Constraining the Dark Matter Particle with Strong Gravitational Lensing

James Nightingale

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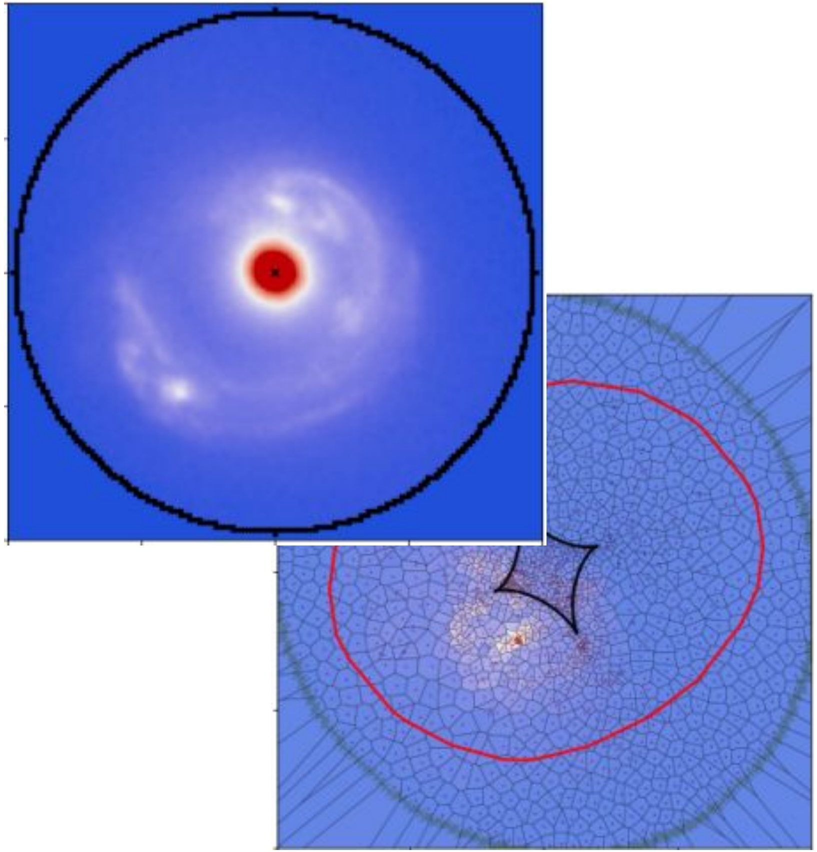
\+ friends



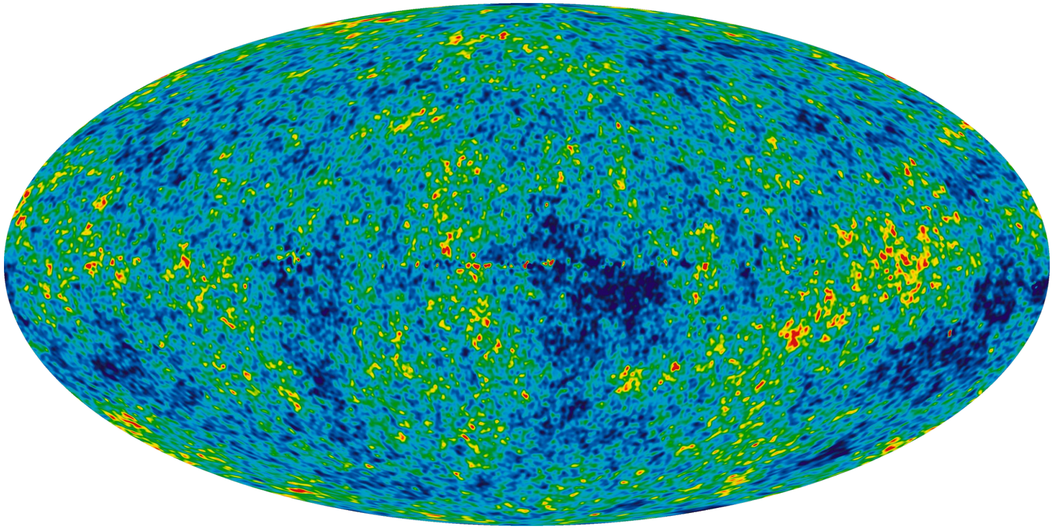
Cold Dark Matter (+ Lambda)

ƛCDM has been the standard cosmological model for over 20 years.

- Tested on **large scales** with observations such as the CMB.

- See also: BAO, bullet cluster, weak lensing, galaxy rotation curves, + many more.

Dark matter particle required, but many candidates fit the data (WIMP's, axions, sterile neutrinos, etc.).



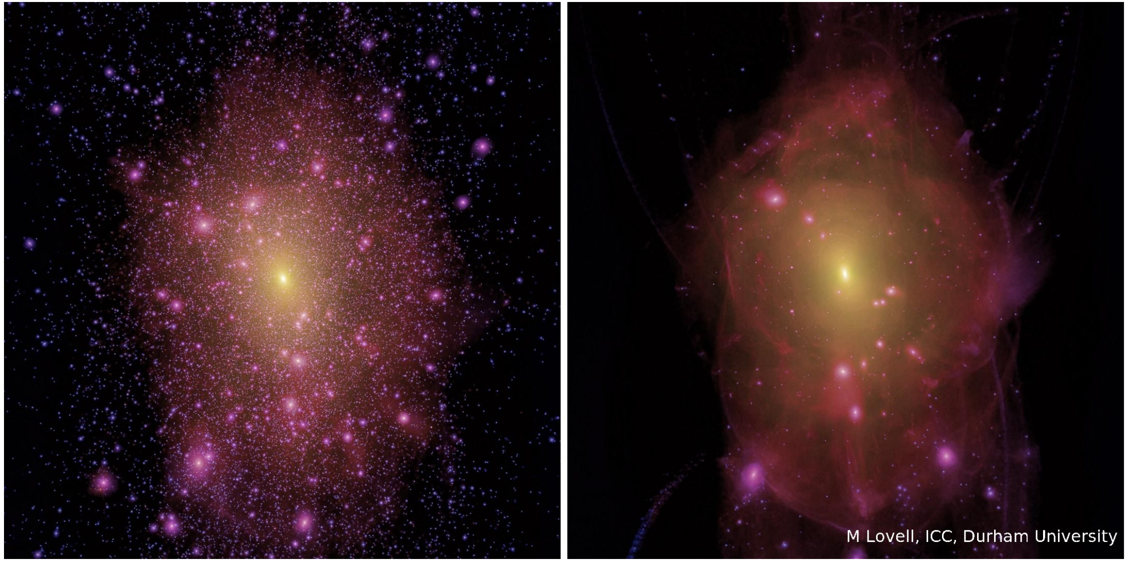
ƛCDM on smaller scales

Untested predictions of DM models and particle masses on smaller scales:

- CDM predicts many low mass dark matter halos with masses below 10^8MSun.

- These halos are absent in `warmer` flavours of DM (e.g. sterile neutrino) with masses ~ 100kev.

See also, core/cusp discrepancy, too big to fail + others



Observing low mass dark matter halos

In CDM, many dark matter halos below masses of 10^8MSun are *completely dark.*

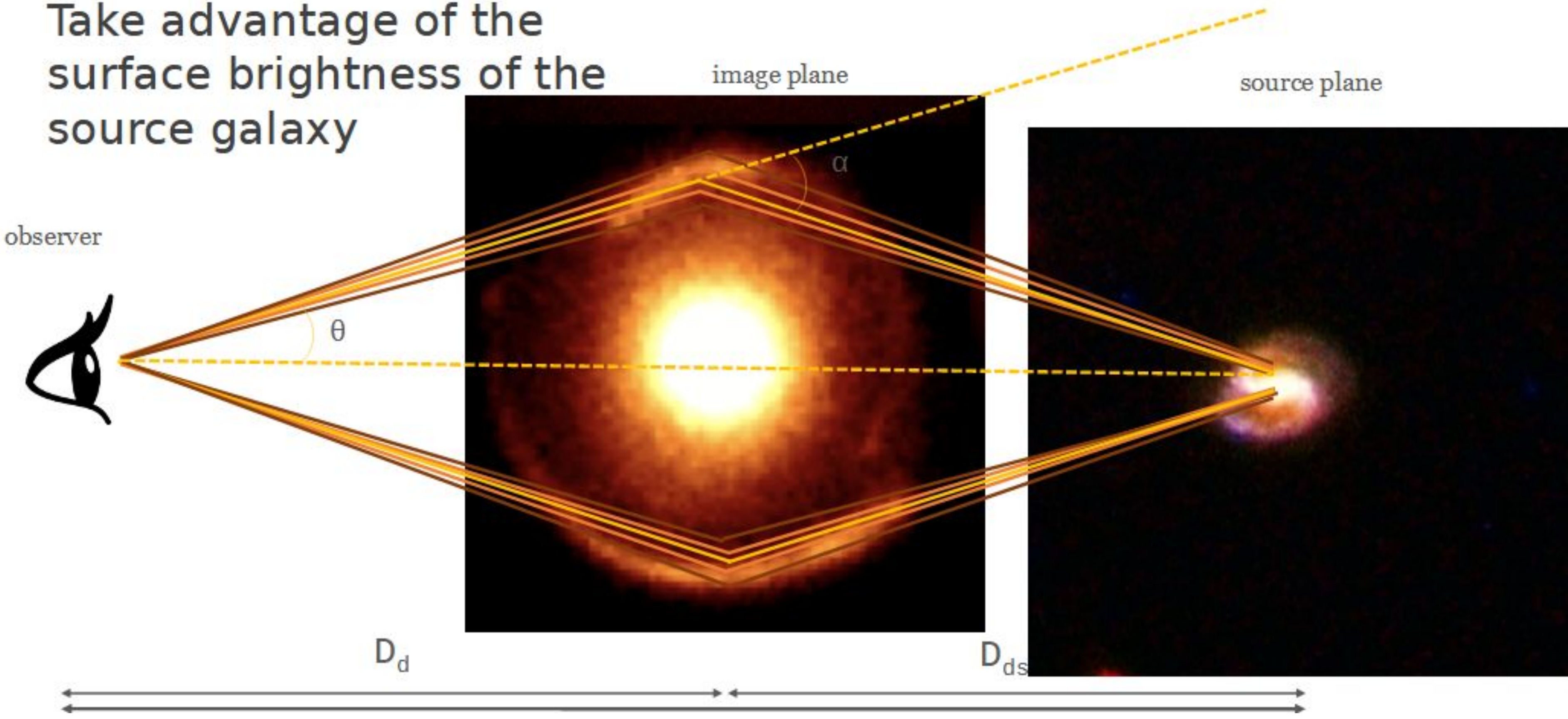
- Star formation ceased in early Universe by ultraviolet radiation background / supernova feedback.
- Makes observing these objects and testing CDM on small scales **challenging.**

Want a method which despite their lack of emission can quantify the number counts of dark matter halos between $10^{6\text{-}10}$MSun.

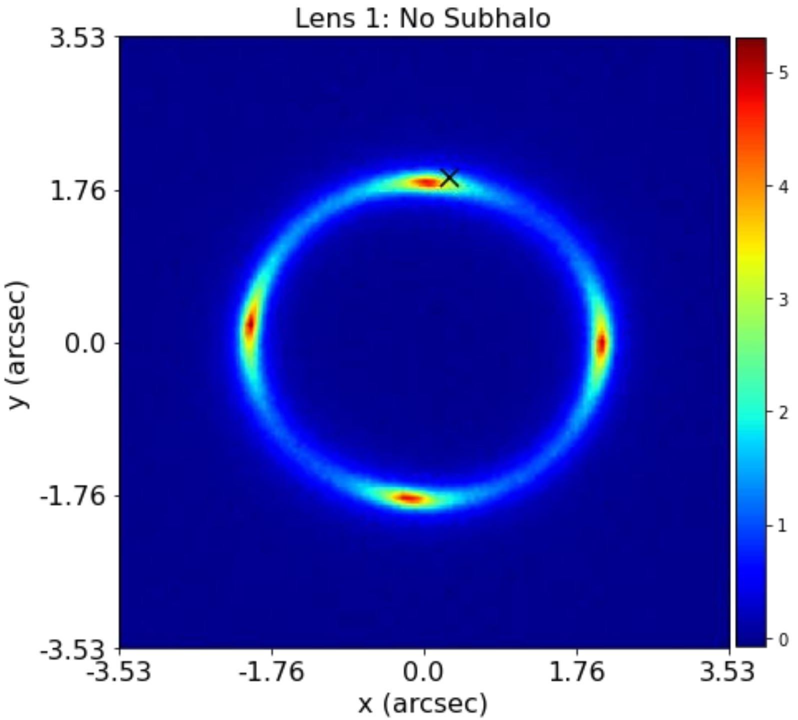
See also: Number counts of Milky Way Satellites (the `Missing satellite problem`), stellar streams.

