Characterising DM substructures in strong lensing images with targeted simulation-based inference

Noemi Anau Montel

with

Adam Coogan · Camila Correa · Konstantin Karchev · Elias Dubbeldam · Christoph Weniger

Coogan et al. (2020)

Karchev et al. (2021)

NAM et al. (2022)

and more very soon!

GRAPPA

GRavitation AstroParticle Physics Amsterdam

UNIVERSITY OF AMSTERDAM

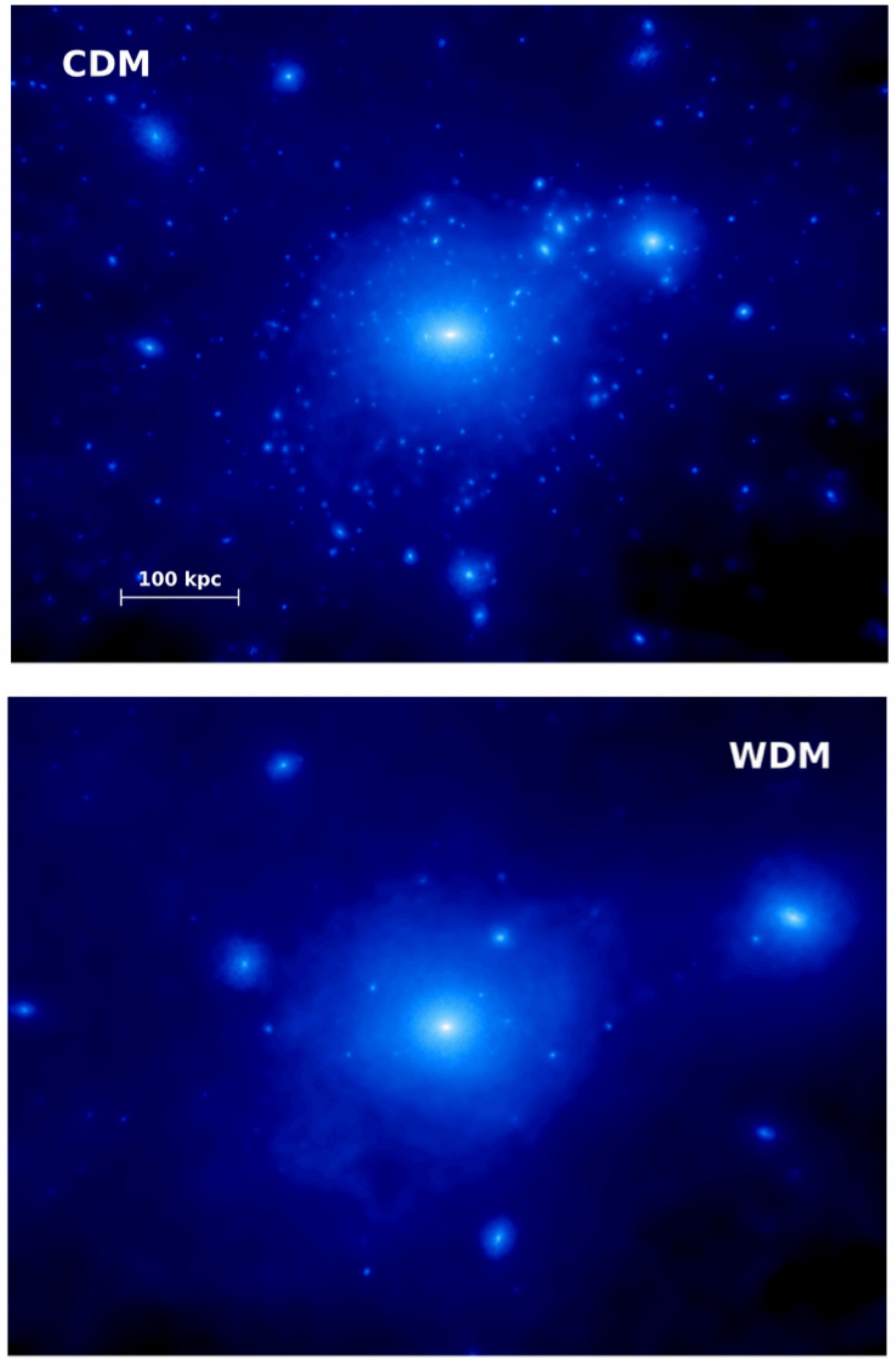
IDM 2022

14th International Conference on Identification of Dark Matter

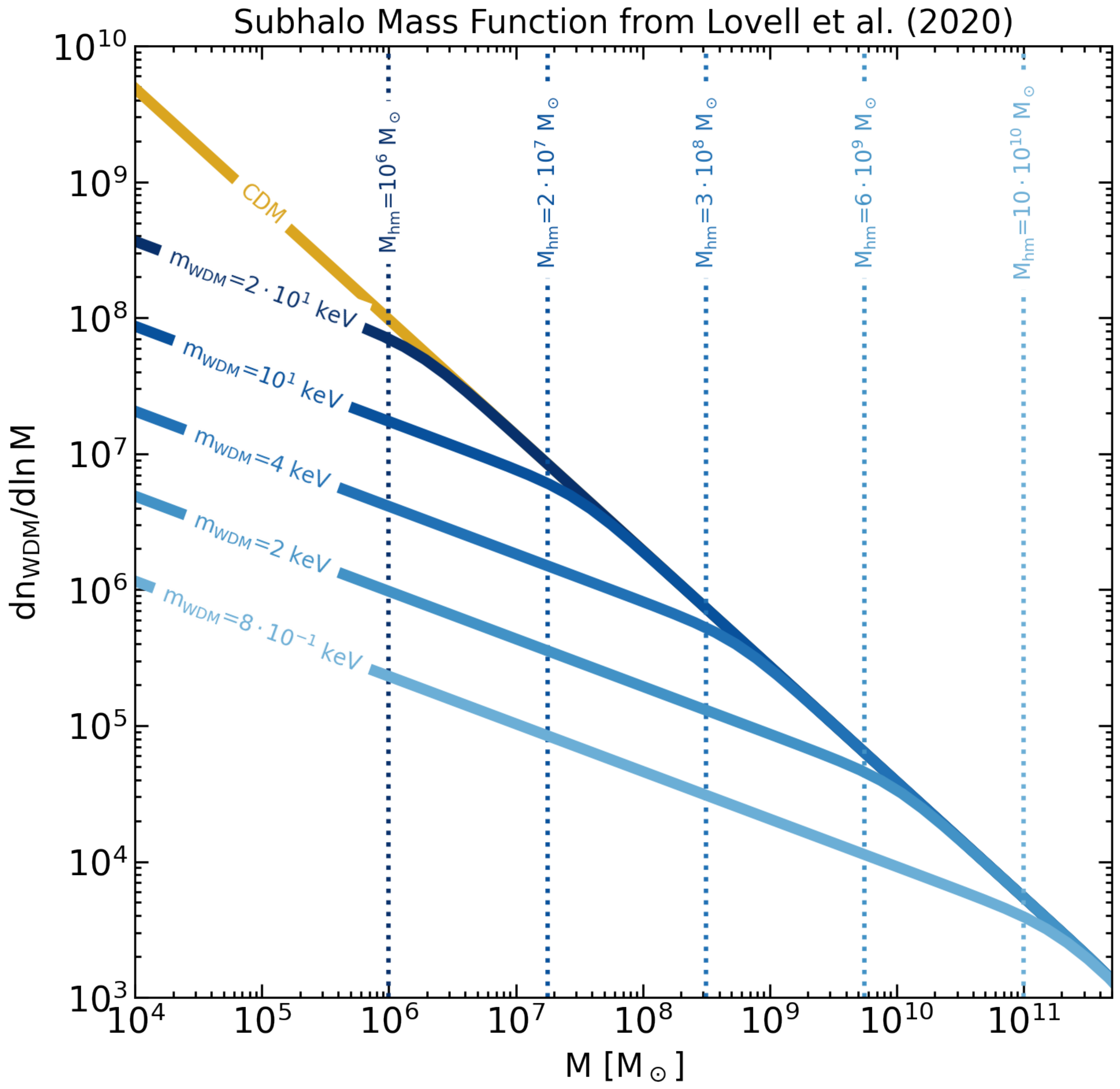
18-22 July 2022
Vienna, Austria

As seen in Carlos Frenk's talk 

DM physics is encoded in the properties of DM halos



Bœhm et al. (2014)



