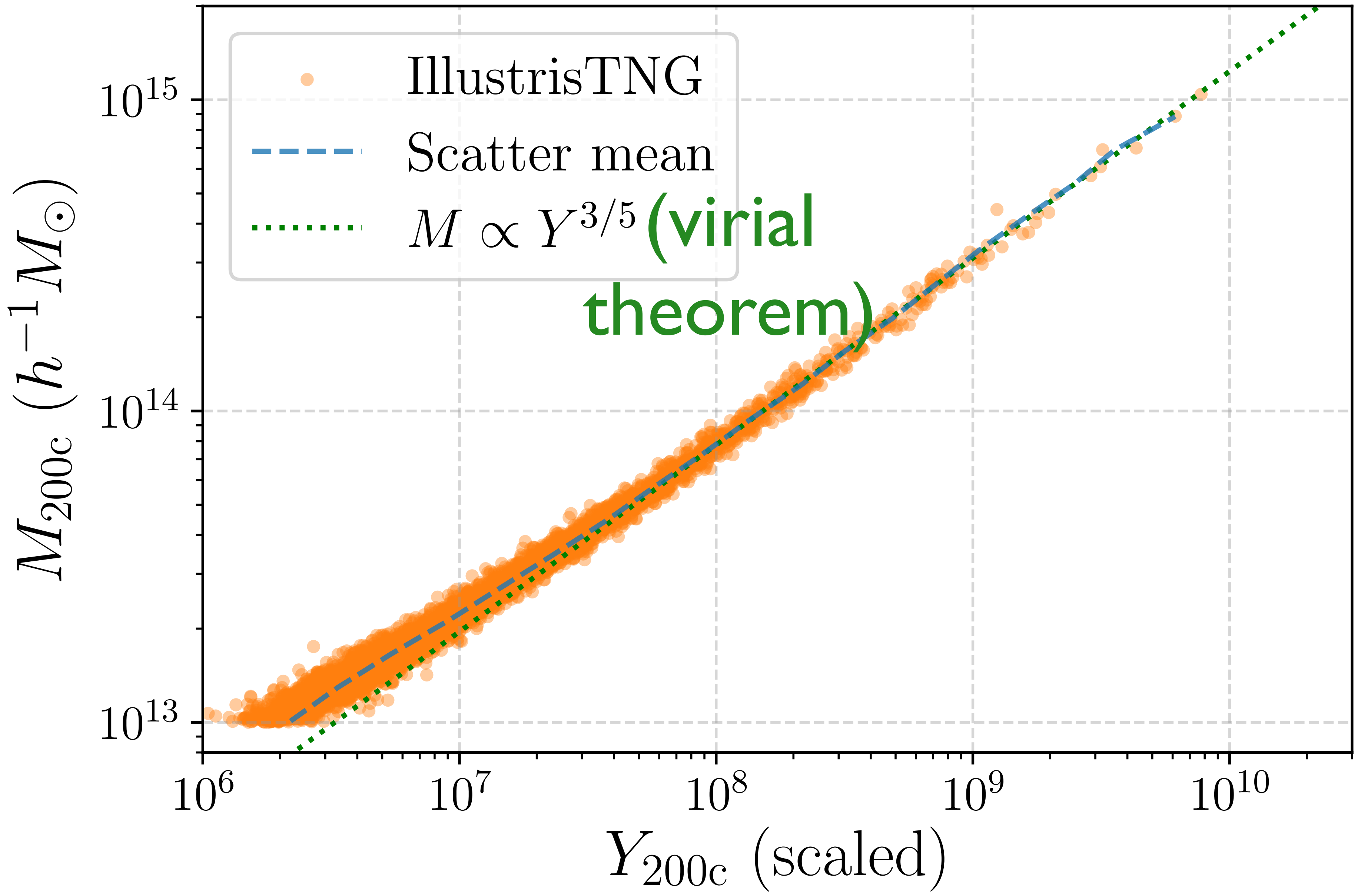












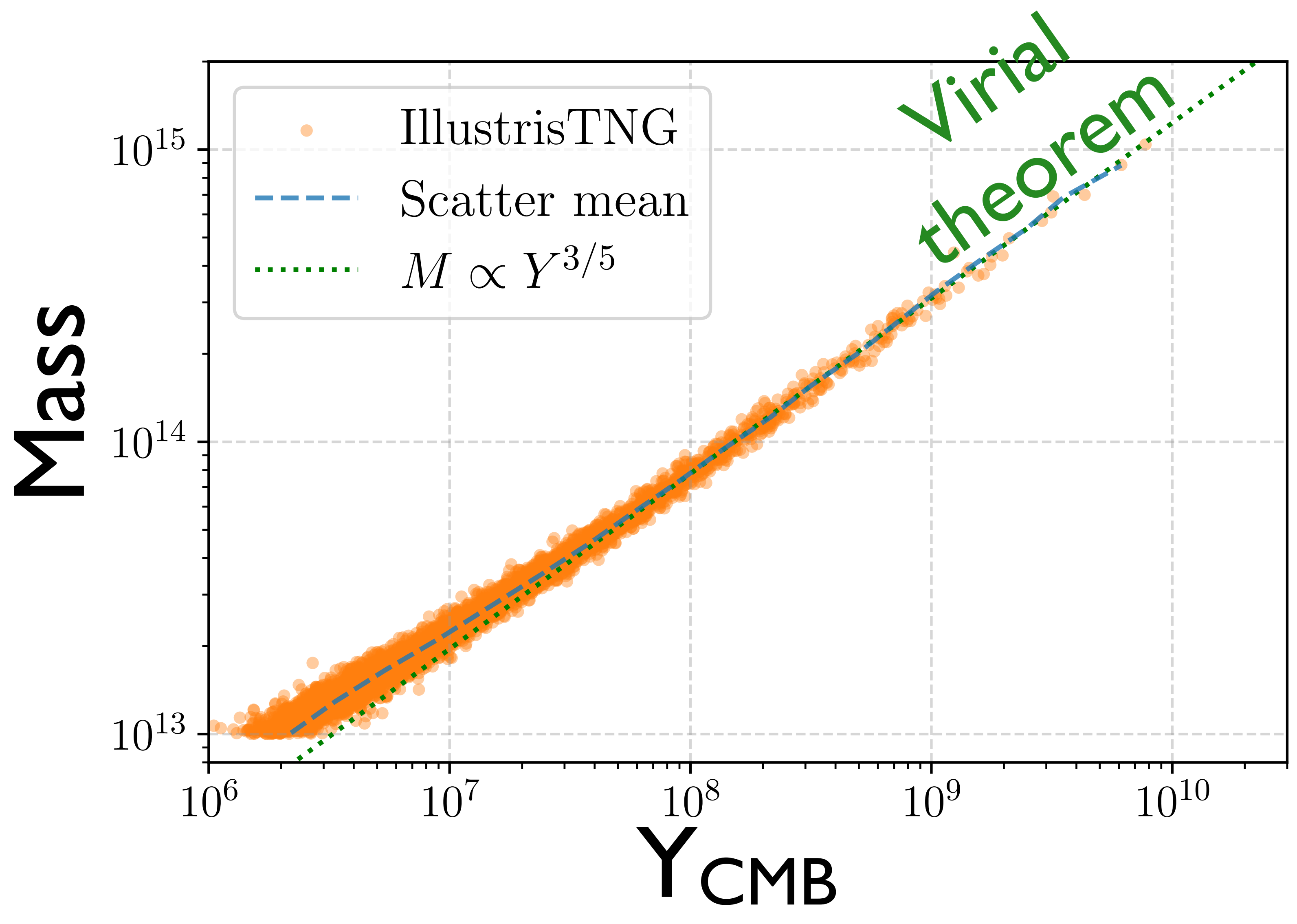
$$Y \propto \int_0^{R_{200c}} P_e(r)\,dV$$

$$\sim M_{\rm gas} T_{\rm gas}$$

(thermal energy of gas)

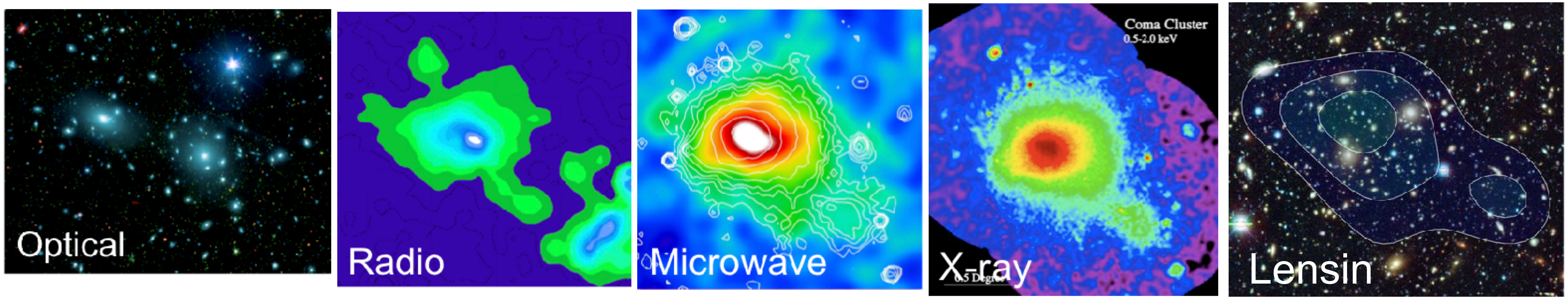
Problem statement

$$M_{\text{cluster}} = f\,(\,Y_{\text{CMB}}^{3/5}\,,\ \text{other observables??}\,)$$



- **X-ray/CMB surveys**
  - Gas density/pressure profile
  - Luminosity profile
  - Spectral temperature
  - Gas concentration/ellipticity
  - ……

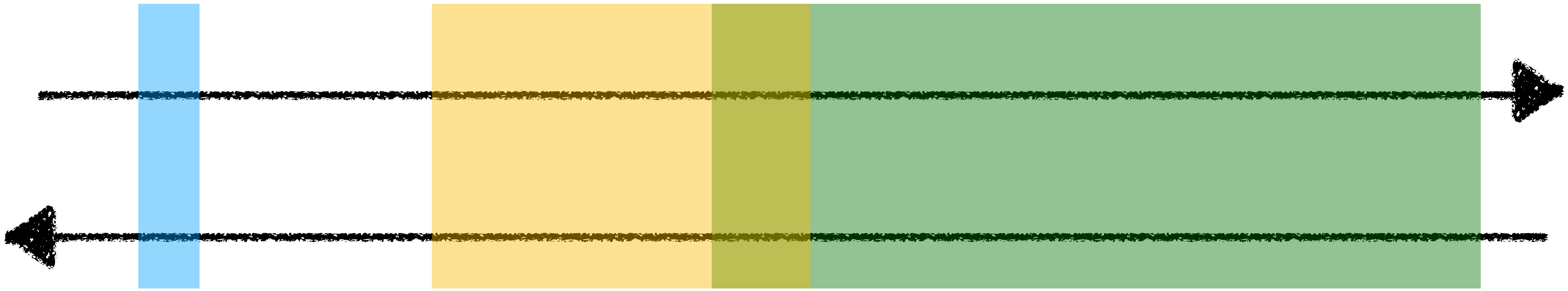
- **Galaxy surveys**
  - Richness
  - Galaxy colors (e.g. fraction of red galaxies)
  - Stellar mass
  - …….