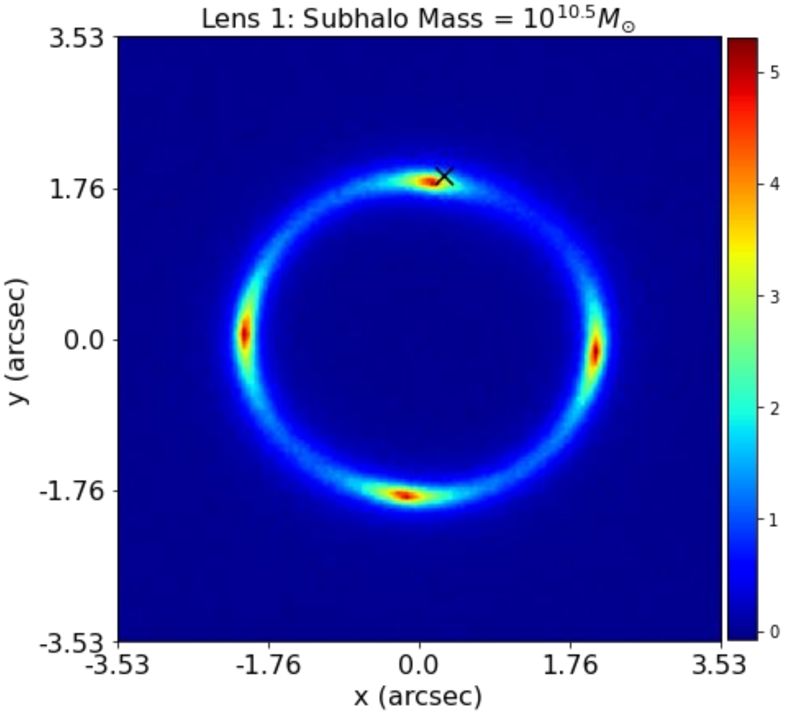
Strong Gravitational Lensing

Take advantage of the surface brightness of the source galaxy



Subhalo Perturbations





Subhalos: Individual Detections

PyAutoLens: Open Source Strong Gravitational Lensing

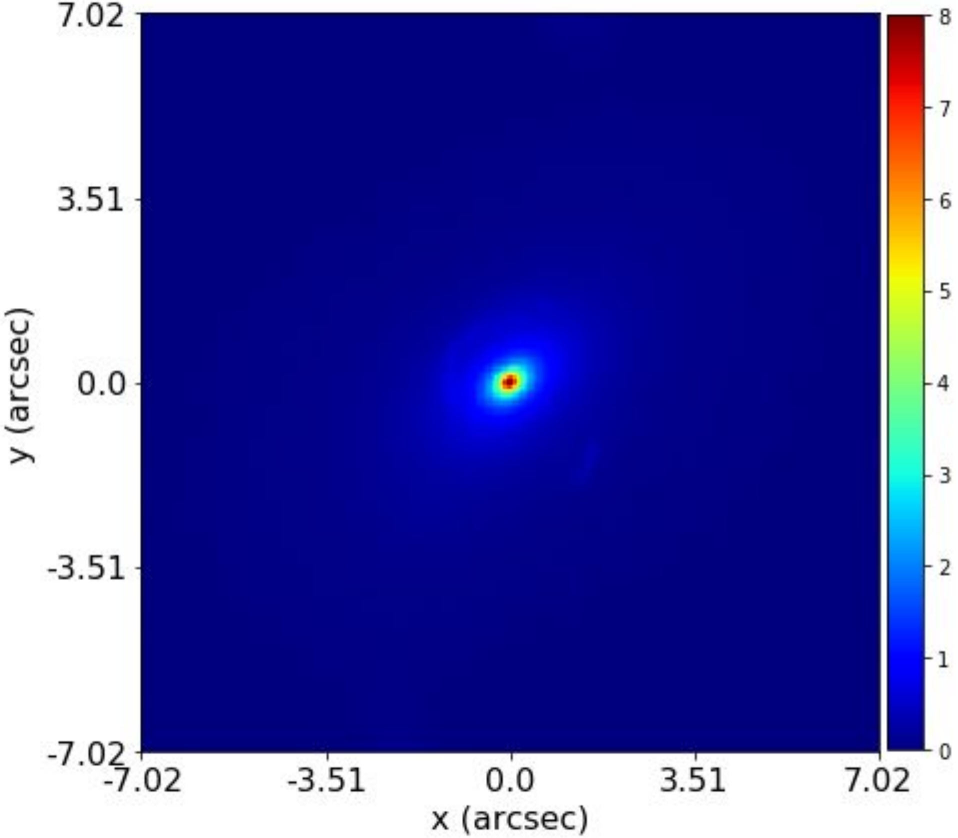
All code publically available (pip / conda), object oriented design, extensive documentation including Jupyter notebooks aimed at undergrads!

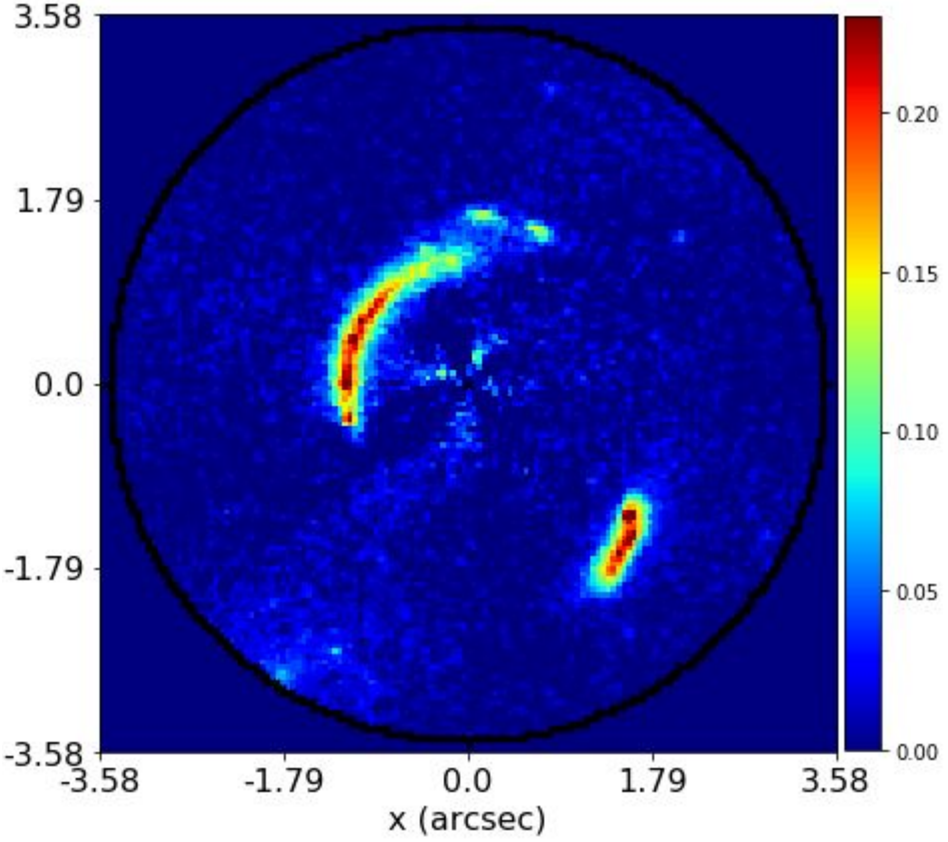
GitHub: https://github.com/Jammy2211/PyAutoLens
Readthedocs: https://pyautolens.readthedocs.io/en/latest/
JOSS paper (in review): https://github.com/Jammy2211/PyAutoLens/blob/master/paper/paper.md

PyAutoLens fully automates the lens modeling procedure.

- Will be **crucial** for modeling the 100 000 strong lenses Euclid is going to find.

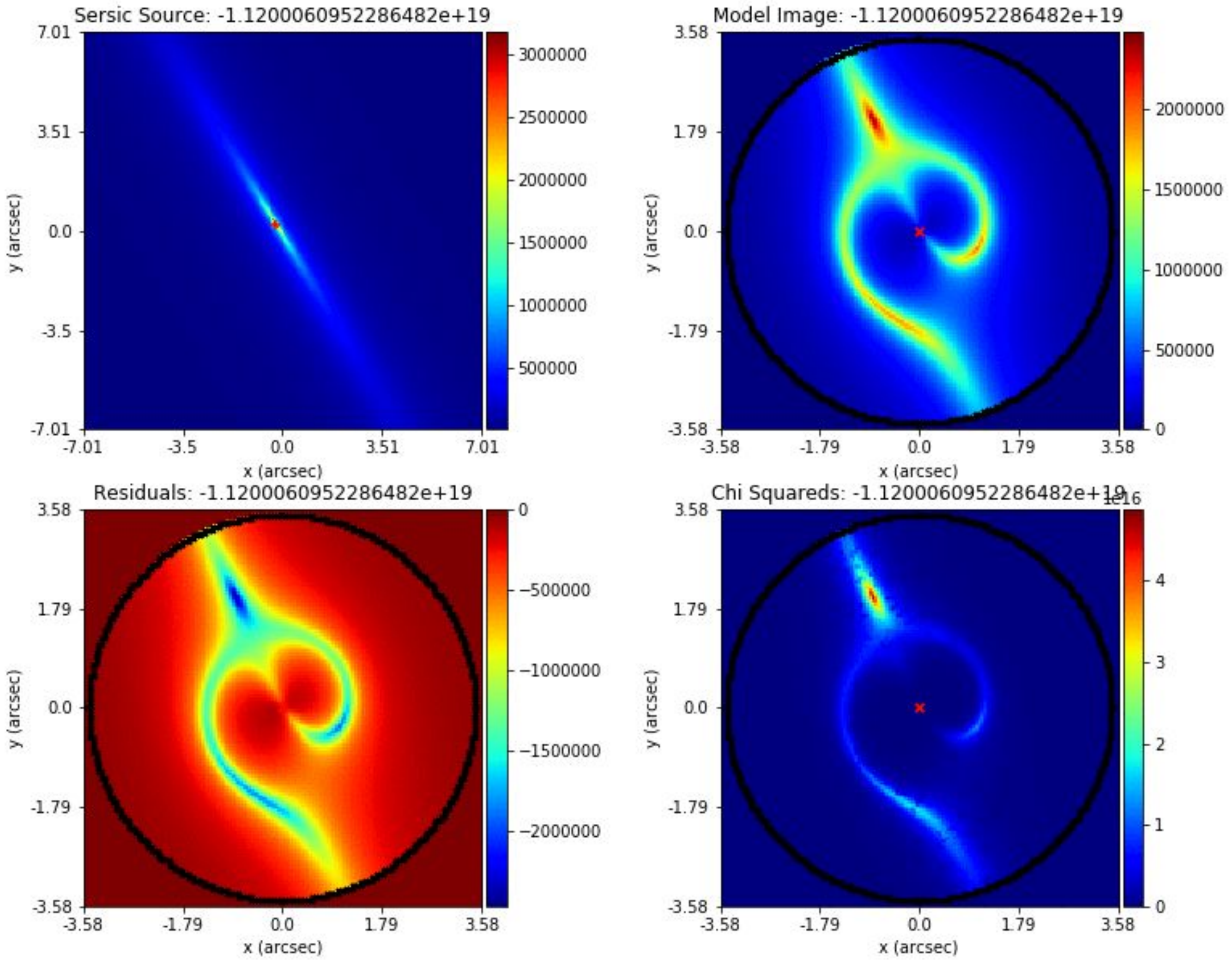
What lens model fits this lens?