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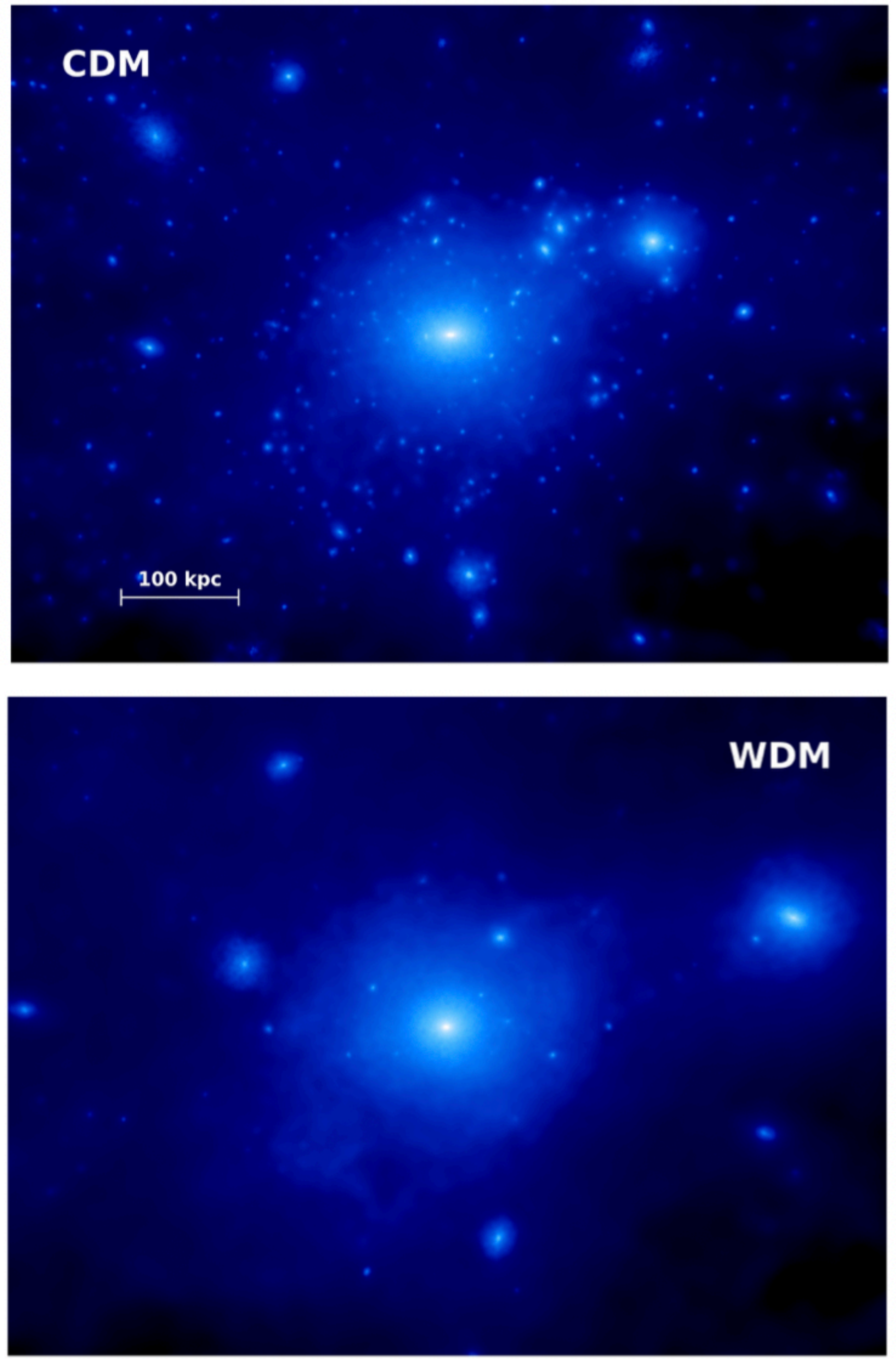

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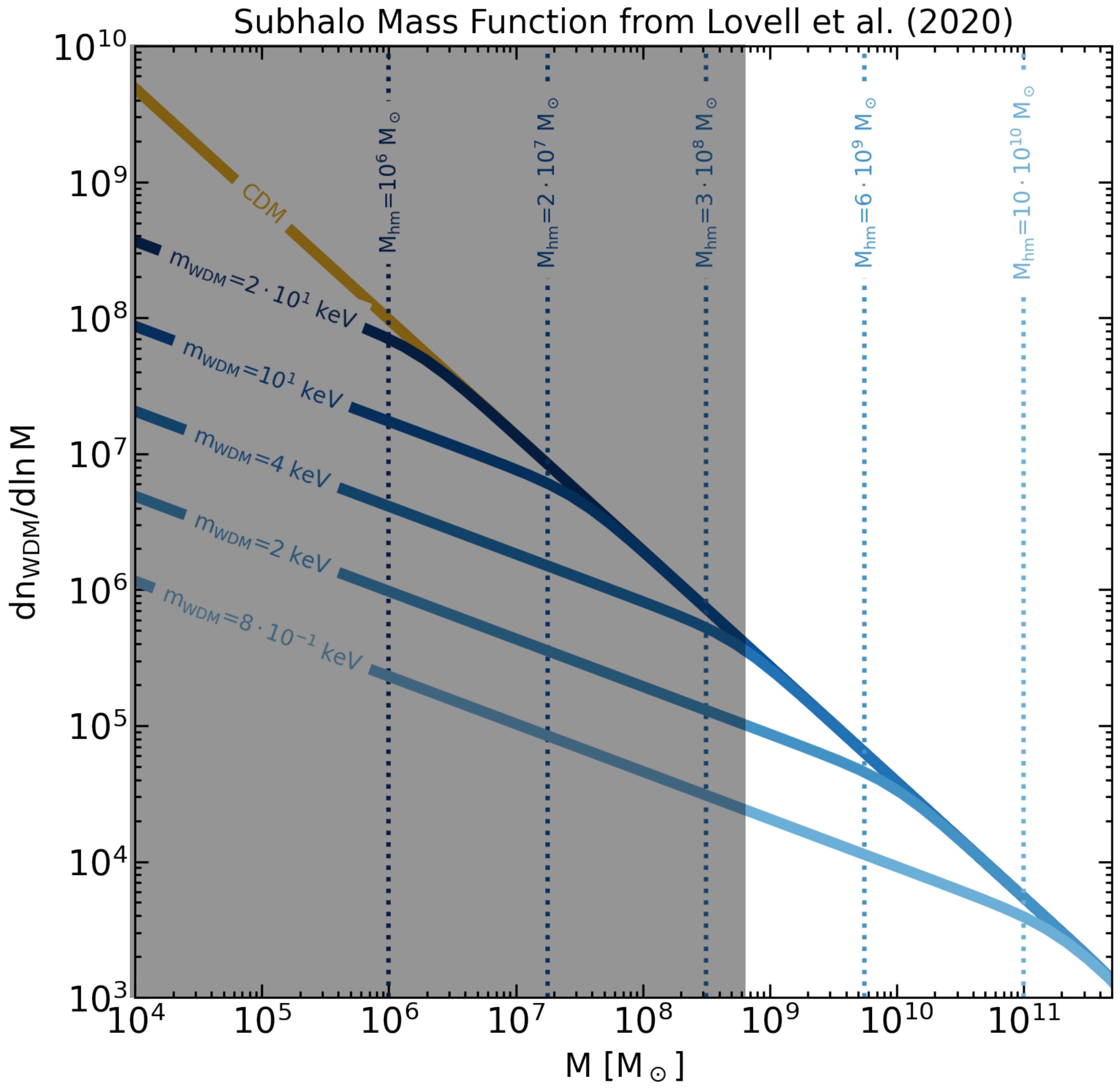

Dark region ⟶ use gravitational lensing

As seen in Daniel Gilman's talk

Strong gravitational lensing

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Strong gravitational lensing → Inference challenge

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$$p(\vartheta \,|\, \vec{x}) \propto \overbrace{\int d\vec{z}_{\text{light}} d\vec{z}_{\text{lens}} d\vec{z}_{\text{source}} d\vec{z}_{\text{halos}}}^{\text{Very hard!}} \, p(\vec{x} \,|\, \vec{z}_{\text{light}}, \vec{z}_{\text{lens}}, \vec{z}_{\text{source}}, \vec{z}_{\text{halos}}) p(\vec{z}_{\text{light}}) p(\vec{z}_{\text{lens}}) p(\vec{z}_{\text{source}}) p(\vec{z}_{\text{halos}} \,|\, \vartheta) p(\vartheta)$$

Signal fo interest: e.g. single heavy small-scale halo position and mass, halo mass function parameters related to DM particle physics etc…

Traditional approaches

- **Likelihood-based approaches**:
  - MCMC methods
  - Nested sampling

→ compute the joint posterior and *then* marginalise, difficult to scale up for more complex models.

Subhalo detections: Vegetti et al. (2010, 2012), Hezaveh et al. (2016).
DM constraints: Vegetti et al. (2018), Ritondale et al. (2019).

- **Approximate Bayesian Computation (ABC)**:

→ likelihood-free, but difficult to get a *good* diagnostic measure, a summary statistics.

