

# Joint analysis constraints on the physics of the first galaxies

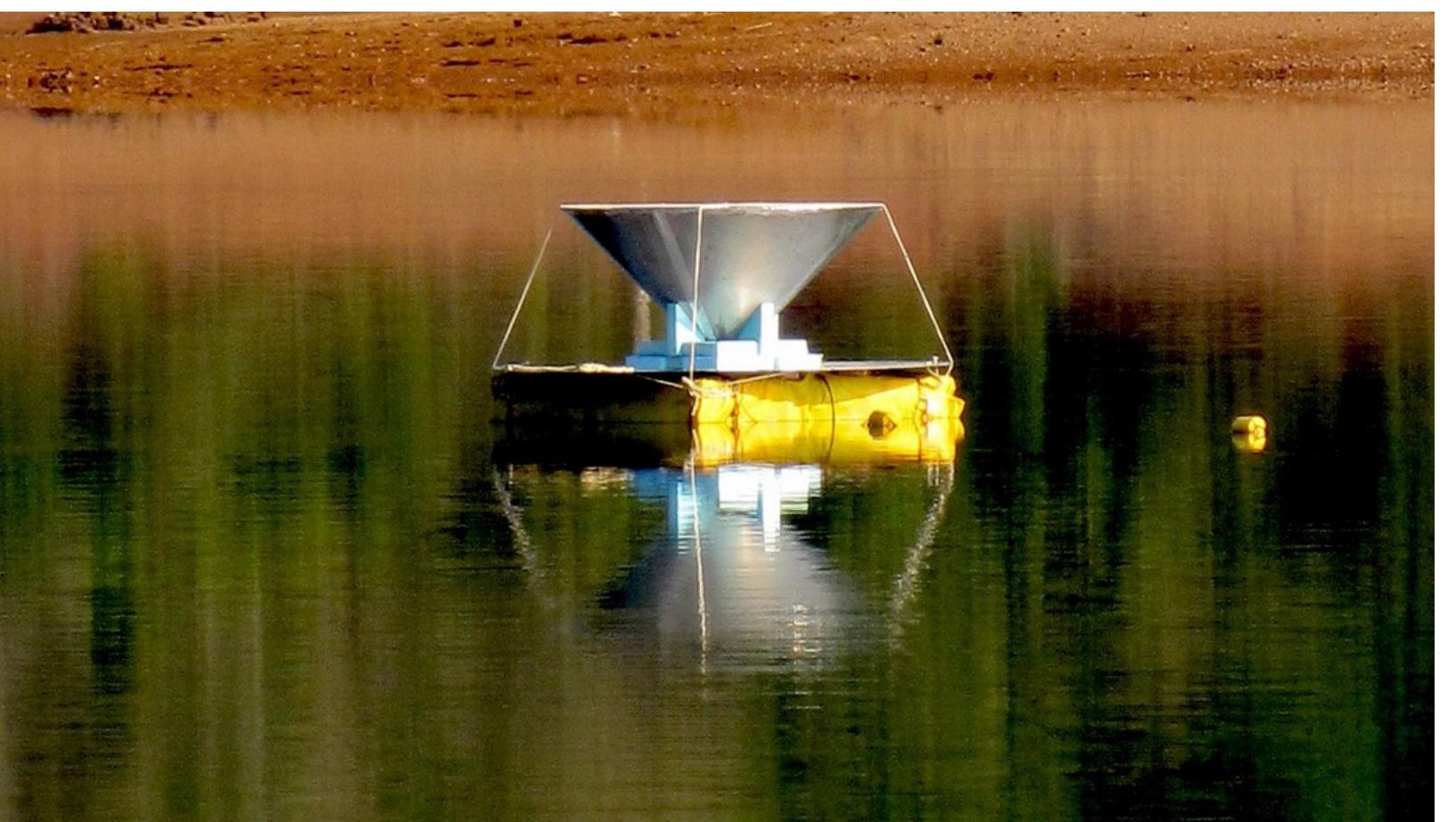
Harry Bevins

With

Stefan Heimersheim, Irene Abril-Cabezas, Anastasia Fialkov, Eloy De Lera Acedo, William Handley, Saurabh Singh, Rennan Barkana