ML tools could be of help

Power
(input dimensionality/
data size)

Generalizability/
Interpretability



Symbolic
regression

Decision-tree
approaches
(e.g., random forests)

Deep neural
networks

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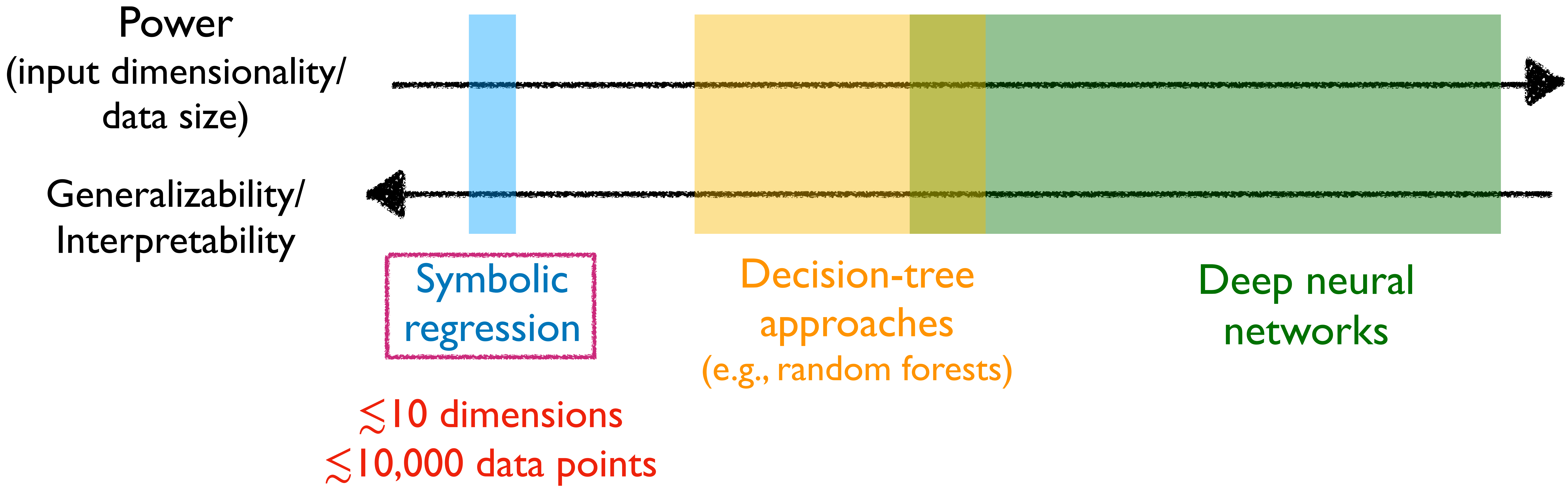

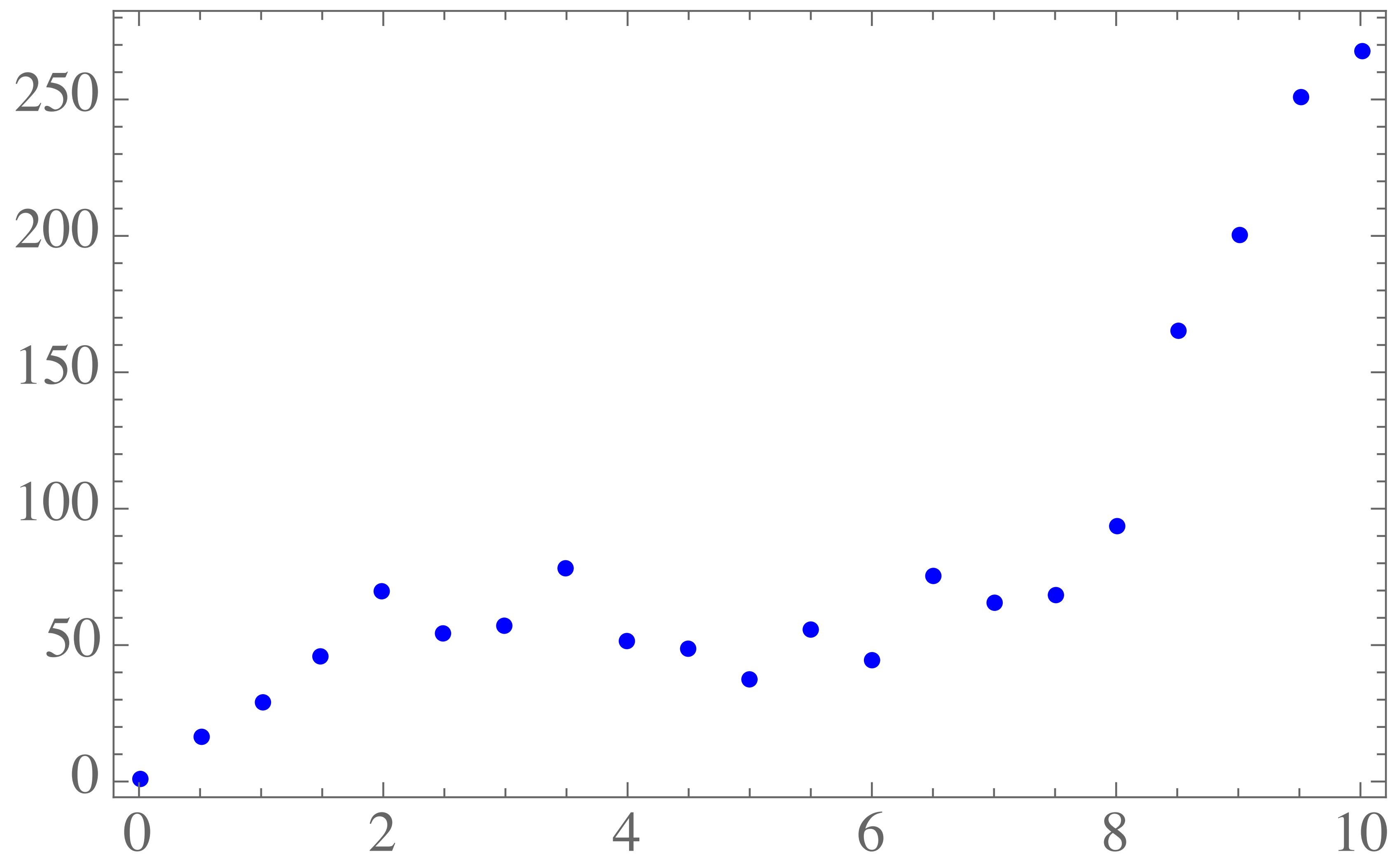

$\cos(x)$ ✘

$a + bx$ (Close)

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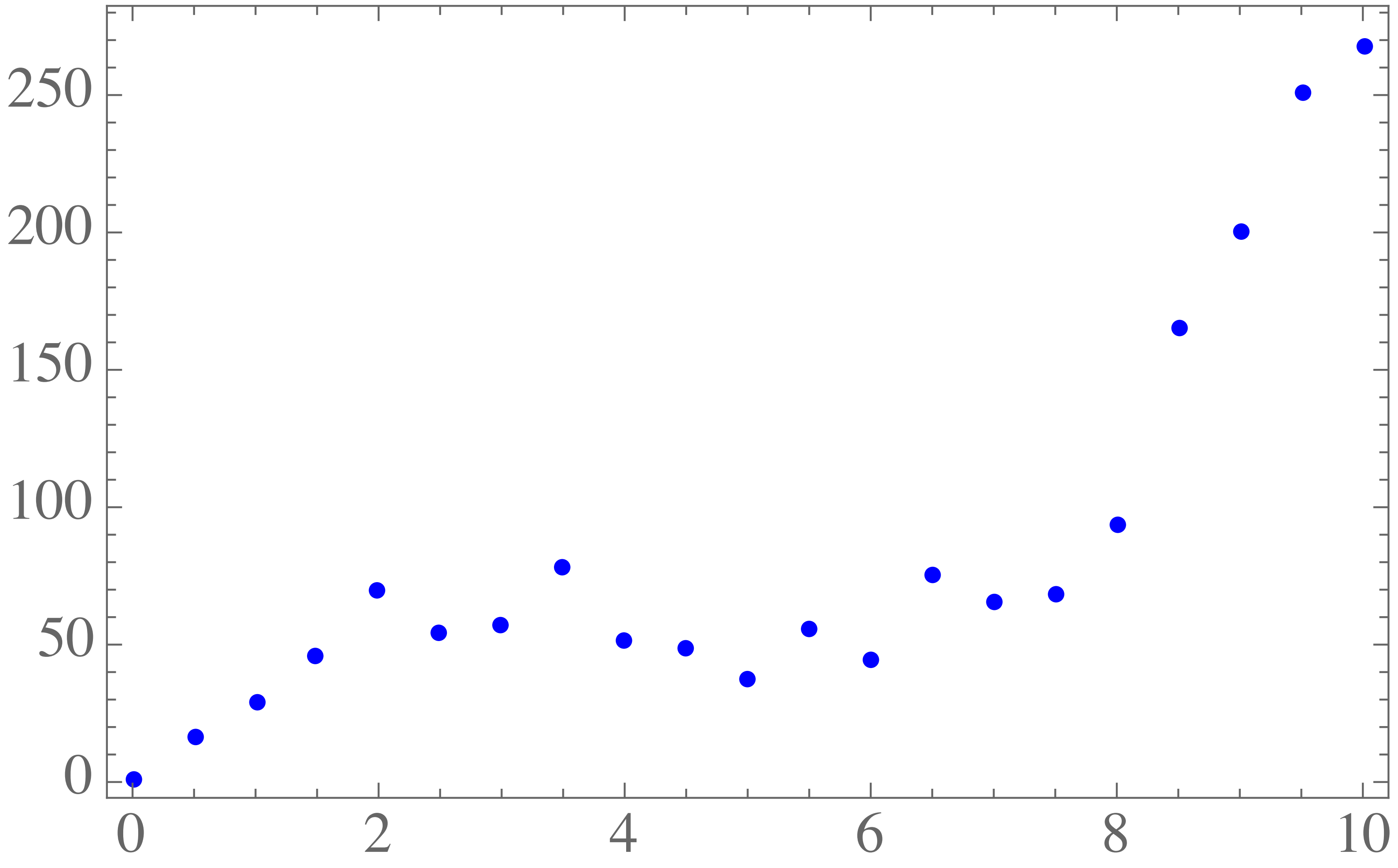
$\lesssim$10 dimensions
$\lesssim$10,000 data points



$\cos(x)$ ✘

$a + bx$ (Close)

$\longrightarrow a + bx + cx^2$ (Closer!)