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Our strategy

***TMNRE* = *Truncated* Marginal Neural Ratio Estimation**

Implementation in swyft

→ For more details: Christoph Weniger’s talk Thu@10

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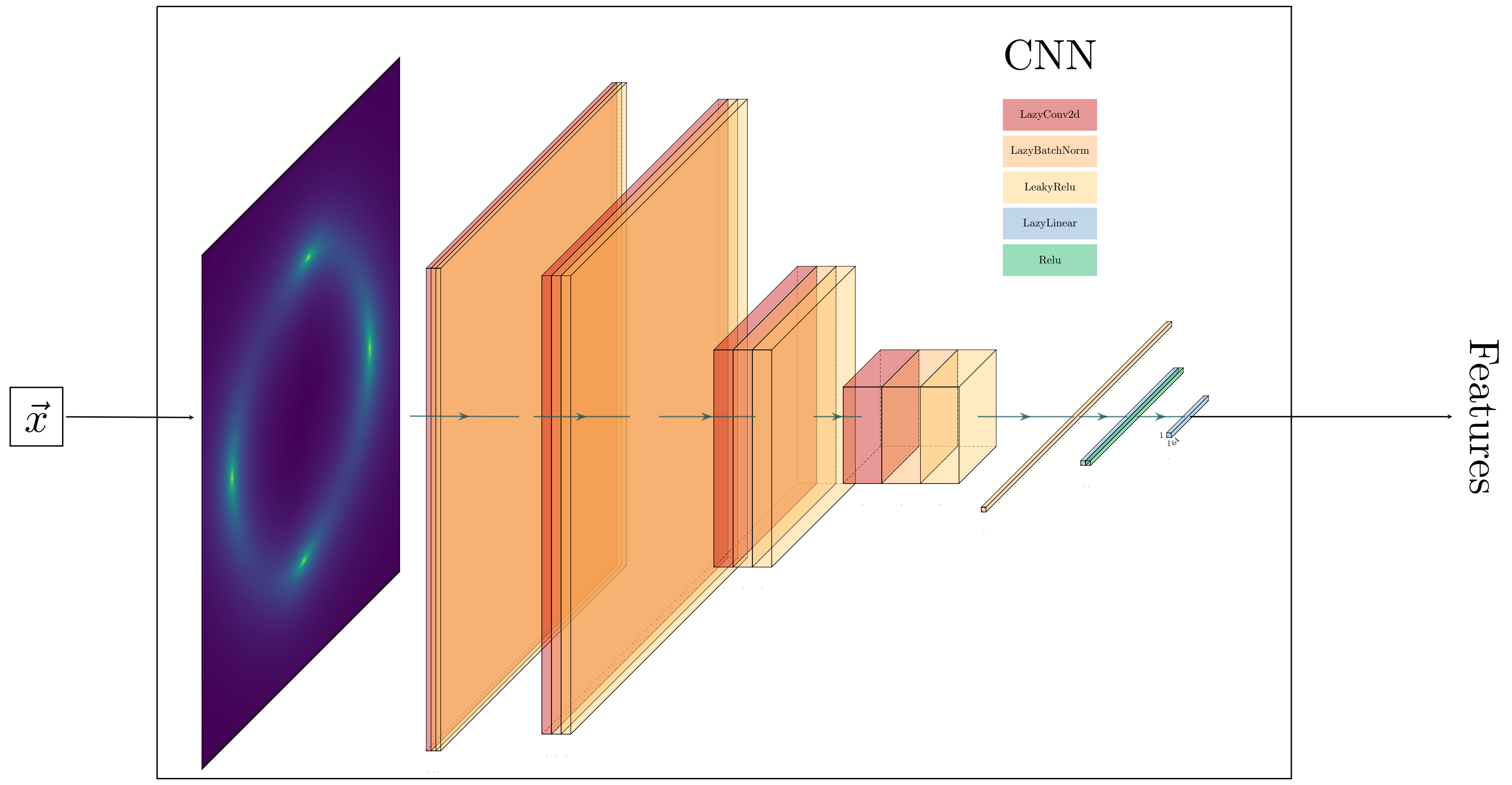
- Uses **NNs** to directly estimate the best summary statistic from the full input data



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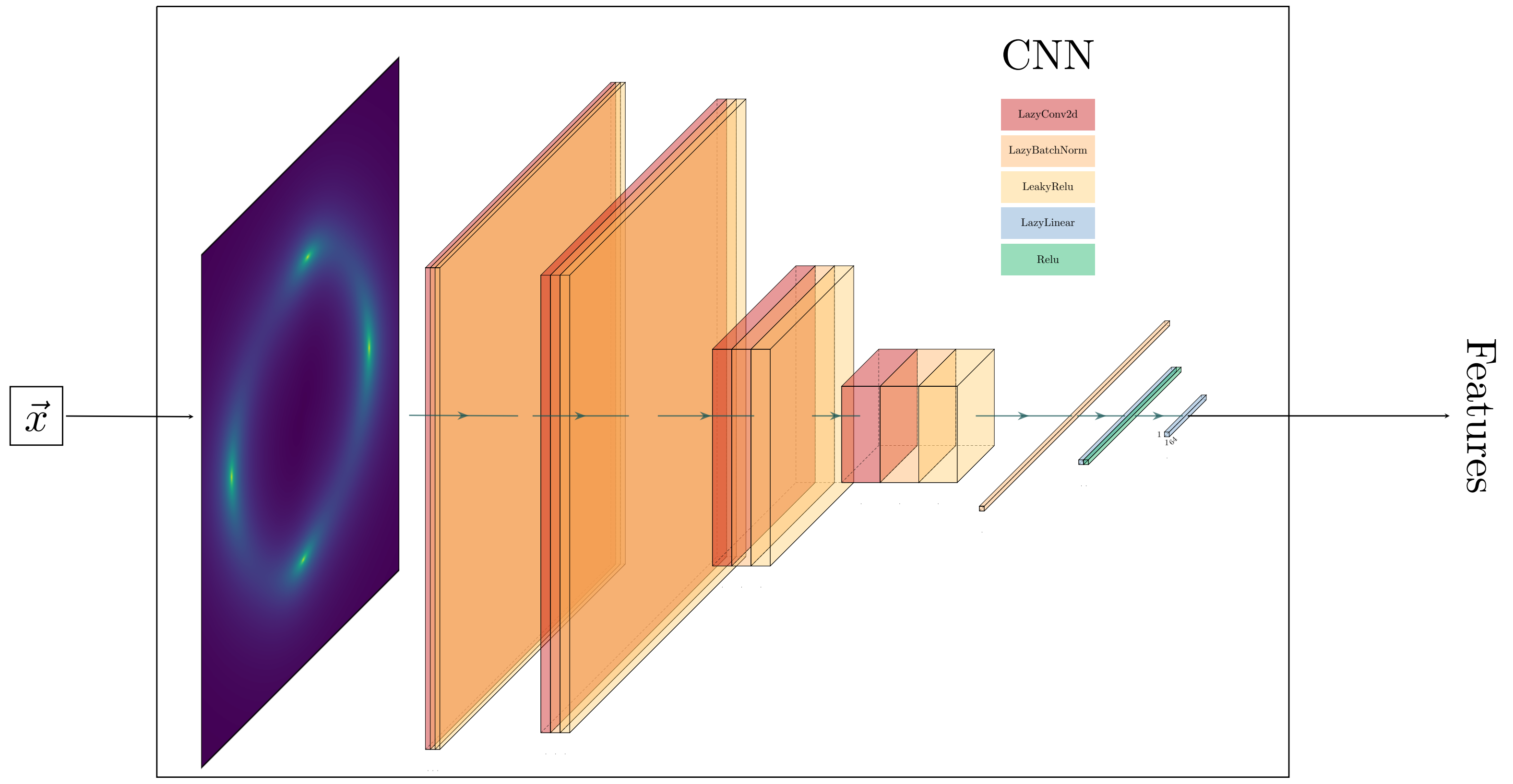

- Directly learns **marginals** posteriors for the signal of interest ϑ:

$$p(\vartheta \mid \vec{x}) = r(\vec{x}, \vartheta) p(\vartheta) = \frac{p(\vec{x} \mid \vartheta)}{p(\vec{x})} p(\vartheta)$$

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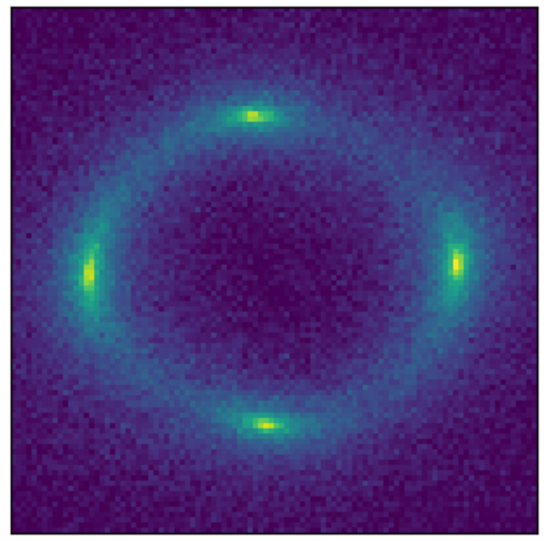
Constrain $\vec{z}_{lens}$ and $\vec{z}_{source}$ parameters with *truncation*

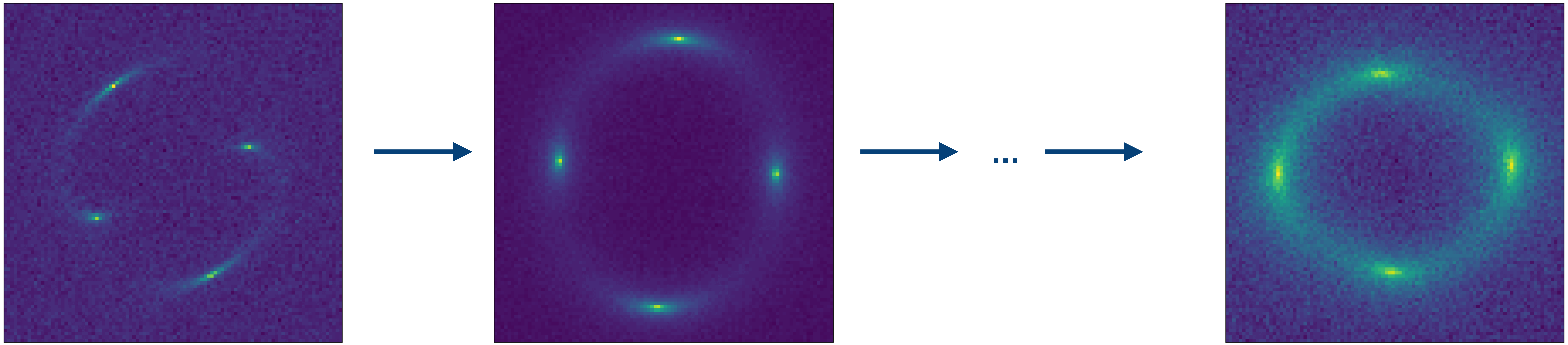
Target mock observation



Truncation **focuses training data generation** in the regions of the parameter space most relevant for analysing a particular observation.

