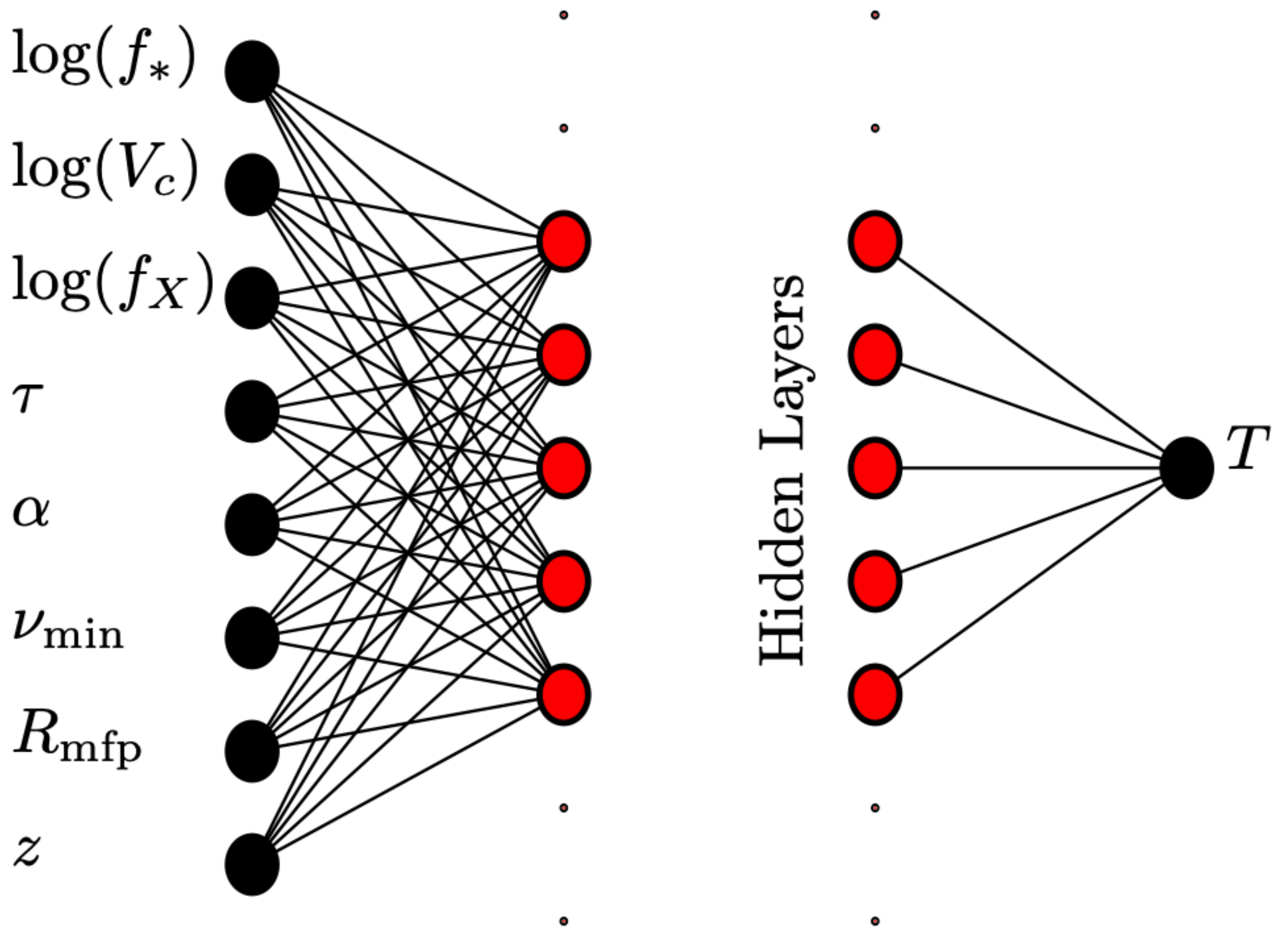
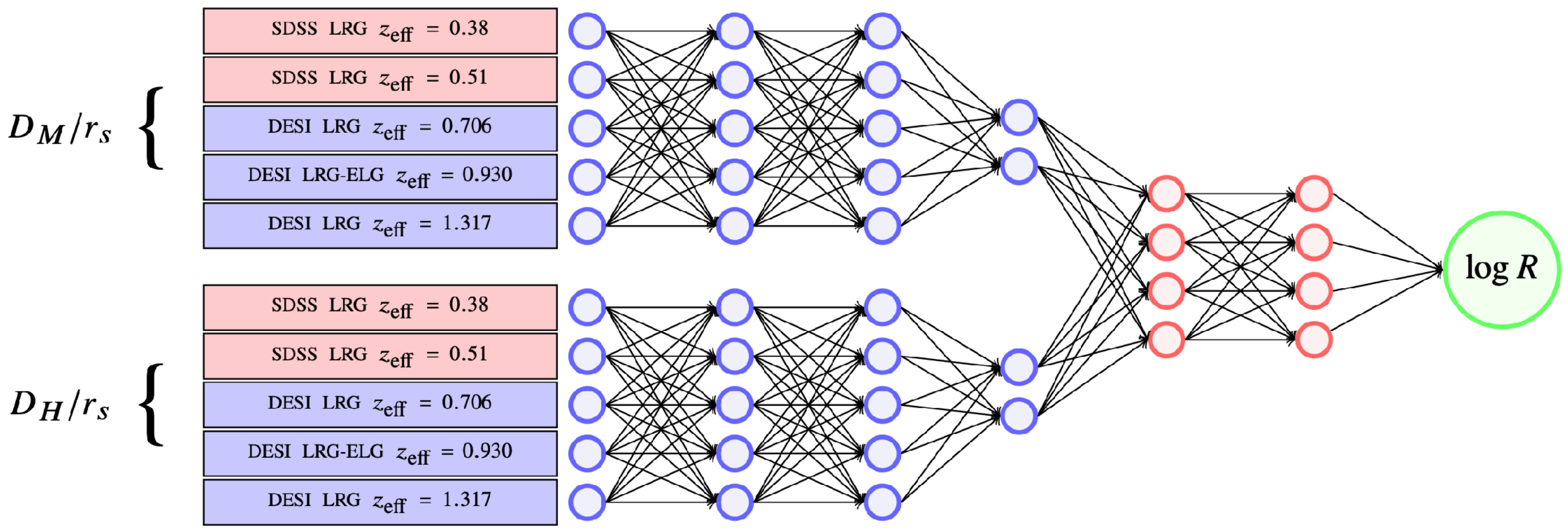
Machine Learning the Infant Universe

Harry T. J. Bevins
Kavli Fellow

My Research

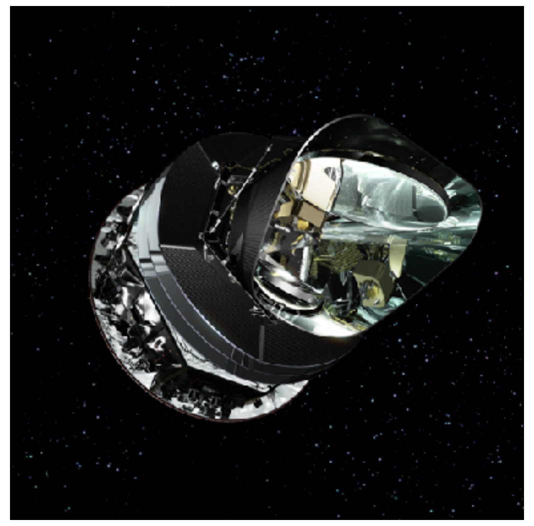
- Pioneering applications of machine learning to studies of the infant universe
- Bringing together a diverse knowledge of instrumentation, theory and statistics
- Constraining the properties of the first stars and galaxies
- Defining the standard for analysis is the field of 21-cm Cosmology
- Published 24 papers and over 39 international conference talks

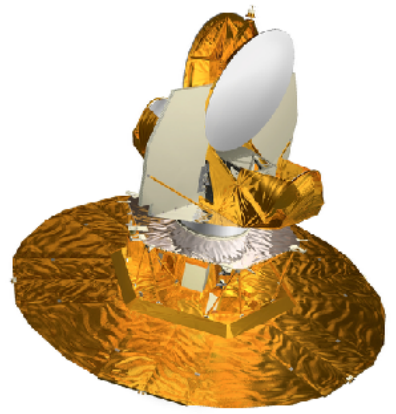


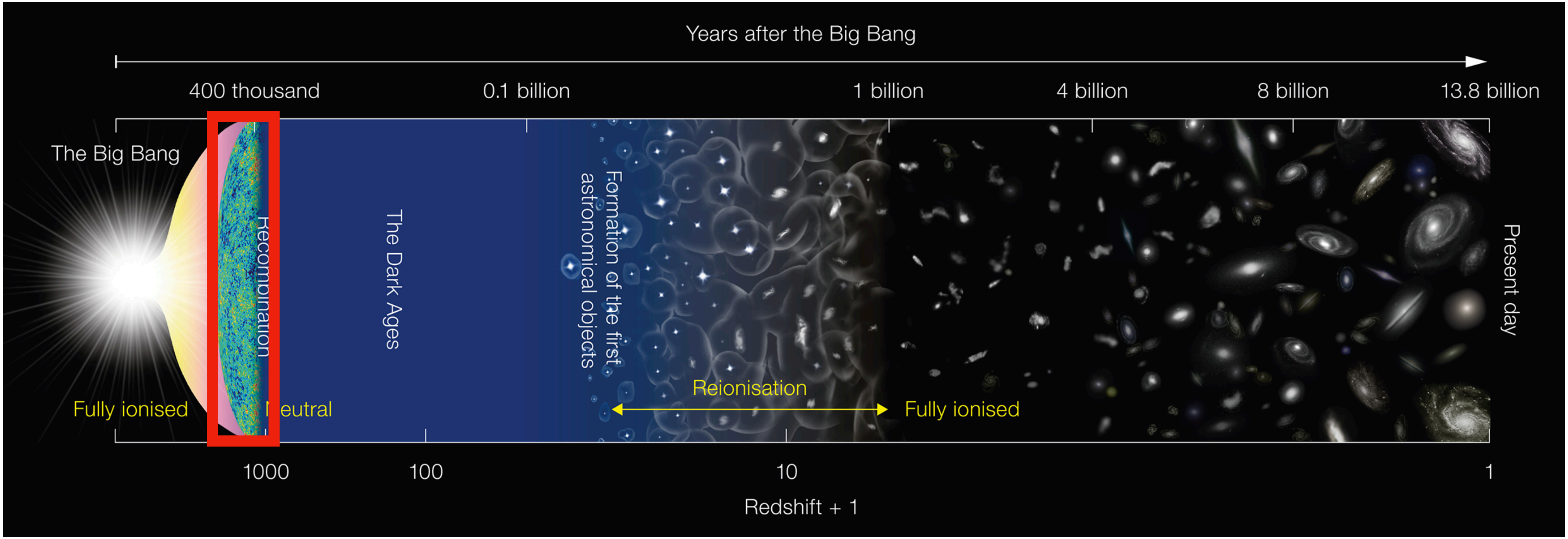


The Infant Universe and 21-cm Cosmology

A brief history of the universe







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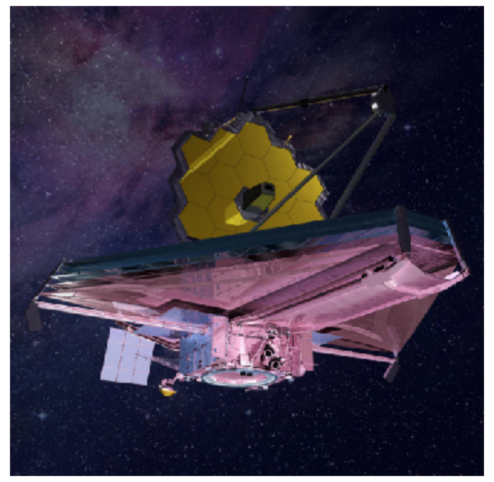