Non-linear Search (Dynesty)

Lens Mass:
[Isothermal + Shear]
Source Light:
[Sersic]

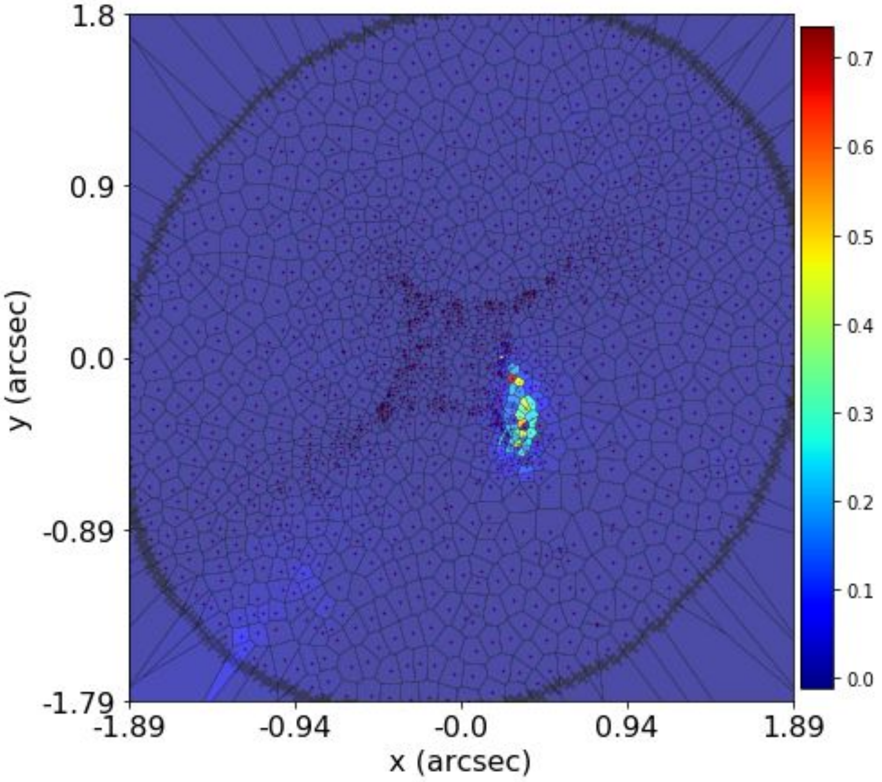


Strong Lens Model Complexity

Gradually increase lens model complexity:

Lens Mass: power-law model + shear.
Source: Pixelized source reconstruction.

No dark matter subhalo in the model so far!



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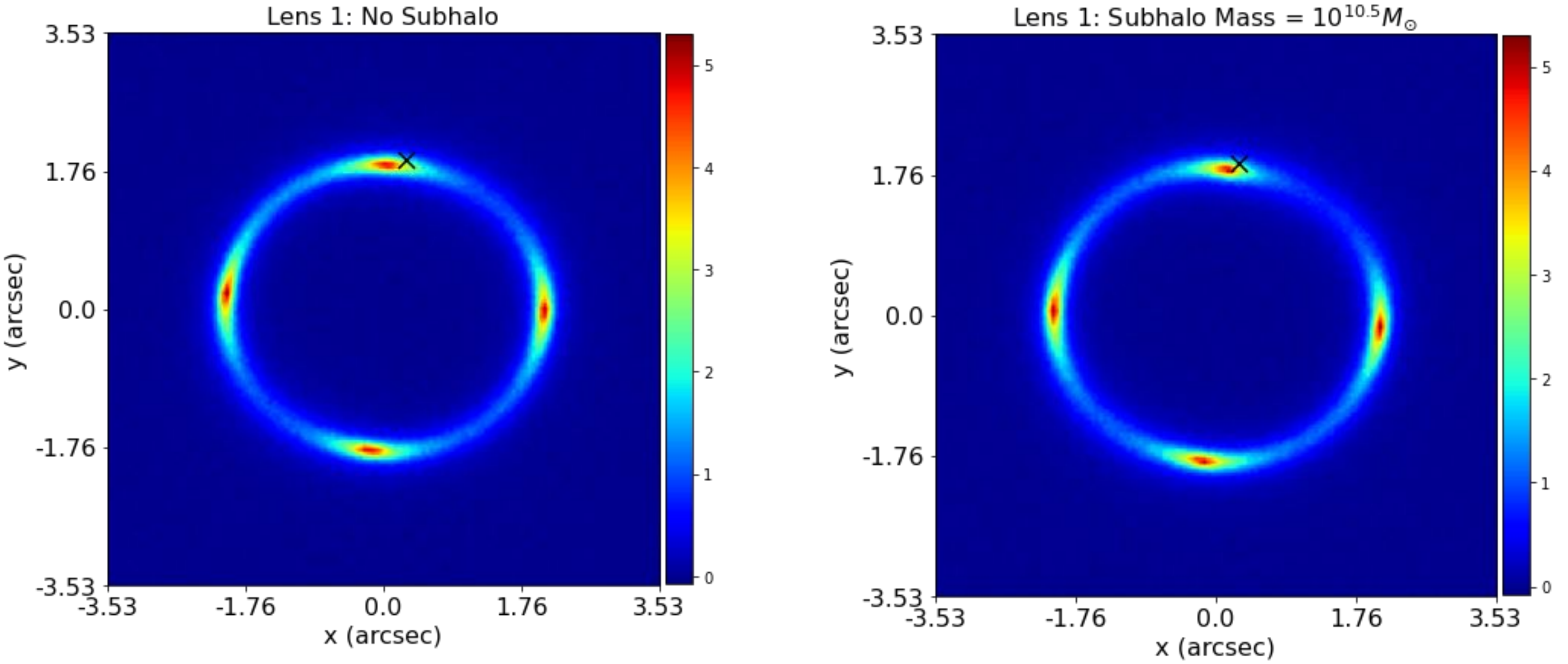

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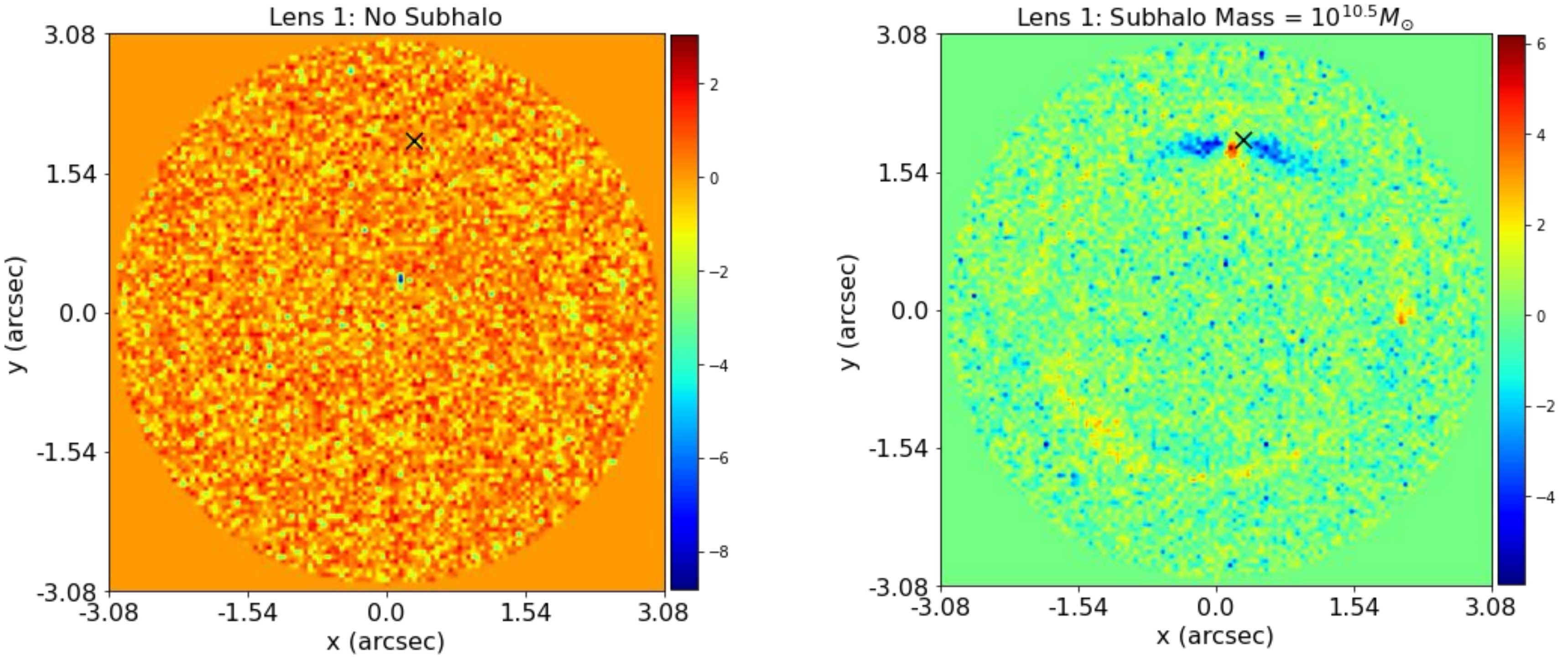
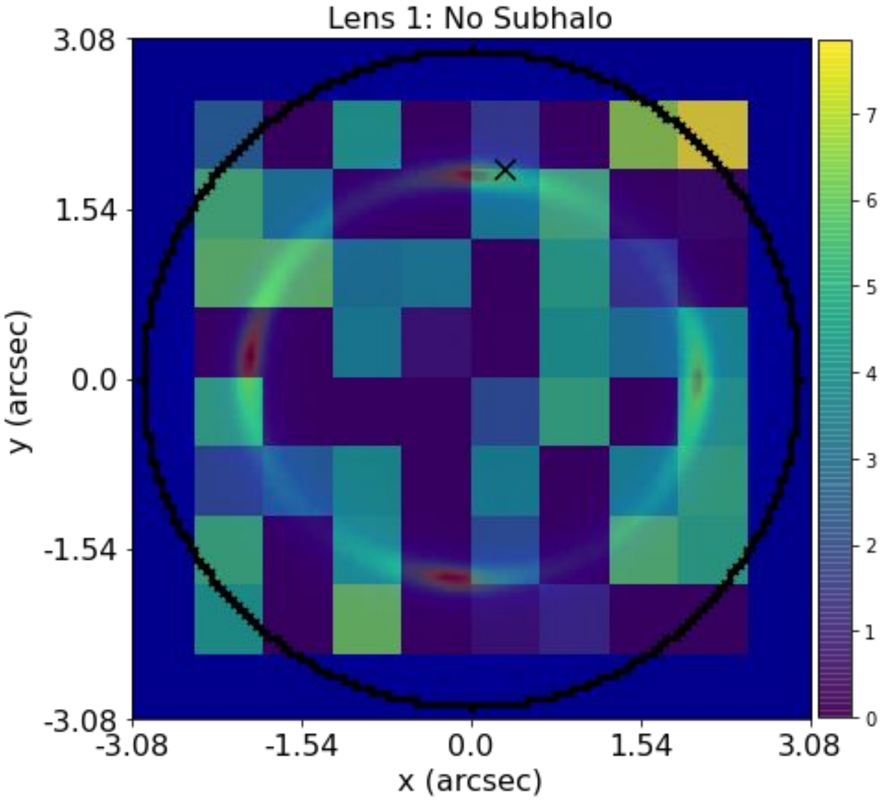
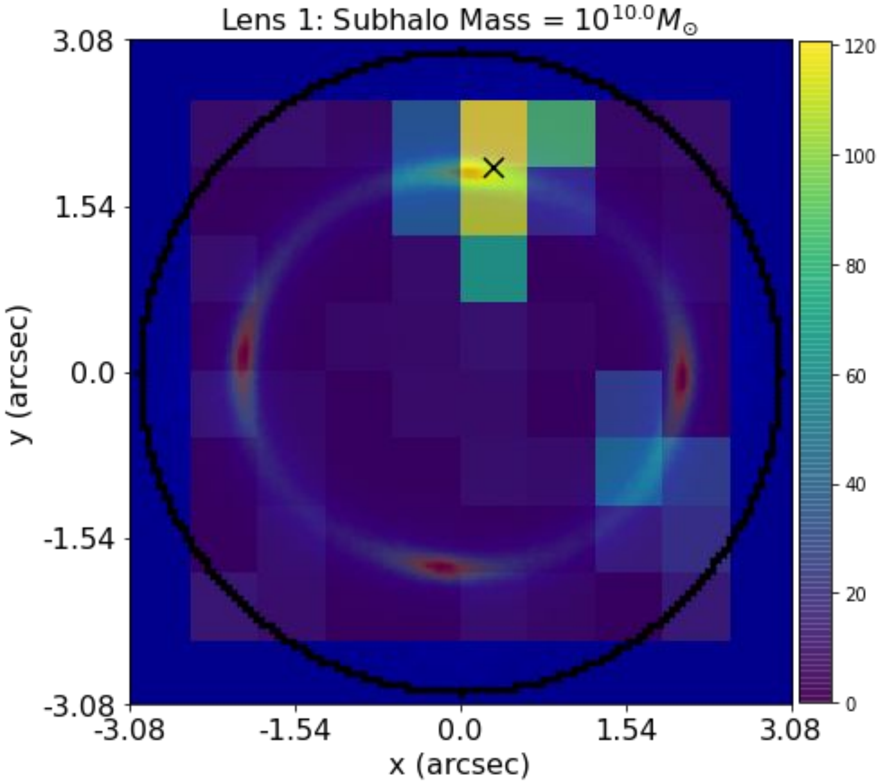