Training data

Round 1 | Round 2 | ... | Round 6



NAM et al. (2022)

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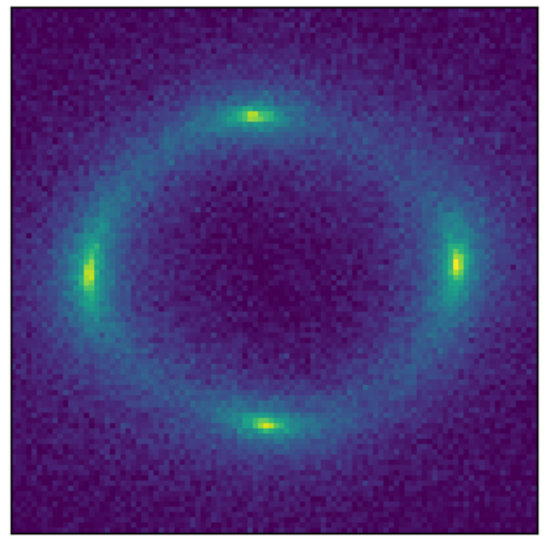

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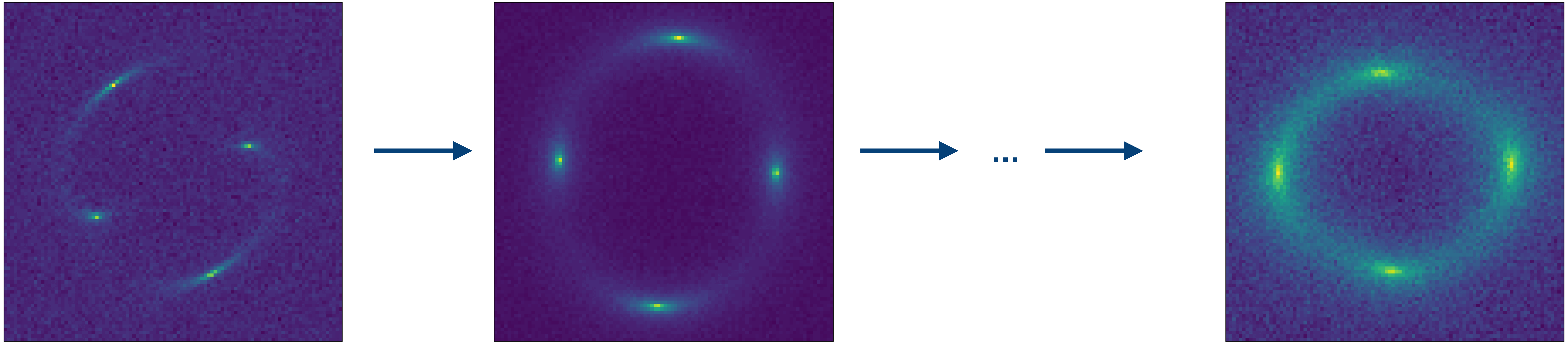
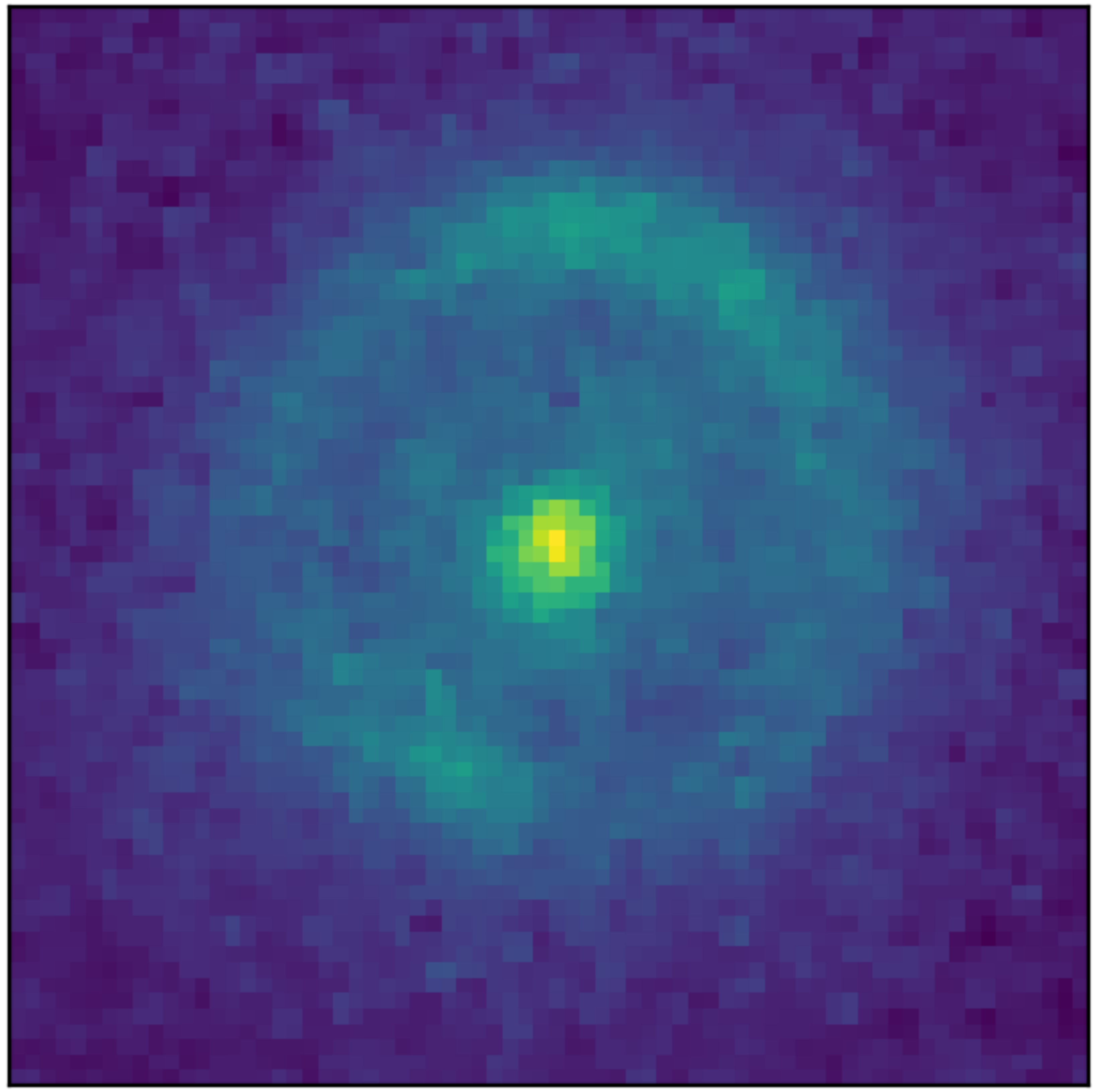


[NAM et al. (2022)]