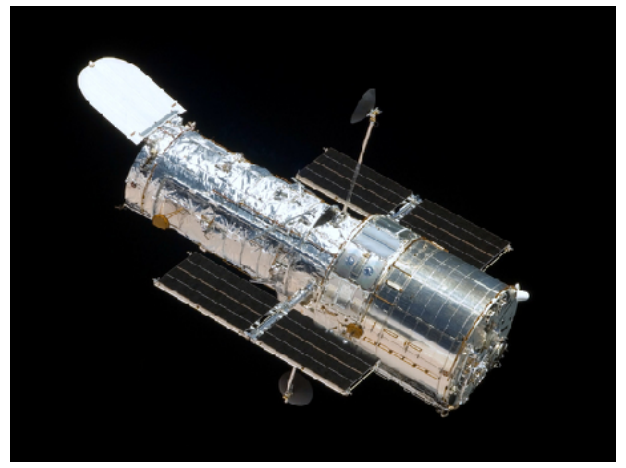

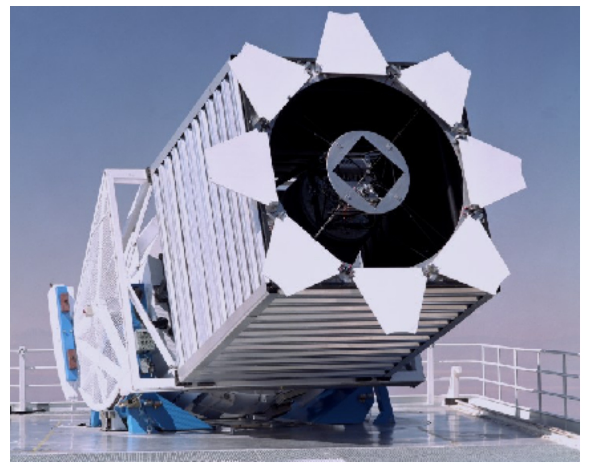

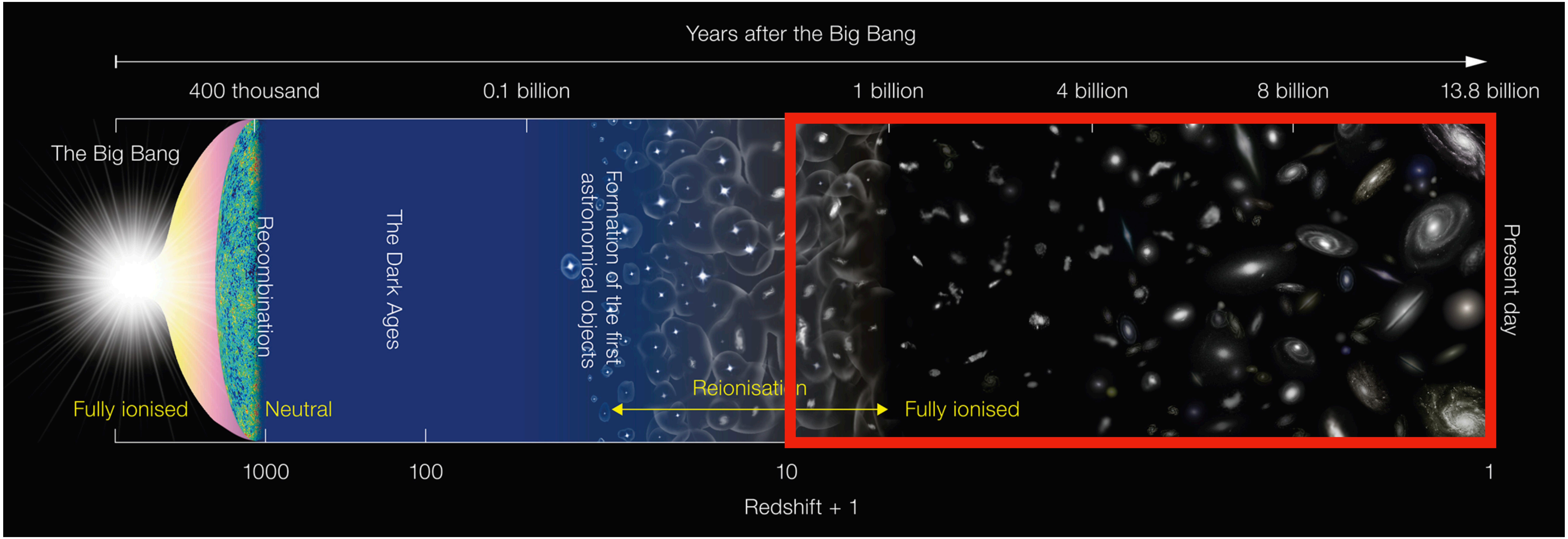

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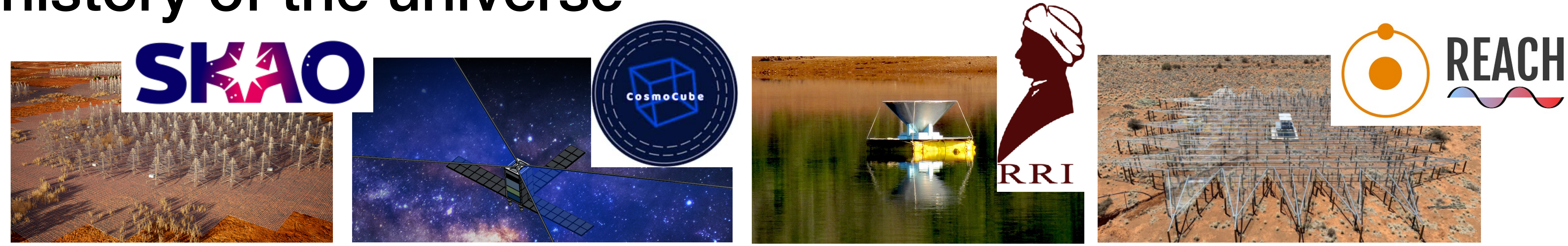
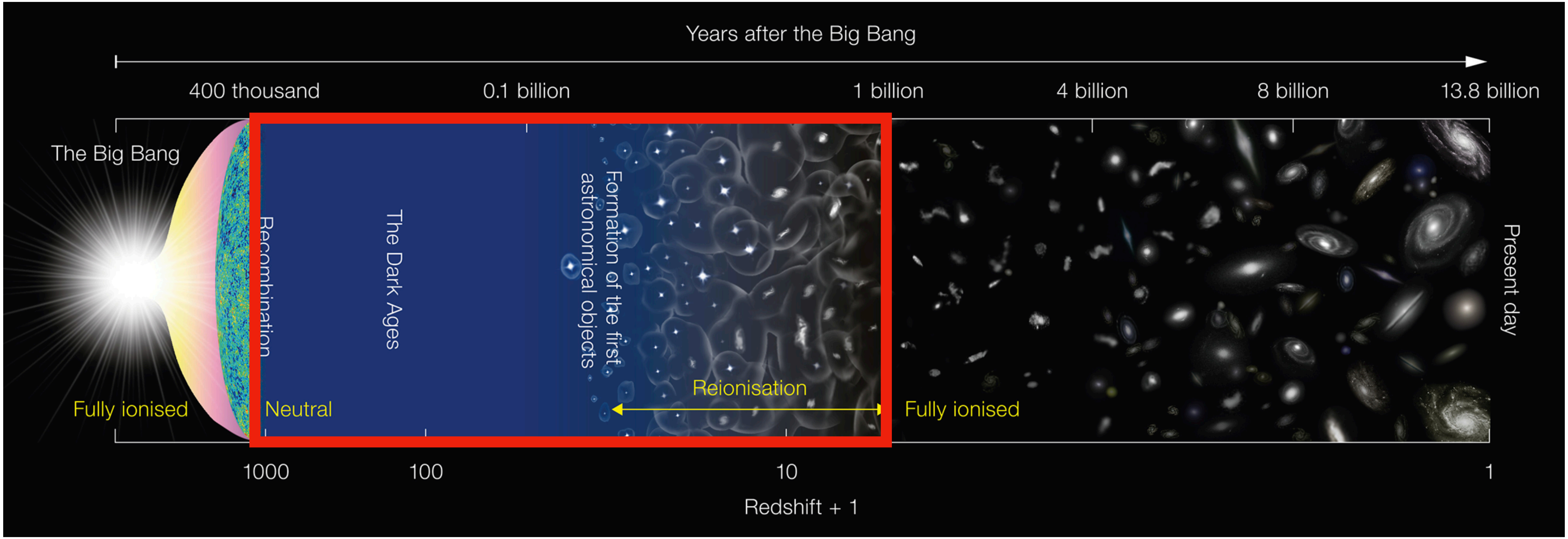
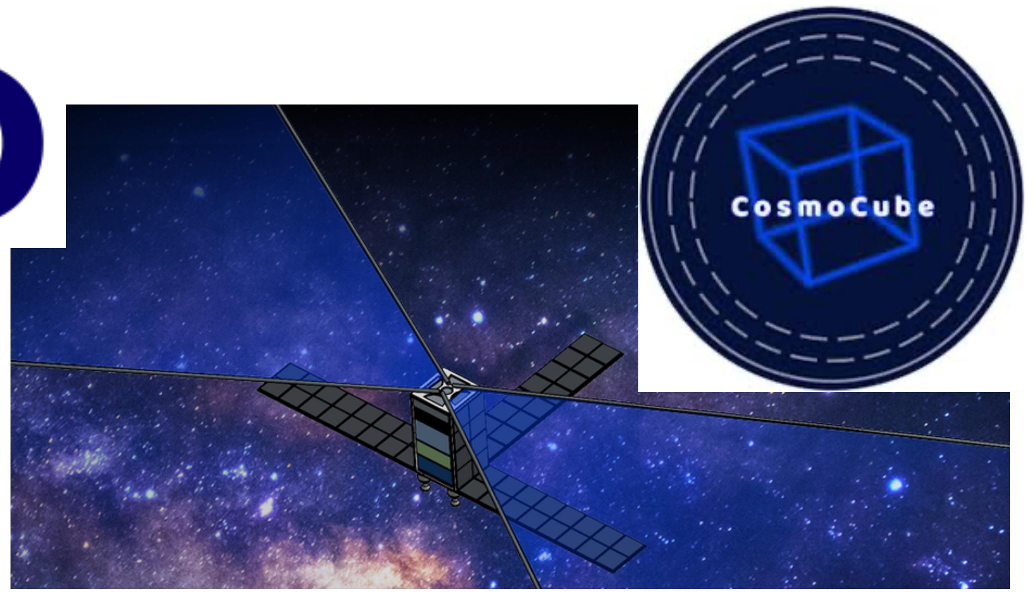
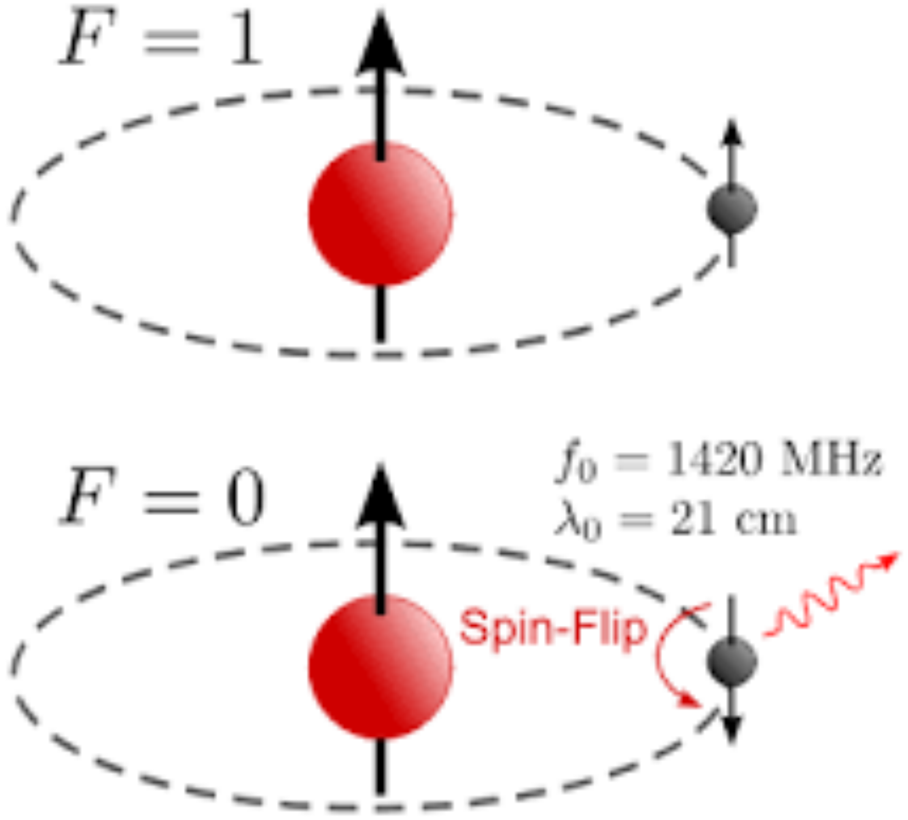


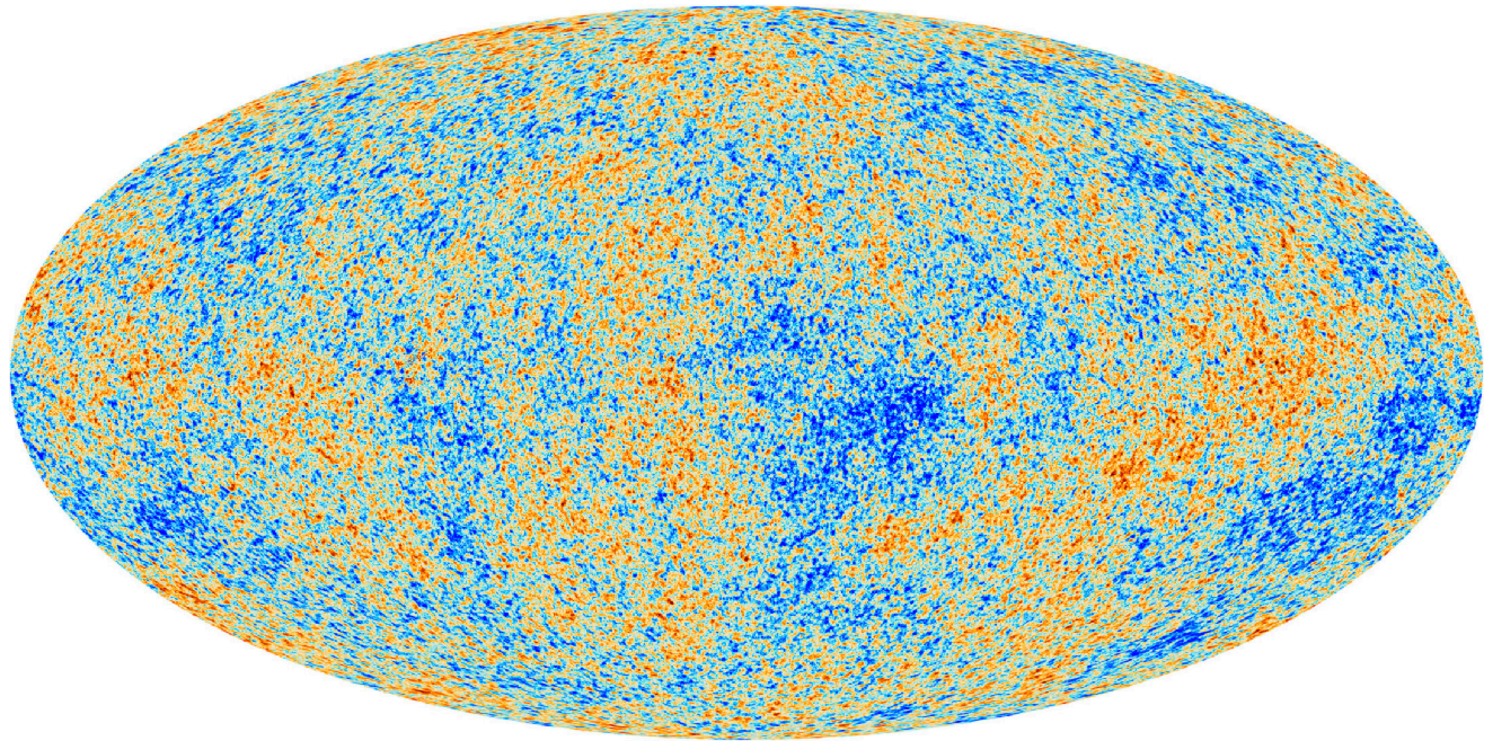


21-cm Cosmology



- Spin-flip transition in neutral hydrogen
- Forbidden transition that can't be seen in the lab
- Define the spin temperature
- Measure relative to the radio background
- To understand the importance of the spin temperature we look at the thermal history of the universe