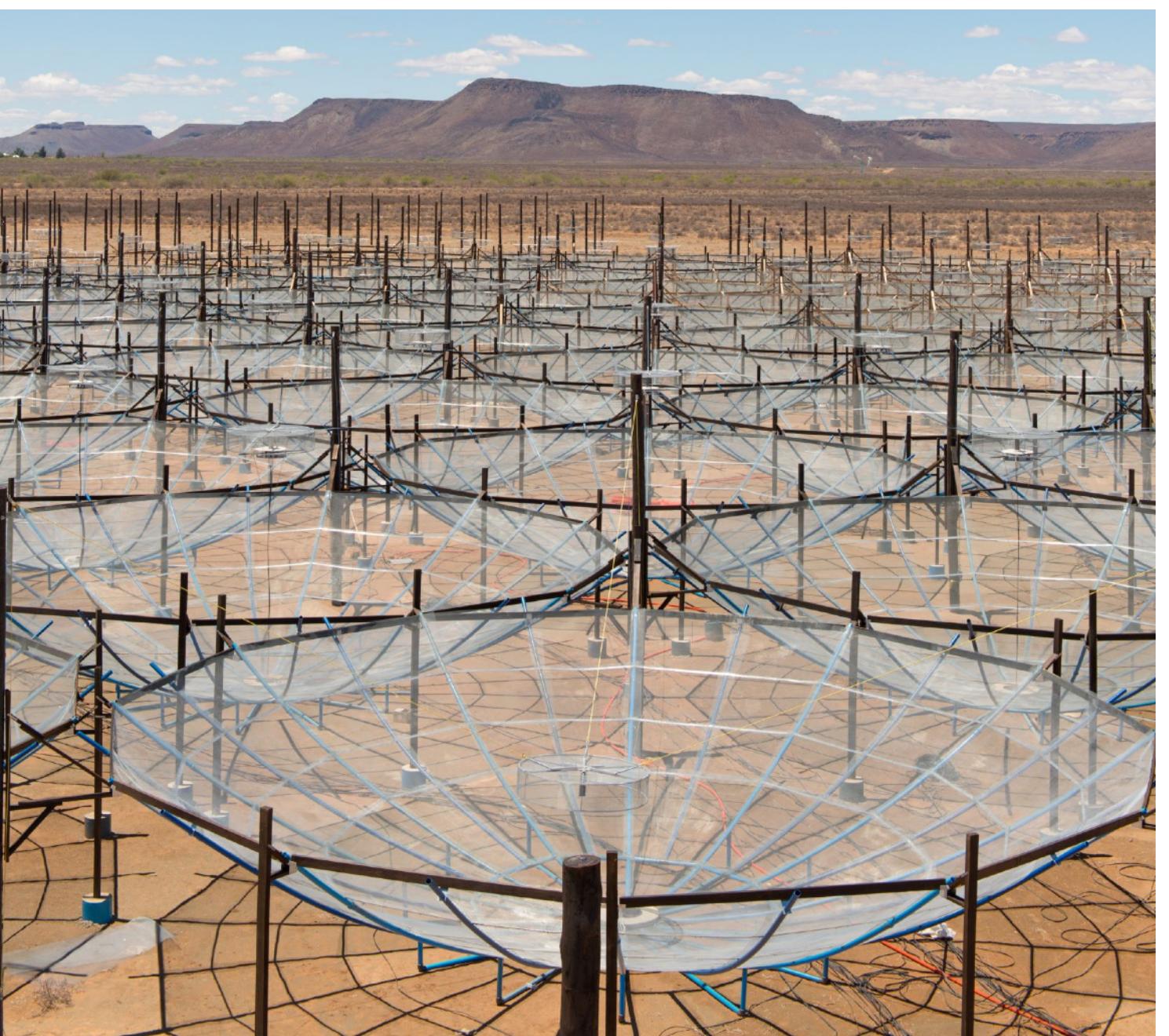
# The Plan

**1. The Goal of the Work**



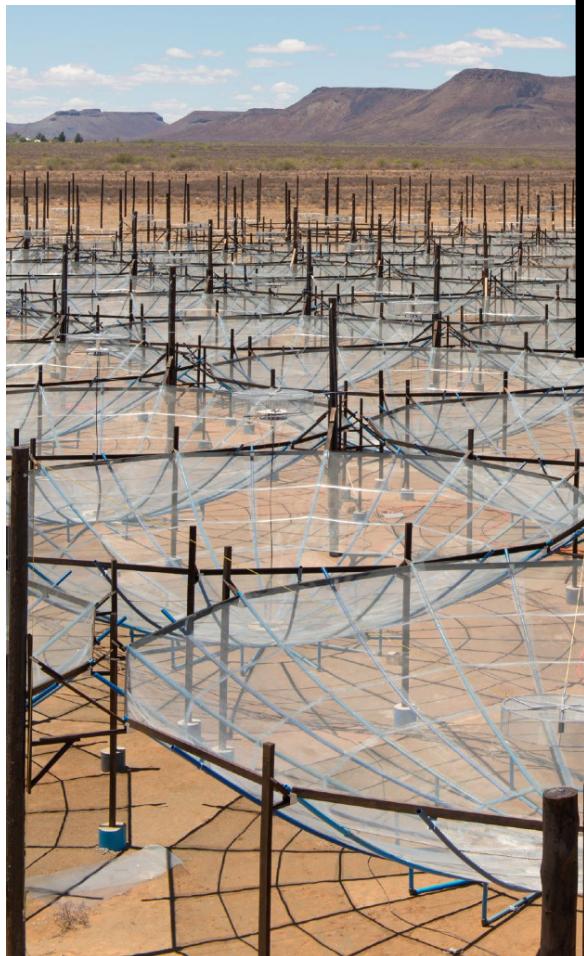
**2. The Methodology**

**3. The Results**



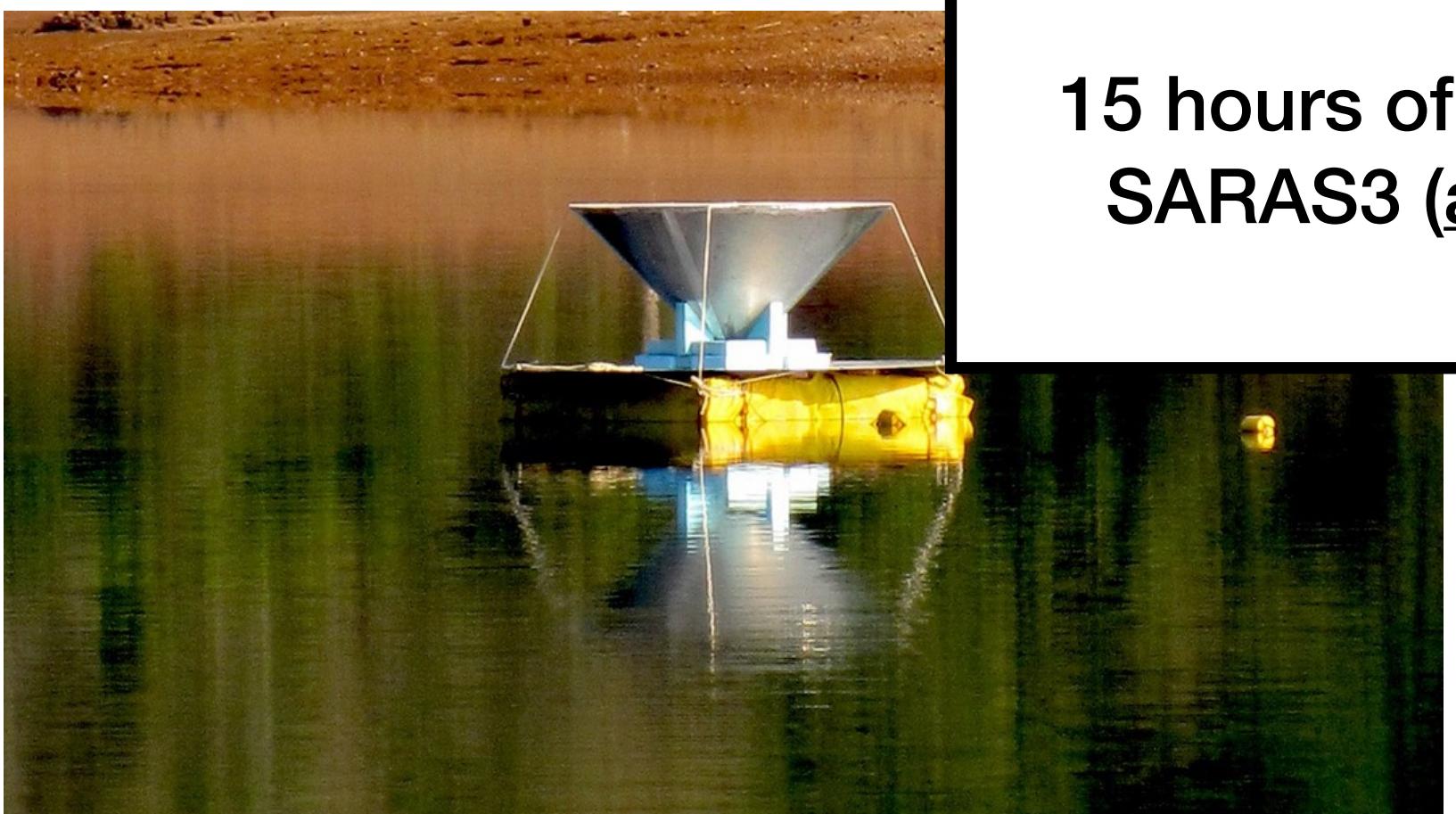
# **The Goal of the work**

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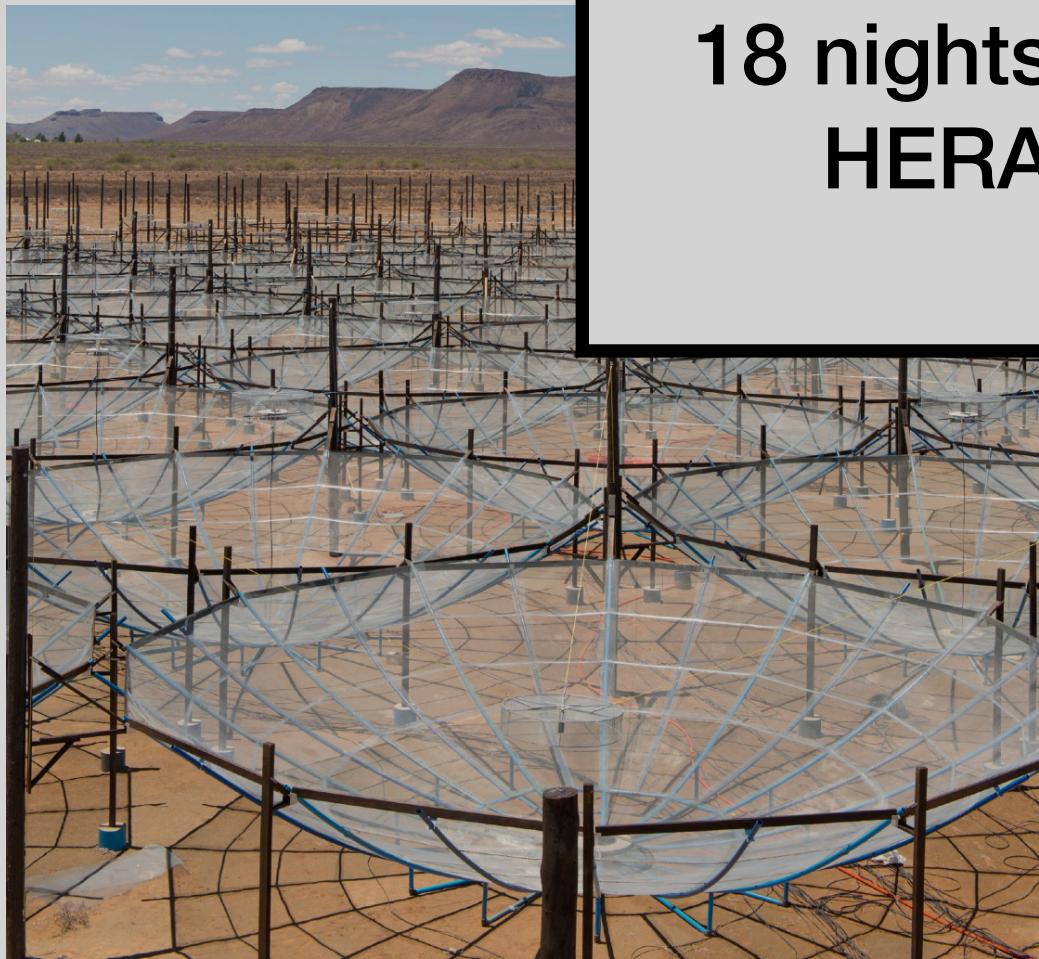
18 nights of observations from  
HERA ([arxiv2108.07282](https://arxiv.org/abs/2108.07282))

Joint analysis of this data?  
Never been attempted before



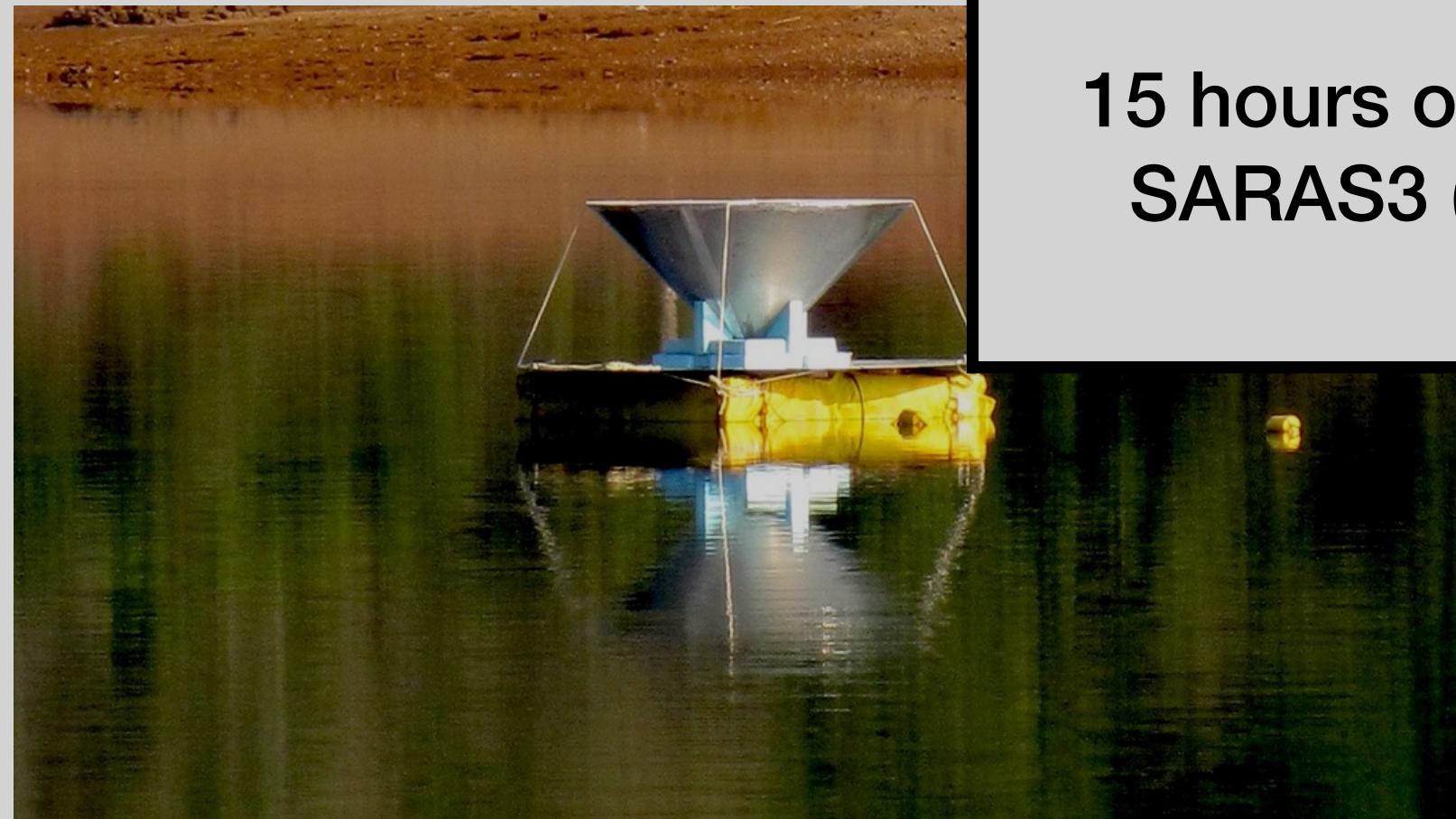
15 hours of observations from  
SARAS3 ([arXiv:2112.06778](https://arxiv.org/abs/2112.06778))

# The Goal of the Work



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How about adding in LOFAR  
([arXiv:1702.08679](https://arxiv.org/abs/1702.08679)), MWA  
([arXiv:2002.02575](https://arxiv.org/abs/2002.02575)) and SARAS2  
([arXiv:2201.11531](https://arxiv.org/abs/2201.11531))?