JVAS B1938+666

Vegetti et al. (2012) - subhalo detection claim

Şengül et al. (2021) - detection reanalysed



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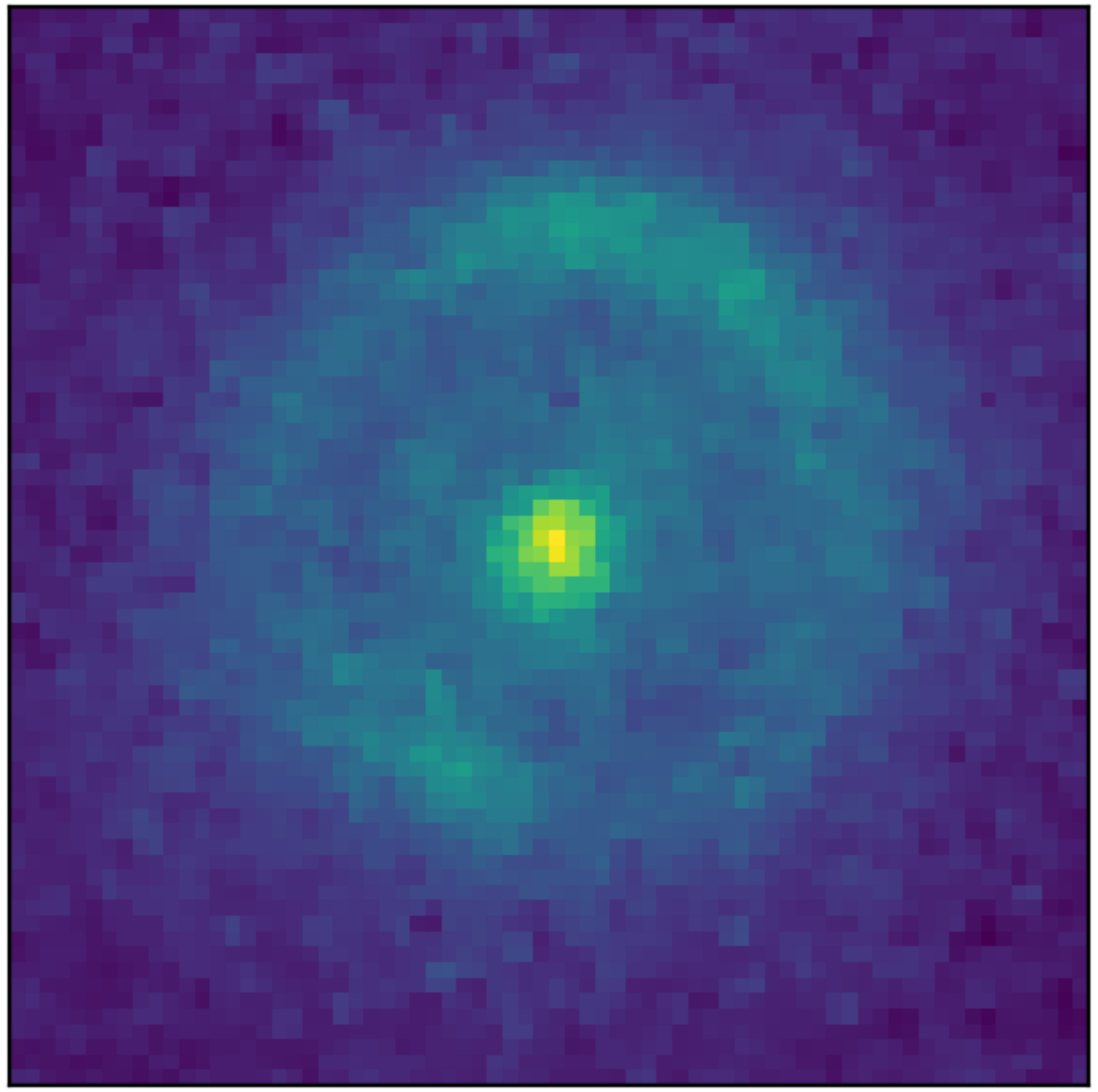
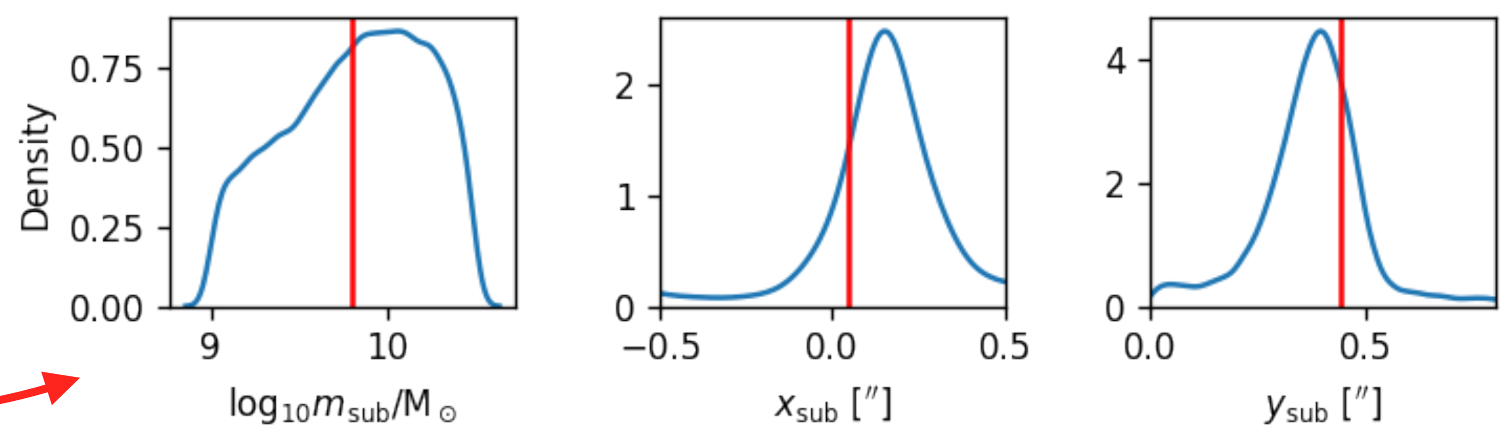
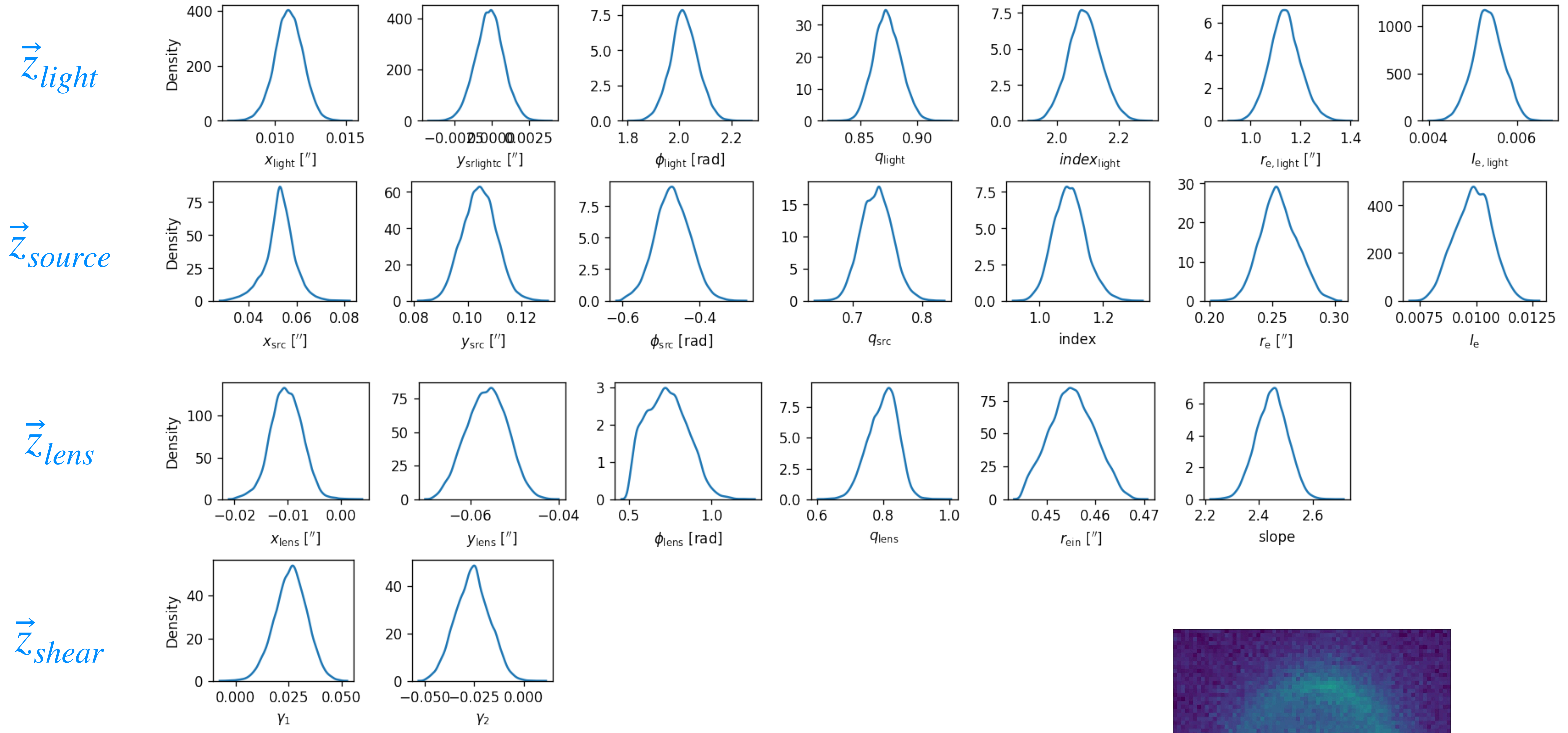


VERY PRELIMINARY

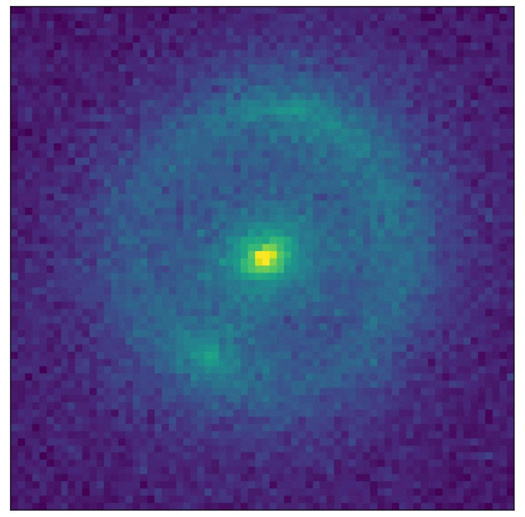
Small-scale halo mass and position





- First analysis to take into account lens light uncertainties!
- Next steps: more complex source model and including PSF and correlated pixel noise.