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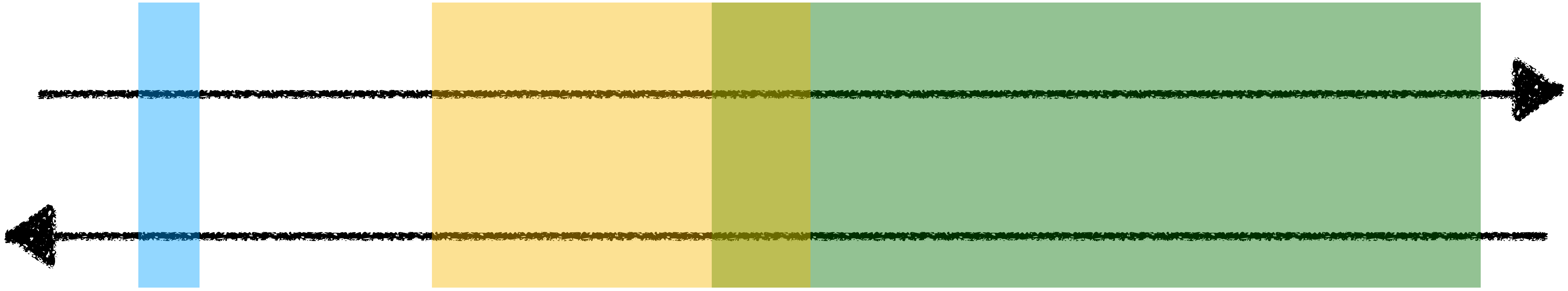

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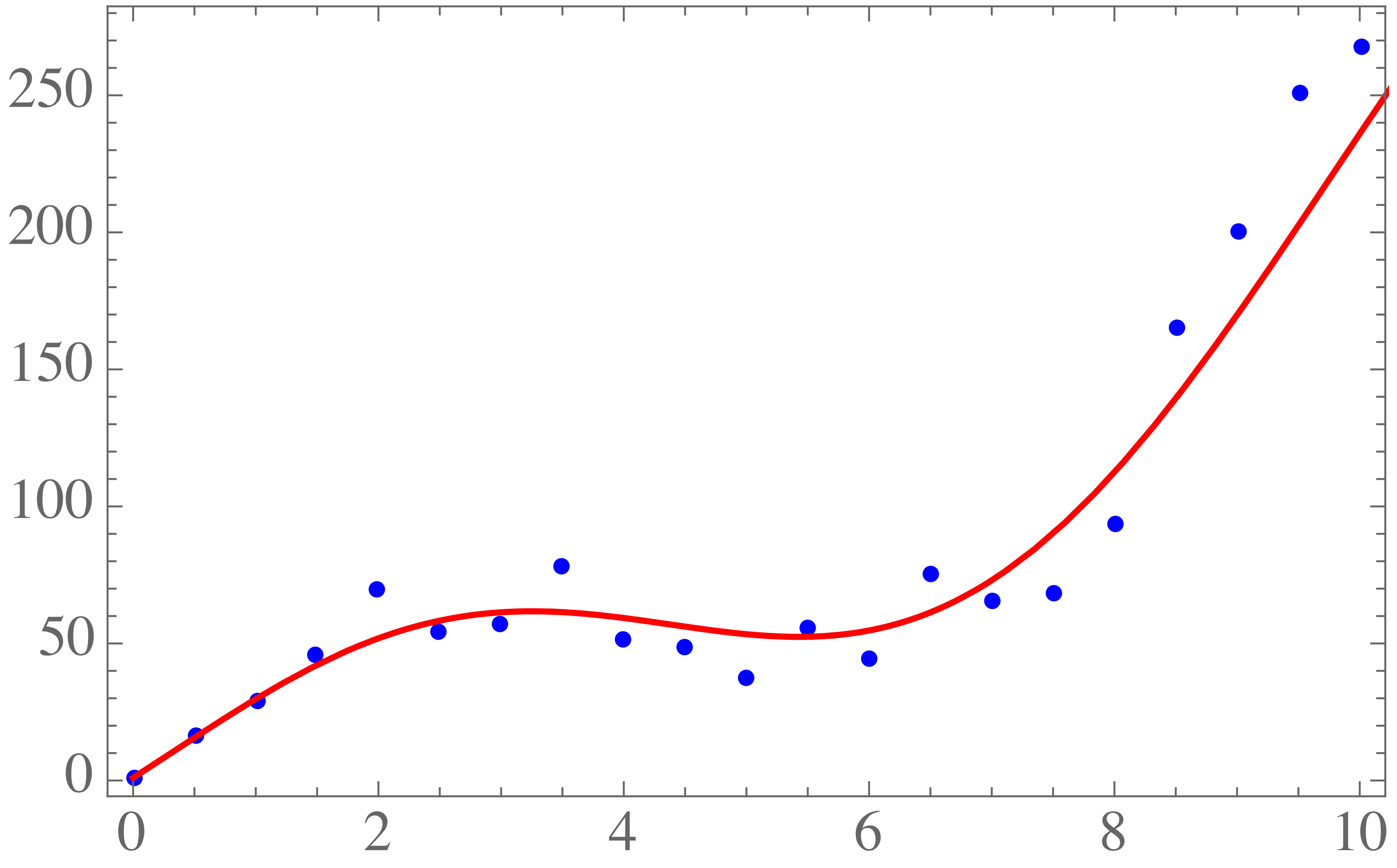

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$a + bx + cx^2 + d\sin(x)$ ✔

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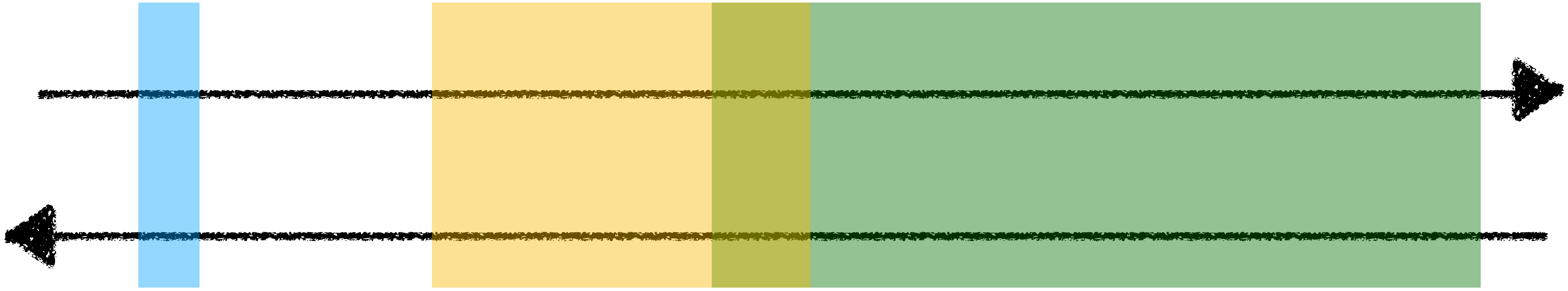

Symbolic
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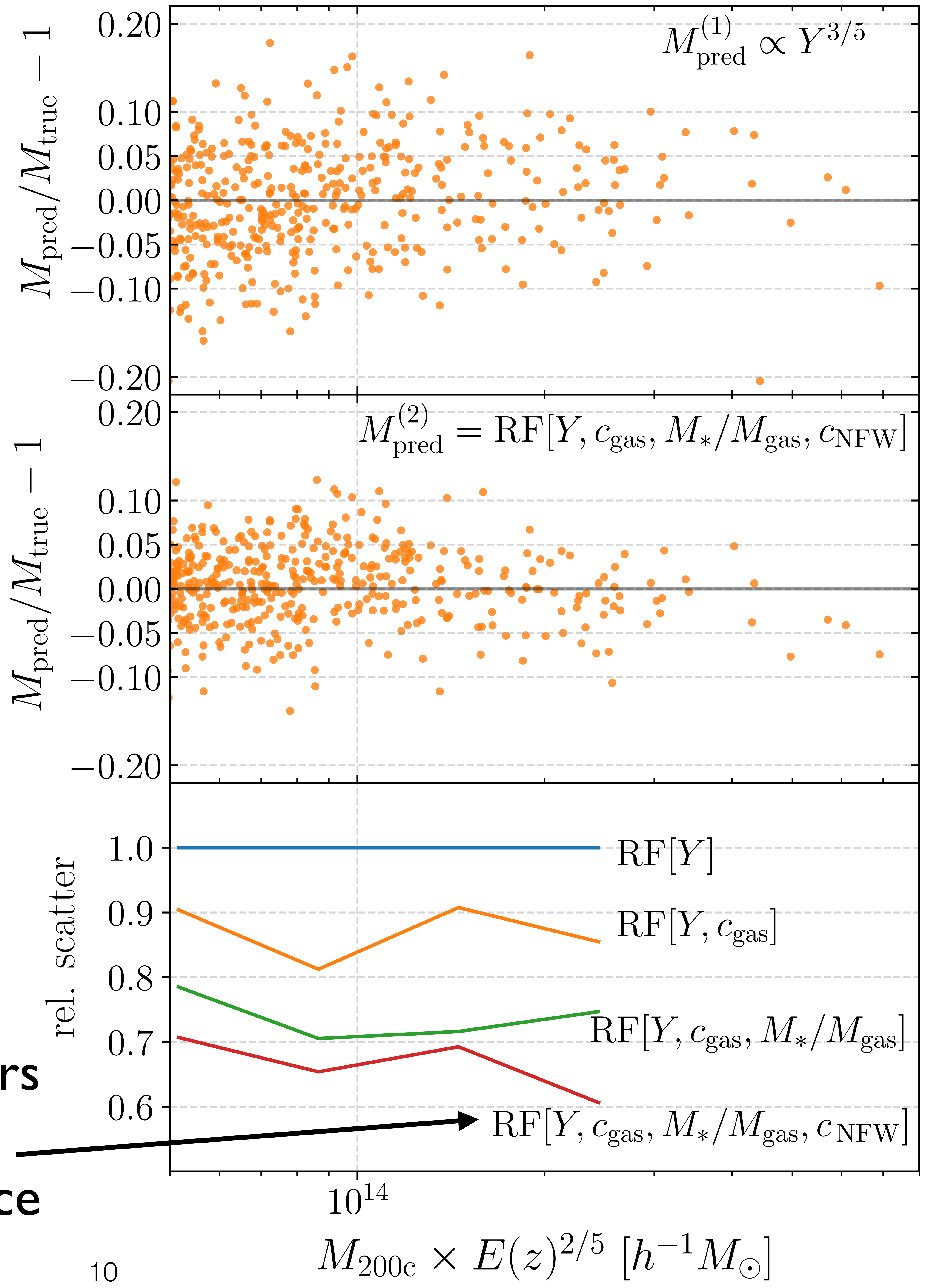
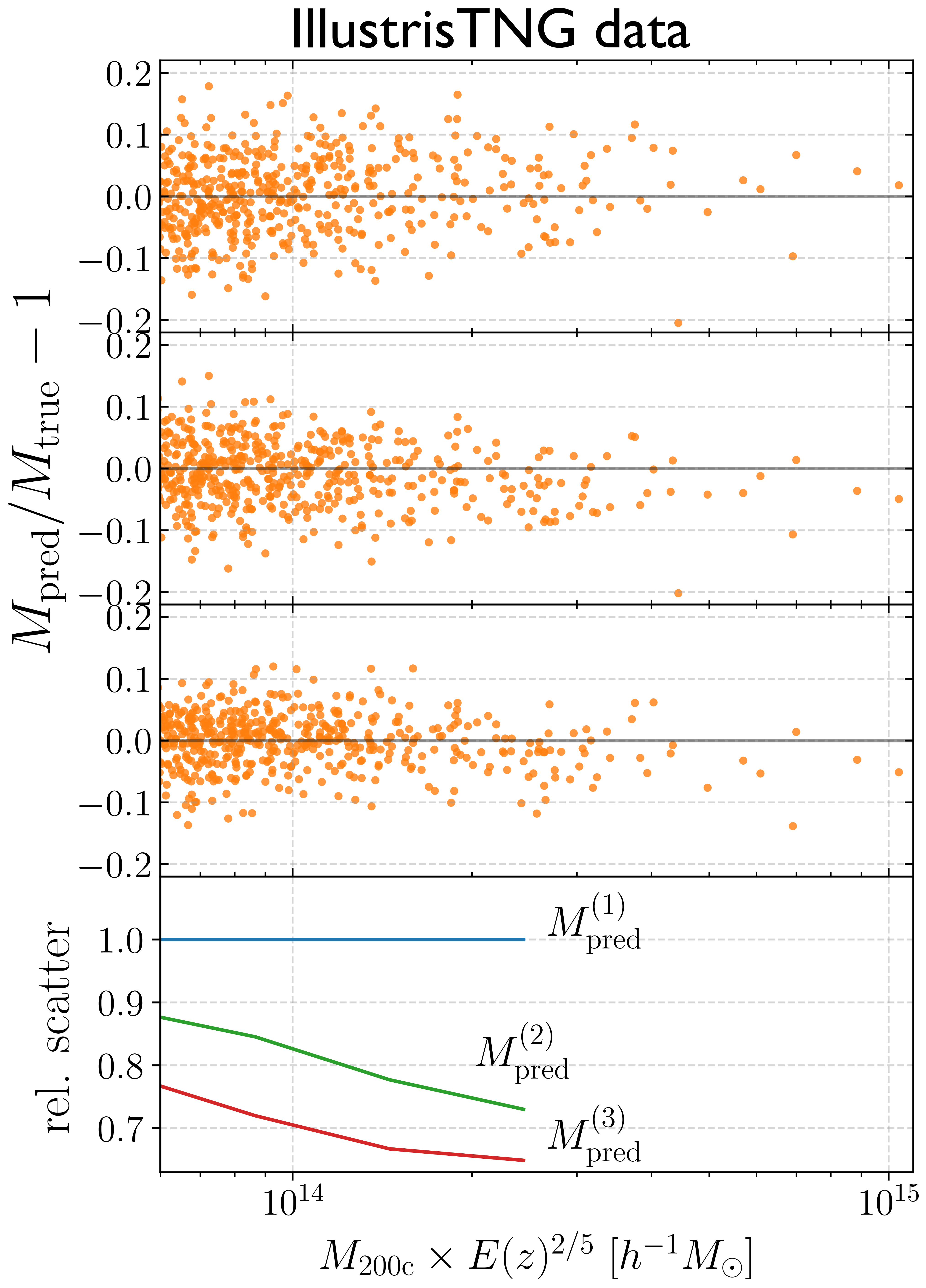
First step:

Use Random Forest (RF) to narrow down the parameter space



We found adding more parameters [M_{gas}, axiality, richness,…] does not improve the performance

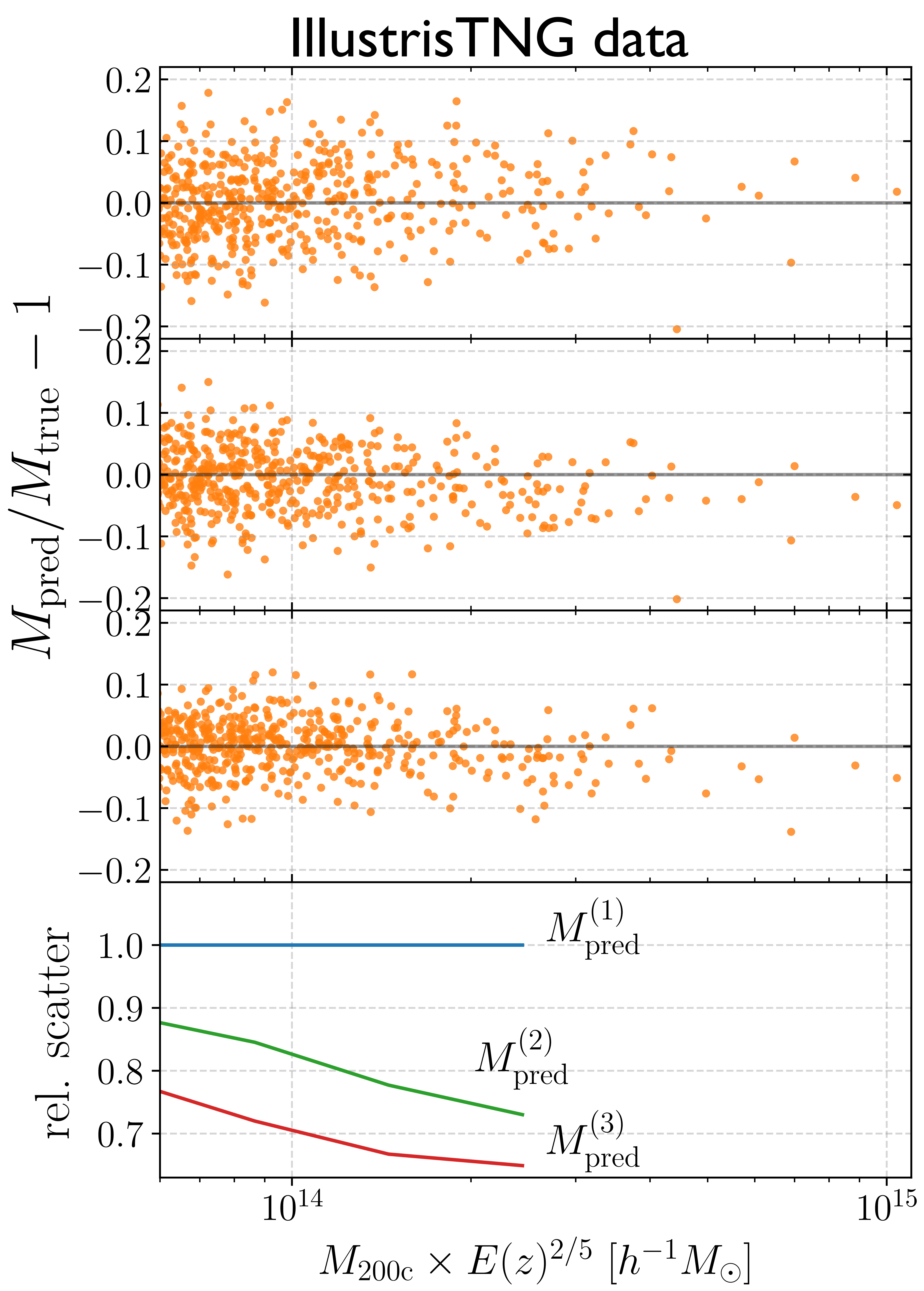
Second step: Symbolic regression



$$M^{(1)}_{\rm pred} \propto Y^{3/5}$$

$$M^{(2)}_{\rm pred} \propto Y^{3/5}\,(1 - A\,c_{\rm gas}) \qquad c_{\rm gas} \equiv \frac{M_{\rm gas}(r < R_{200c}/2)}{M_{\rm gas}(r < R_{200c})}$$

$$M^{(3)}_{\rm pred} \propto Y^{3/5}\left(\frac{B}{c_{\rm NFW}}\right)^{M_*/M_{\rm gas}}$$



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Reasons for dependence:

1. Central regions of clusters are noisier
   (conc. can be used to down-weight central regions)

2. Conversion of gas to stars reduces Y

Kravtsov et al. 06, Arnaud et al. 10

But IllustrisTNG has only one configuration of baryonic feedback and initial conditions?

Do the results hold in a more general setting?