# **The Methodology**

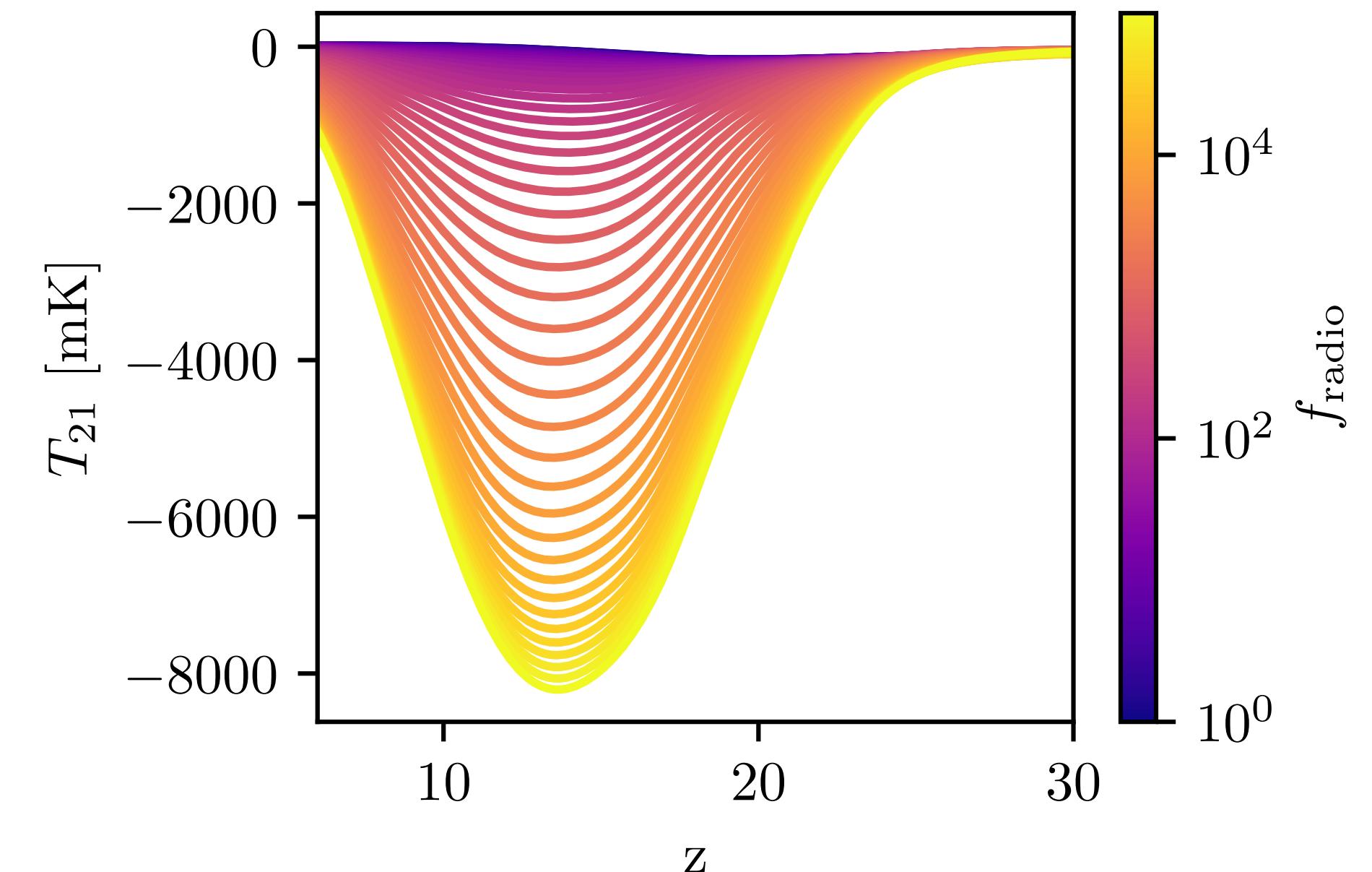
# The Methodology: Signal Modelling

Any joint analysis requires consistent modelling of the signal.

Our models (Fialkov et al.) include:

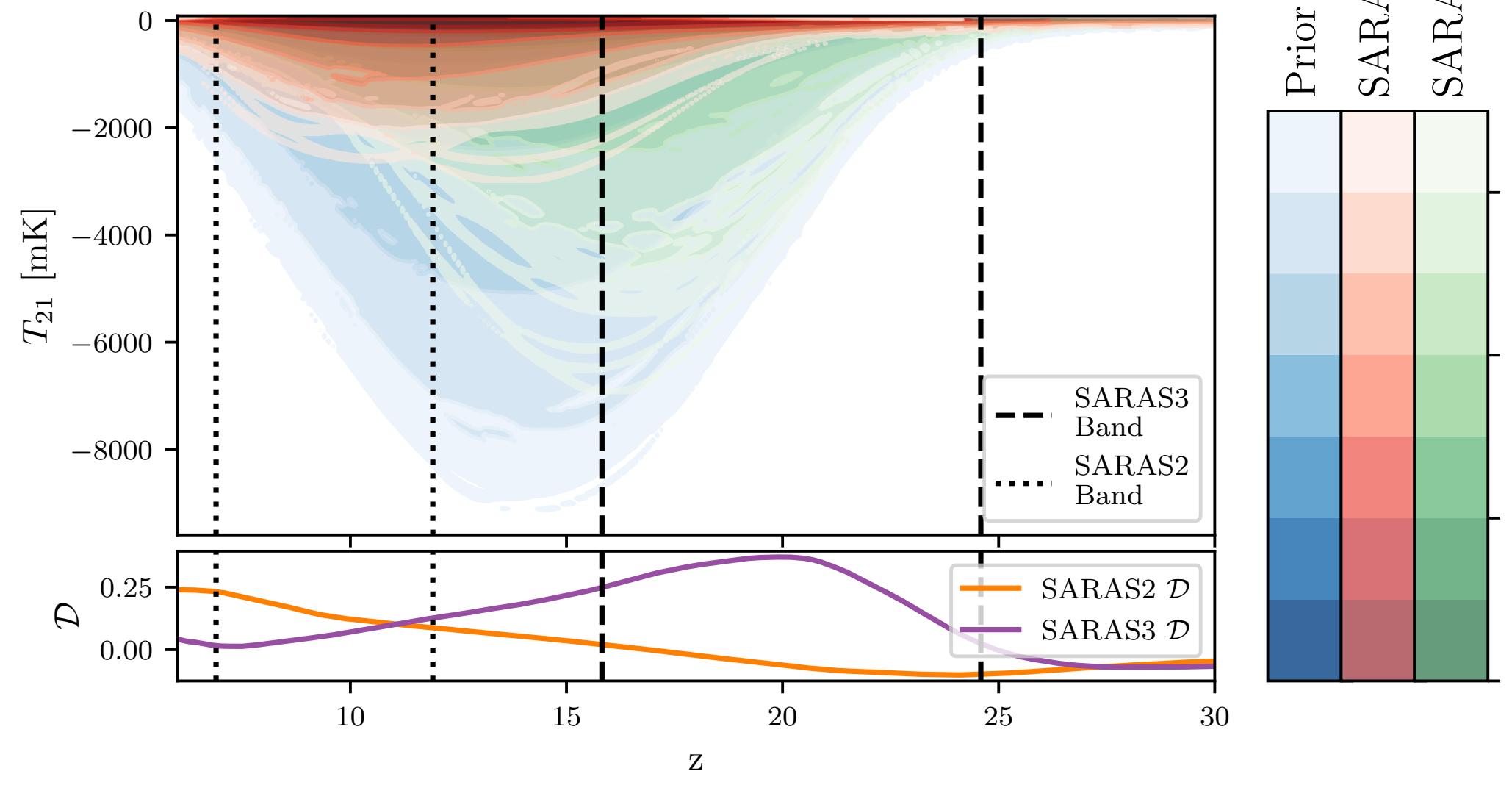
- A contribution to the radio background from high- $z$  galaxies
- Lyman- $\alpha$  heating, CMB heating and X-ray heating
- Multiple scattering of Lyman- $\alpha$  photons

Parameterised by star formation, X-ray and radio production efficiencies ( $f_*, f_X, f_{\text{radio}}$ ), the CMB optical depth ( $\tau$ ) and minimum halo mass for star formation ( $M_c \rightarrow V_c$ ).