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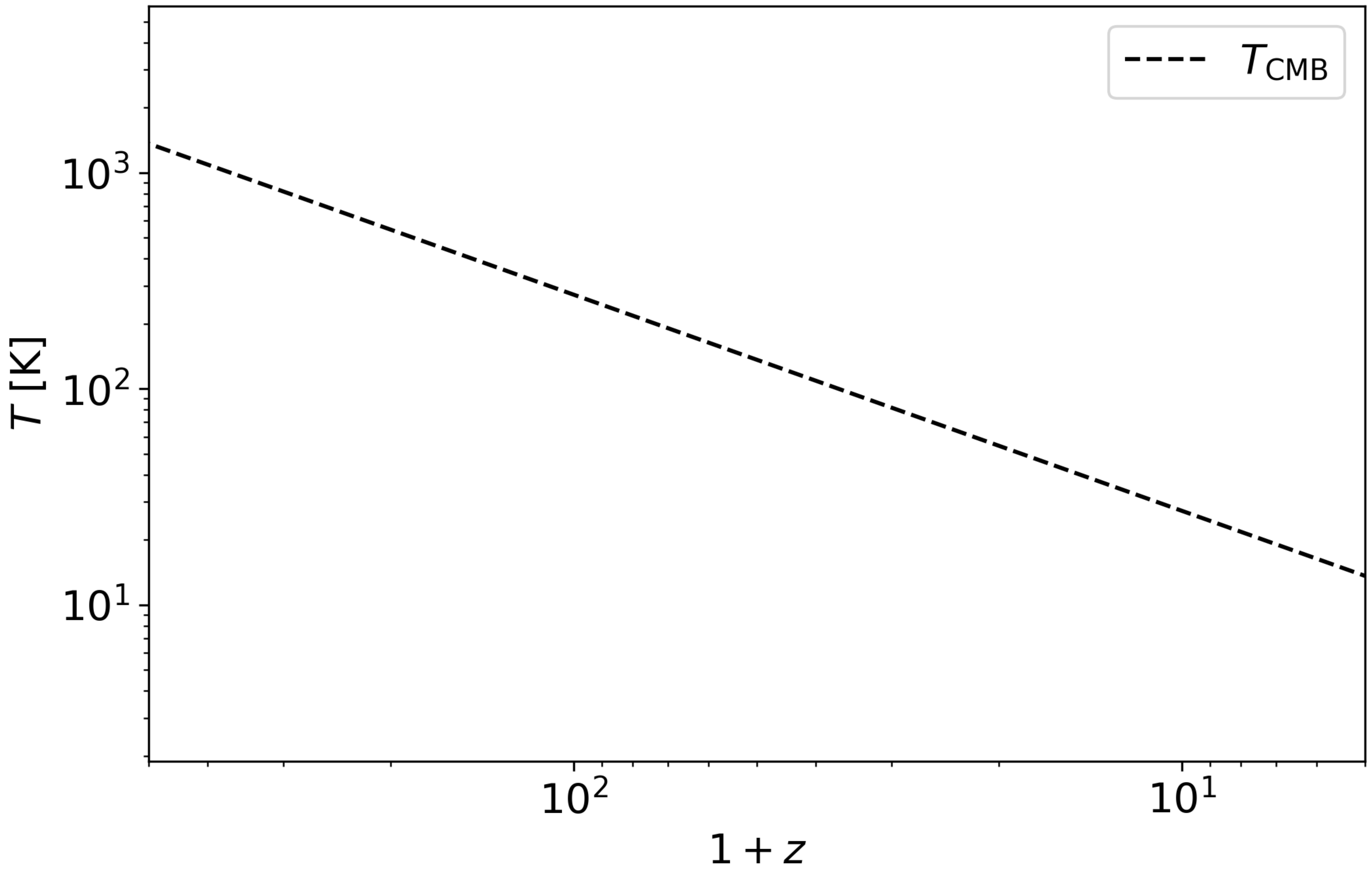