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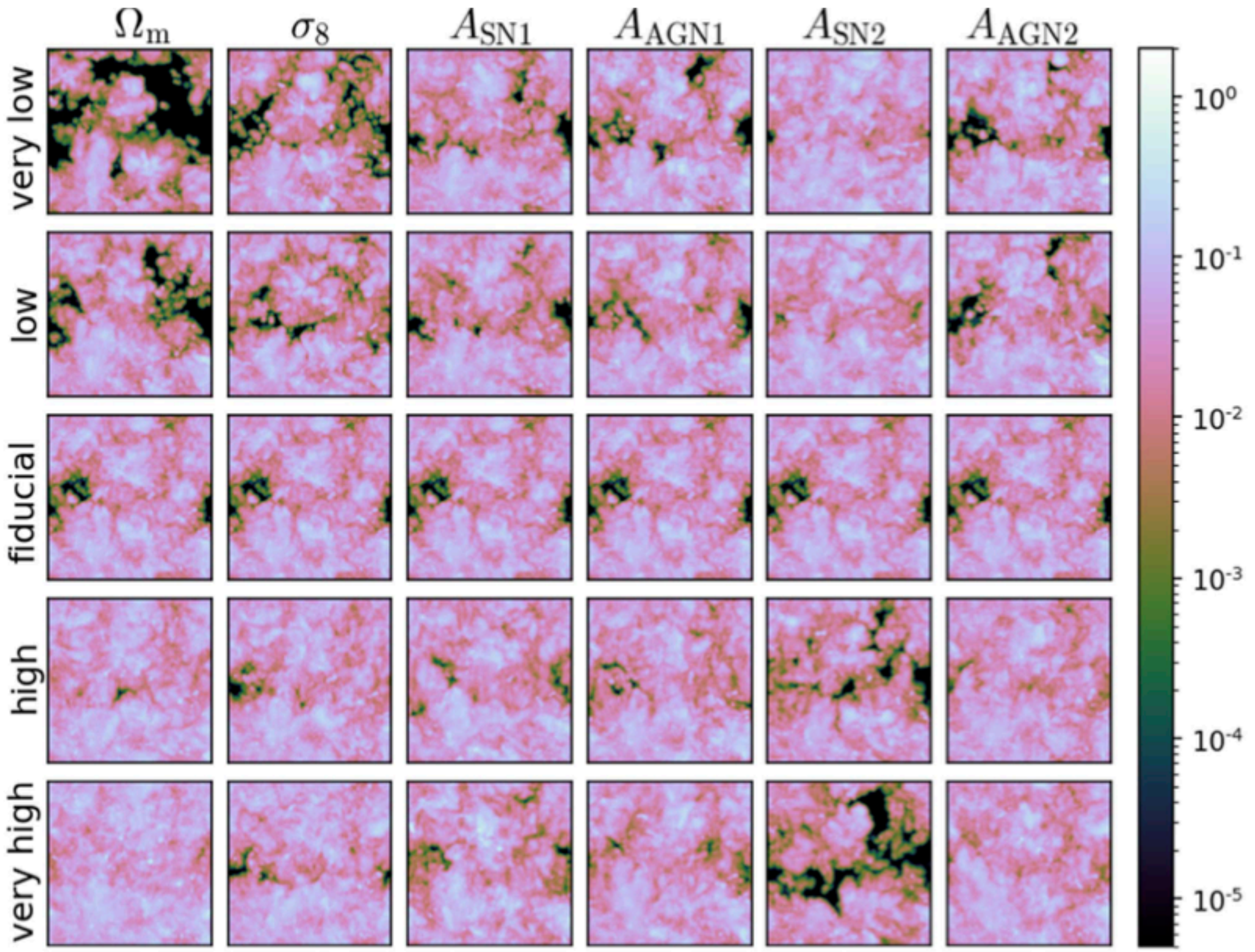
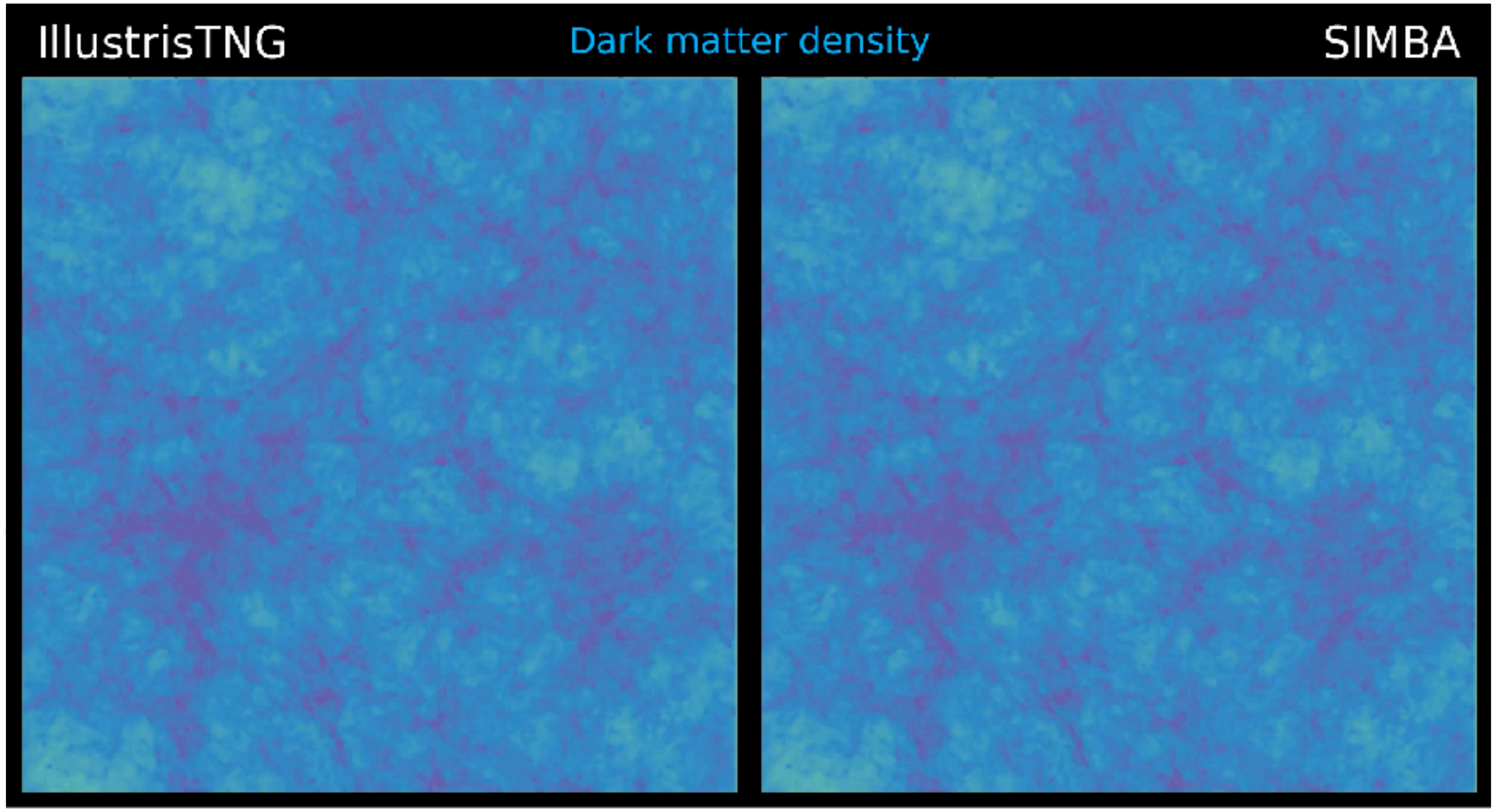
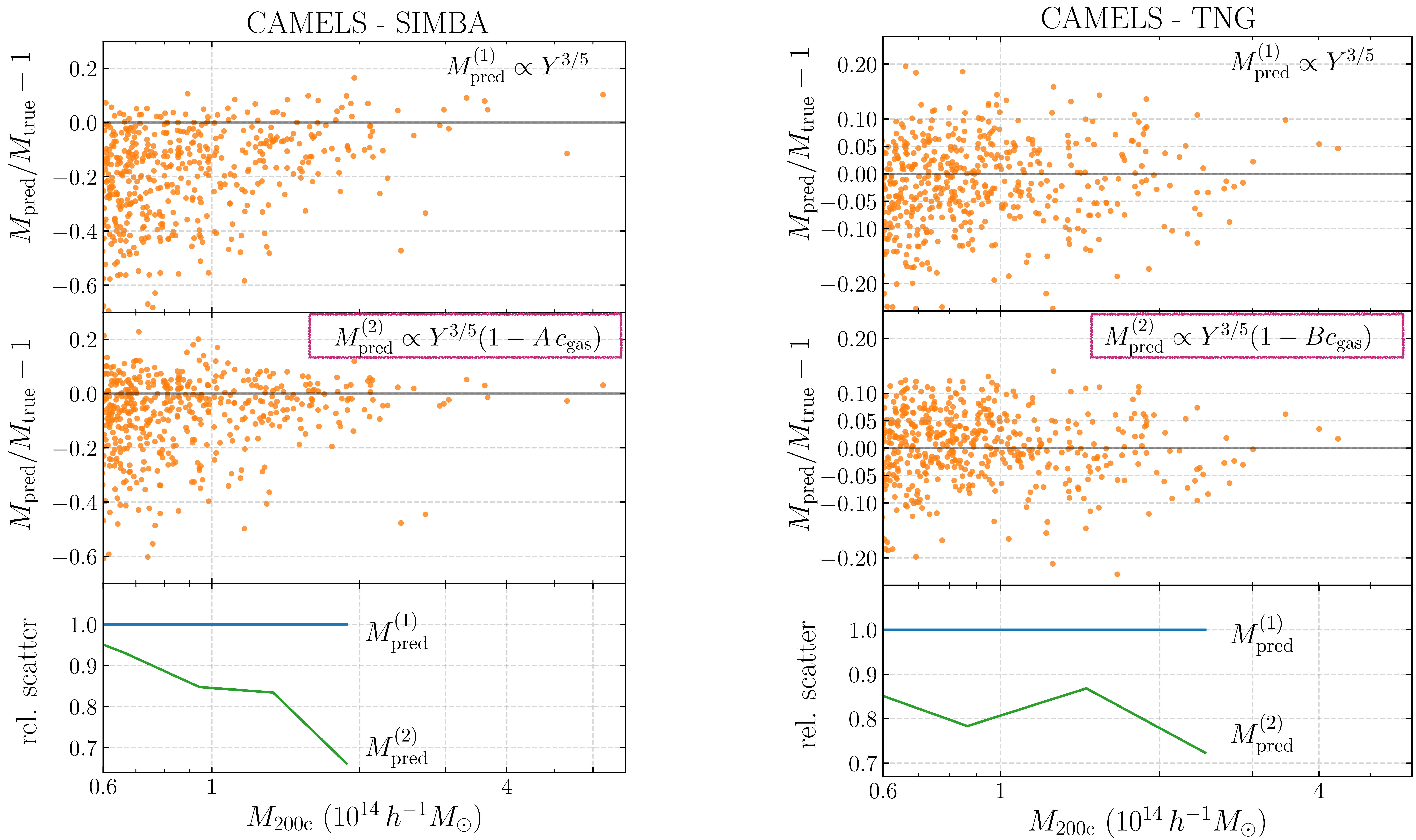


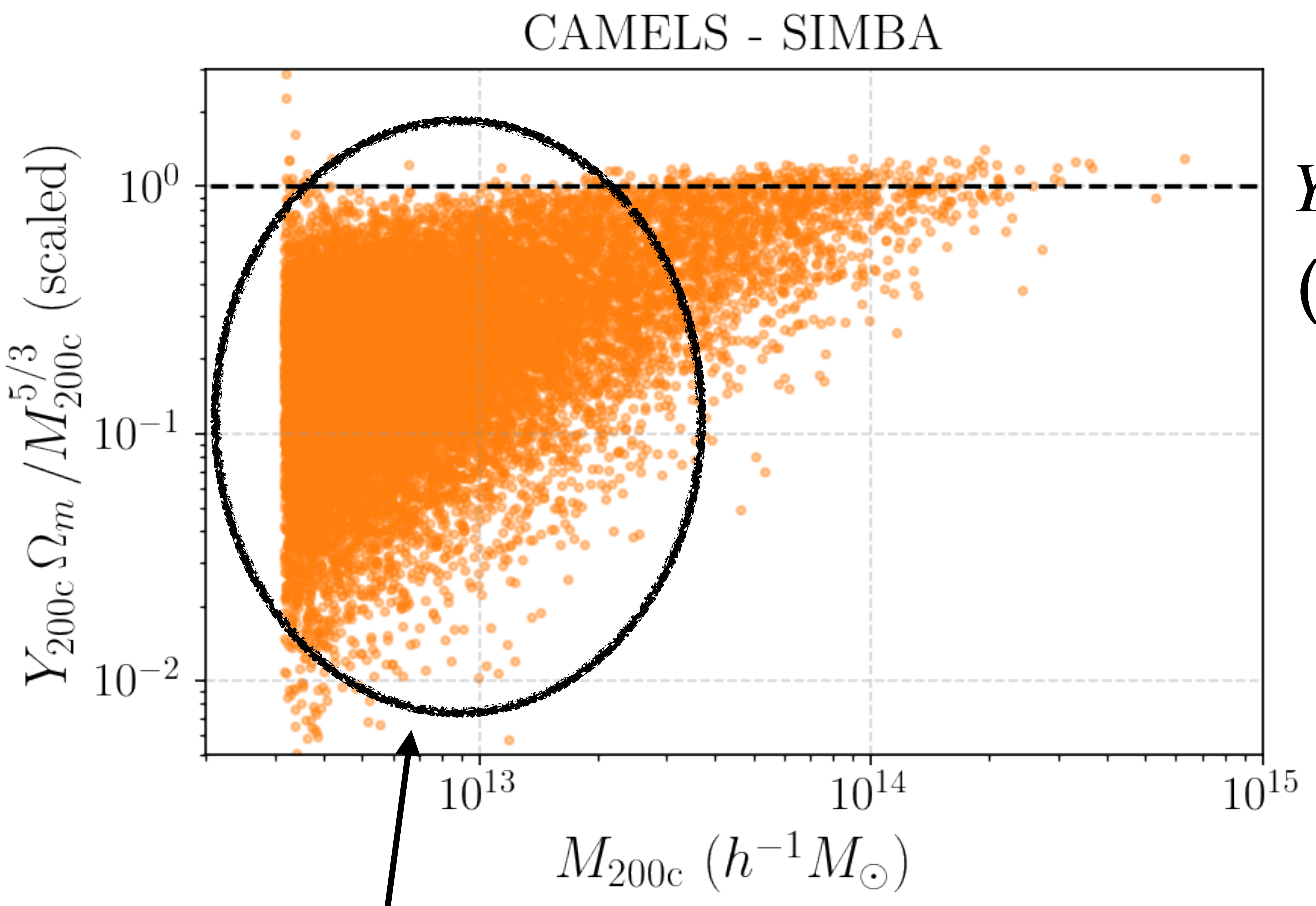


CAMELS simulations
(Villaescusa-Navarro et al. 21)