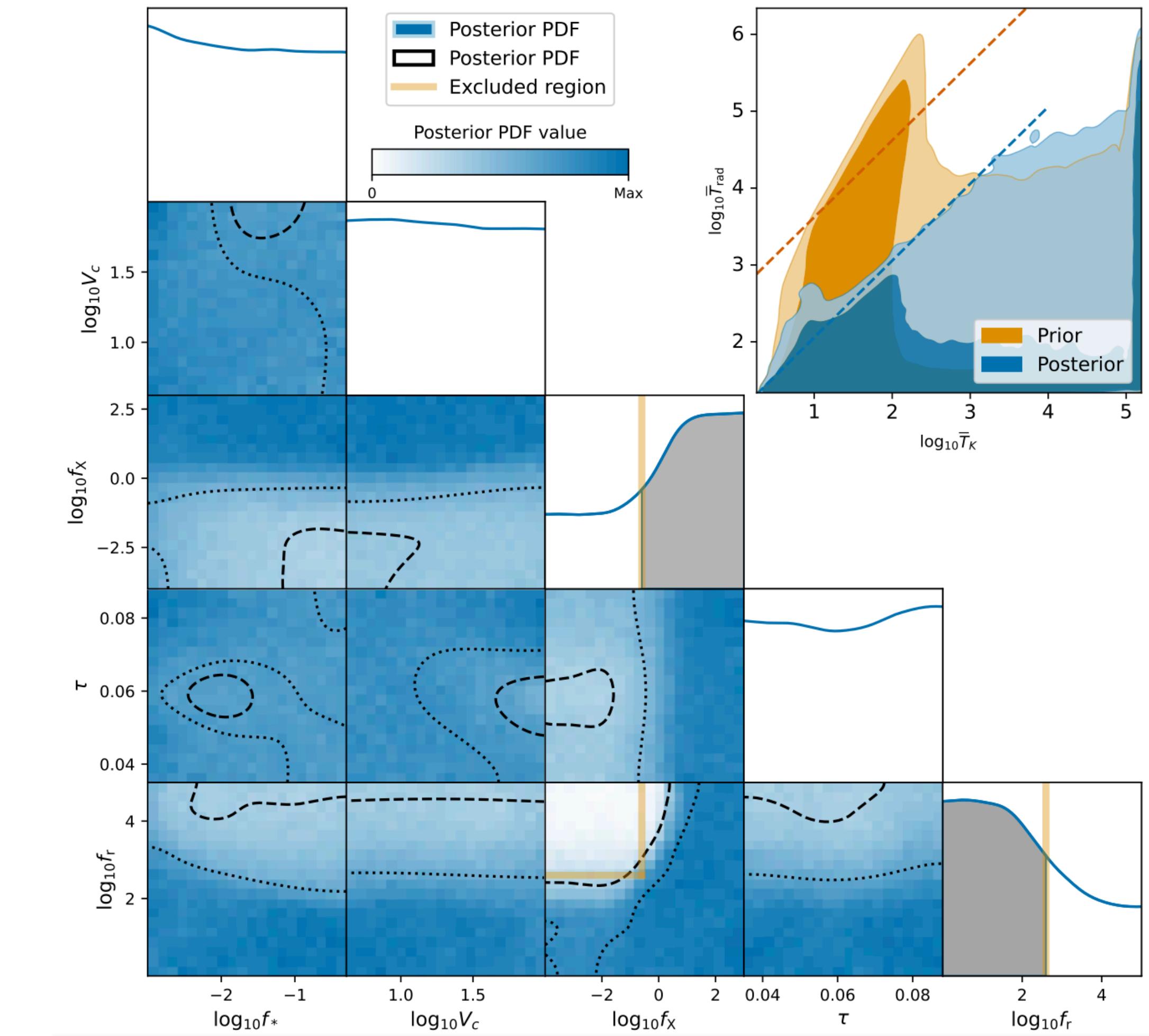


# The Methodology: But we have existing constraints?

- We already have constraints from HERA and SARAS3 on this class of models.
- Can we take advantage of this existing body of work?



Bevins et al. 2022 ([arXiv:2112.06778](https://arxiv.org/abs/2112.06778))



The HERA Collaboration, 2022 (2108.07282)

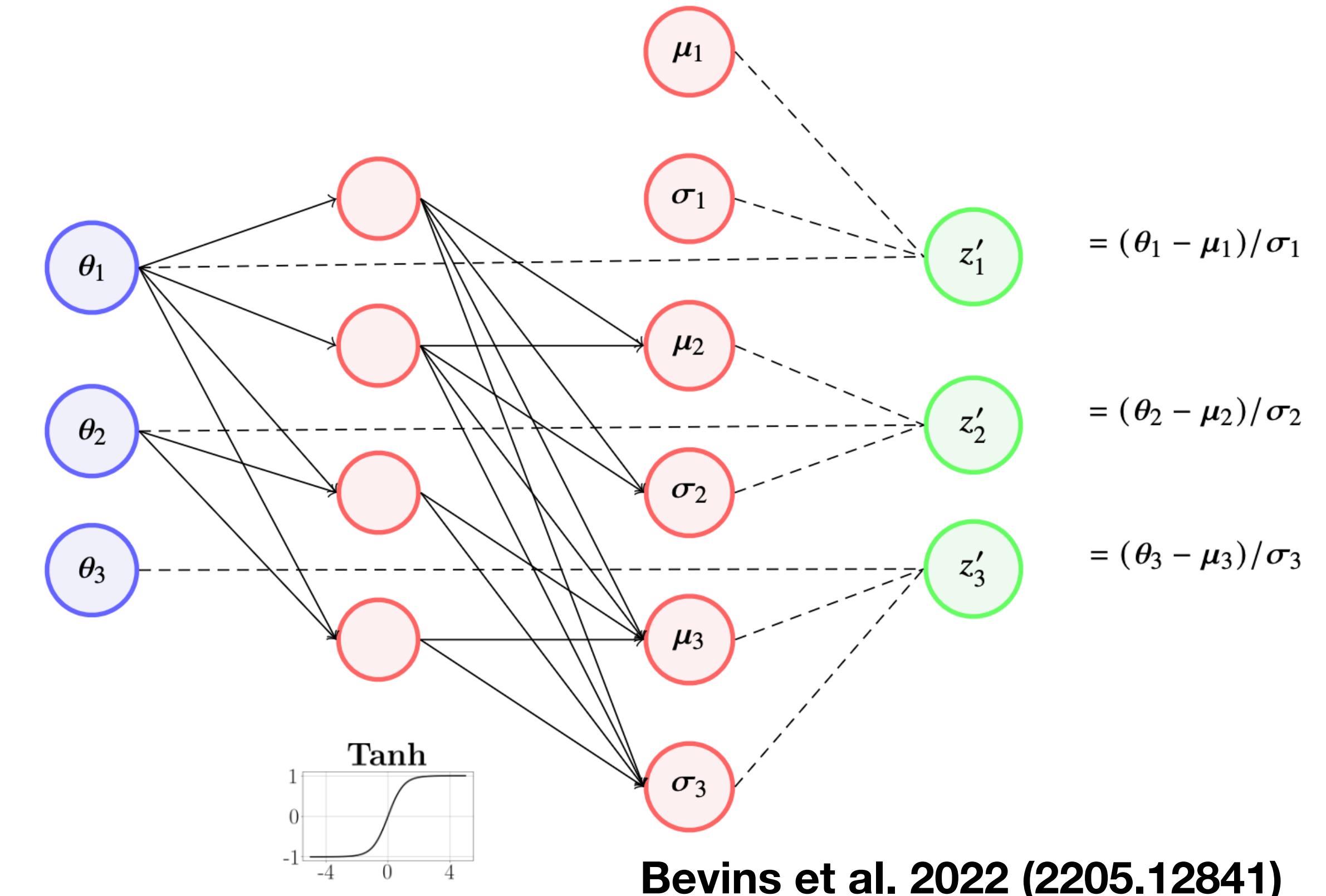
# The Methodology: Utilising Normalizing Flows?

Normalizing flows parameterise a transformation from a known base distribution to a target distribution

Trainable and bijective density estimators

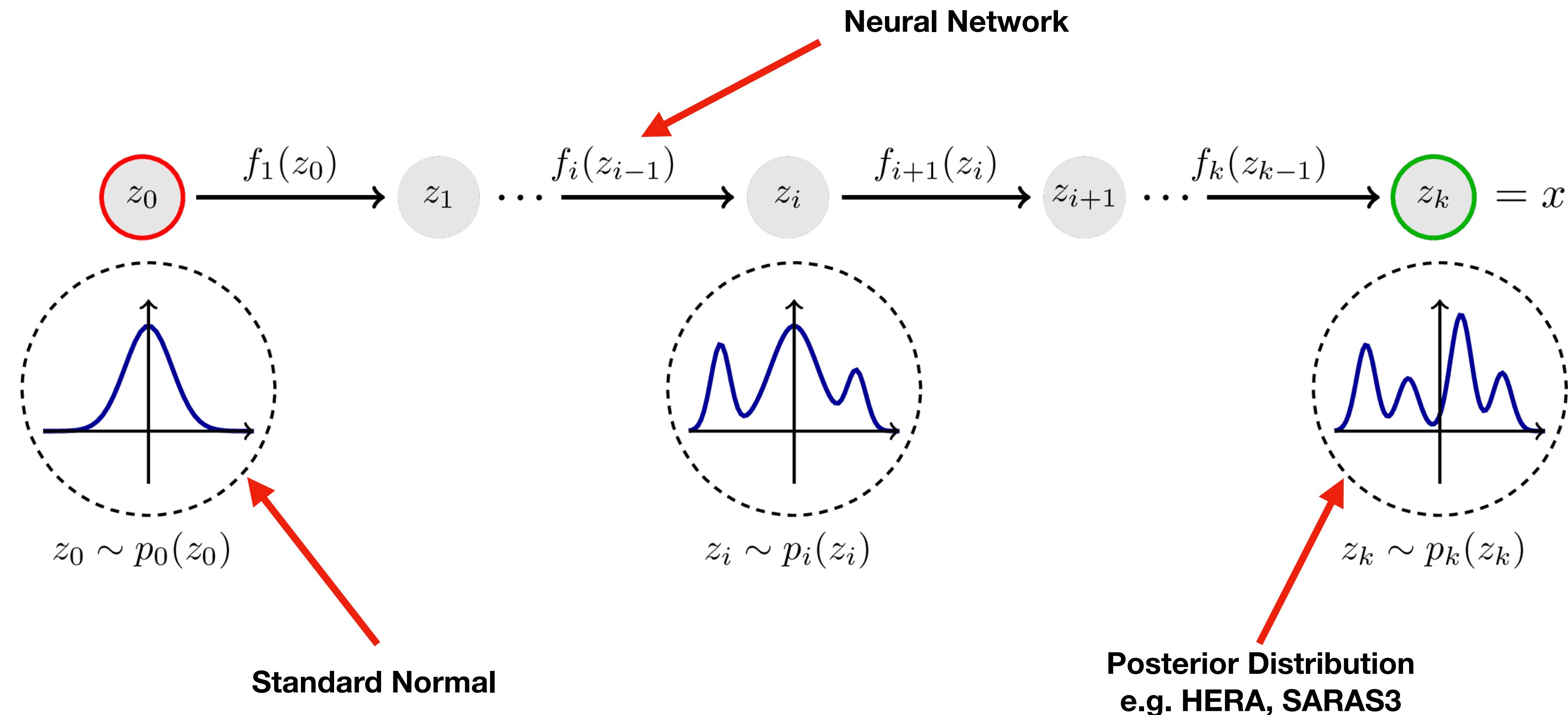
Bijective property allows us to do lots of cool things!