Subhalo Detections



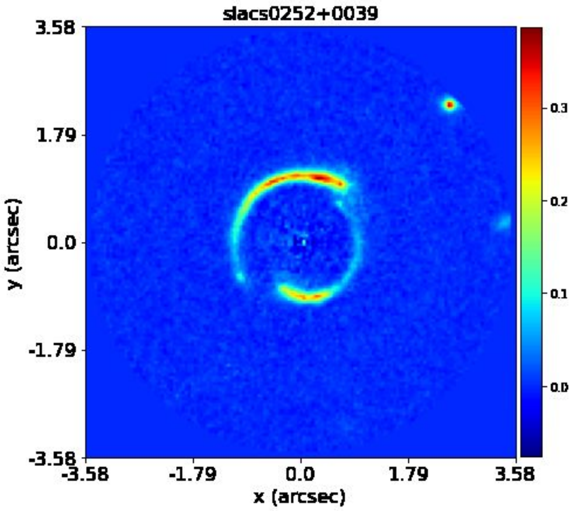


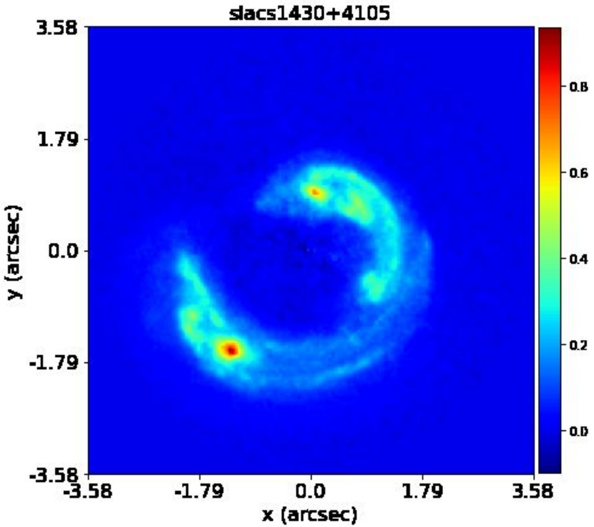
Results

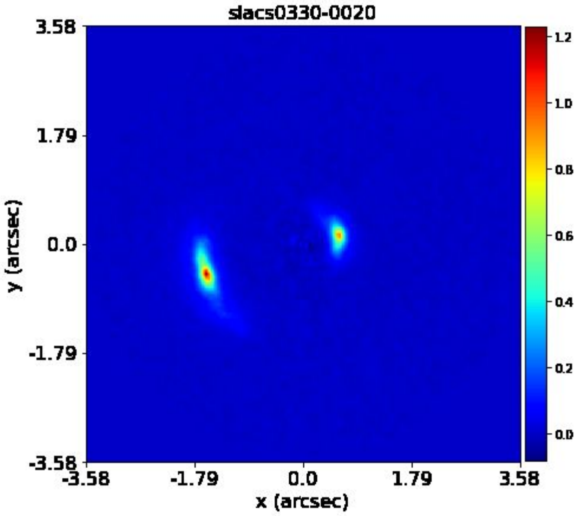
Subhalo Detections

Our group is now modeling a sample of over 50 strong lenses (double the size of previous studies).

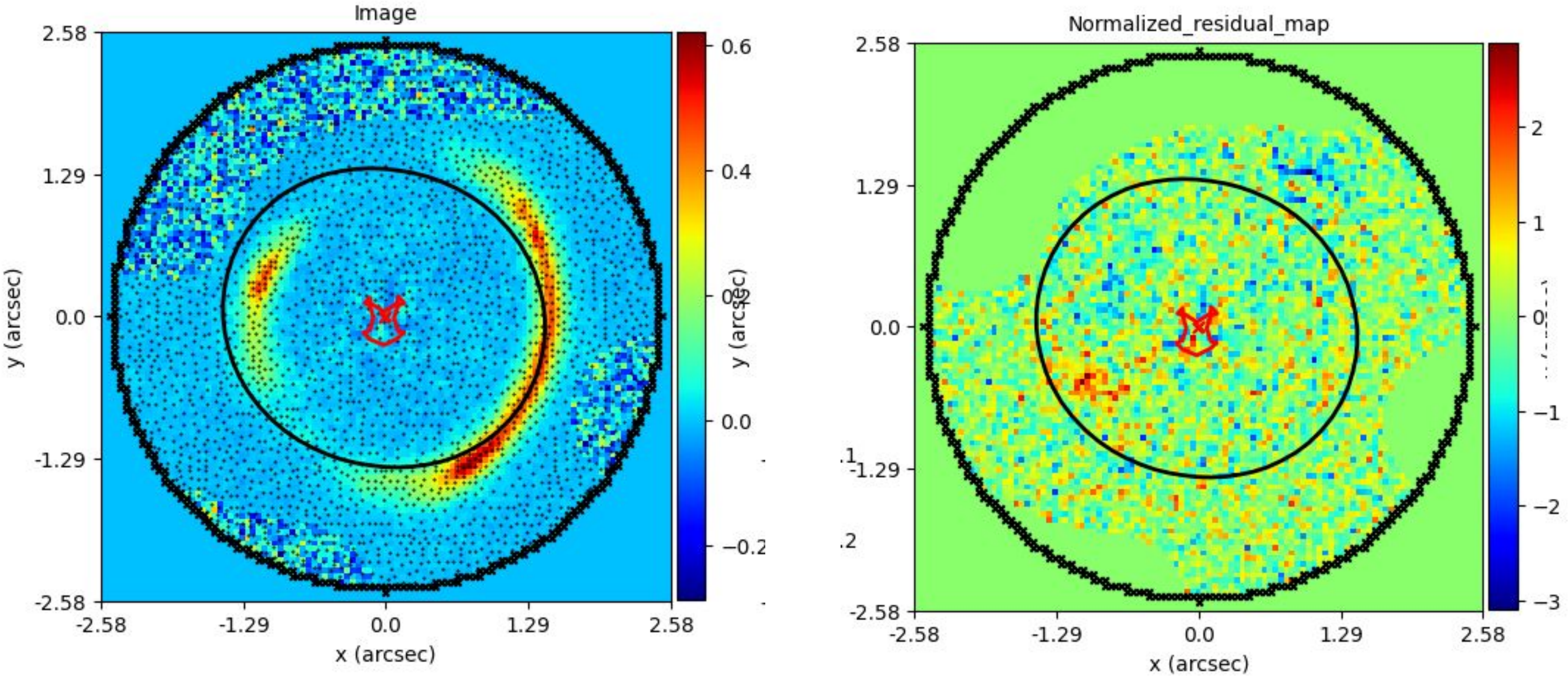
- Independent analysis from Vegetti et al.







SLACS 0946+1006

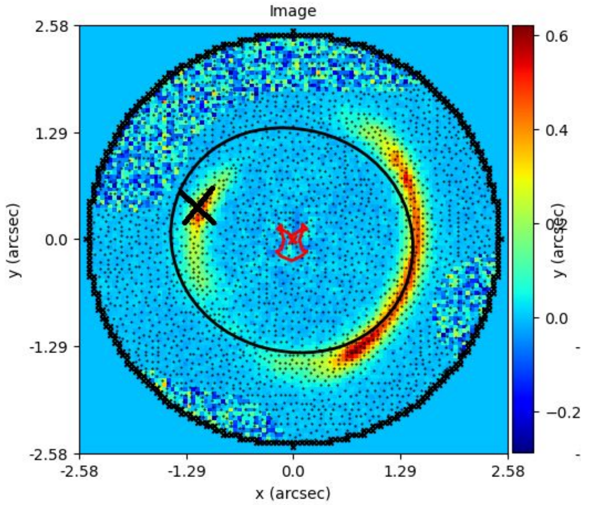


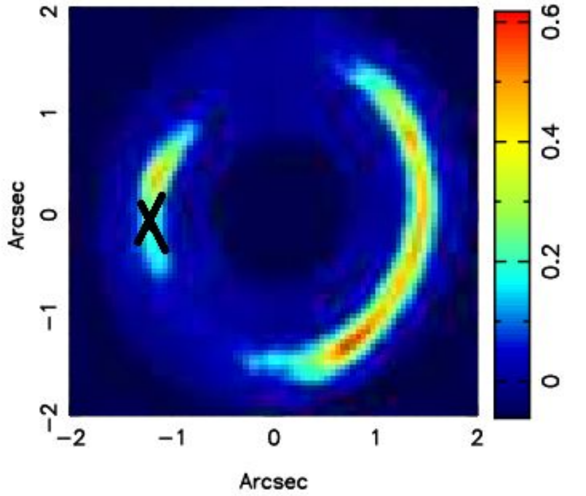
SLACS 0946+1006

Detect a subhalo at the same location as Vegetti et al 2009.

- Bayesian Evidence increase ~ 50 (> 10sigma).
- (y,x) position and mass consistent within 3 sigma.
- Our inferred mass is **7.8 +- 2.0 x 10^{10} solMass** for a spherical NFW mass profile.

I apologise for the rubbish visualization!



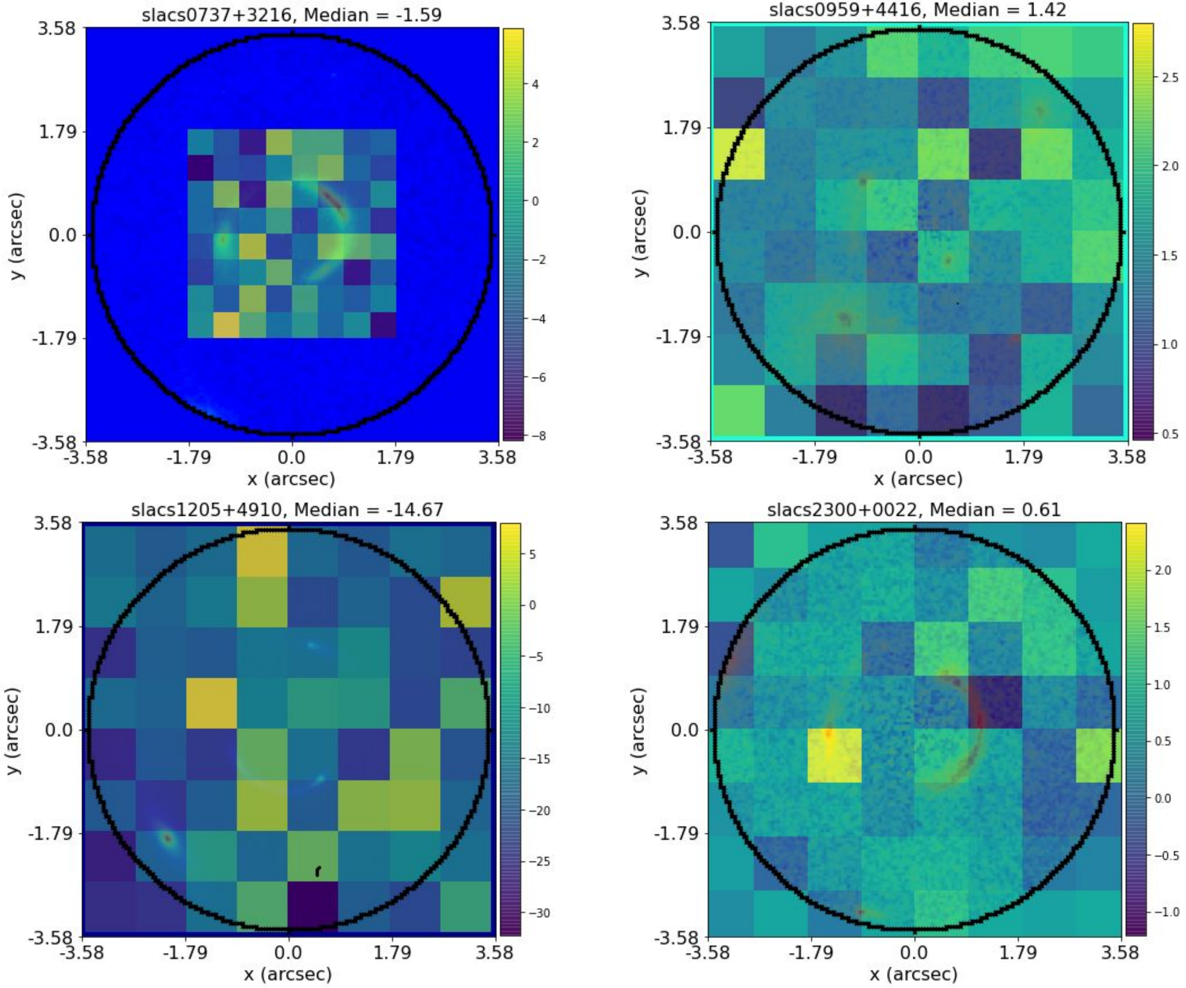


Non-Detections

Equally important for constraining dark matter models.