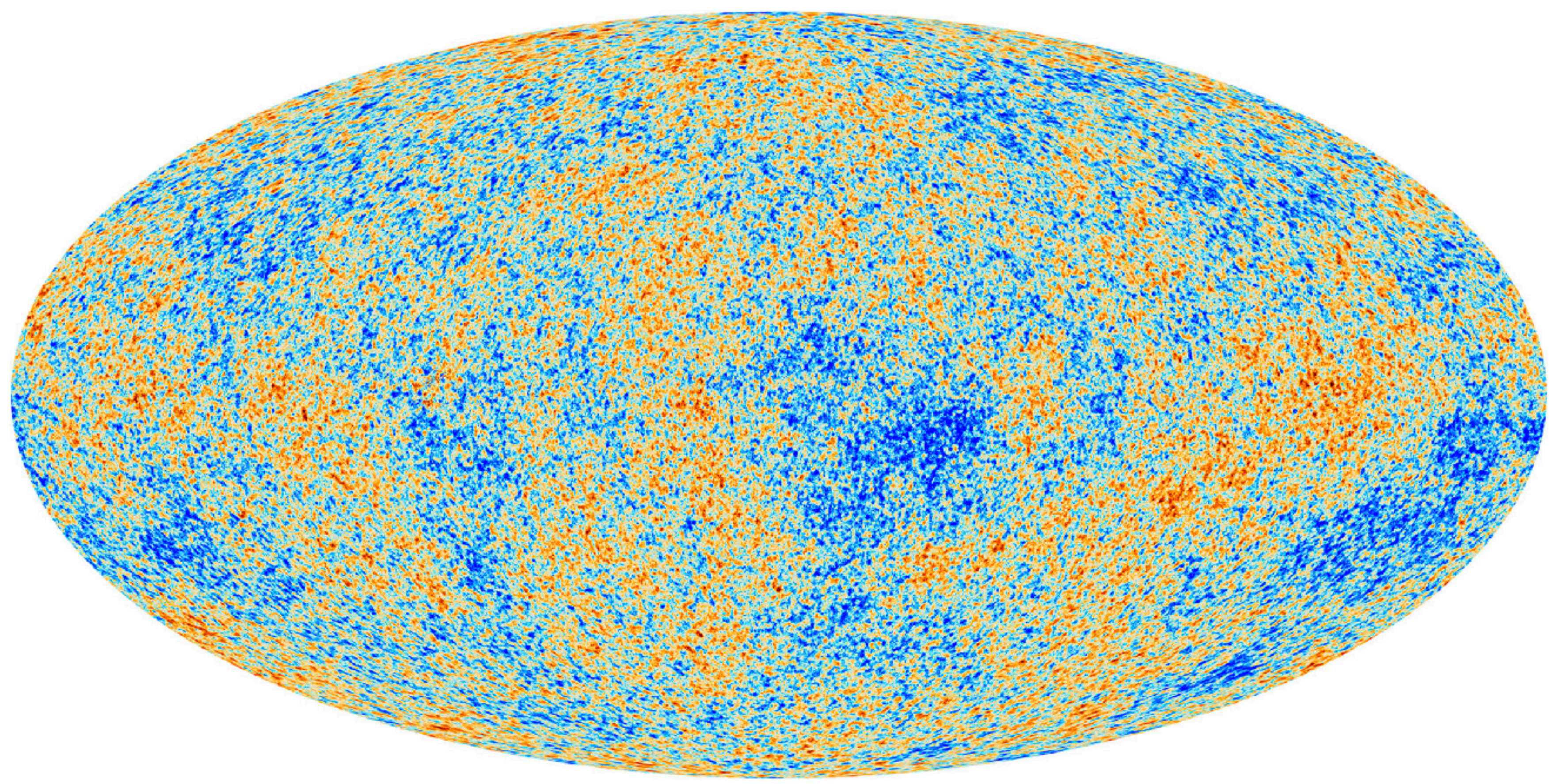

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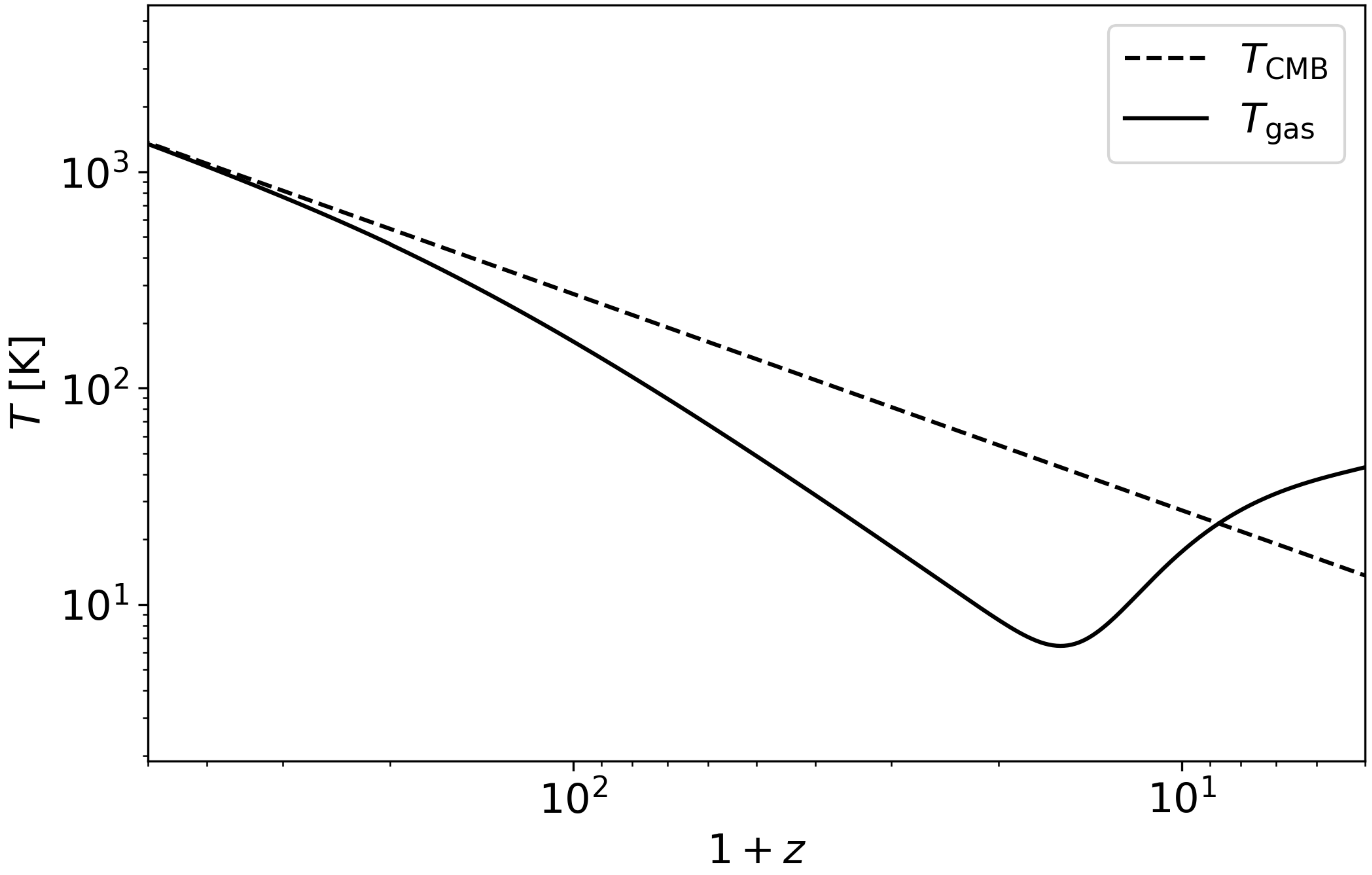
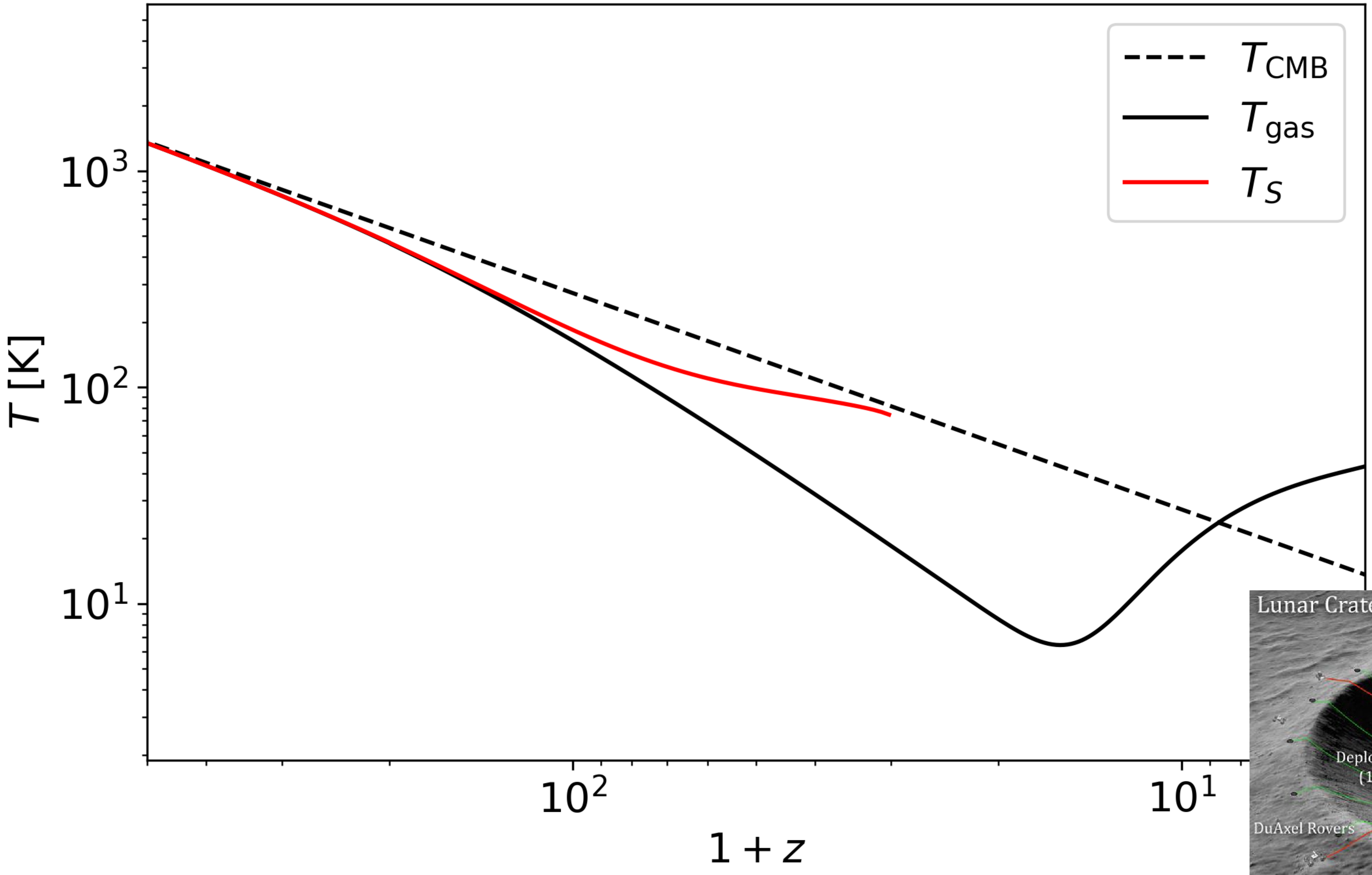
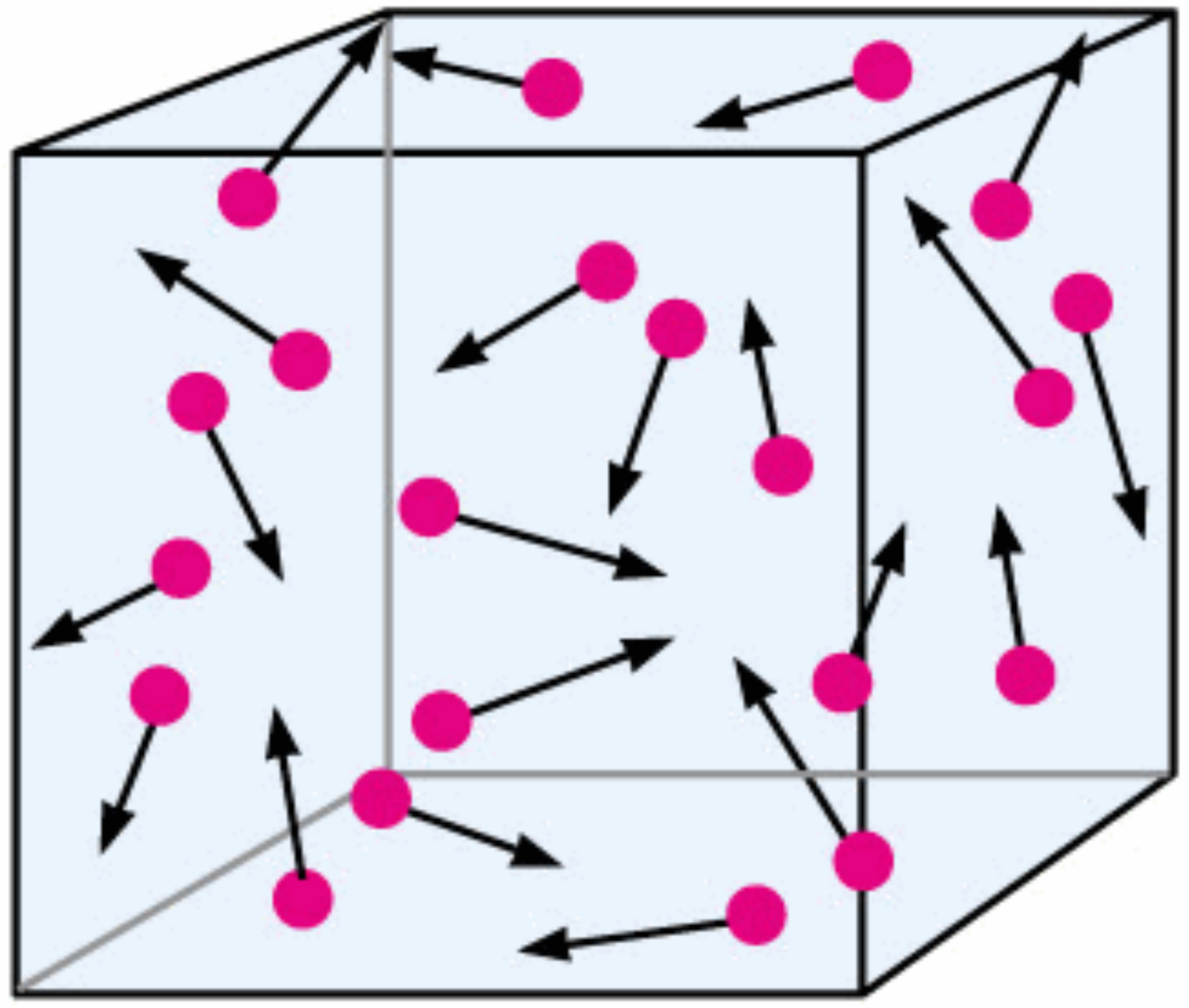
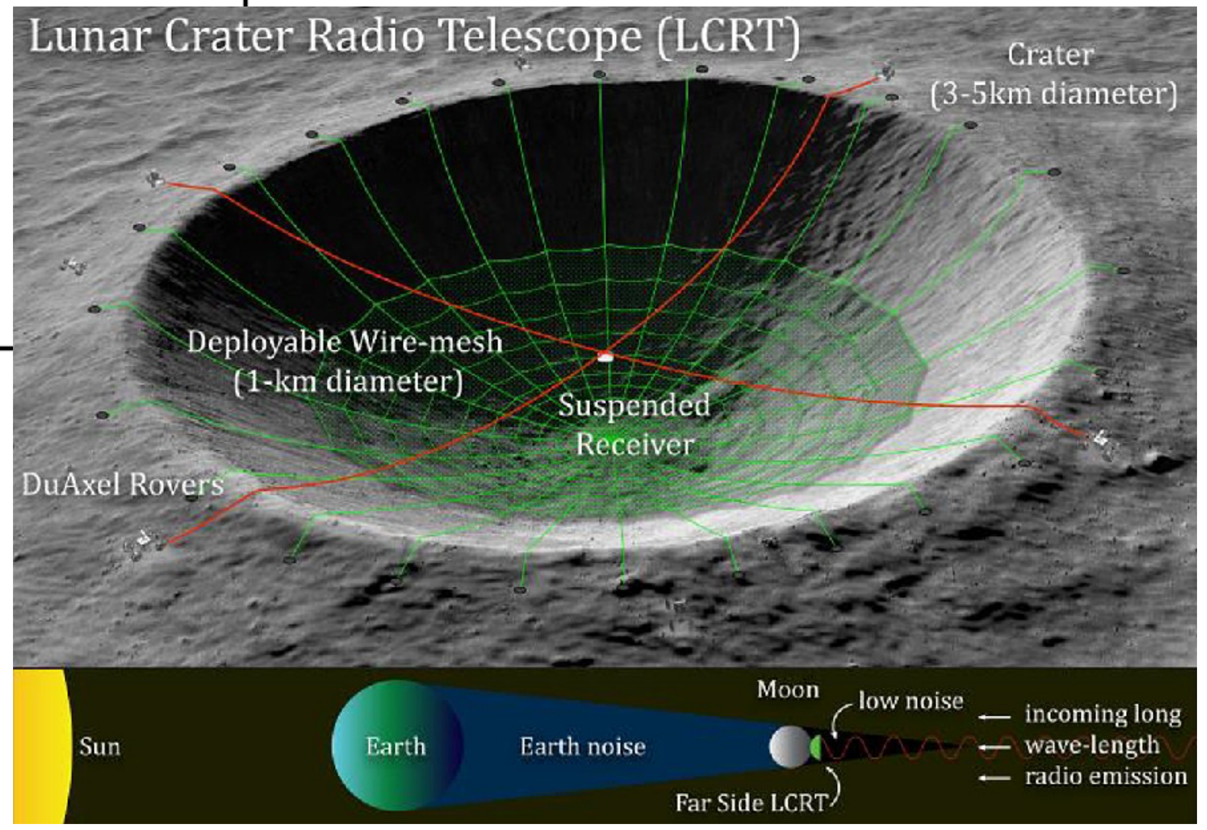
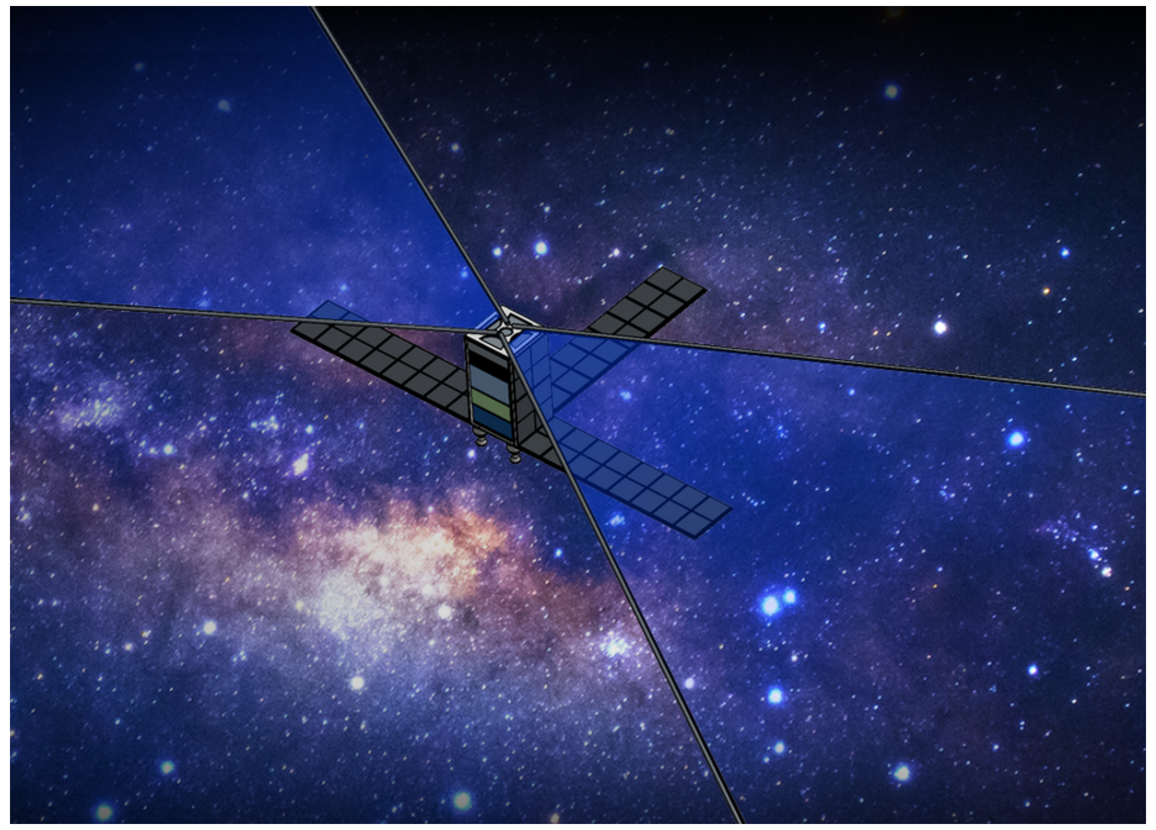


Dark Ages ($z \lesssim 30; t \lesssim 0.5$ Gyr)