Using the package *margarine* (<https://github.com/htjb/margarine>)



Bevins et al. 2022 (2205.12841)

# The Methodology: Utilising Normalizing Flows?

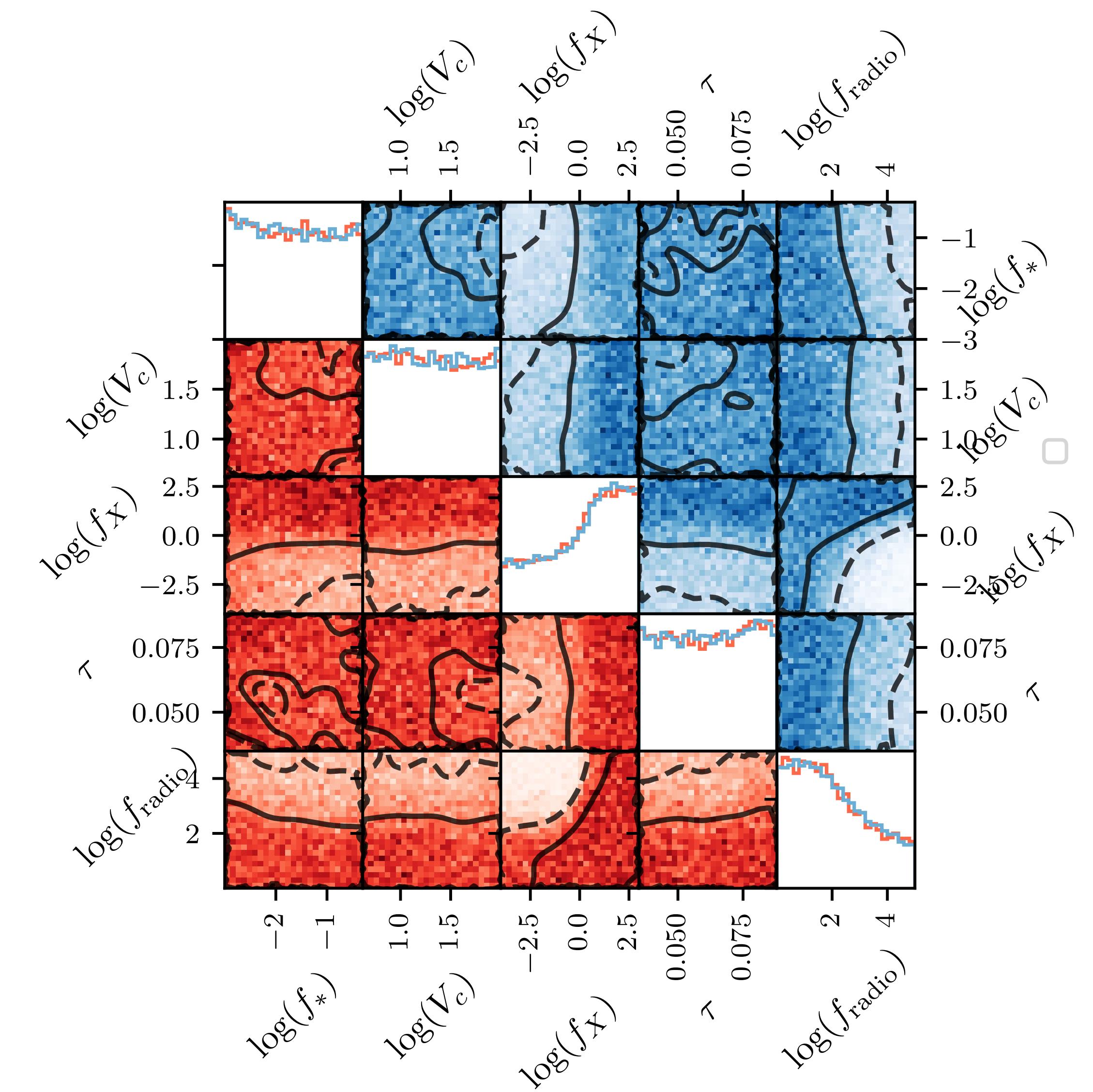


# The Methodology: How are the flows useful?

Flows allow us to:

- Draw samples from the target distribution
- Derive non-trivial priors
- Calculate log-probabilities on the target distribution for a set of parameters

See Bevins et al. 2022a,b and 2023  
(2205.12841, 2207.11457, 2305.02930)



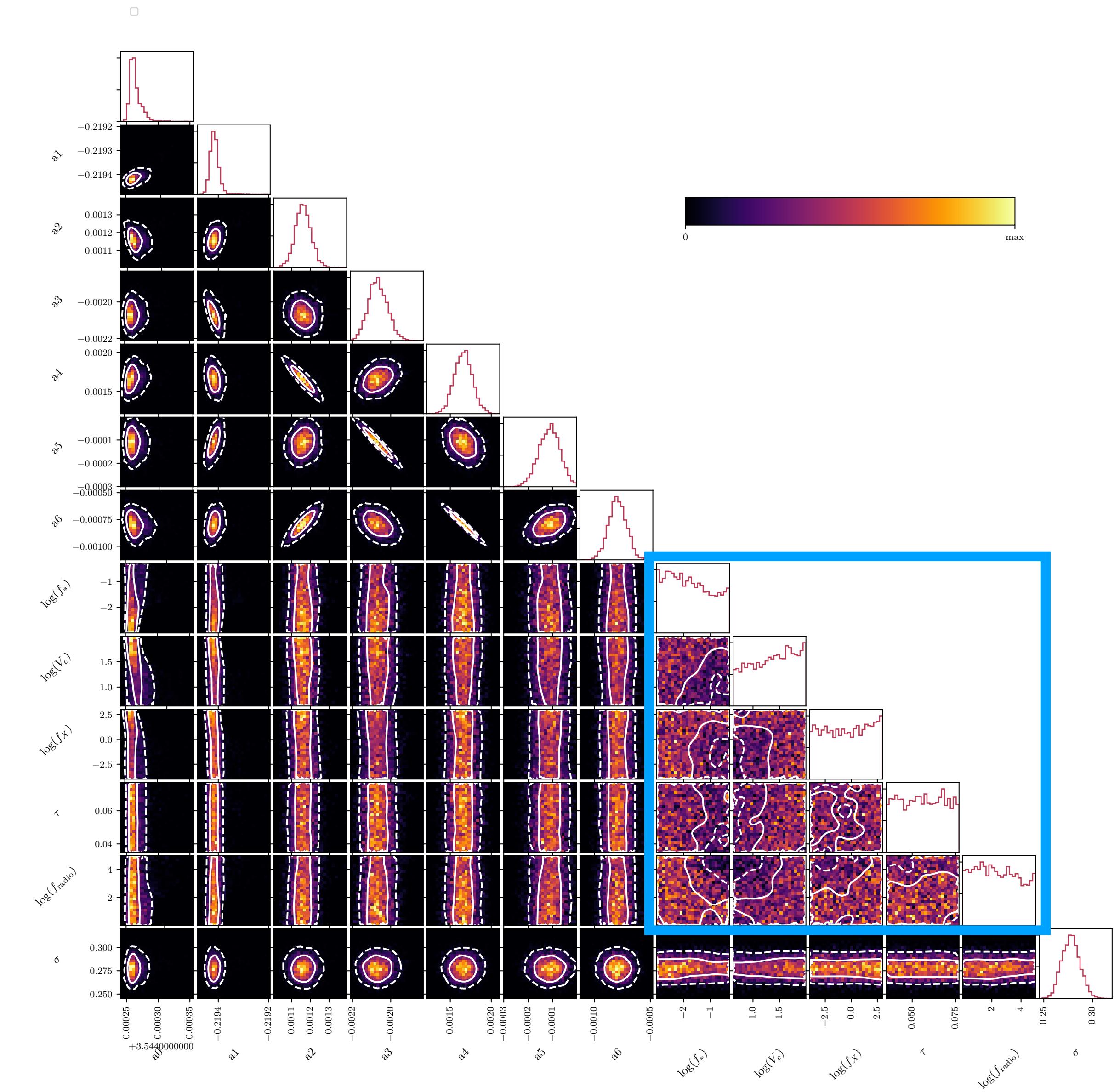
# The Methodology: Why bother with normalizing flows?

Why not just run a joint likelihood over all of the parameters in an analytic likelihood?

The SARAS3 model has foreground parameters... but we are not really interested in these!

We refer to these as *nuisance* parameters!