WDM models predict we should detect **nothing** below certain masses.

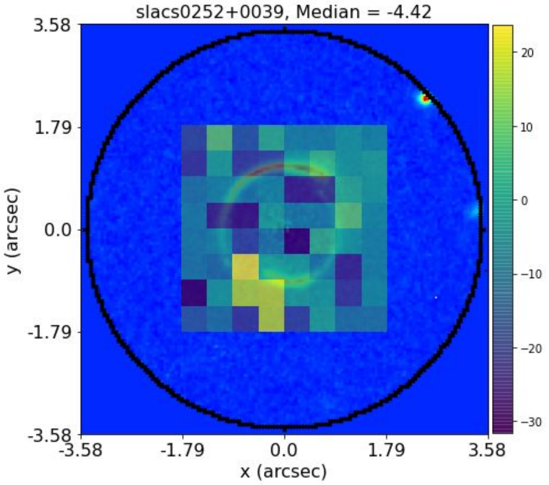
These 4 lenses were all non detections in Vegetti 2014.

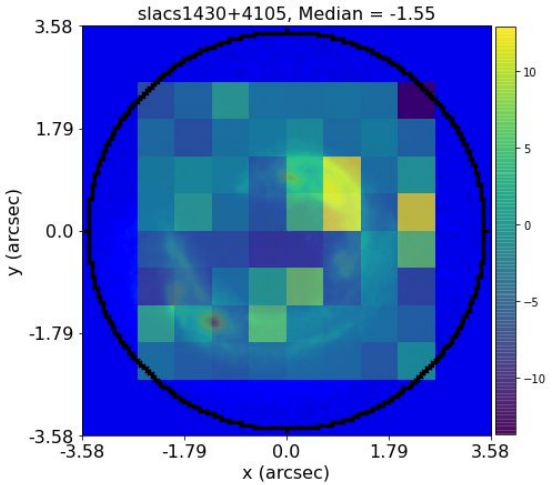


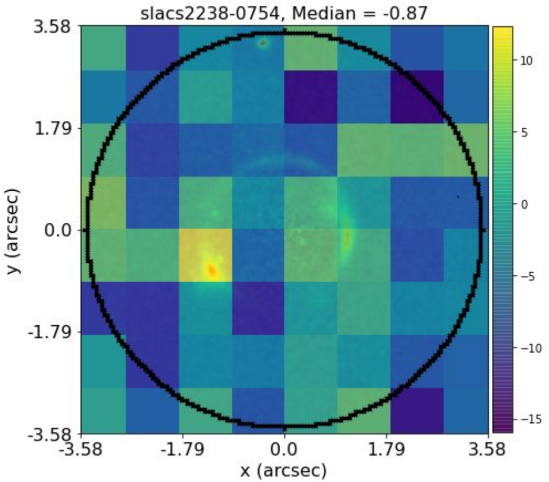
Detections?

These 4 lenses were also all non detections in Vegetti 2014.

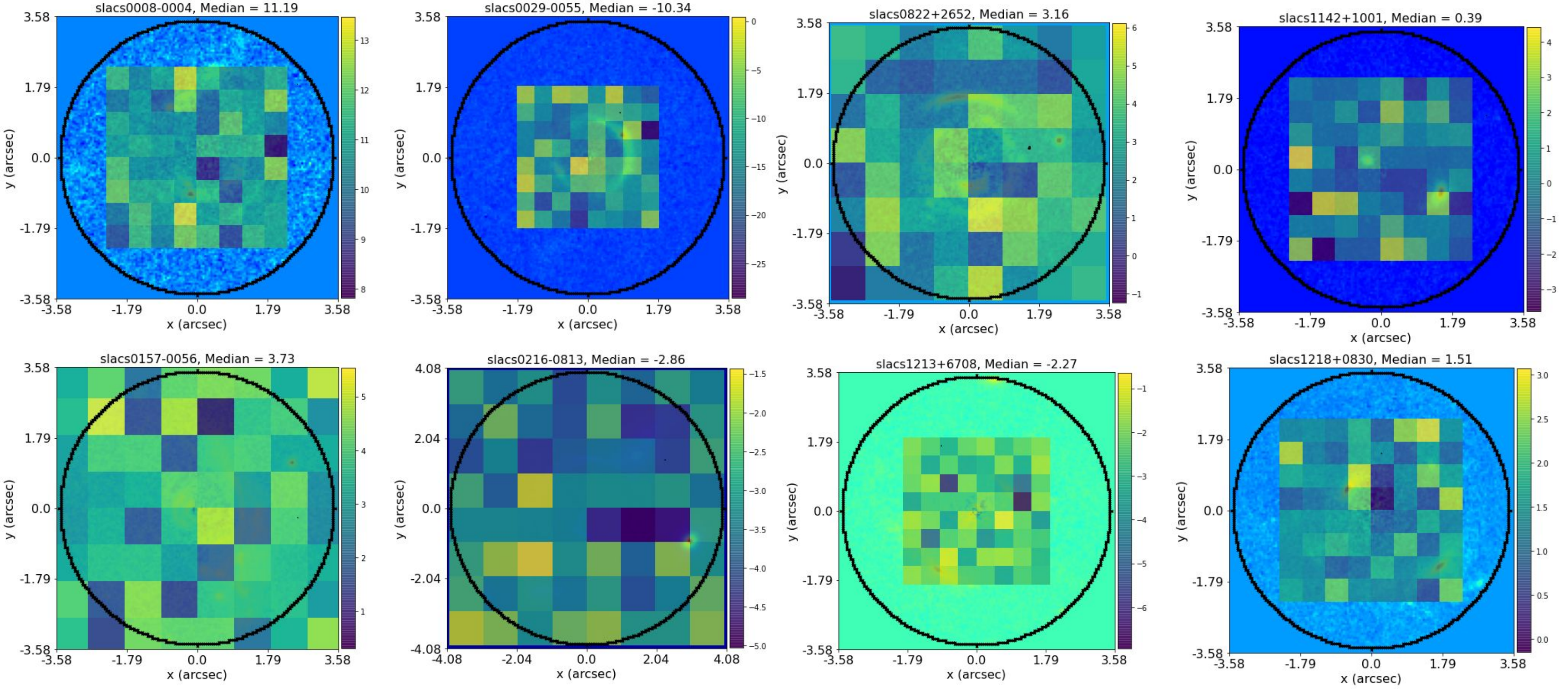
They require a Bayesian evidence increase of **over 50** to claim a detection.







Non-Detections



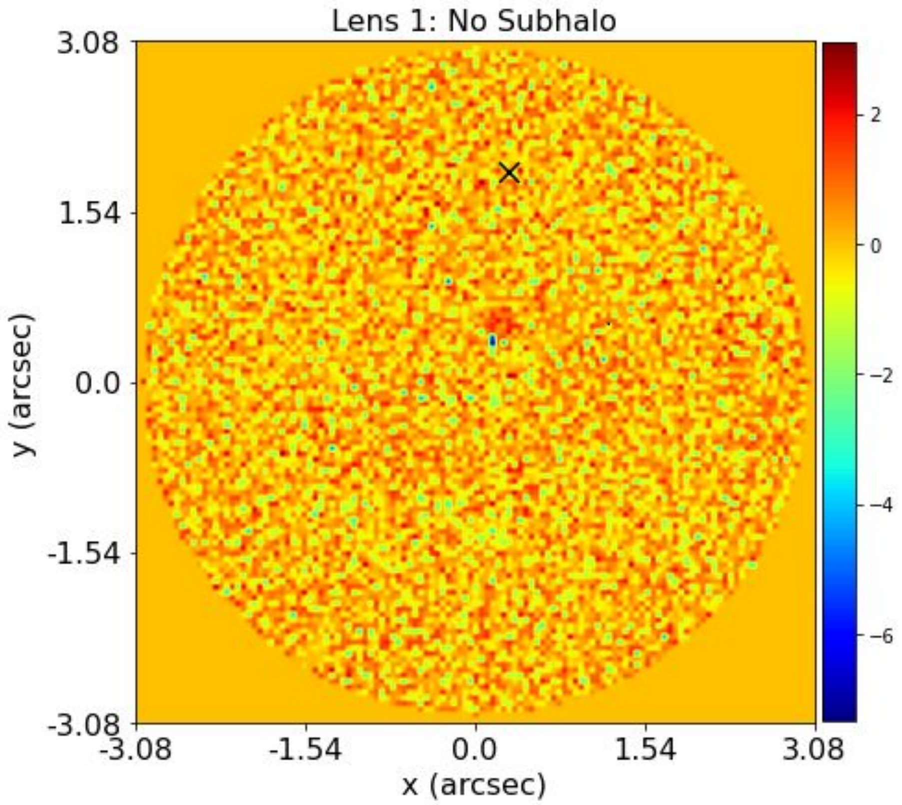
What should we detect?

Cosmological Constraints

We know how many dark matter subhalos **we did** detect.

We do not know how many dark matter subhalos **we could of detected**.

Next step is therefore to perform sensitivity mapping to determine (statistically) how many dark matter substructures we could have detect.