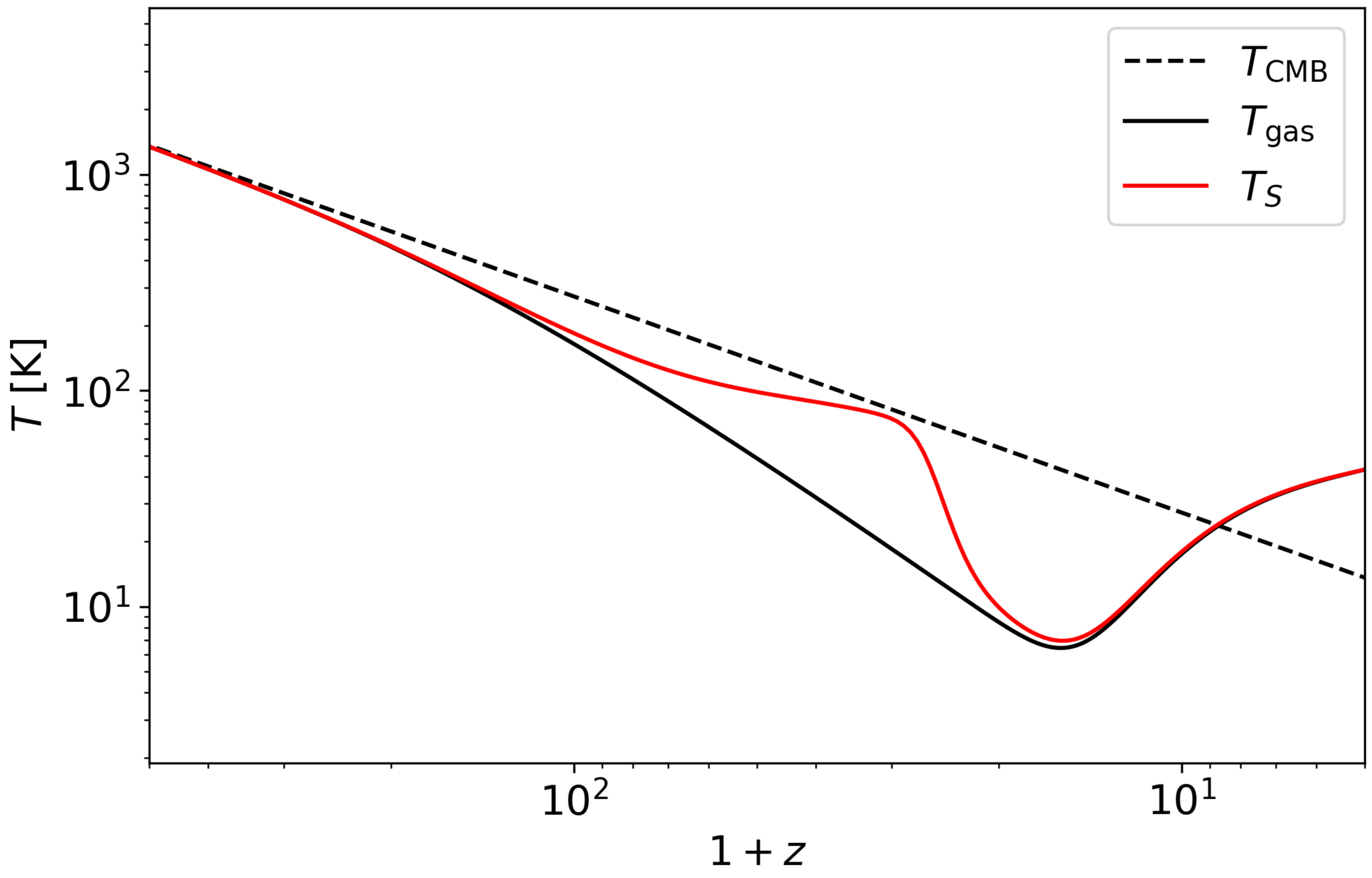


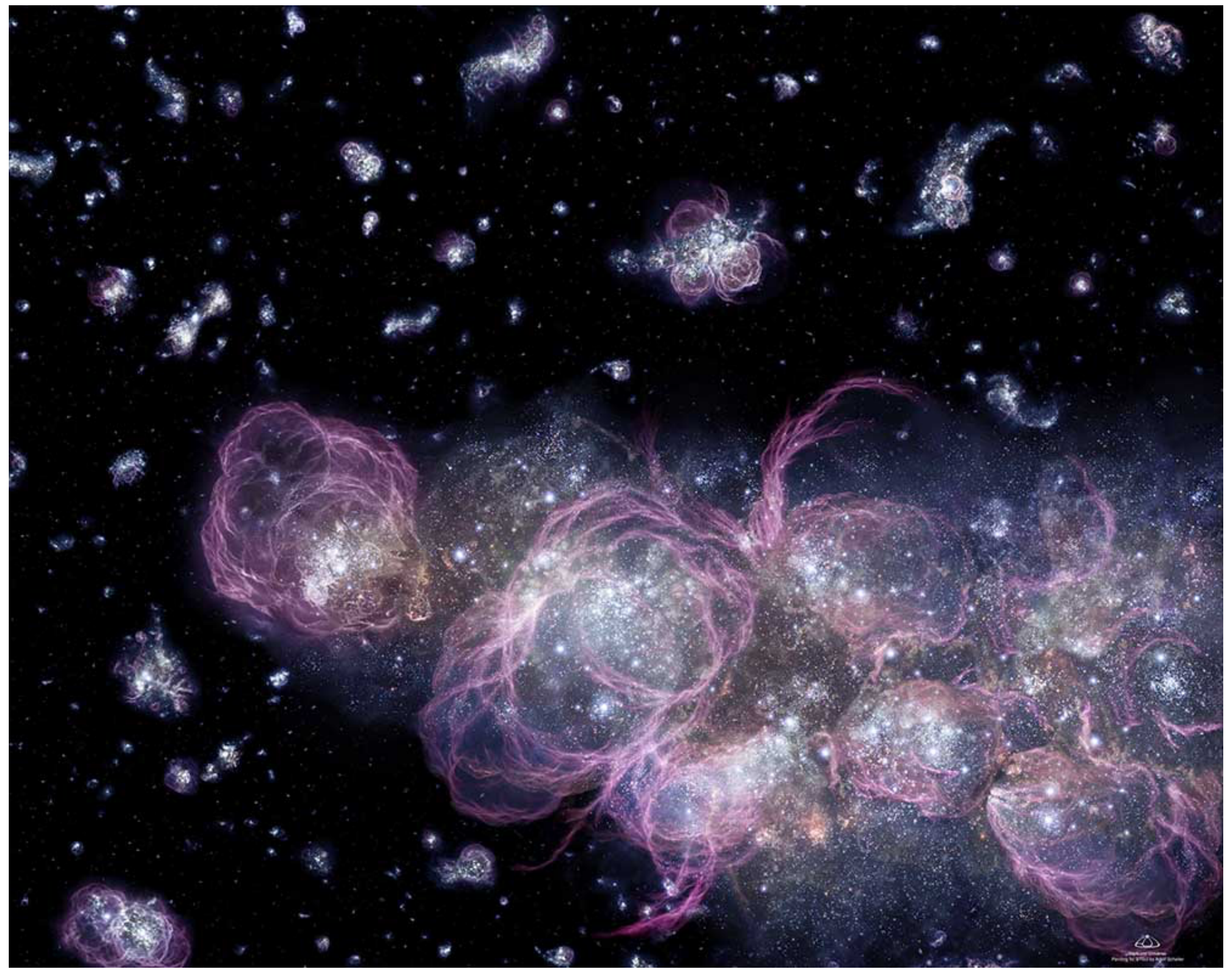


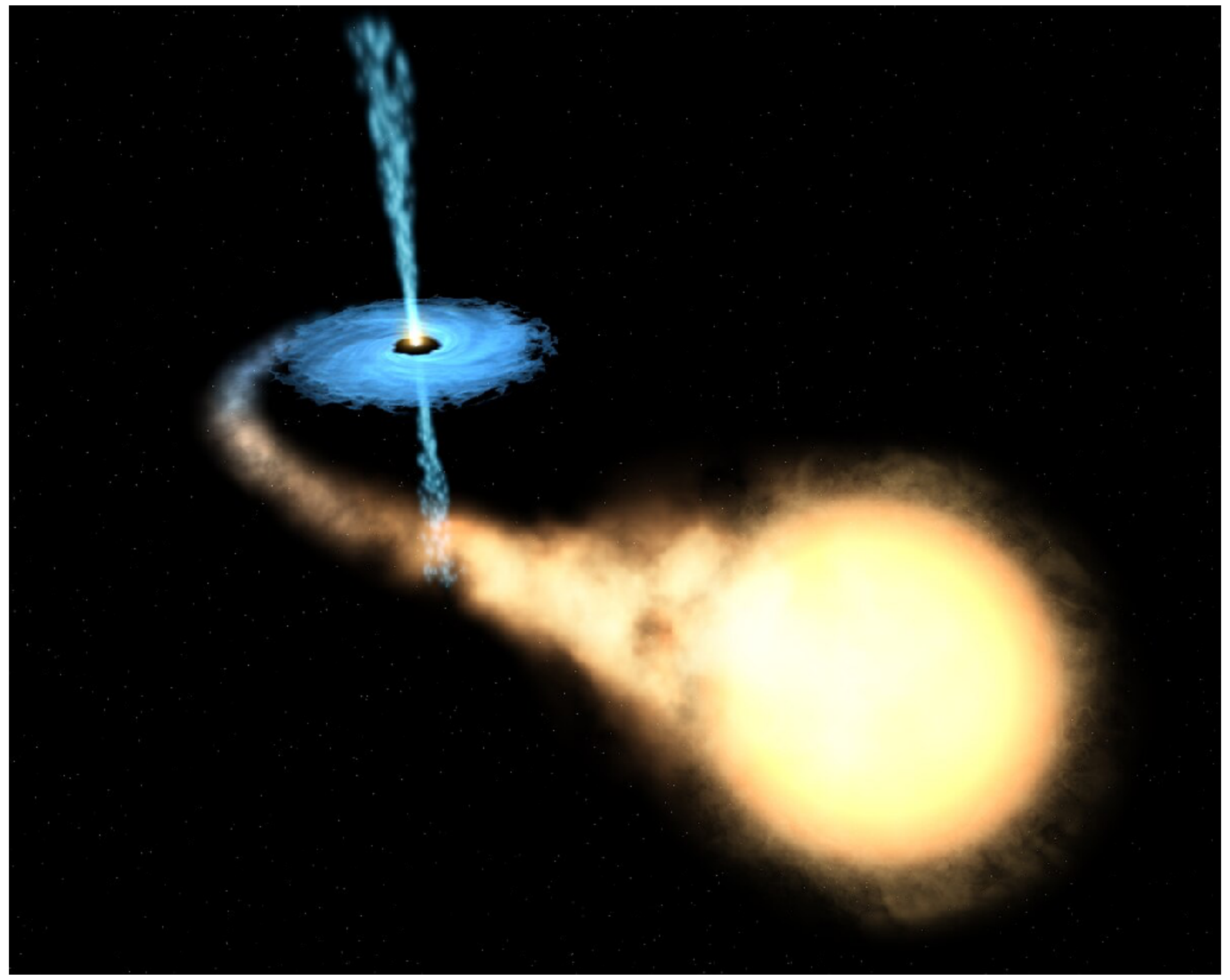


Cosmic Dawn and Reionisation

$(30 \lesssim z \lesssim 5; t = 0.5 - 12.5\ \mathrm{Gyr})$

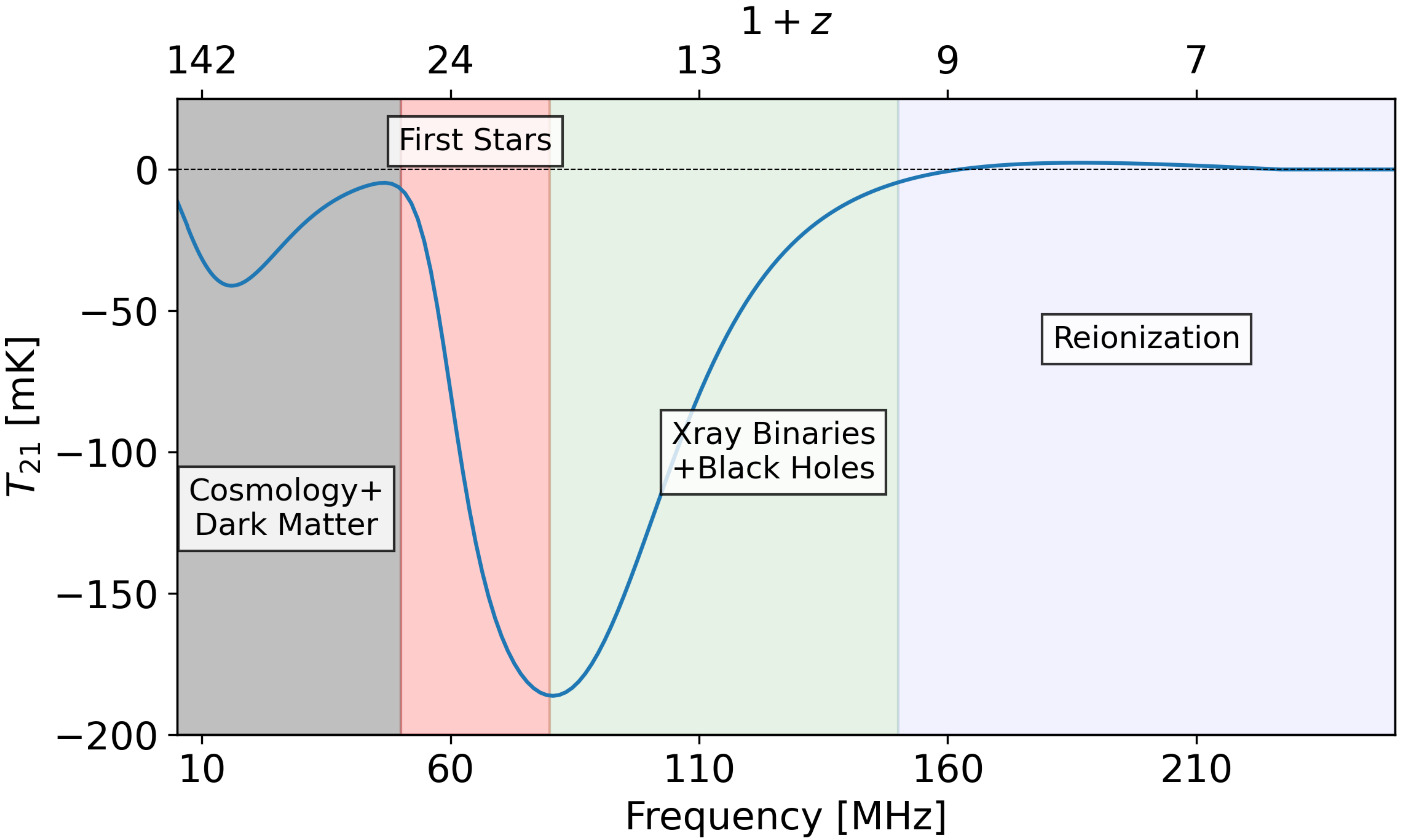


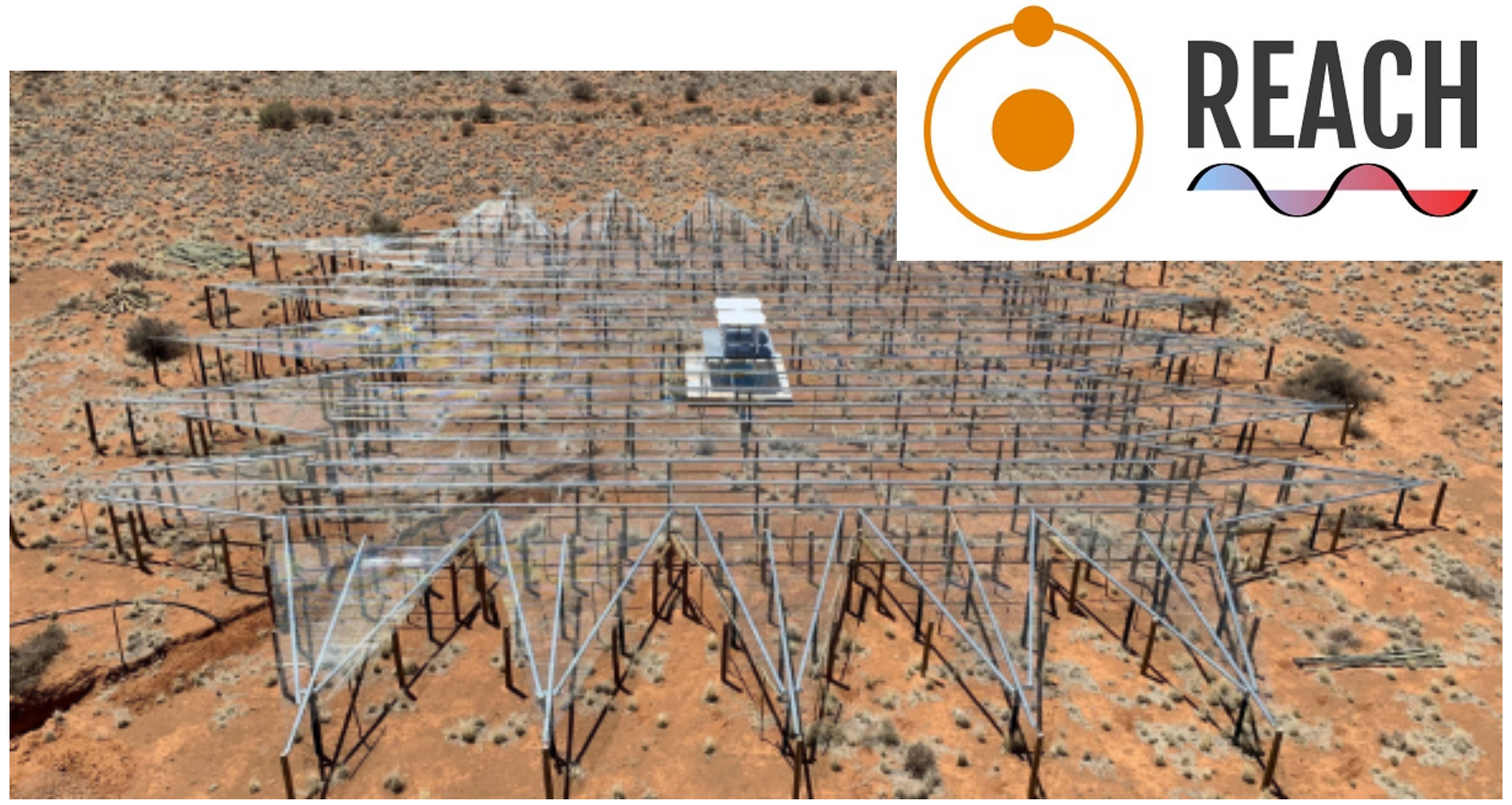




REACH and the Cosmic Dawn

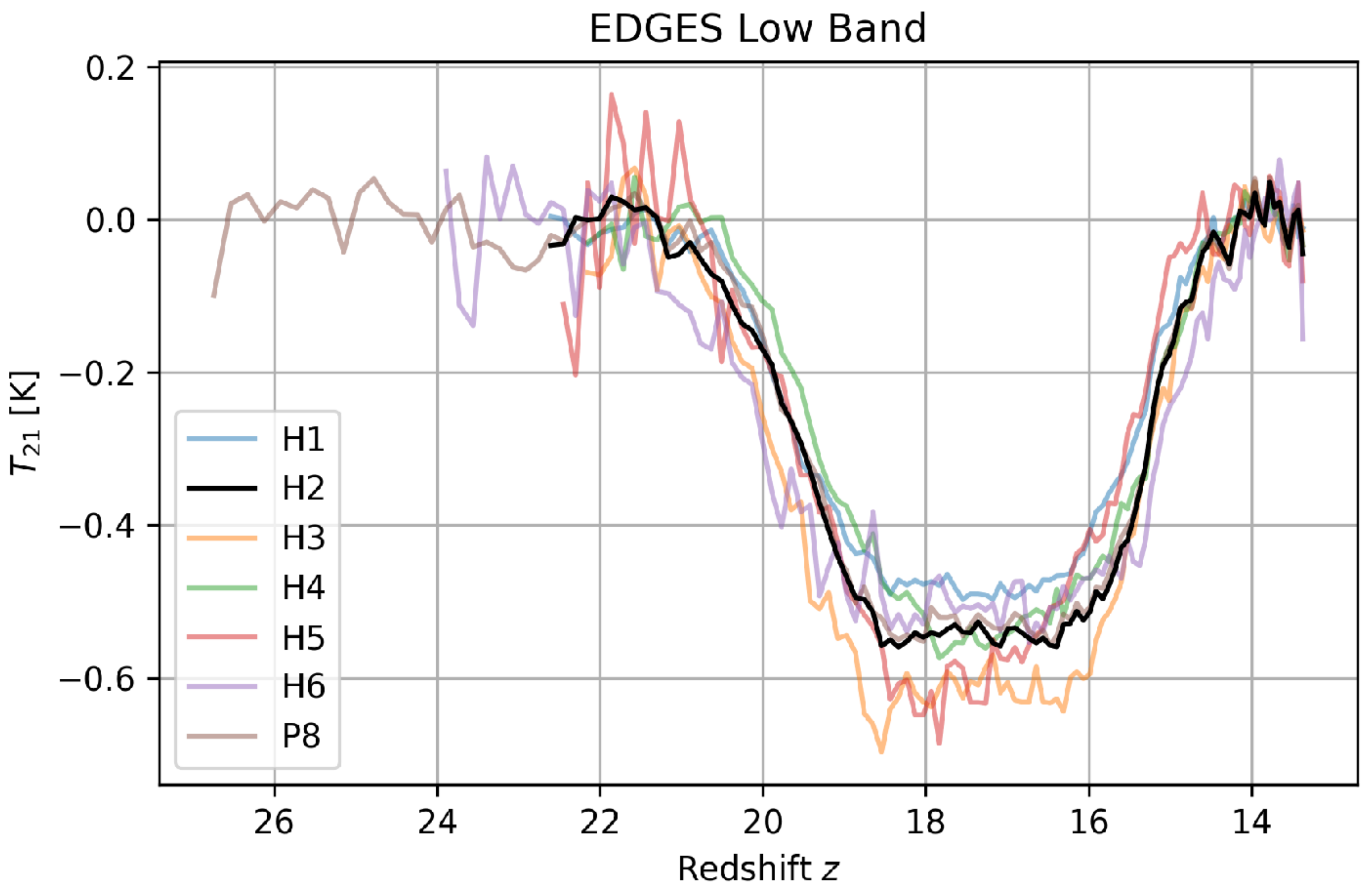
Sky Averaged 21-cm Signal

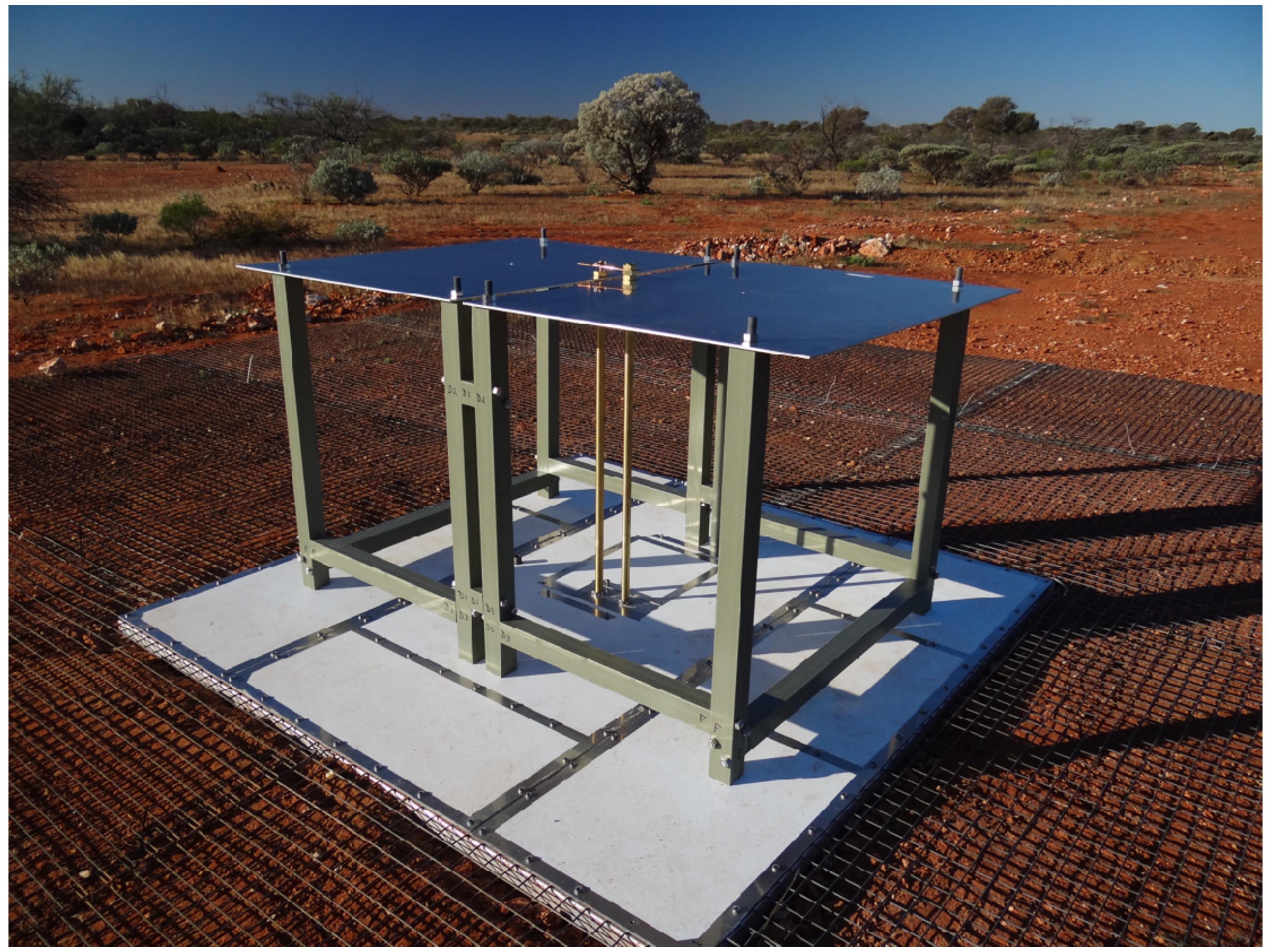




EDGES

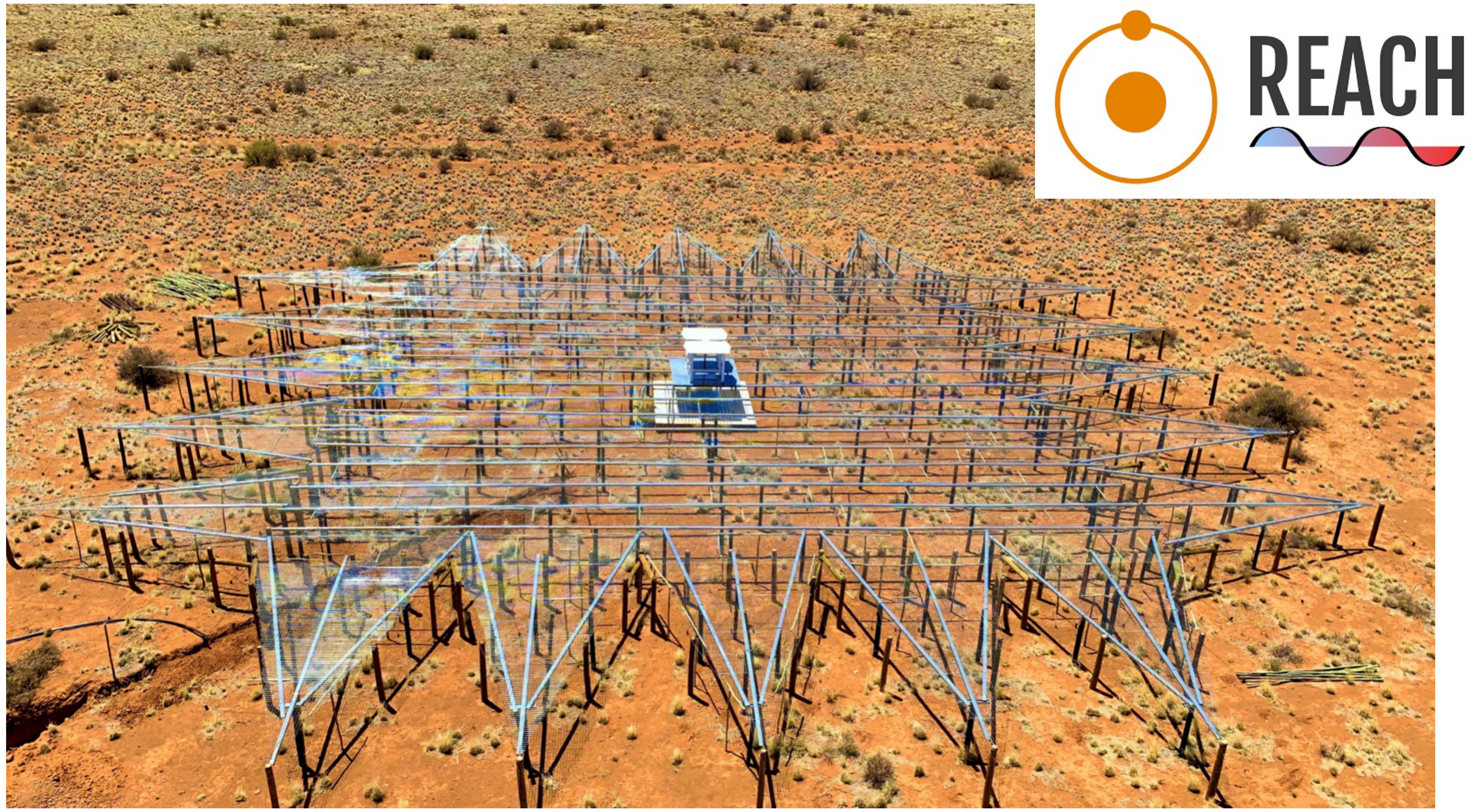
- EDGES low band instrument [Bowman et al 2018]