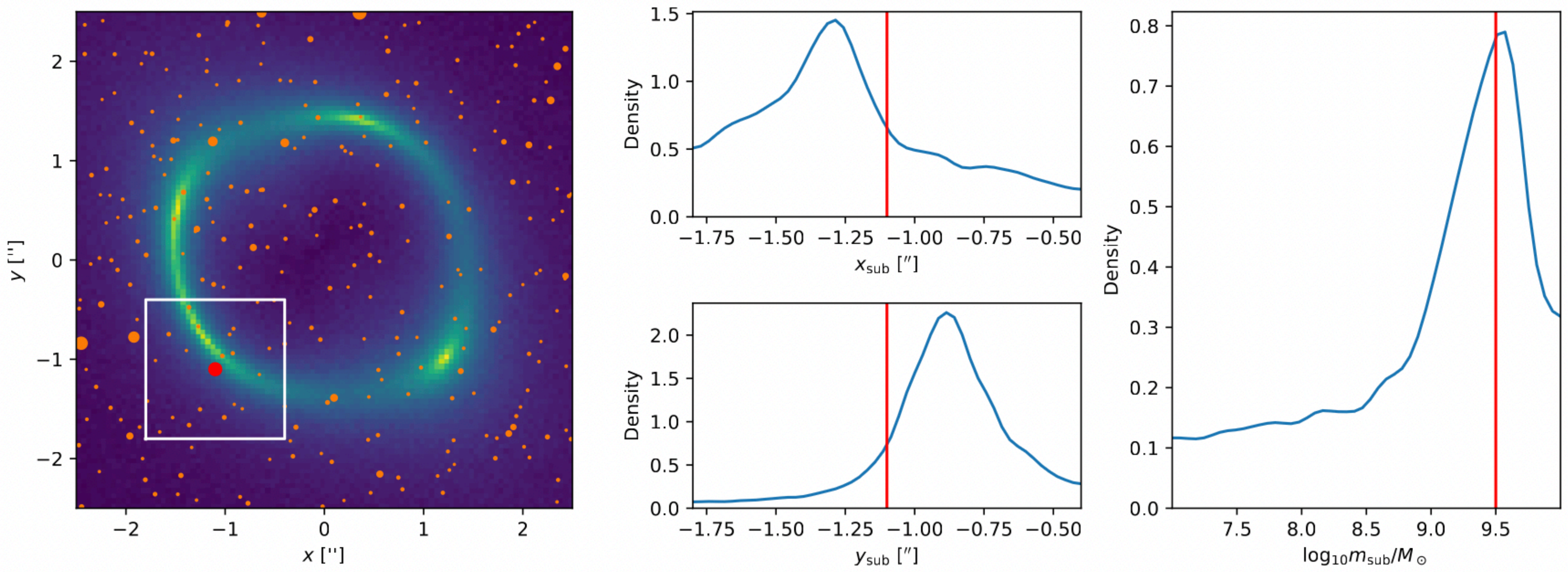
Training data:



Improving the realism of the model

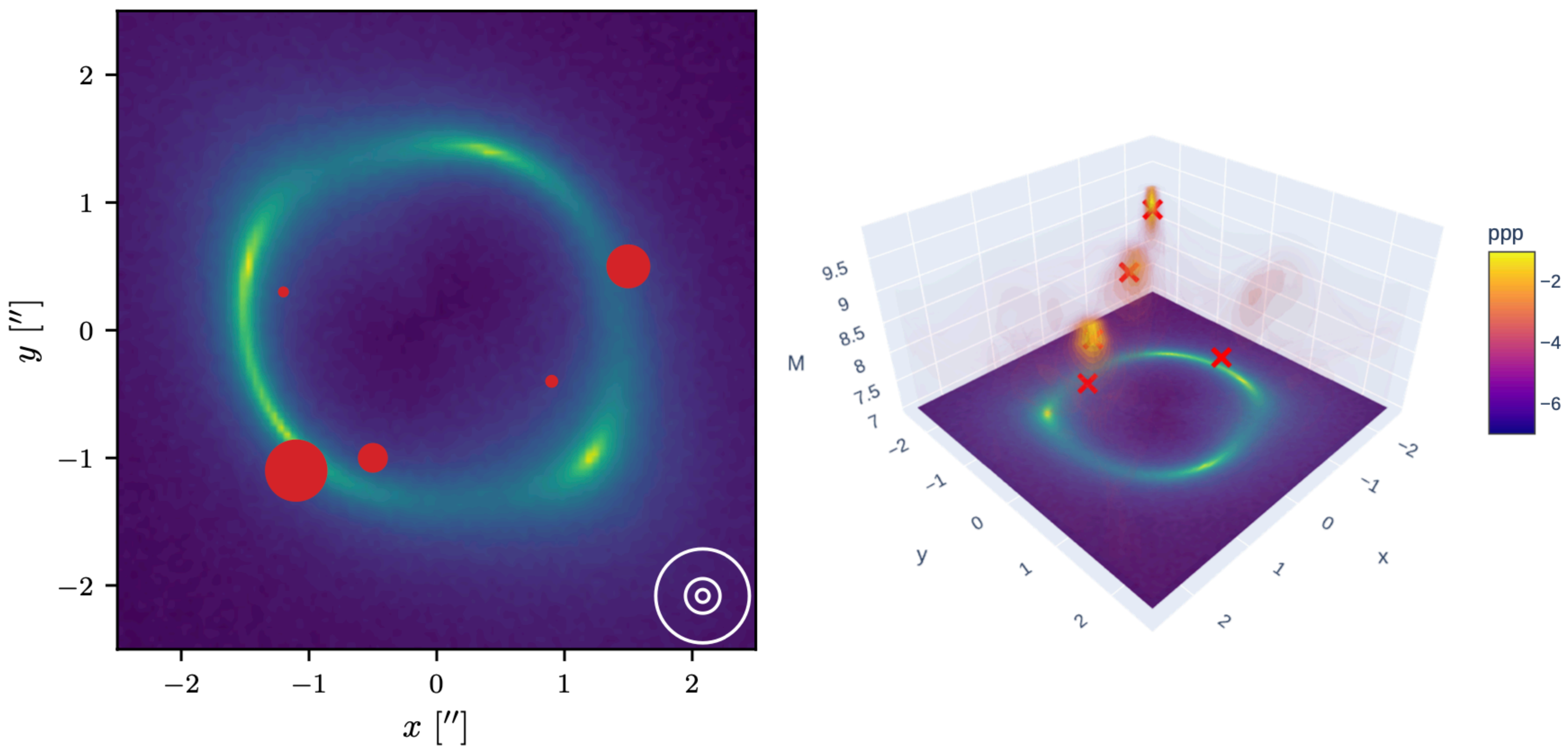
Measuring a single subhalo position and mass marginalising over source and lens uncertainties and a population of other subhalos and line-of-sight halos.

PRELIMINARY on mock images



Probabilistic image segmentation to measure multiple subhalos.