Our result seems robust w.r.t feedback prescriptions



Part II : Reducing deviation from self-similarity (pow. law)

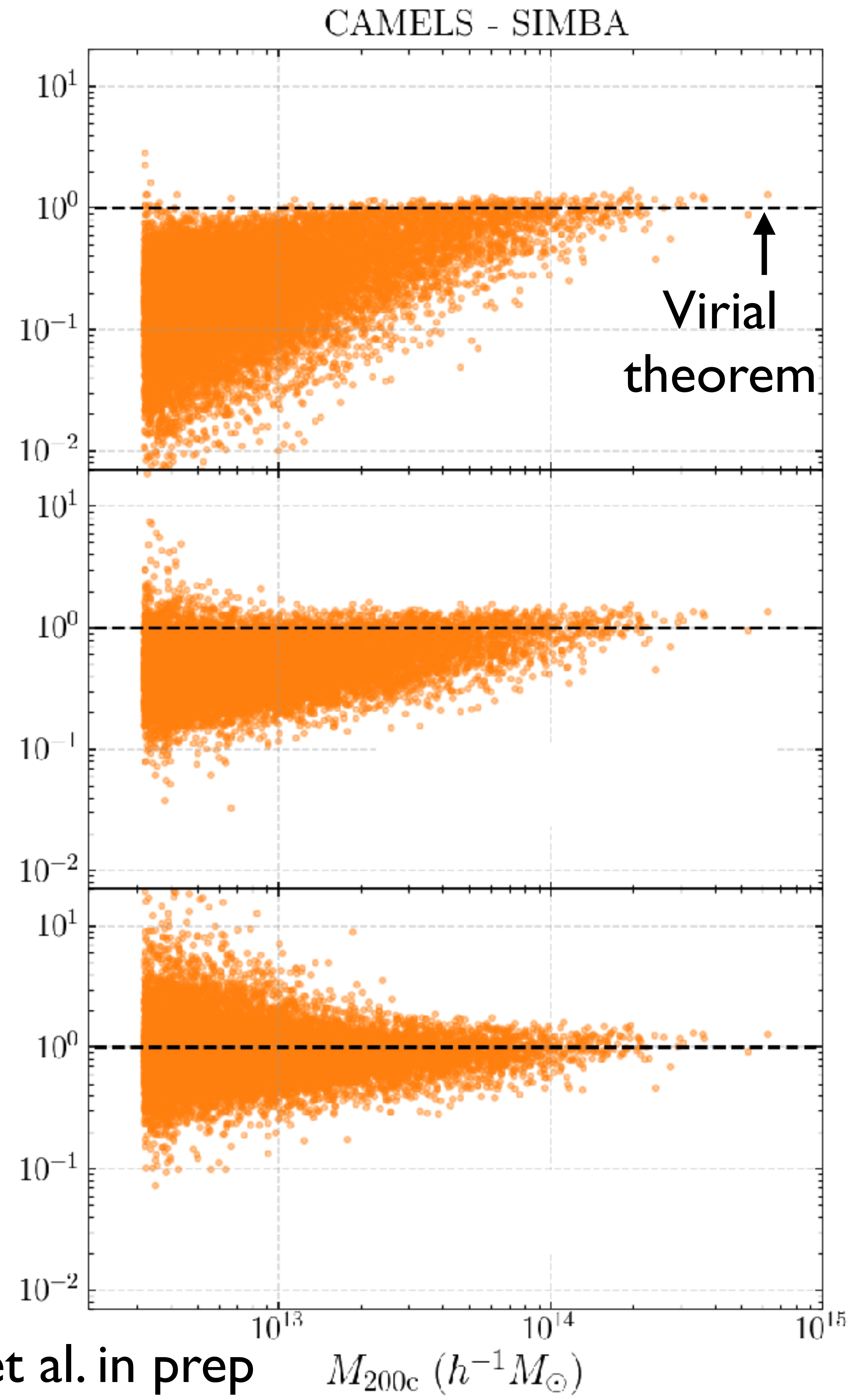


$Y \propto M^{5/3}$

(virial theorem)

Due to ejection of gas from clusters/groups due to AGN/SN feedback

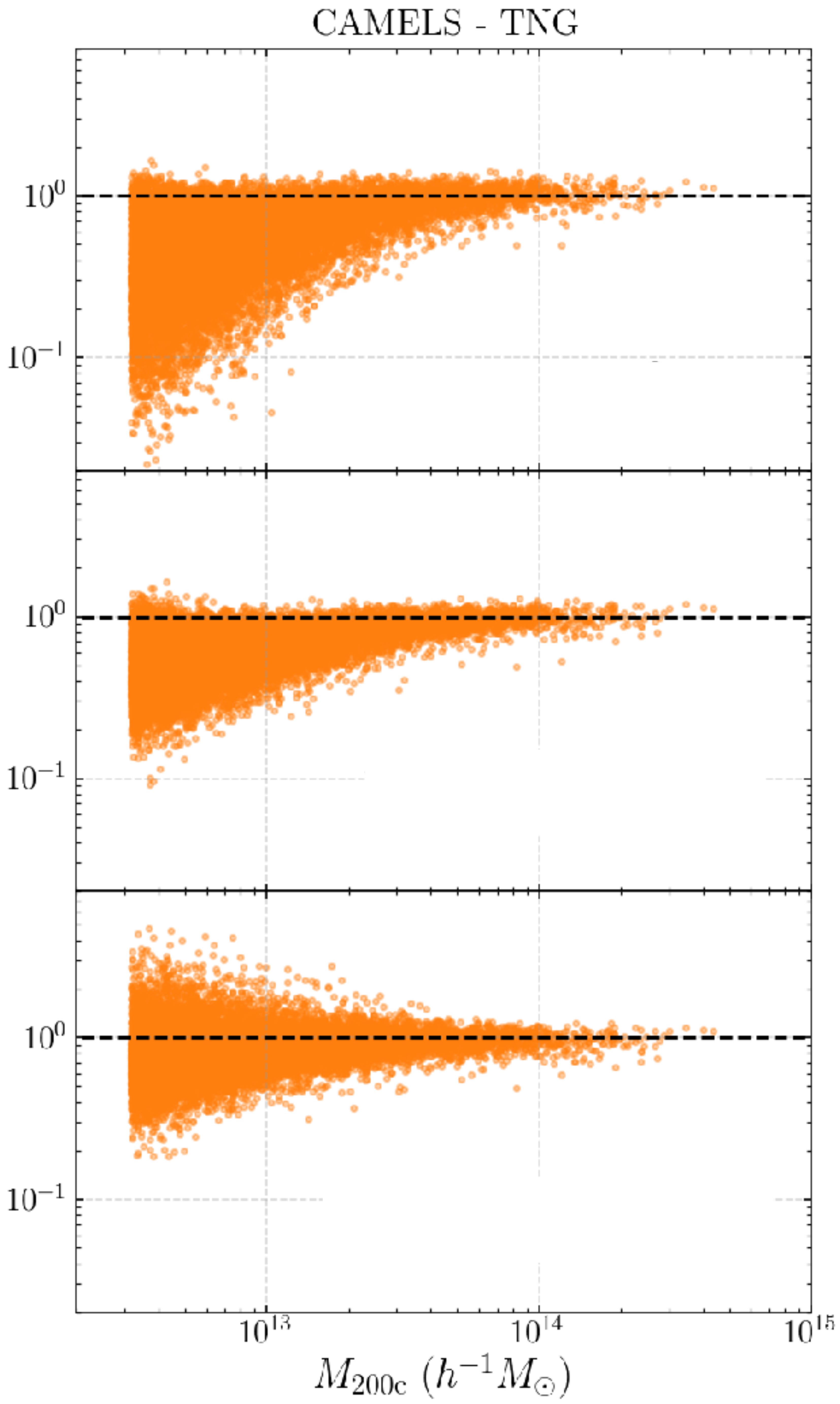
Results



Y

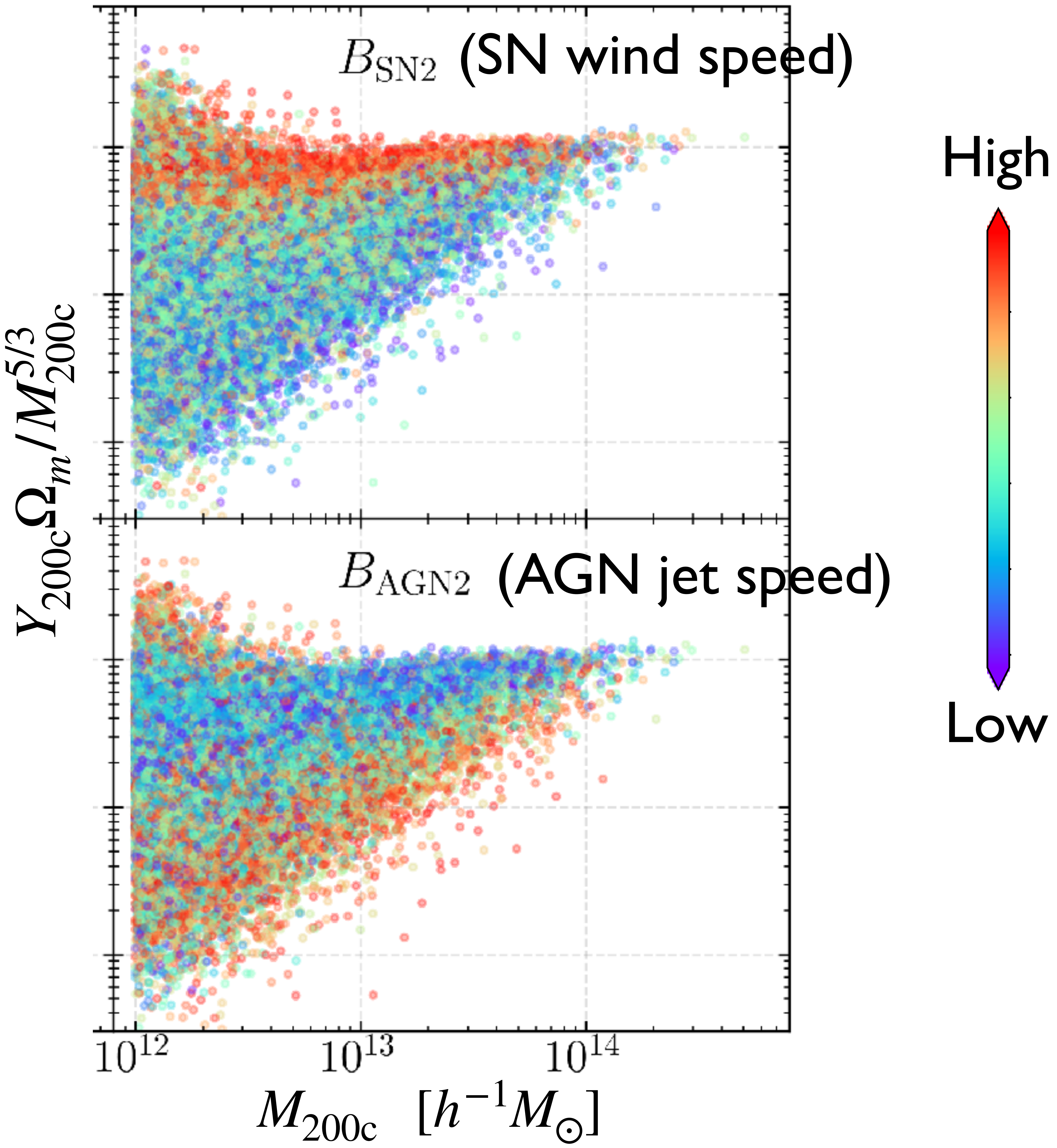
$$Y\left(1+\frac{M_*(r<R)}{M_{\rm gas}(r<R)}\right)$$