Flows allow us to learn marginal parts of the parameter space



# The Methodology: Joint likelihood?

$$\mathcal{P}(\theta|D, \mathcal{M}) = \frac{\mathcal{L}(\theta)\pi(\theta)}{\mathcal{Z}} \quad \theta = \{\theta_I, \theta_{fg}, \theta_{21}\}$$

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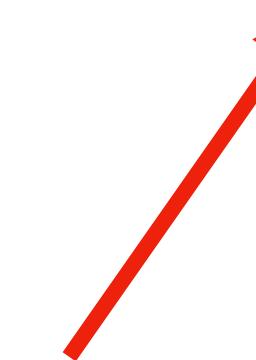
$$\log(\mathcal{L}_{\text{joint}}(\theta_{21})) = \log(\mathcal{L}_{\text{HERA}}(\theta_{21})) + \log(\mathcal{L}_{\text{SARAS3}}(\theta_{21}))$$

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$$\mathcal{L}(\theta_{21}) \equiv \frac{\int \mathcal{L}(\theta_{21}, \alpha)\pi(\theta_{21}, \alpha)d\alpha}{\int \pi(\theta_{21}, \alpha)d\alpha} = \frac{\mathcal{P}(\theta_{21}|D, \mathcal{M})\mathcal{Z}}{\pi(\theta_{21})}$$



Need to be able to evaluate  $\mathcal{P}(\theta_{21}|D, \mathcal{M})$  and  $\pi(\theta_{21})$  for a set  $\theta_{21}$

# The Methodology: Joint likelihood?

$$\mathcal{P}(\theta|D, \mathcal{M}) = \frac{\mathcal{L}(\theta)\pi(\theta)}{\mathcal{Z}} \quad \theta = \{\theta_I, \theta_{fg}, \theta_{21}\}$$

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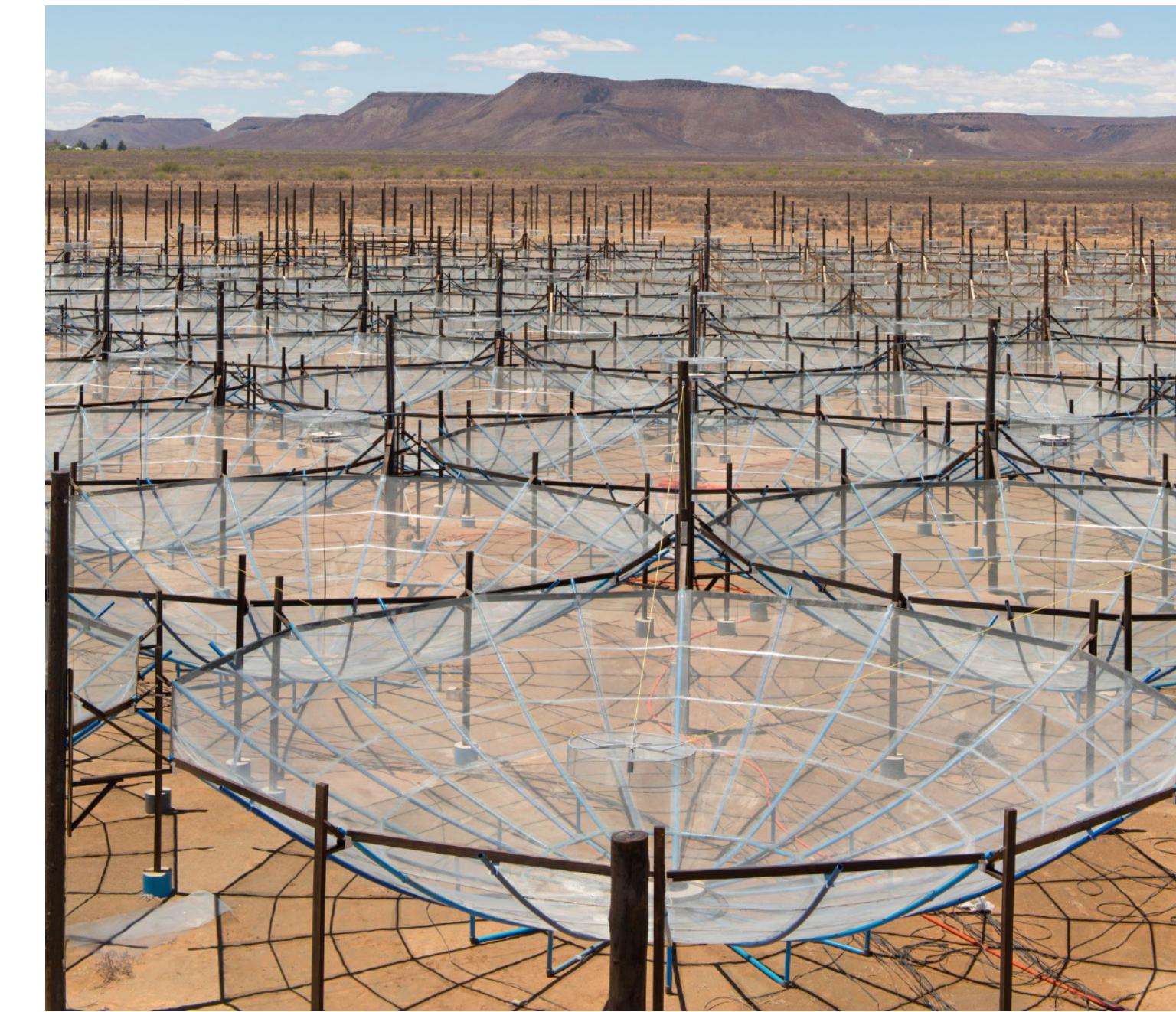
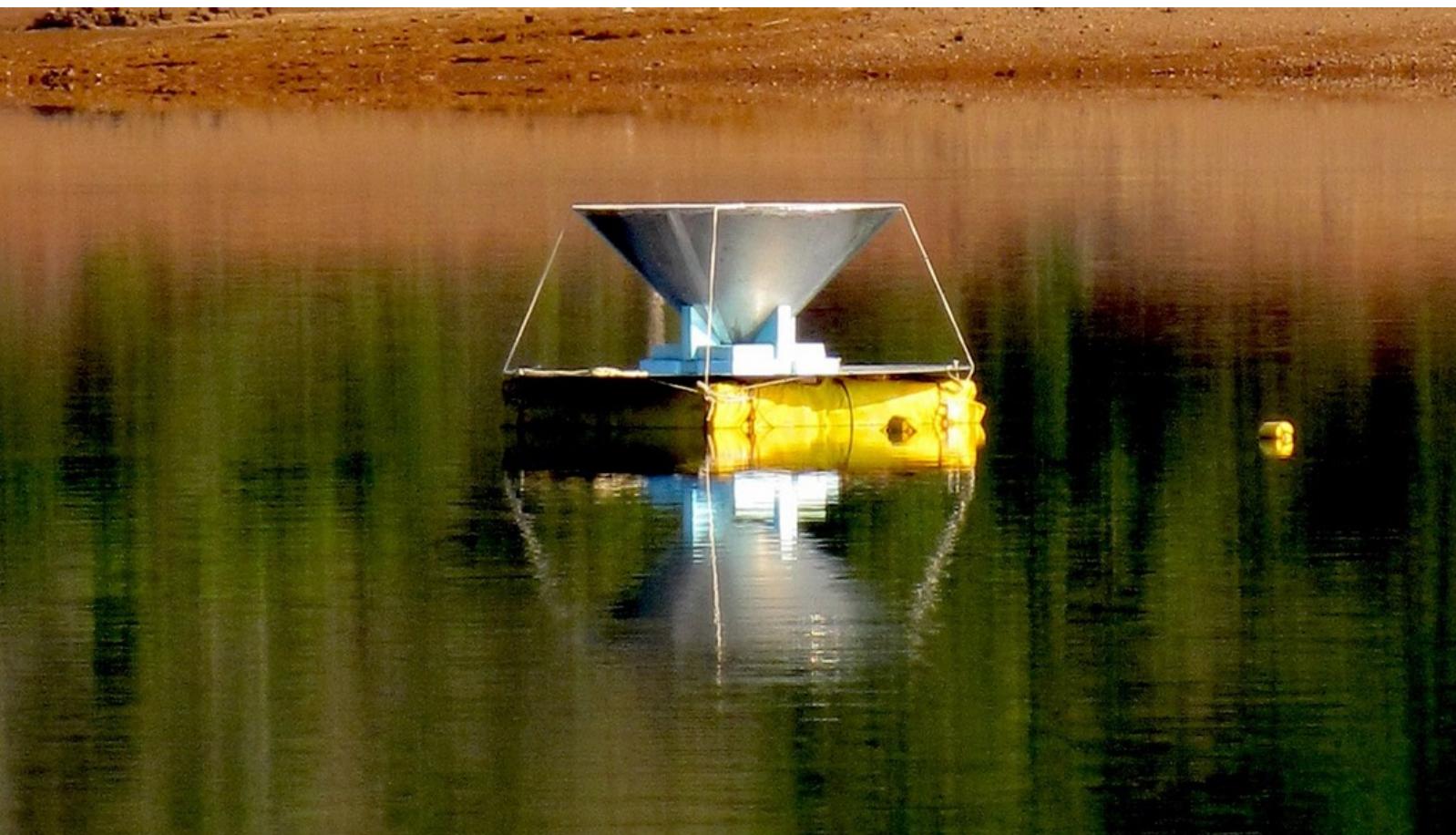
**For an individual experiment we have...**

$$\theta = \{\theta_I, \theta_{fg}, \theta_{21}\} \rightarrow \{\theta_{21}\} \rightarrow \boxed{\text{MARGARINE}} \rightarrow \log(\mathcal{P}(\theta_{21}|D, \mathcal{M})) \rightarrow \log(\mathcal{L}(\theta_{21}))$$