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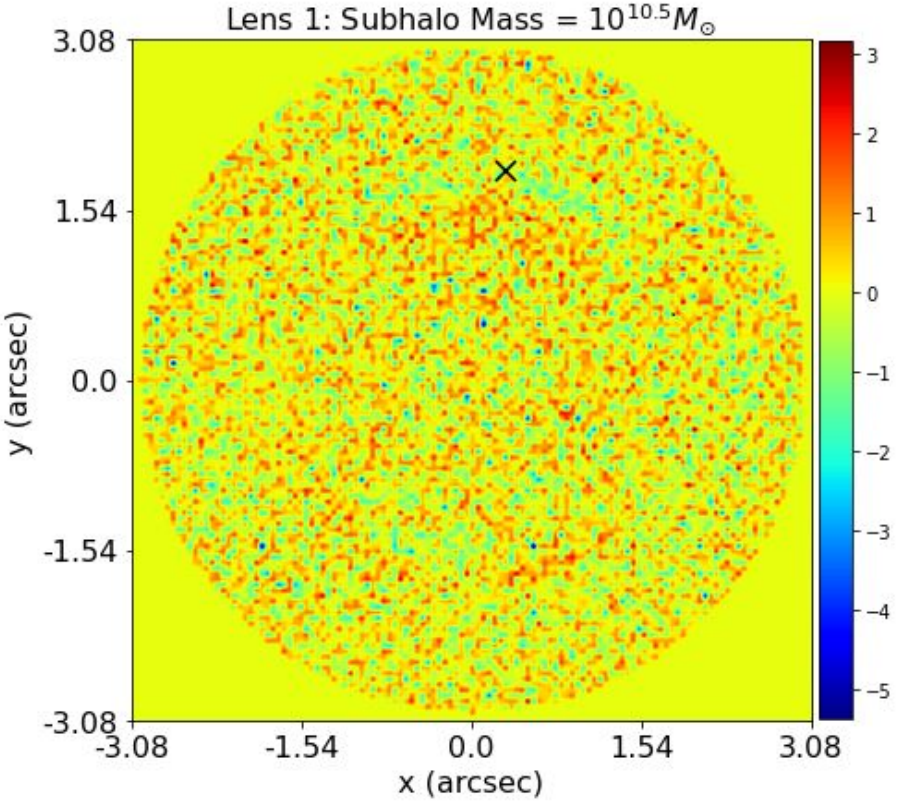


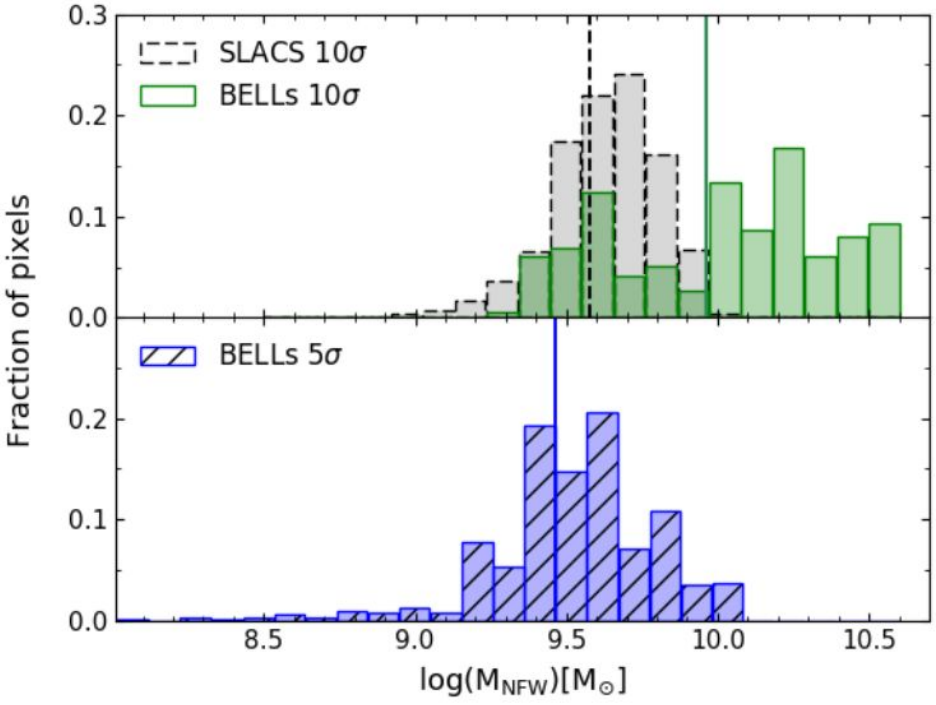
Sensitivity Expectations

Based on Vegetti et al:

- In a CDM Universe, we should expect to detect ~1 CDM halo of mass ~$10^{9.5\text{-}10.5}$MSun for every 30 strong lenses **given HST quality data**.

This is why **large sample statistics** is crucial and a clear understanding of systematics pivotal.

Using **higher resolution data (e.g. ALMA)** will also make us sensitive to lower mass dark matter subhalos!



Ritondale et al 2018

Summary

- We’re able to detect dark matter substructures with strong lensing.
- We’re even better at detecting nothing.
- We’re building up the statistics to constrain the dark matter subhalo mass function between $10^{6\text{-}10}$MSun.

Thanks for Listening!

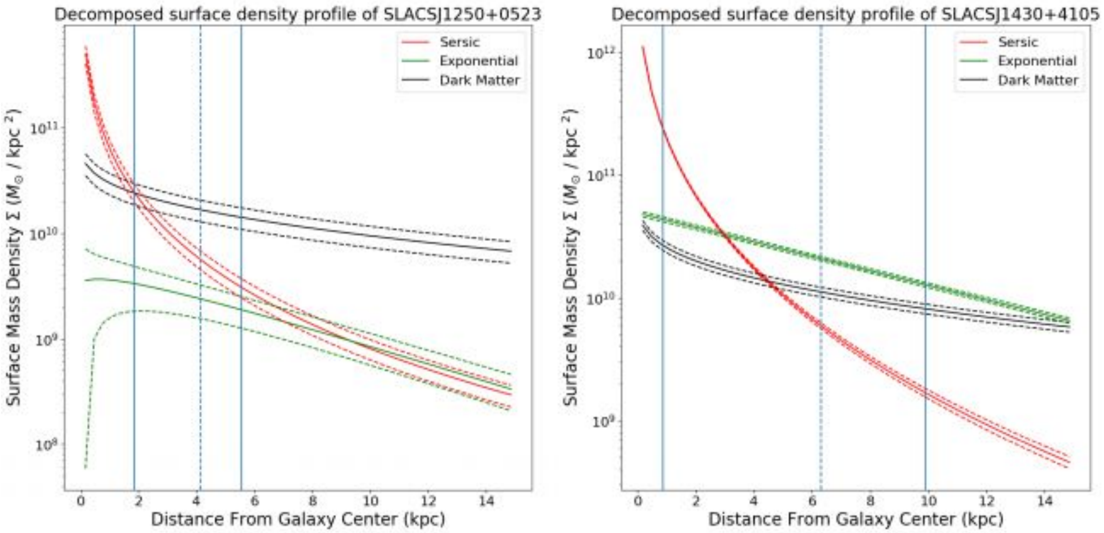
Other Approaches

Increase the lens model complexity

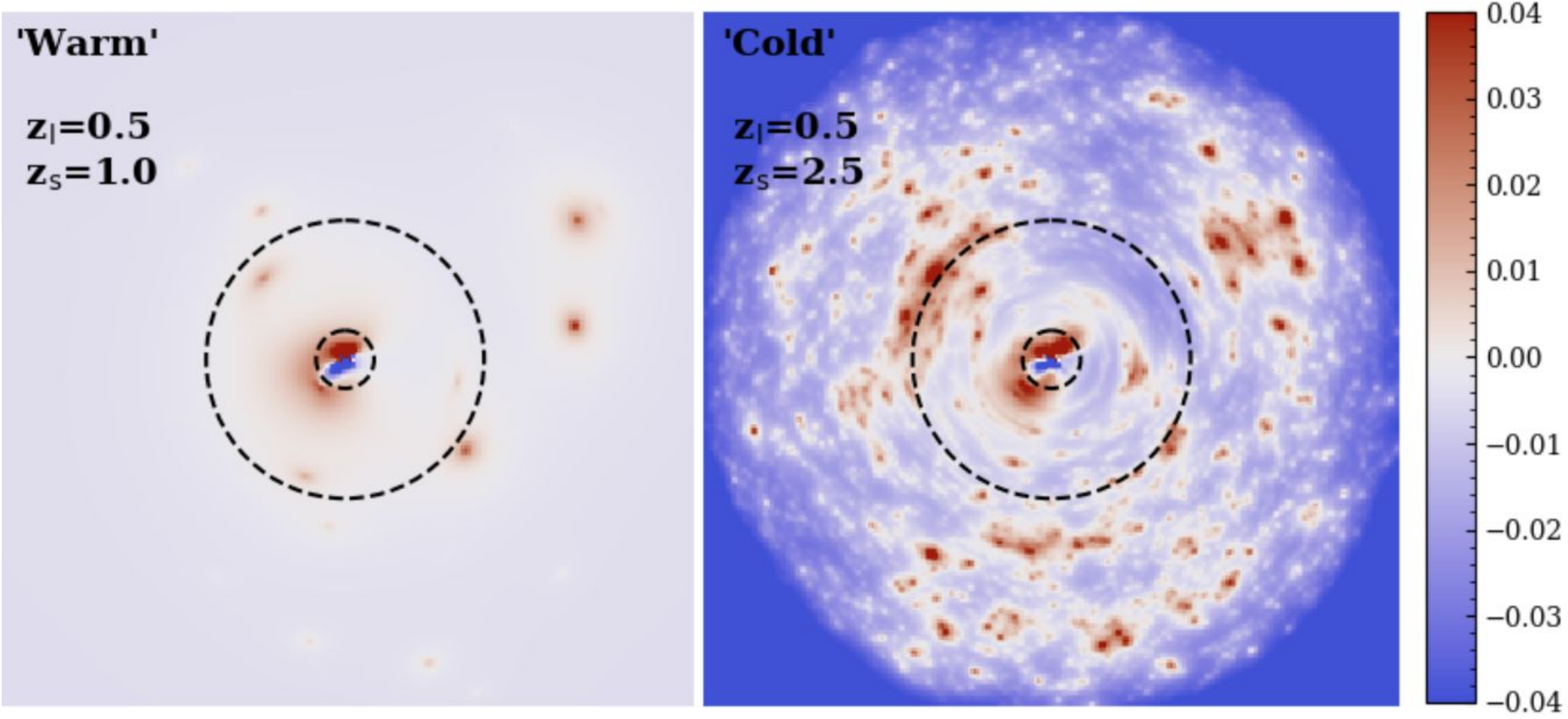
Fit a decomposed stellar + dark matter mass model.

- More complexity, remove false positives?
- Uses light to constrain stellar mass, more sensitivity to DM subhalos?

Fit for the subhalo redshift as a free parameter.

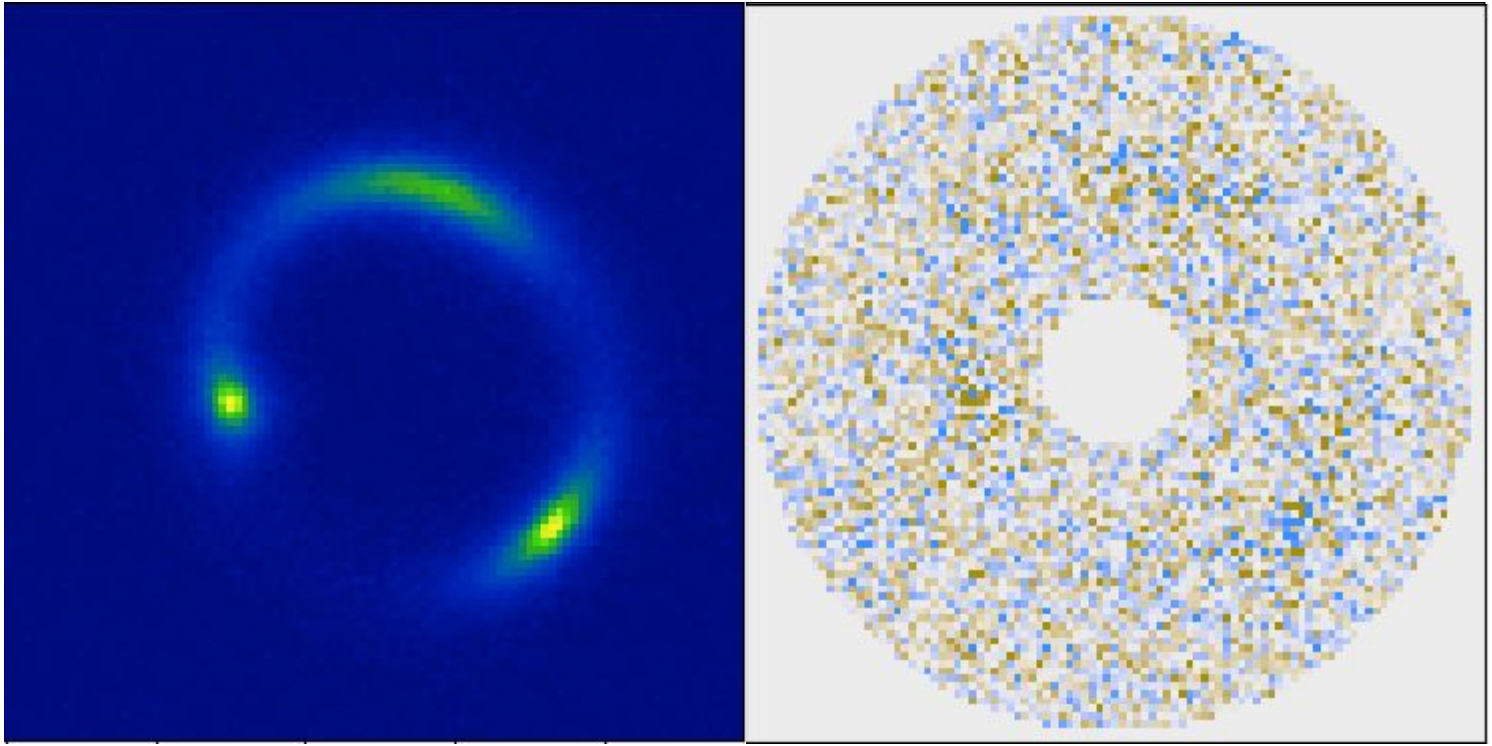


Cumulative Strong Lensing (Qiuhan He)