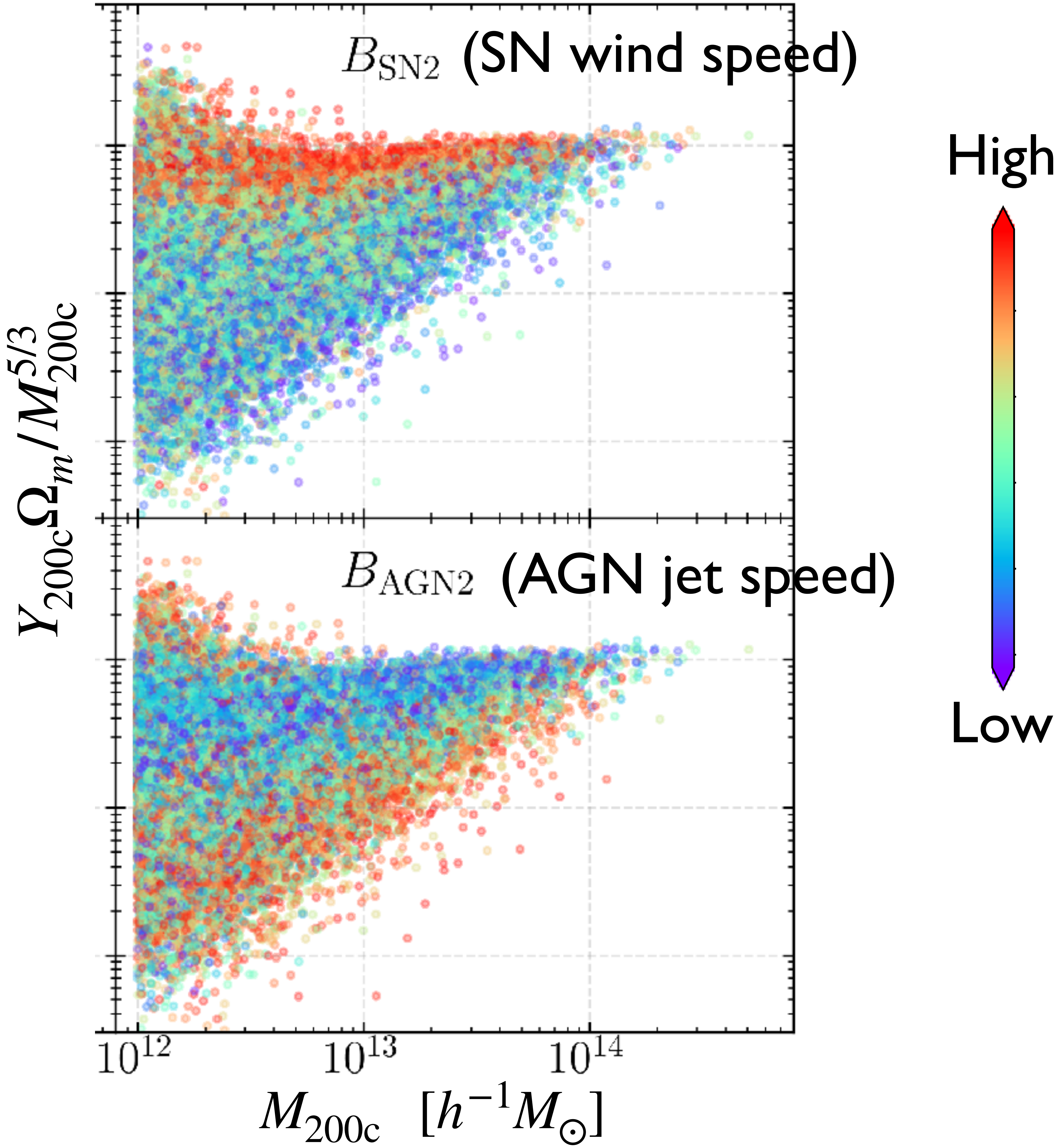
$$Y\left[1+\frac{M_*(r<R/2)}{M_{\rm gas}(r<R/2)}\right]$$



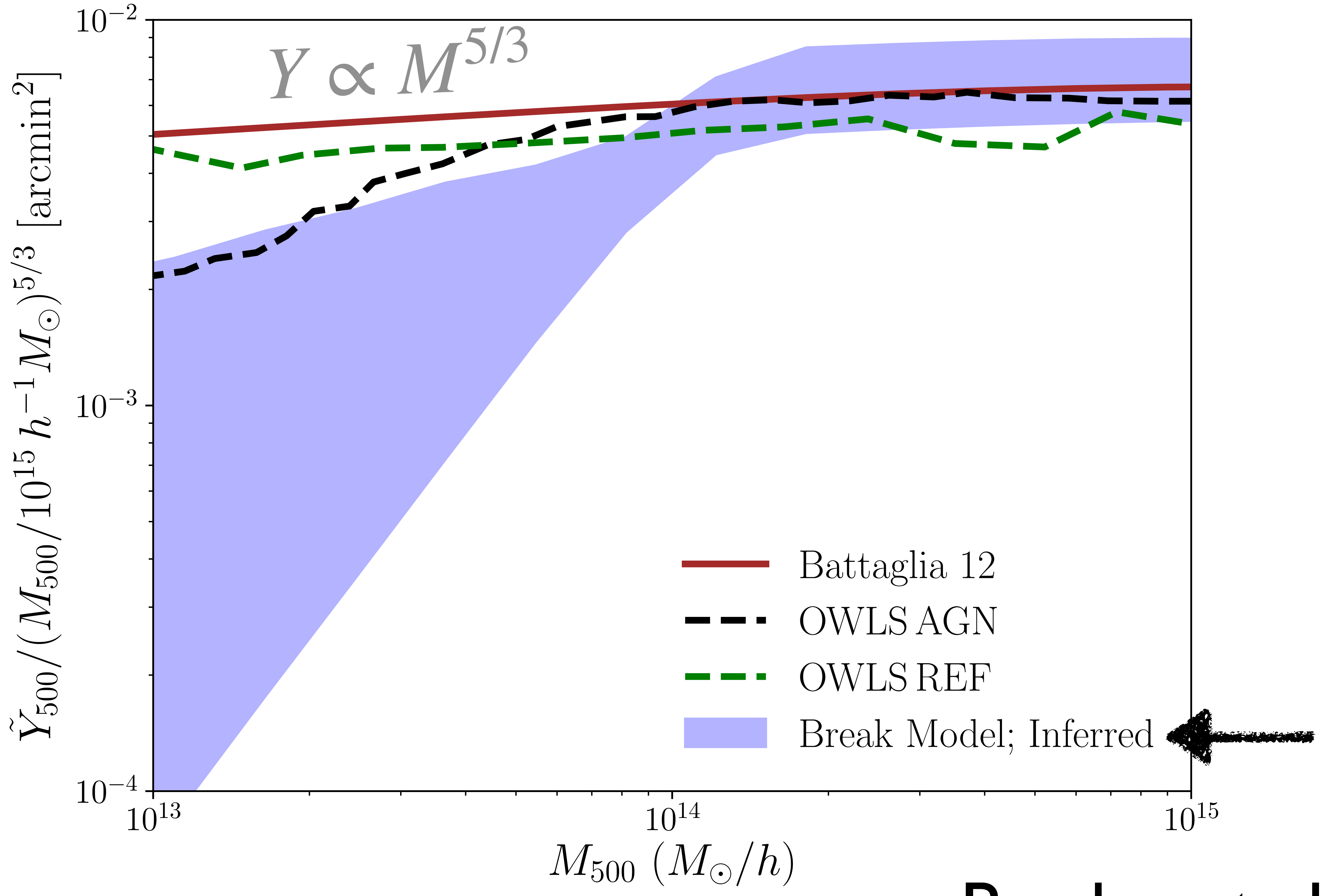
DW et al. in prep

Part III : Can we use the Y-M measurements to constrain baryonic feedback?