- Uncertainty about cosmological nature of the signal if real
- Signal is much deeper than expected and the shape is hard to explain
- Need an excess radio background above the CMB [e.g. Reis et al 2020] or cooling of the gas via dark matter-baryon interactions [e.g. Driskell et al 2022]
- Explain the data with systematics and no 21-cm signal [**Bevins et al 2021**]





REACH

- REACH is sky-averaged 21-cm experiment based in the Karoo in South Africa
- Leading member of the data analysis and calibration working groups
- Currently have 40 members from across Europe, India and South Africa
- Goal is to forward model the observations and instrument
- The REACH Collaboration, Nature Astronomy, 2022



REACH

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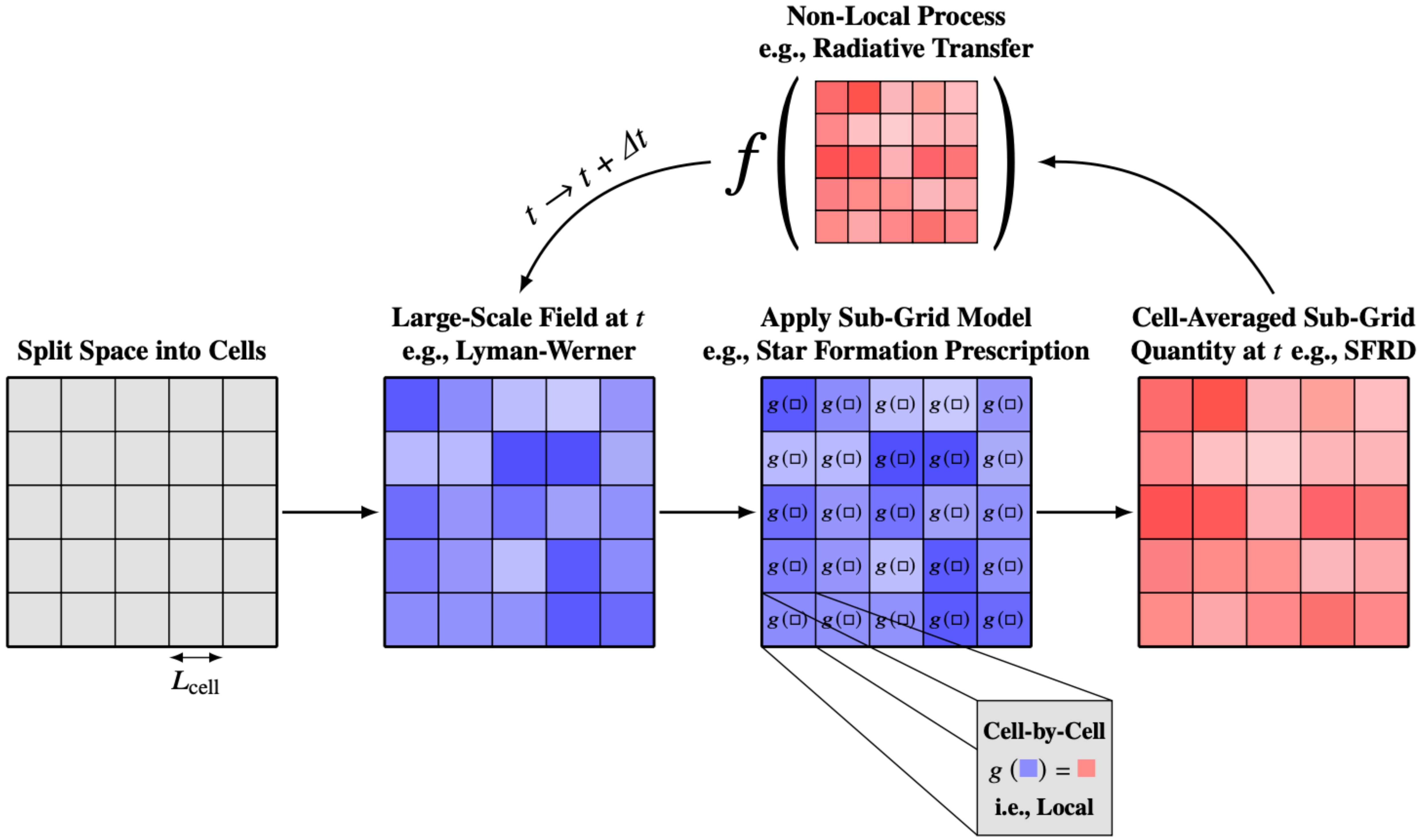
Modelling the signal

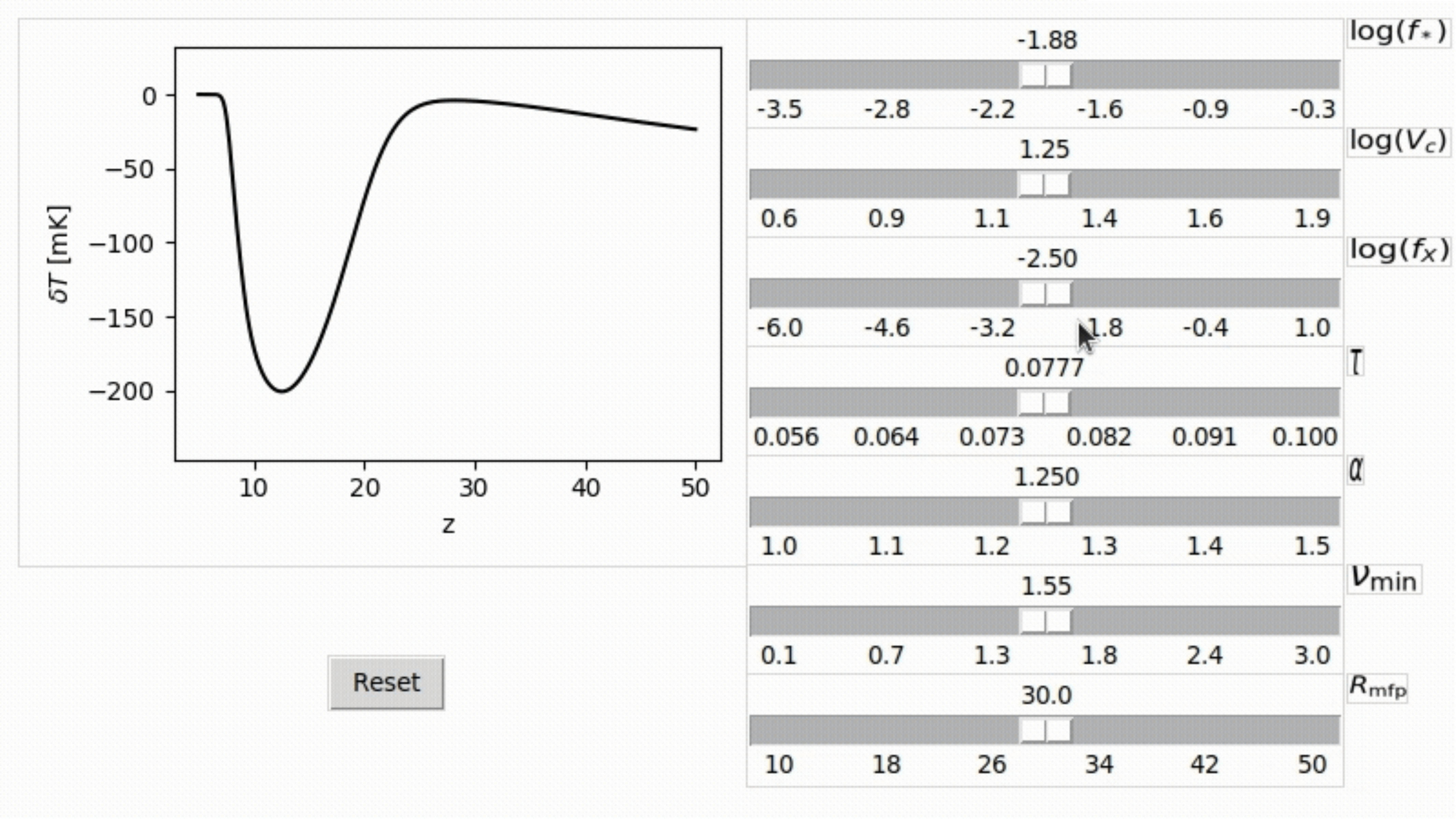
- Complex dependence on structure formation, cosmology, star formation, emission from X-ray binaries, cosmic rays, cosmic strings…
- Semi-numerical simulations offer an efficient way to model the signal with a good level of detail
- Need to be able to look at the data in the context of our model