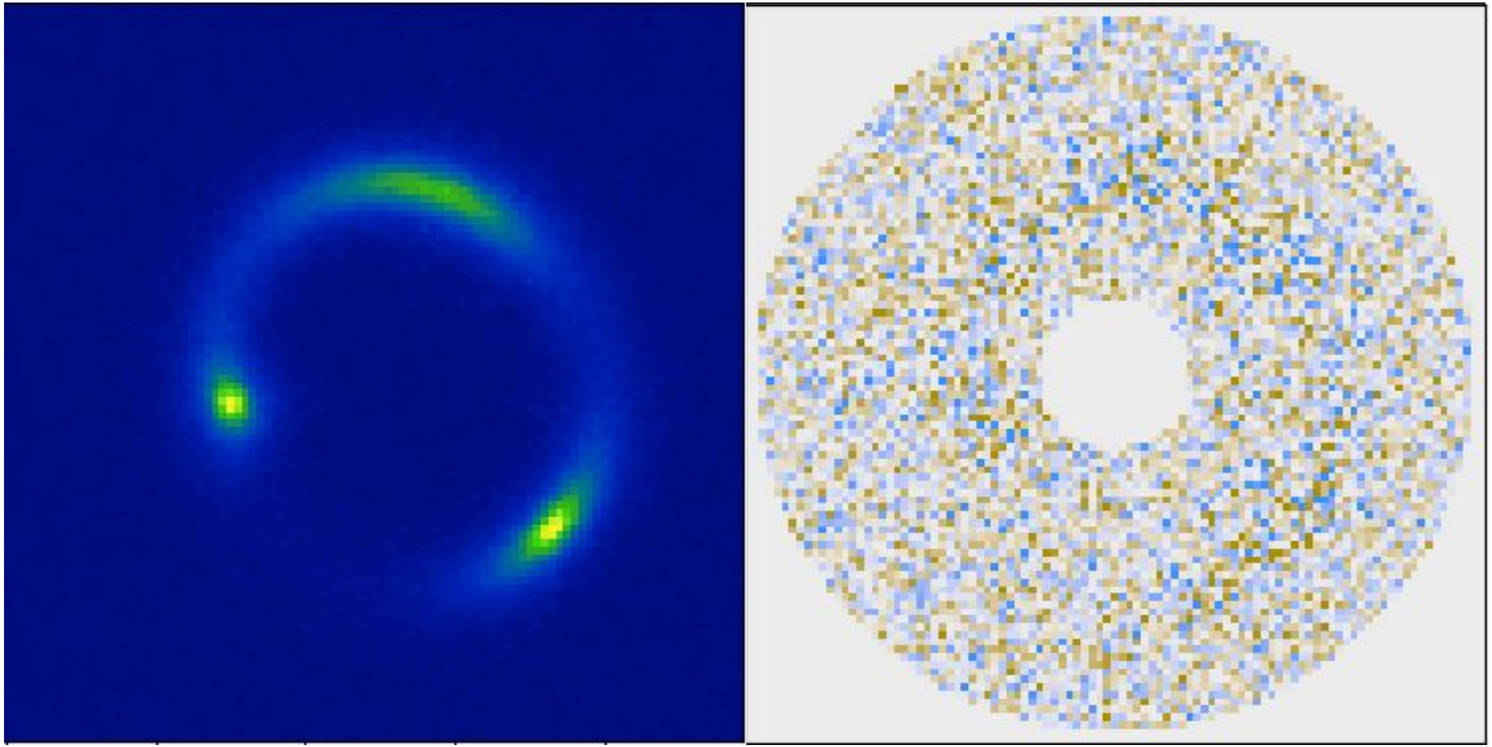
Strong Lensing: Residuals

Cold (M_{hf} [MSun] : 7.41)



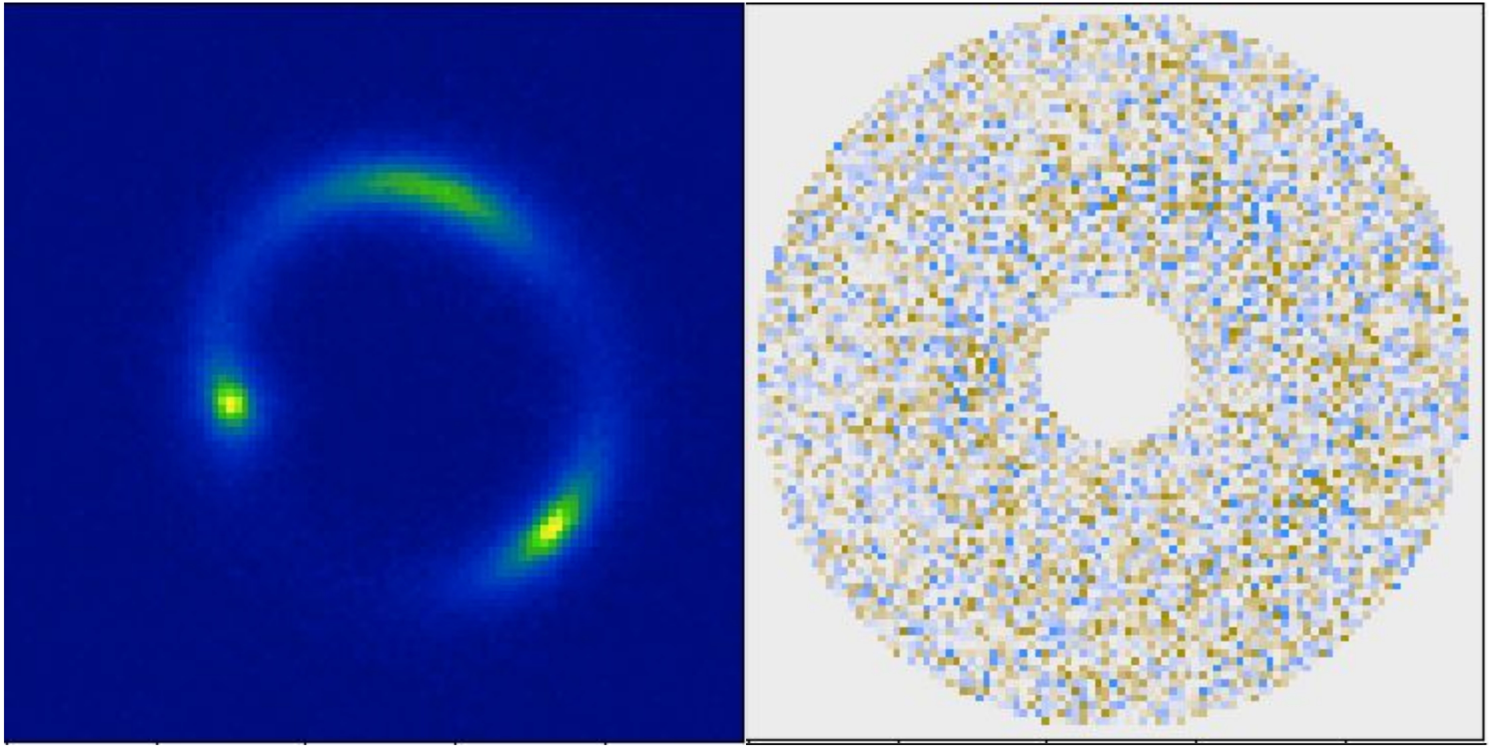
Strong Lensing: Residuals

Warmer (M_{hf} [MSun] : 8.21)



Strong Lensing: Residuals

Warm (M_{hf} [MSun] : 9.55)

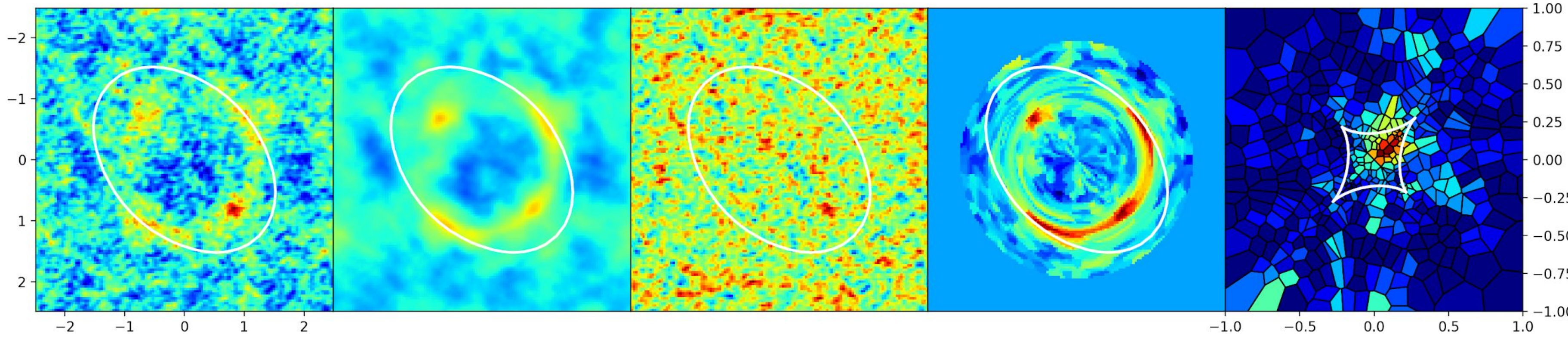


Interferometry (Aristeidis Amvrosiadis)

Using higher resolution ALMA data to detect lower mass substructures.

- Perform all lens modeling in the uv-plane via a non-uniform FFT, linear operator algebra and with self-calibration!

These tools are open-source are suitable to non lens analysis!



Take Home Point

Euclid wide field imaging of strong lenses contain a signal that can rule out or validate warmer flavours of dark matter.

- The results of He et al. make many simplifying assumptions.
- There is a long way to go until this can be reliably applied to real data.

However, the results show this signal will be there!

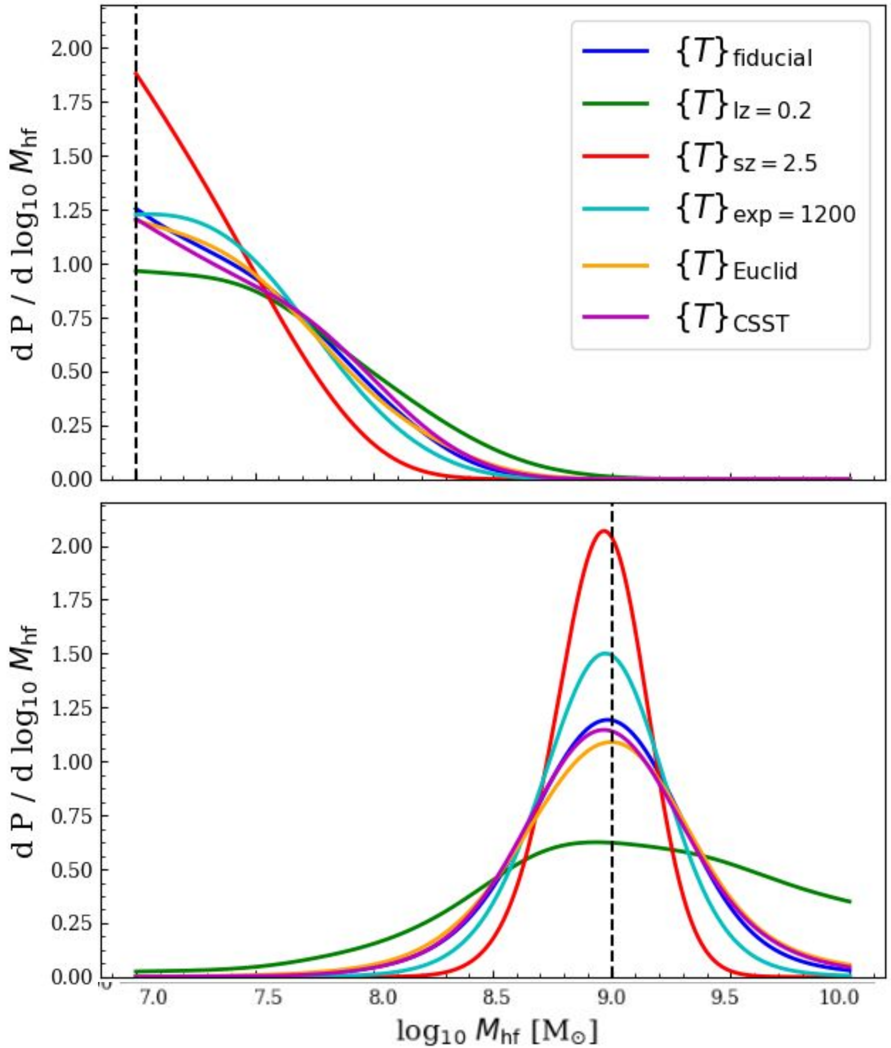
- The hard work starts now!