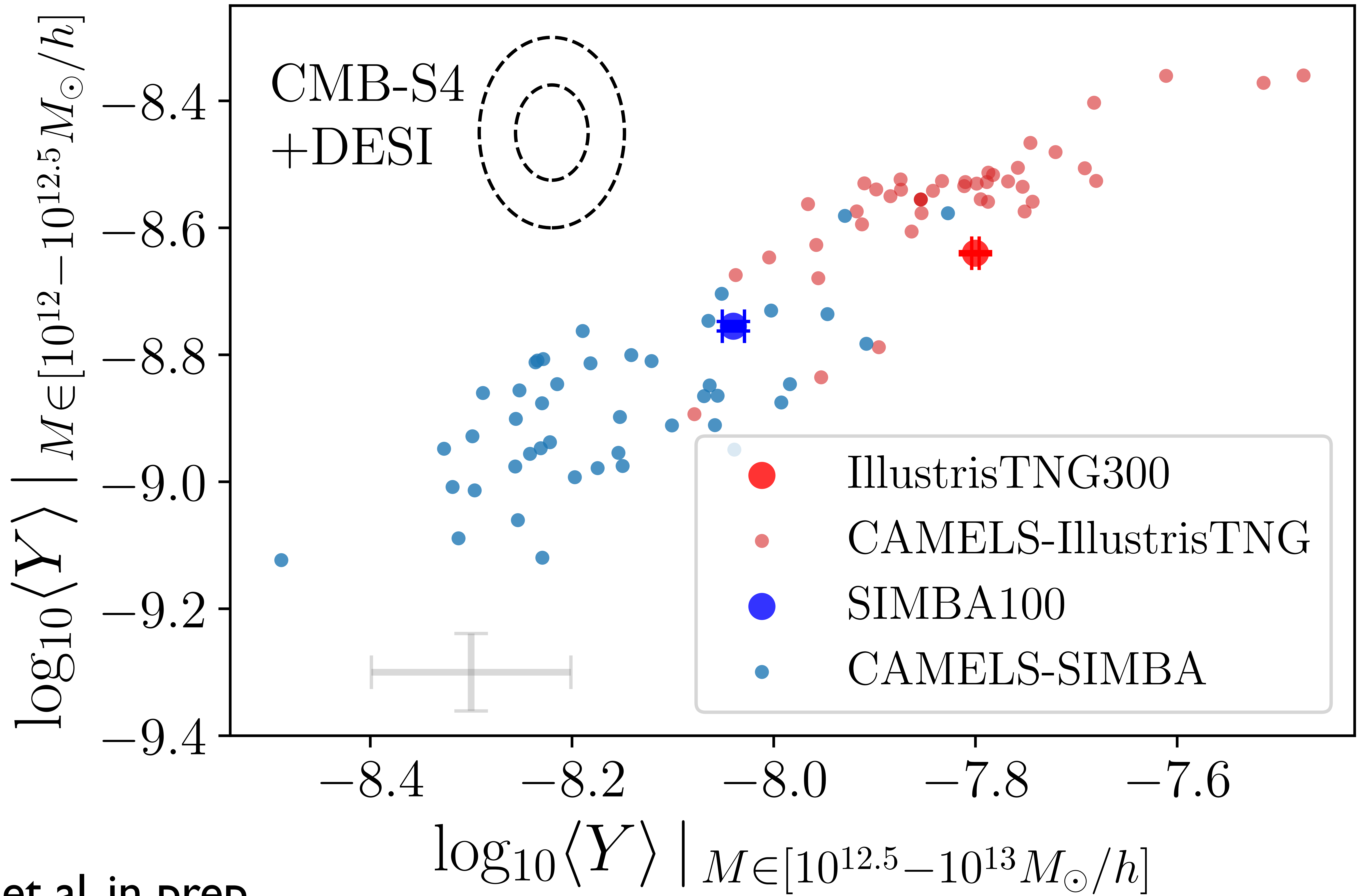
Observations



Pandey et al. 21
(ACT x DES)

Le Brun et al. 15
Hill et al. 18

Constraints on sub-grid models



DW et al. in prep

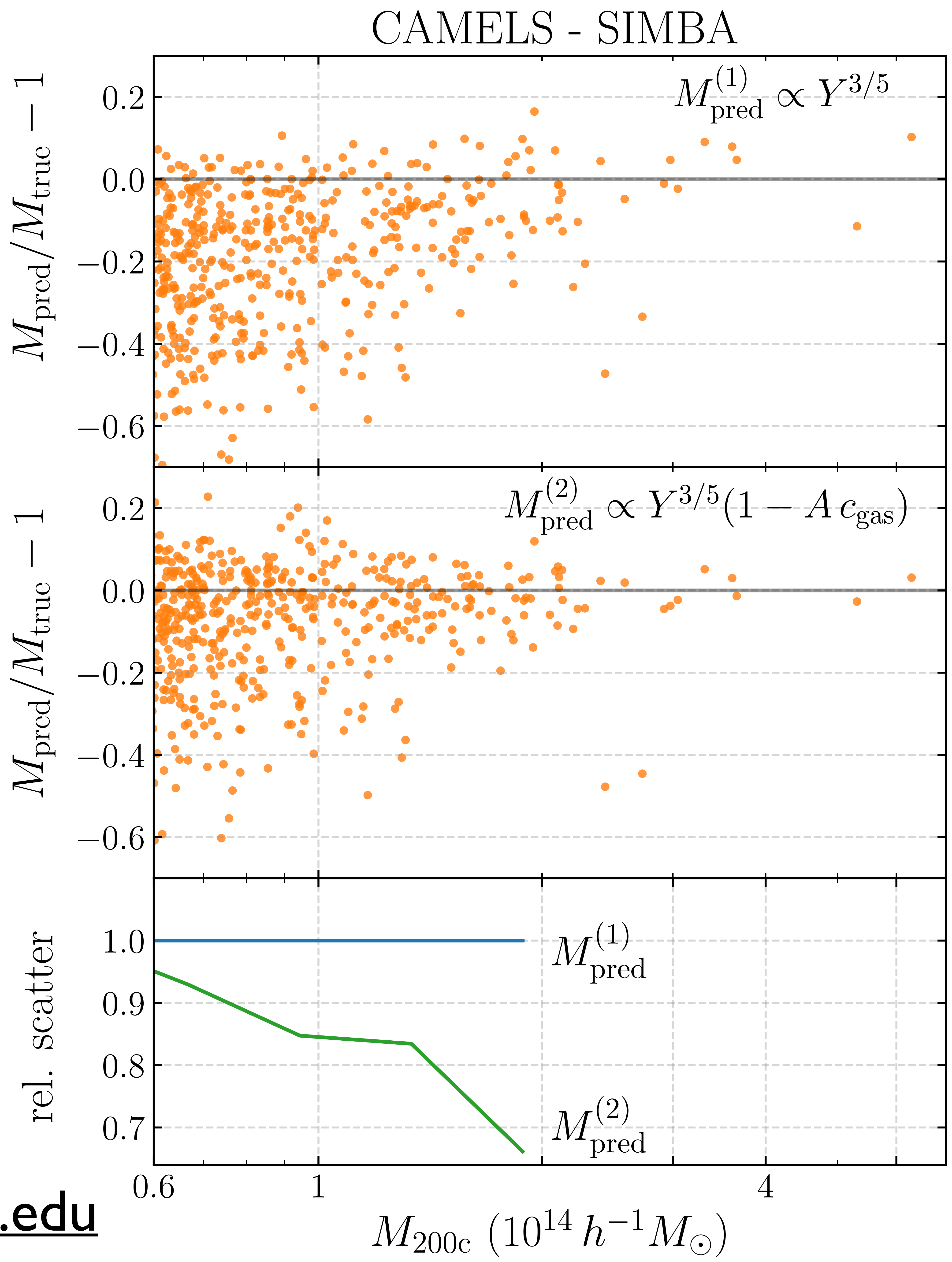
Summary

★ ML tools like symbolic regression can be used to improve astrophysical scaling relations

- Using gas conc. reduces scatter in SZ mass estimates by 20-30% for large clusters

- Including stellar to gas mass ratio reduces deviation from self-similarity by factor >2

➡ Suggestions for other scaling relations?



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Application to other scaling relations?

Delgado/DW et al. 21

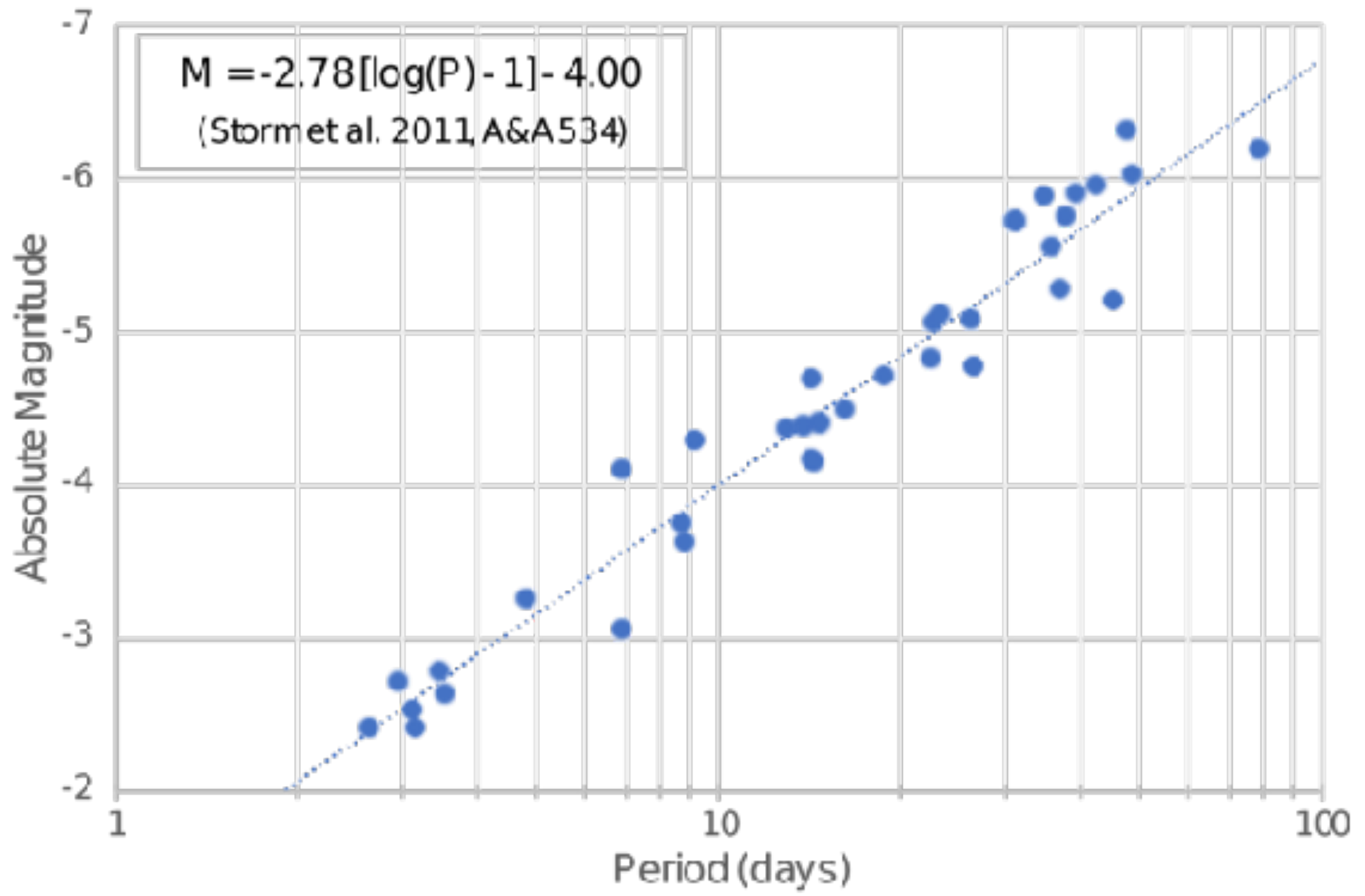
$N_{\rm gal}$ or $M_{\rm HI}$ = f (Halo mass, *secondary props.*)

{*env., conc, shear,….*}

$$\frac{M_{\rm HI}}{M_{\rm HOD}} = 0.81 + 1.44\,\alpha'_{0.5}\,m_{10} - 0.57\,(\alpha'^2_{0.5}\,m^2_{10} + \alpha'_{0.5}\,\delta'_5)$$

- Cepheid P-L relation (useful for measuring H_0)

$$M_{\rm v} = A(\log_{10}P - 1) - B$$



- Philips relation for supernovae

$$M_{\rm max}(B) = -21.726 + 2.698\,\Delta m_{15}(B)$$

- Tully fisher relation
- Black hole-bulge mass relation
- Fundamental plane relation
- ….