# The Methodology: Joint likelihood?

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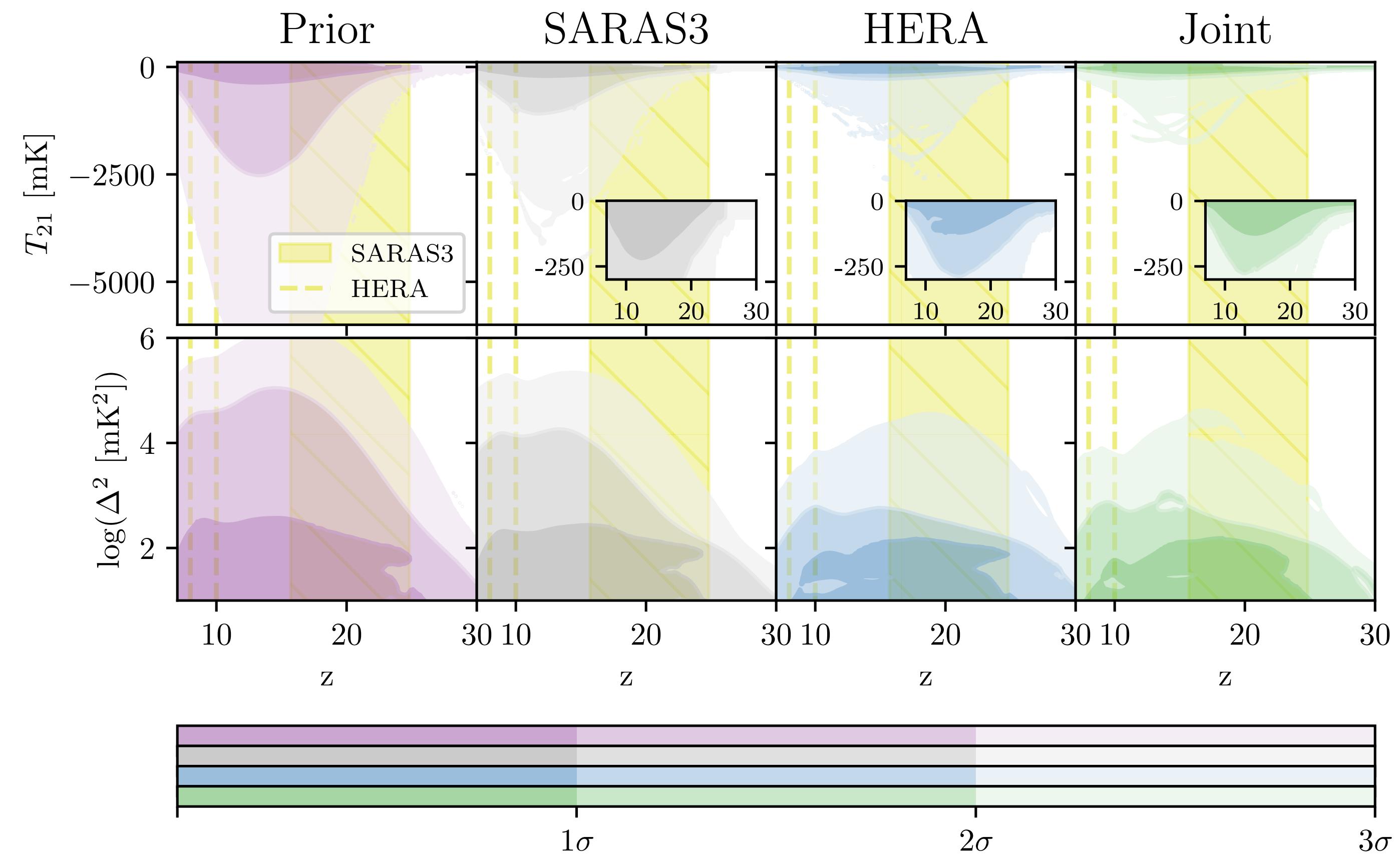


# **The Results**

# The Results: Constraints?

We get tighter constraints on the parameter space

Translates to tighter constraints on the 21-cm signal and the power spectrum

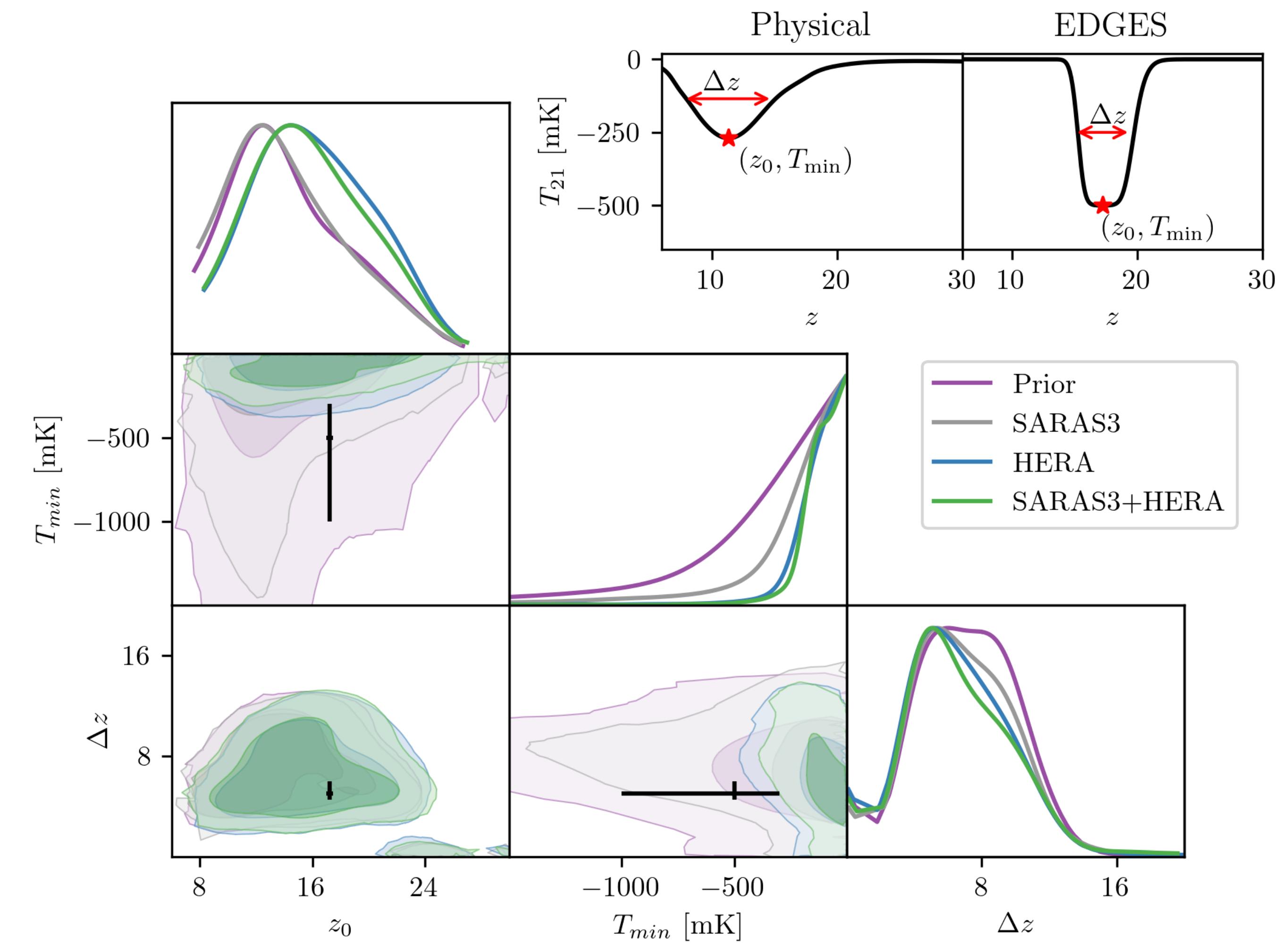


# The Results: What can we say about EDGES?

We can take an approximate width, depth and central frequency

Both SARAS3 and HERA allow for physical signals with a depth consistent with EDGES...

... however together they disfavour this class of signals with two sigma confidence!



# Conclusions

- Developed a novel method for performing joint analysis of different data sets
- Shown that by combining power spectrum and sky-averaged 21-cm signal data we can get improved constraints

# Future Work

- Peter Sims - Looking at applications of the method to REACH
- Thomas Gessey-Jones - joint analysis constraints on Cosmic Strings
- Simon Pochinda - updated constraints with additional information from probes of the X-ray background
- Continued improvements to margarine