Extra Slides

Results

He et al. give more detailed overview of results.

https://arxiv.org/abs/2010.13221



What about baryonic feedback?

Strong lensing can potentially *not be subject to degeneracies with baryonic processes.*

For individual subhalos detections:

- The DM halo is either a subhalo of the lens or a line-of-sight object at a different redshift to the lens.
- If within the lens, it'll be subject to stripping, disruption, etc.
- If line-of-sight, it has most likely **never seen a baryon in its life.**

For cumulative subhalo inference:

- Contributions from both lens subhalos and line-of-sight objects.
- Depends on lens and source redshifts, can select samples which are **mostly line-of-sight objects.**

What about your galaxy mass model?

The mass models we currently assume are:

- **Individual detections:** a power-law + shear model.
- **Cumulative measurements:** singular isothermal ellipsoid (very simplified).

With PyAutoLens we will soon be relaxing both these assumptions:

- Decomposed stellar (e.g. x3 Sersic) + dark (e.g. elliptical gNFW) mass model.

This uses the lens galaxy's light to constrain its stellar mass model, information we have not yet exploited.

Subhalo Detections

We must now demonstrate the strong lens model *with a subhalo* fits the data better than one *without a subhalo.*

- Extremely challenging non-linear parameter spaces to sample.
- Although low dimensionality (N = ~ 12-18), they are *highly multi-modal*.

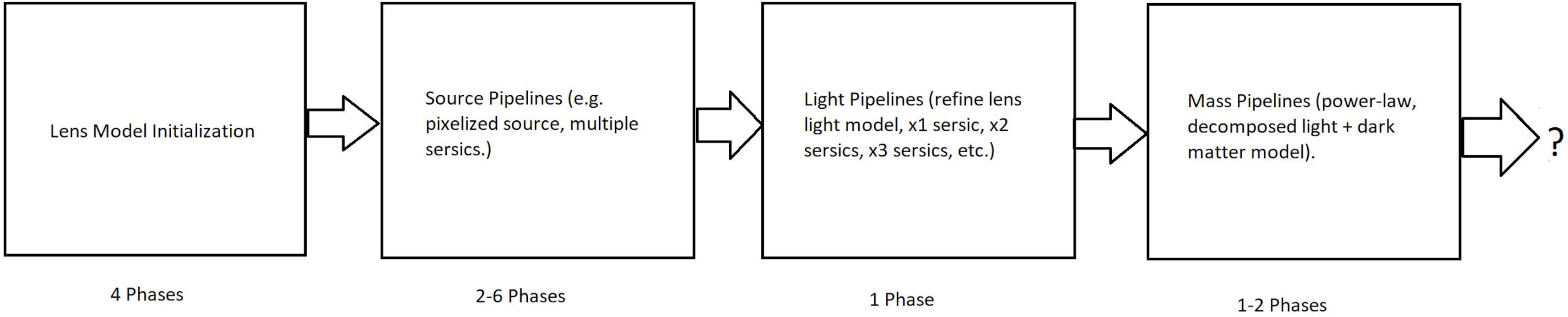
Trying to detect a subhalo using one non-linear search has never succeeded for us.

- Instead perform an 8x8 *grid search* of dynesty non-linear searches.
- *Remove multi-modal* nature of parameter space.
- Would be expensive, but can be *trivially parallelized!*

Automation

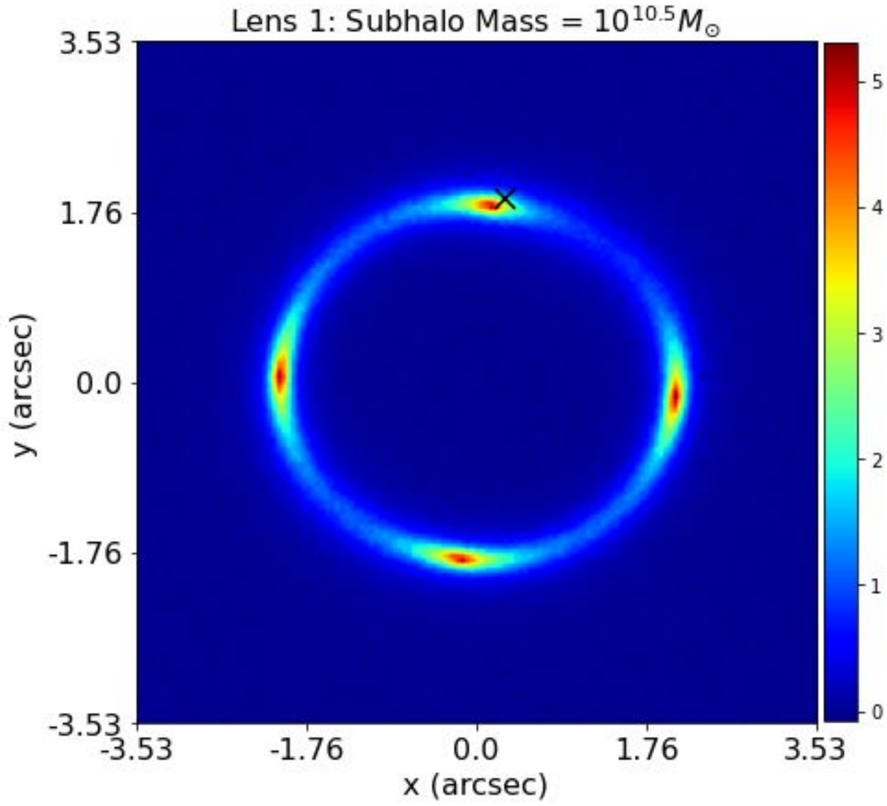
PyAutoLens fully automates the lens modeling procedure using transdimensional model fitting pipelines.

- Not got the time to give the details on this today (feel free to ask me at coffee!).
- Will be **crucial** for modeling the 100 000 strong lenses Euclid is going to find.
- **For substructure, means we can exploit massively parallel computing.**



Sensitivity Mapping

1) Simulate data of strong lens with a subhalo in it at a given position (y,x) and mass M.



Sensitivity Mapping

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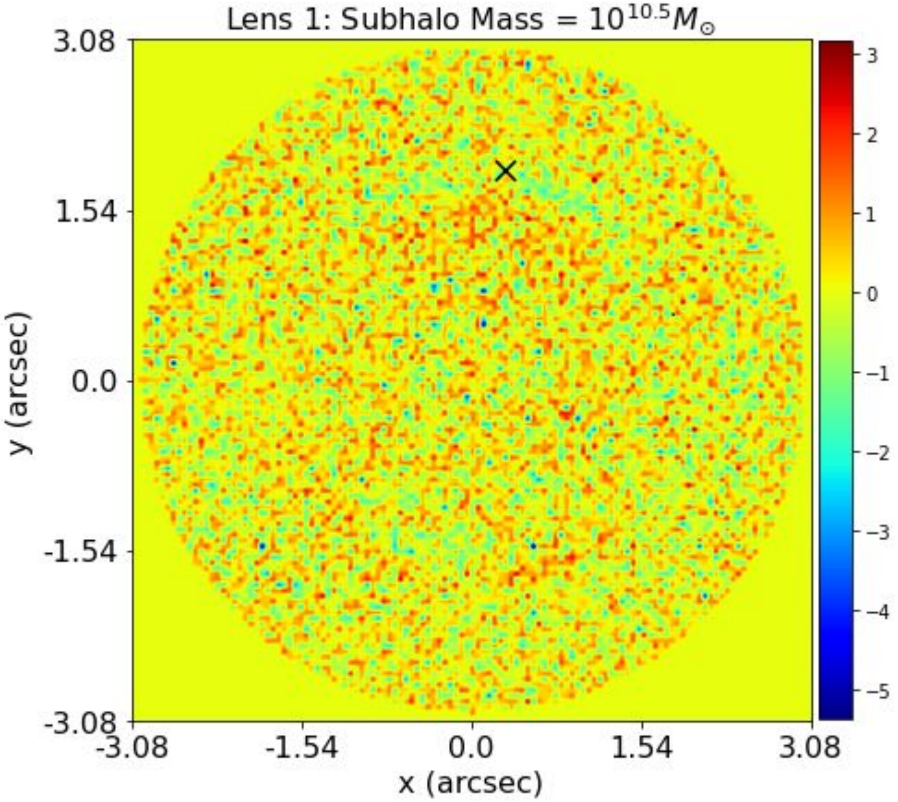
2) Fit data **twice, with and without a subhalo.**
3) Estimate Bayesian evidence increase due to presence of subhalo.
4) Repeat for a grid of y, x, M.



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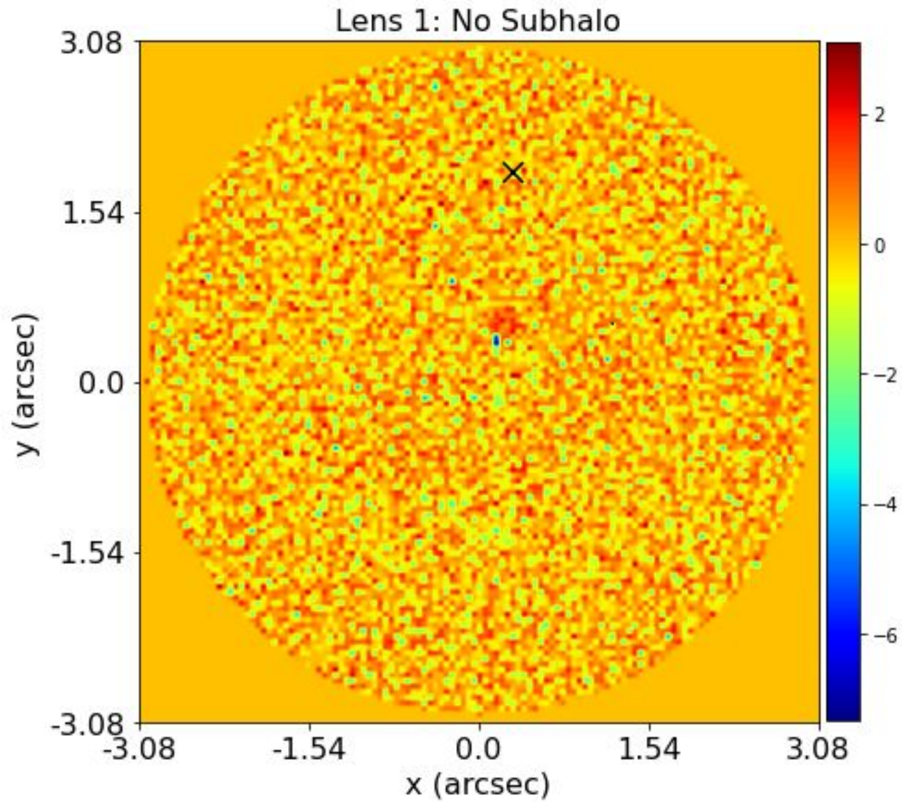

False Positives

There are clear examples of lenses that 'break' our machinery.

- All no subhalo models (except) one decrease evidence relative to model without subhalo.
- Numerous cells with Evidence increases > 50.

These are uncommon, need to be understood if we are to truly automate this analysis.