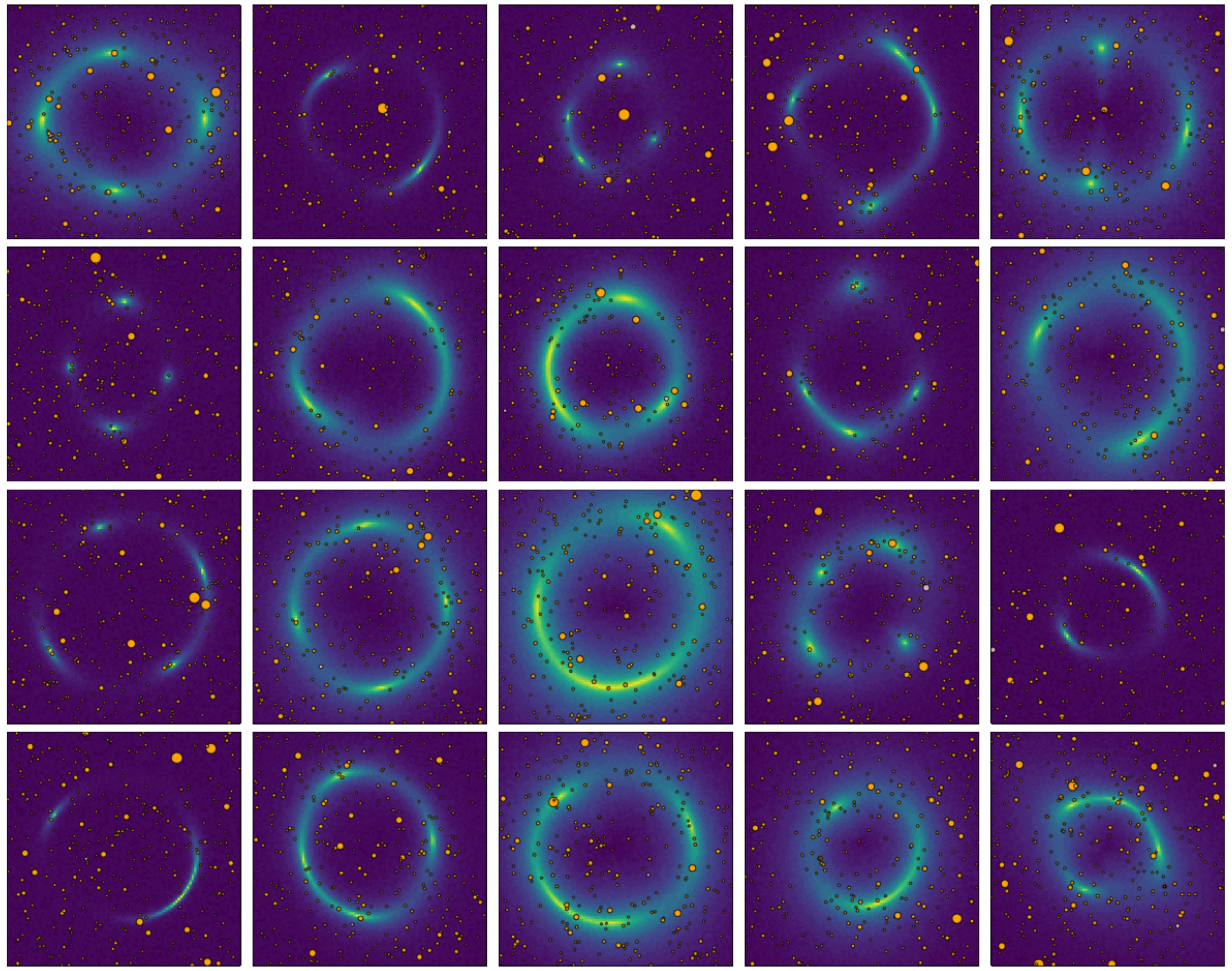
PRELIMINARY on mock images

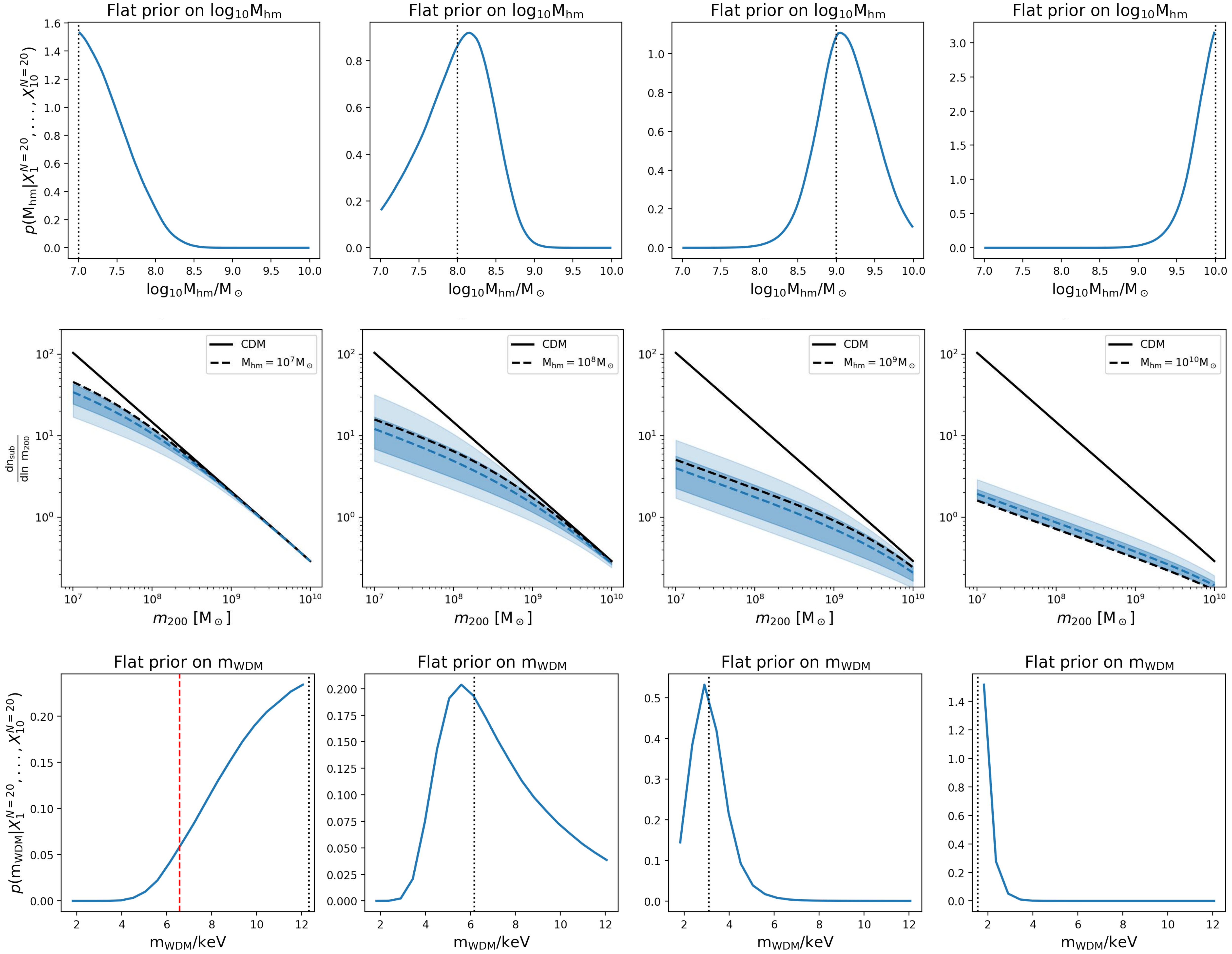


[Coogan et al. (in preparation)]

[credit: Elias Dubbeldam]

Inferring the SHMF cutoff scale from a population of subhalos and line-of-sight halos *combining different mock observations*





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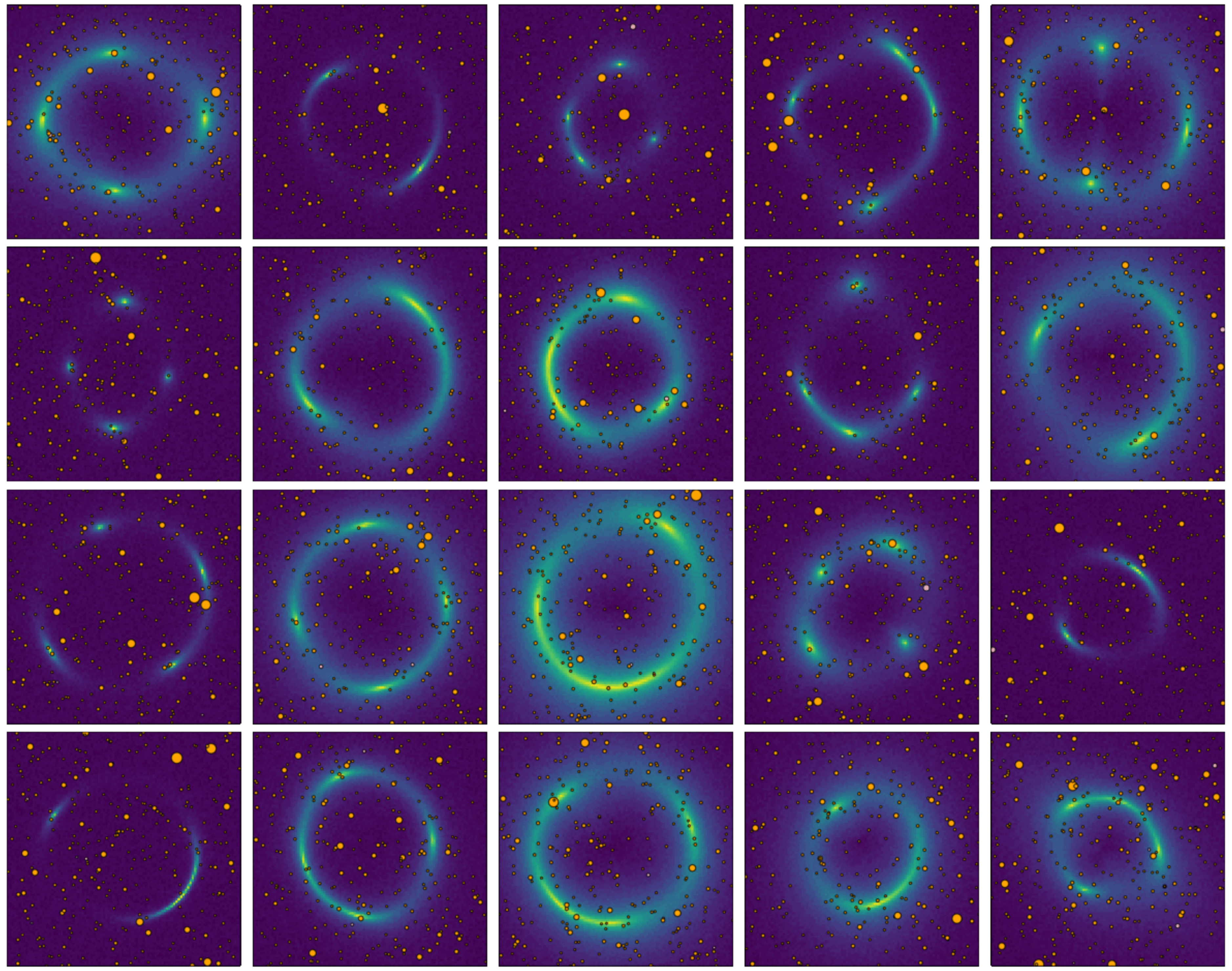