Joint Analysis Paper



Methods paper



# Bonus Slides

# The Results: Constraining power?

Quantify constraining power with the *marginal* KL divergence via *margarine*

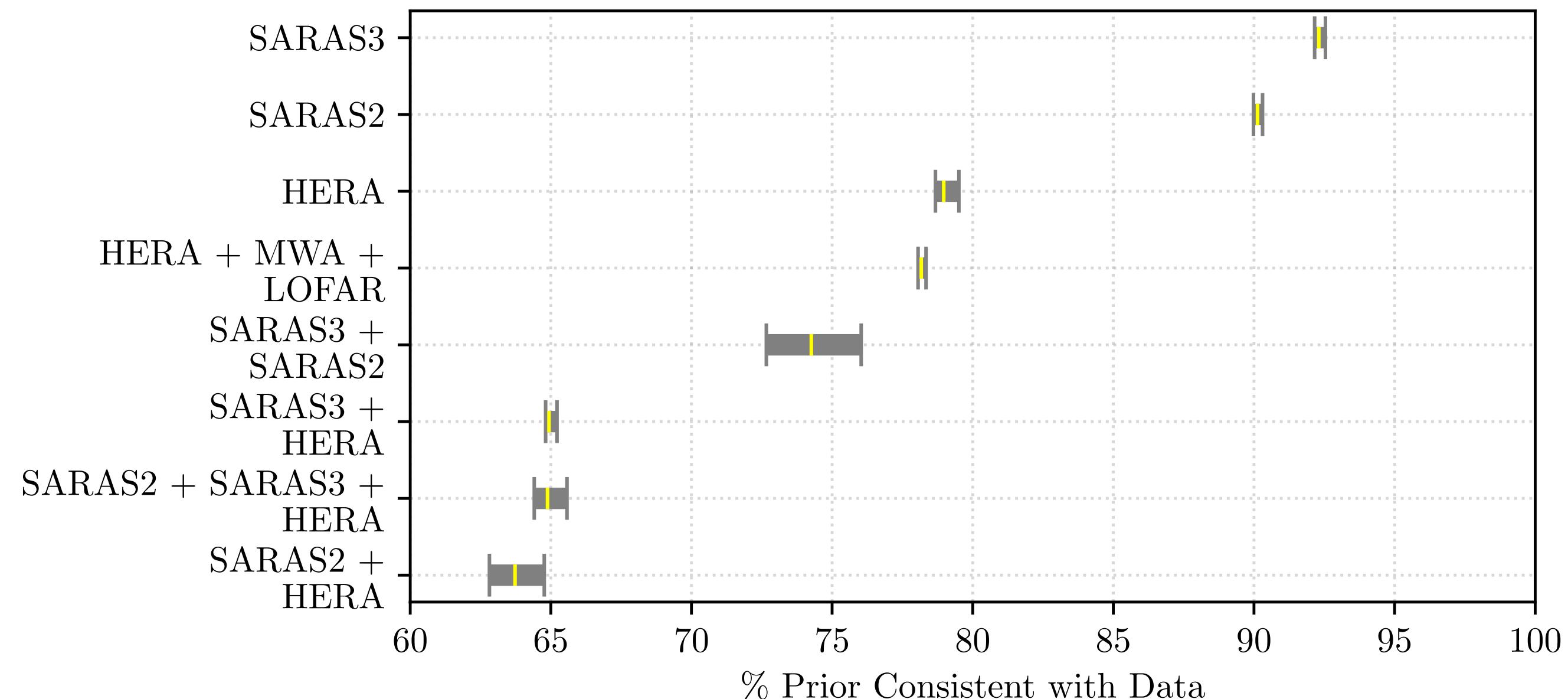
$$\mathcal{D}(P \parallel \pi) = \left\langle \log \frac{P(\theta_{21})}{\pi(\theta_{21})} \right\rangle_{P(\theta_{21})} \approx -\log \frac{V_P}{V_\pi}$$

Contraction of prior on to posterior

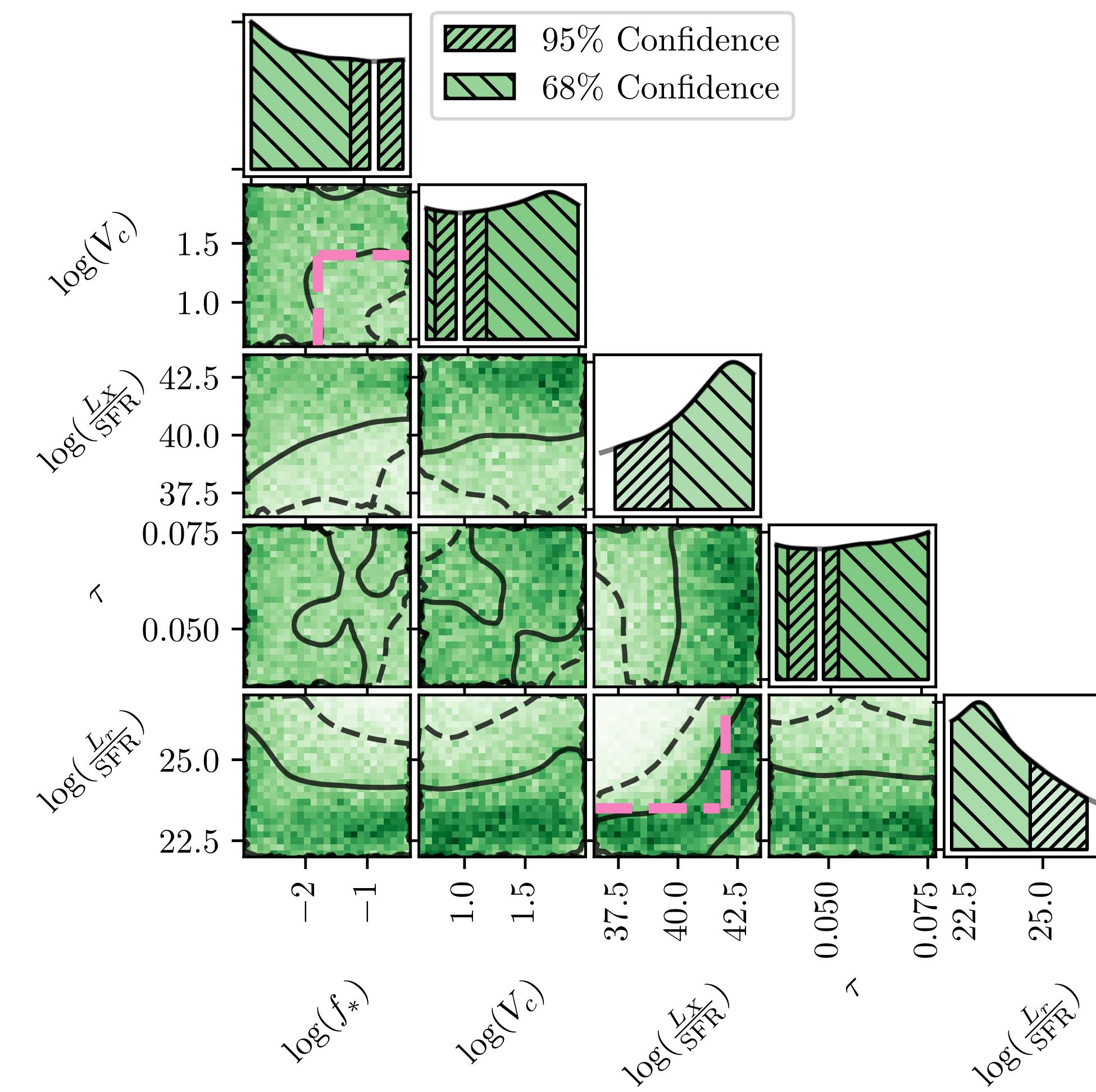
SARAS3  $\approx 93\%$

HERA  $\approx 78\%$

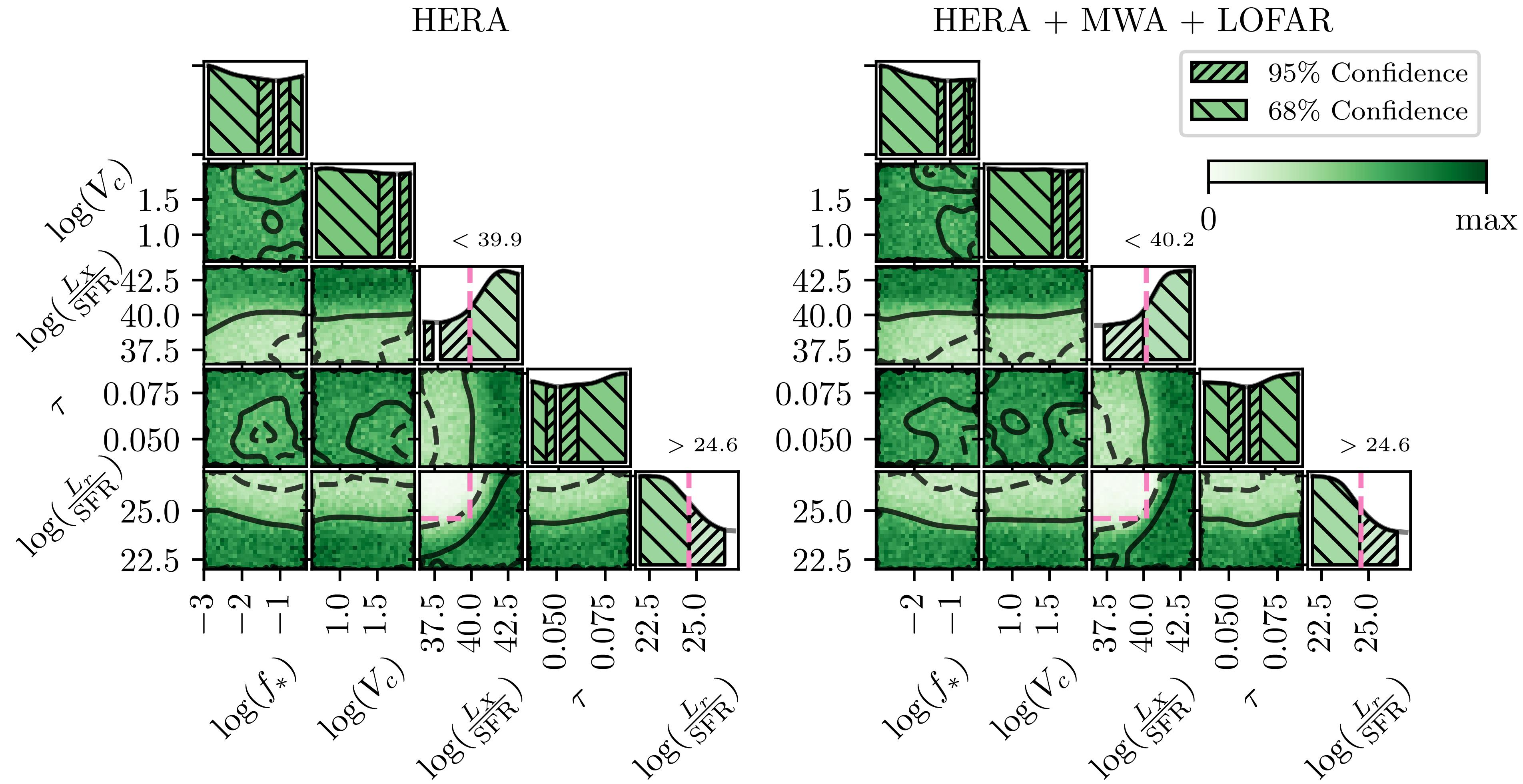
SARAS3 + HERA  $\approx 65\%$



# The Results: Parameters?



# The Results: Parameters?



# The Results: Other Global?