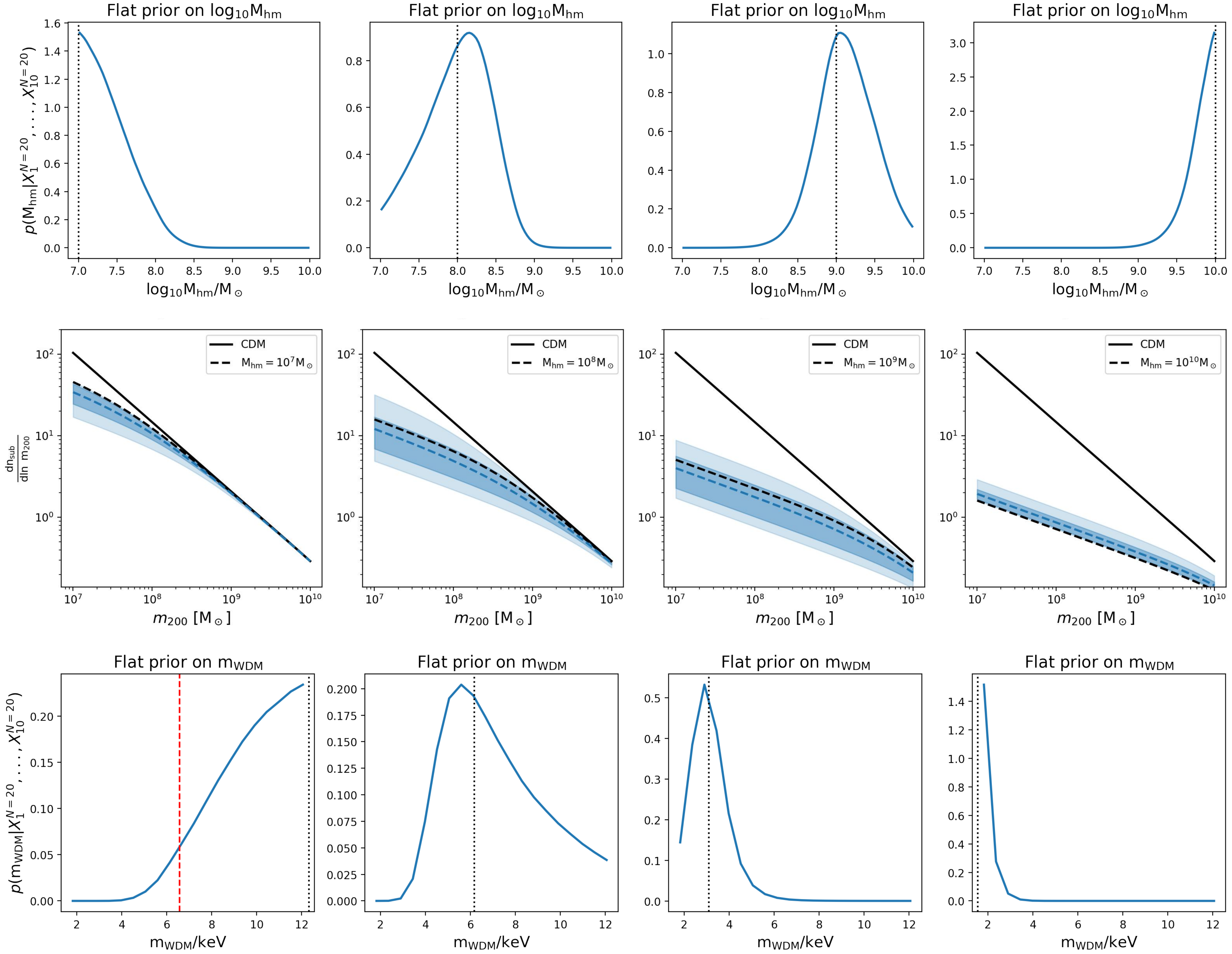

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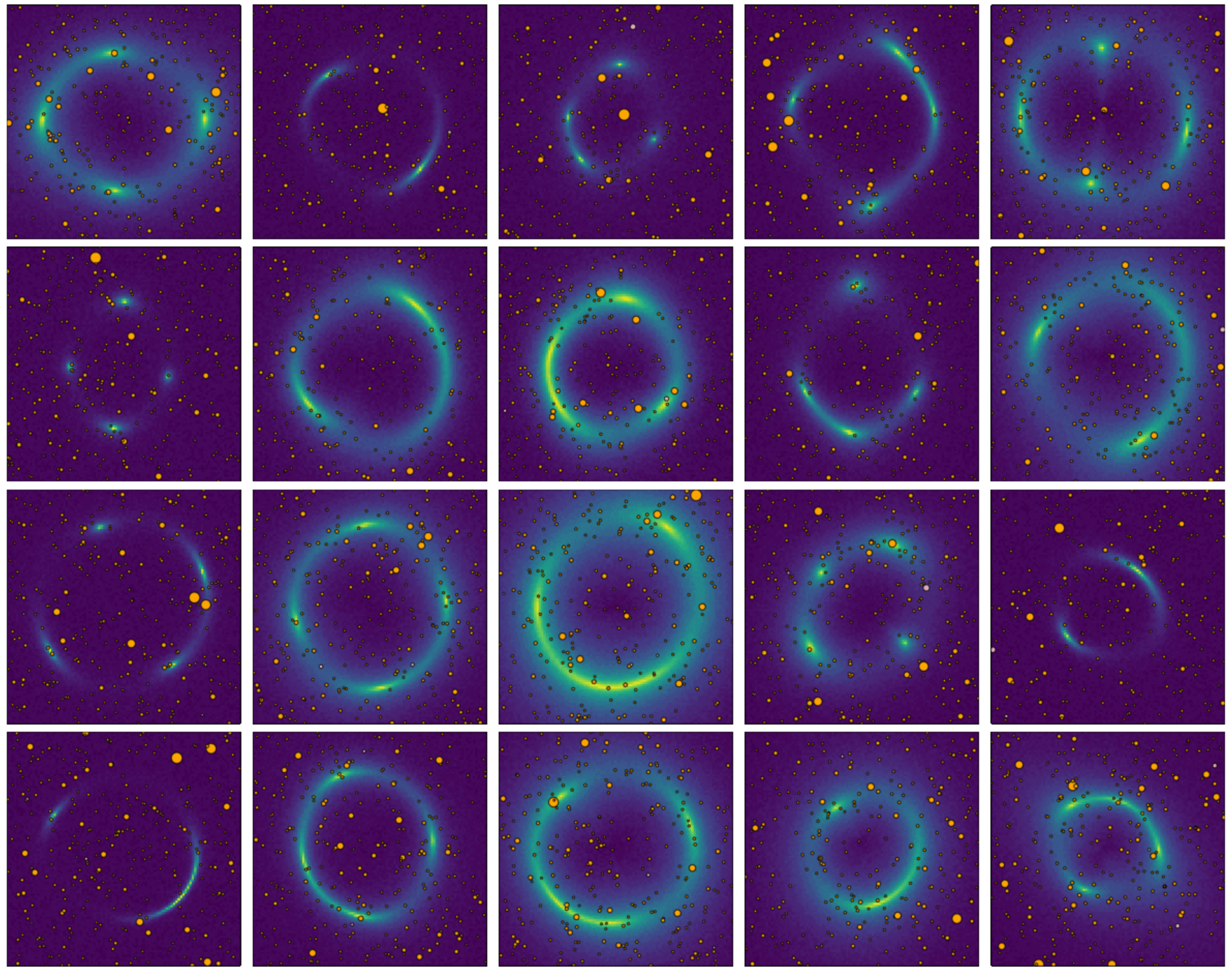

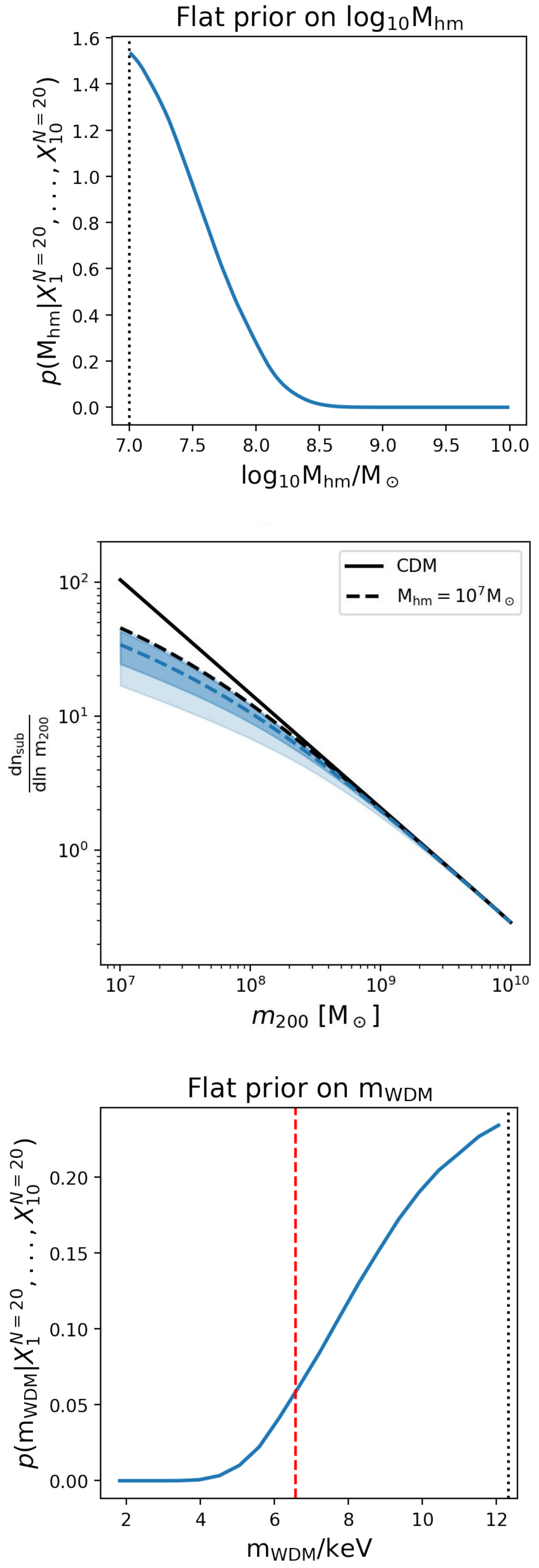

In case of the scenario closest to CDM in our SHMF cutoff scale range ($M_{hm} = 10^7 M_\odot$), we obtain an expected 95% credible lower limit around $6.5\ \mathrm{keV}$ on DM mass.

NAM et al. (2022)

Conclusions

- Measuring **individual halos** and **halos collective properties** is an important component of dark matter lensing analyses.
- **Truncated marginal neural ratio estimation** enables **full marginalisation** over light, lens, source and small-scale halos population.
- **Next steps**: implement more complex source, light, lens, noise models.
- These first results demonstrate that this method is **imminently applicable** to existing lensing data and to the large sample of lenses that will be delivered by near-future telescopes.

Soon ~ $\mathcal{O}(10^5)$ observations from JWST, Euclid, ELT Rubin (Collet 2015)

Image credit: NASA, ESA, CSA, and STScI

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THANK YOU!