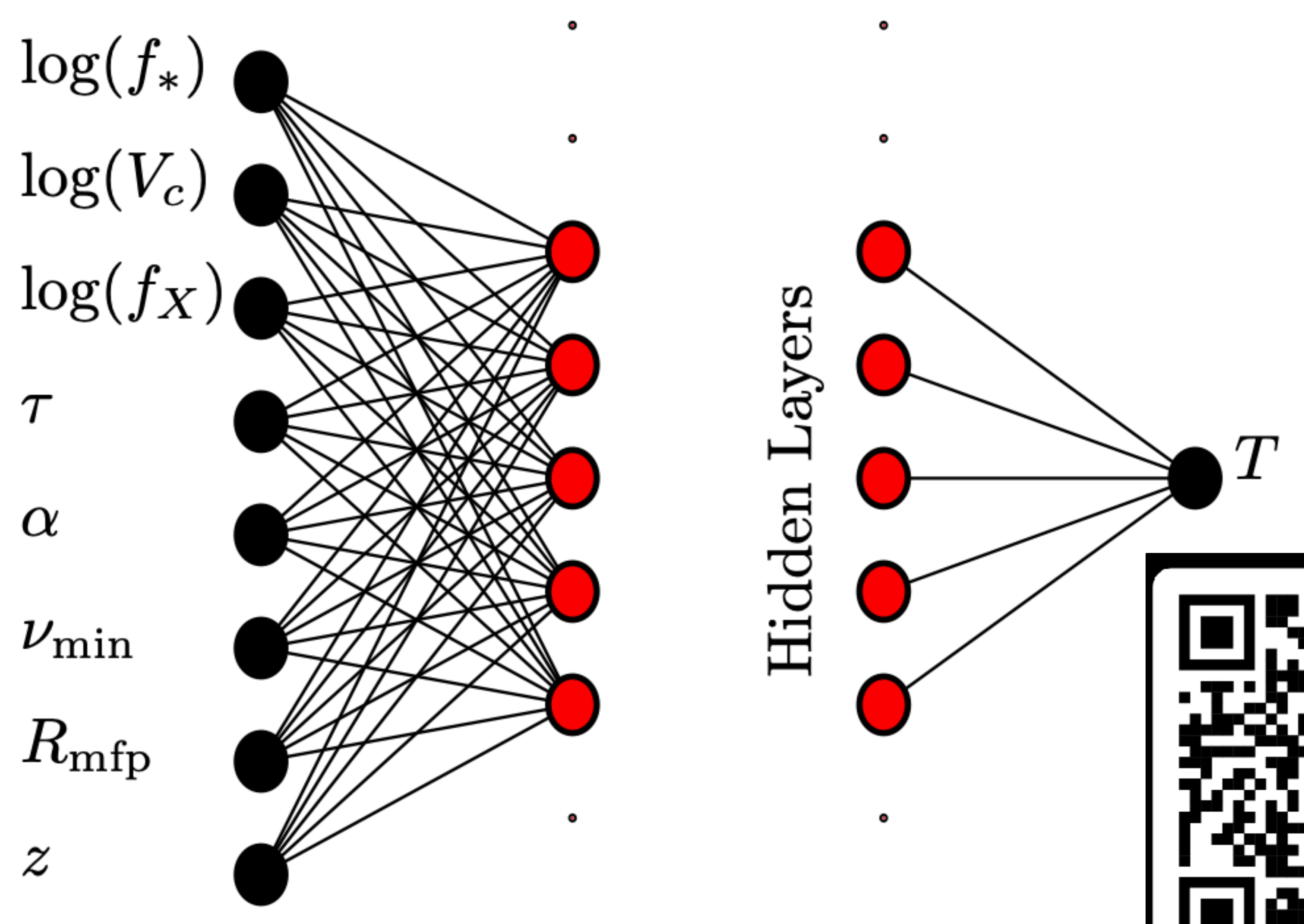


Gessey-Jones, 2024

Emulating the 21-cm signal

- Semi-numerical simulations are too computationally expensive
- I built an emulator ***globalemu*** [Bevins et al. 2021]
- $102\times$ faster than the state of the art emulators and $2\times$ as accurate
- Independent variable as an input to the network and vectorised call to recover the signal
- Adapted for power spectrum with HERA [The HERA Col. 2023 ApJ]





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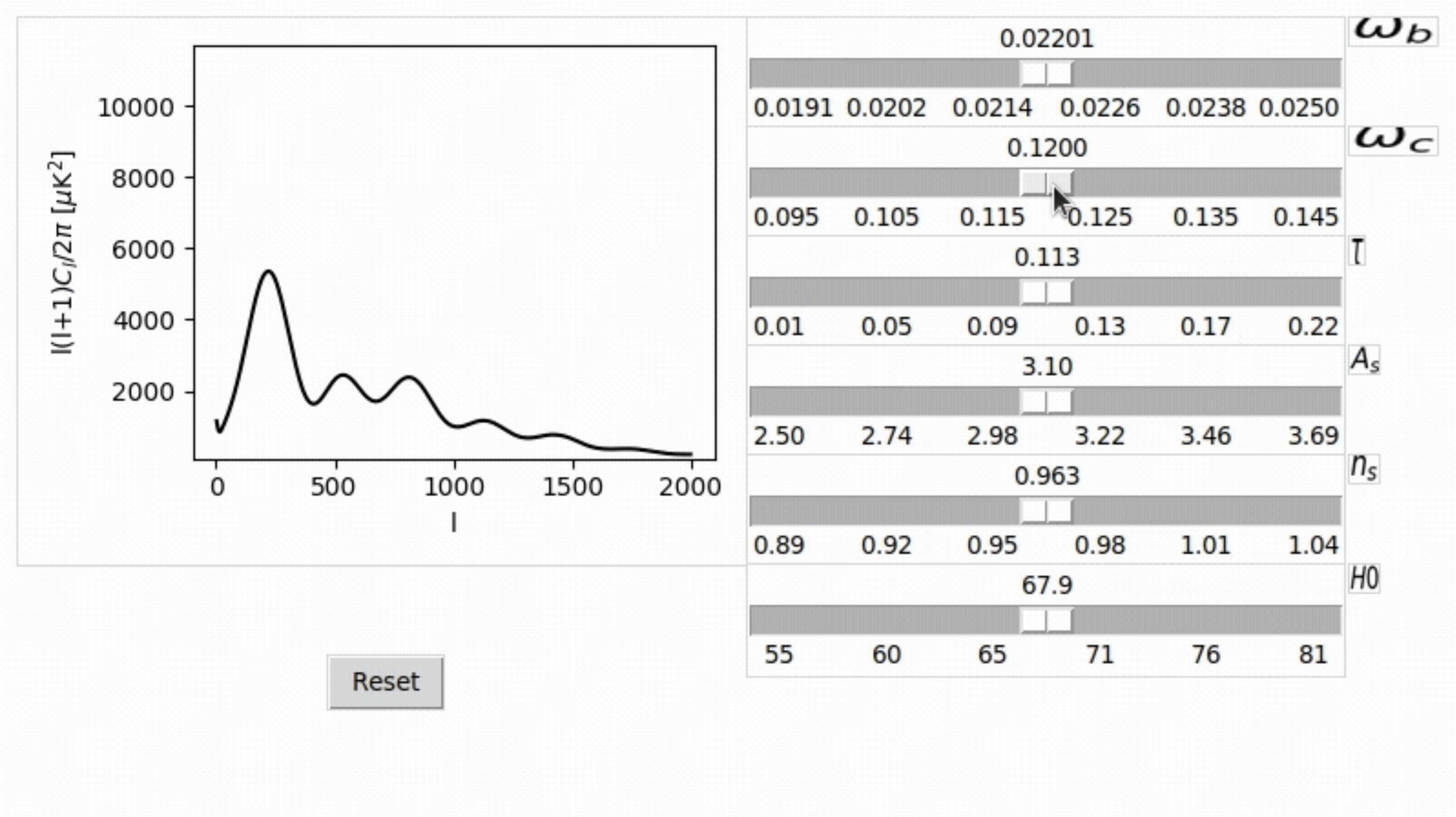
UKRI 2024 HPC Resources: Next generation of emulators

- I led and won a UKRI Autumn call to develop the next generation of emulators (≈2.3 Million CPU hrs)

- Generic framework for emulation of all astrophysical data

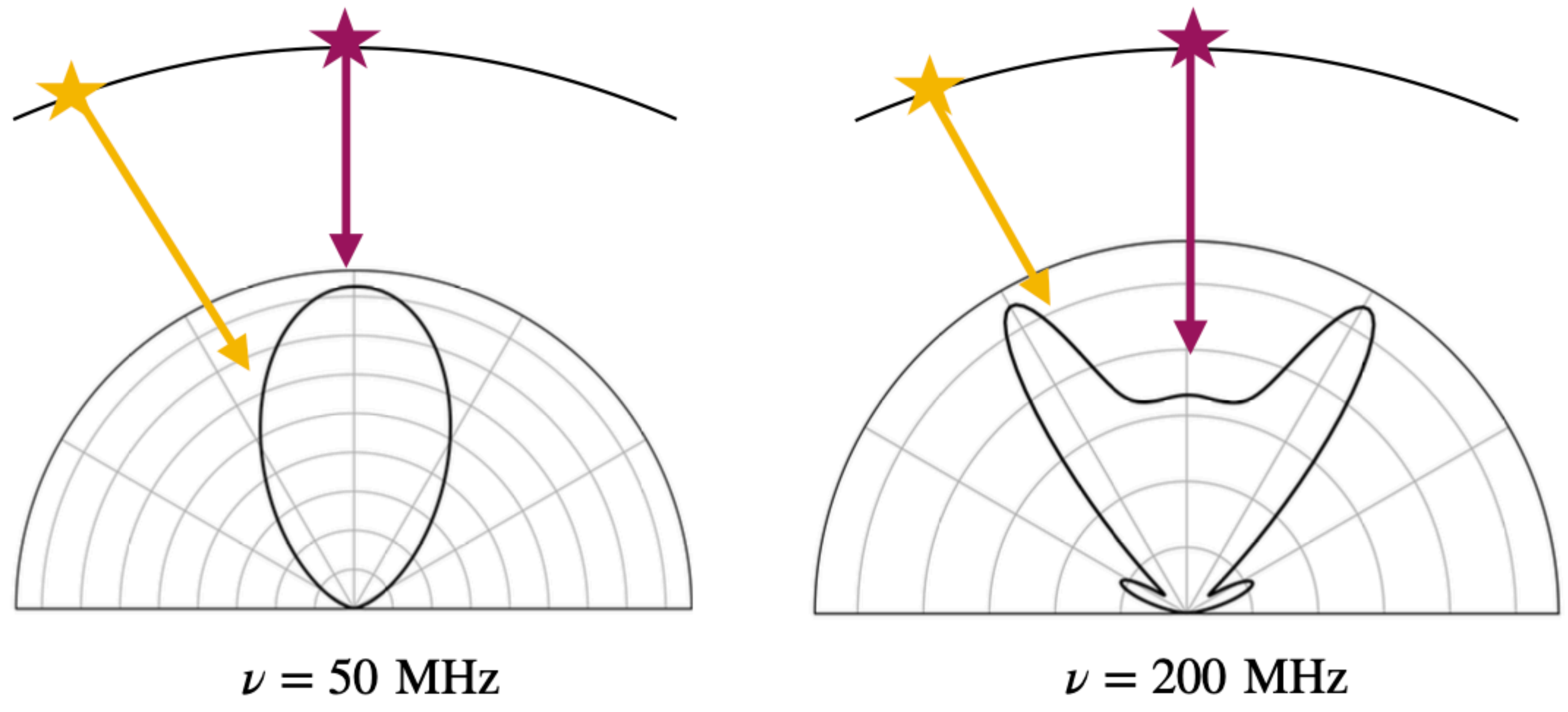
- Recent work in **Bevins et al. 2025** on accuracy of recovered posteriors

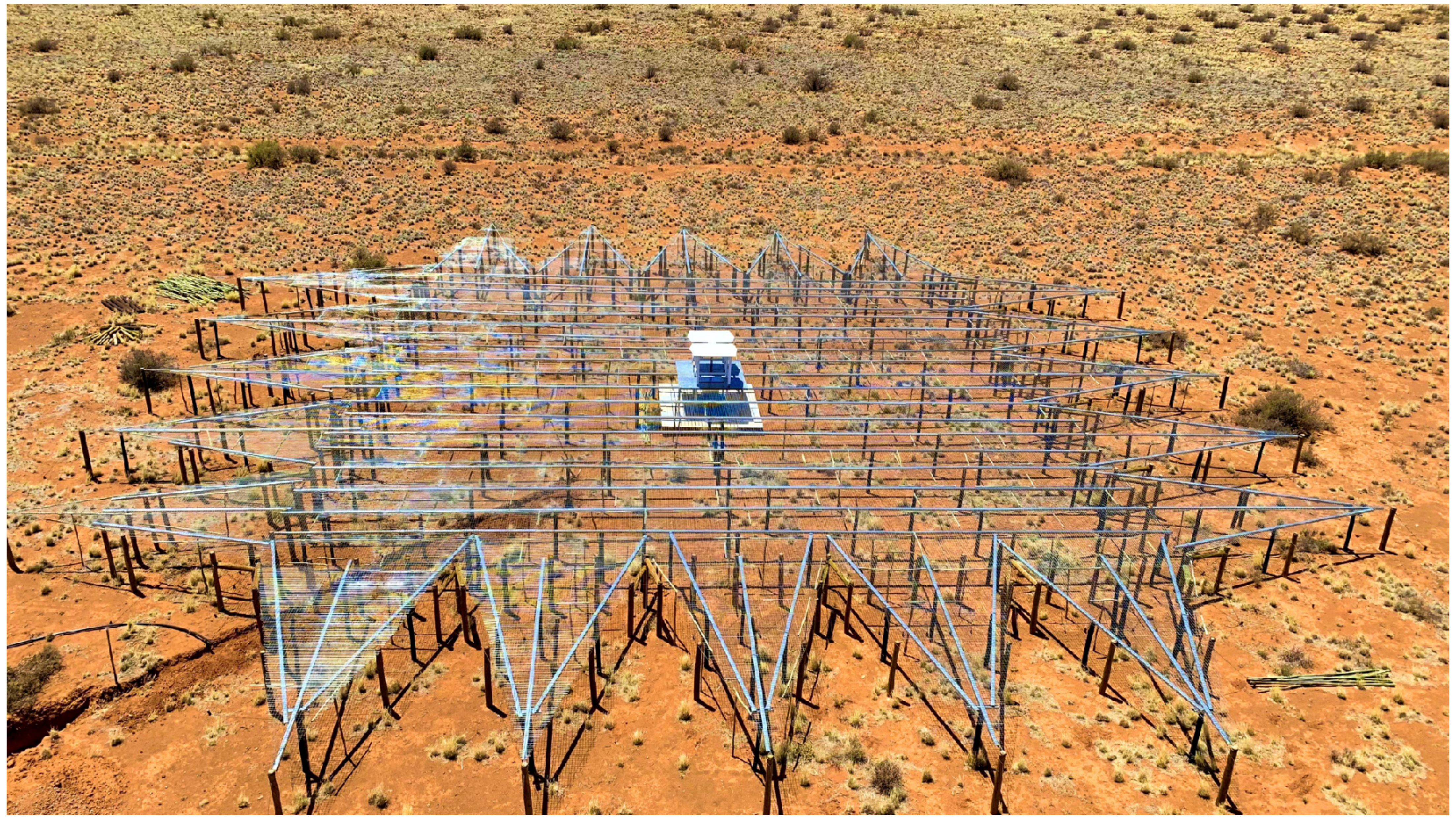
- Test on:
  - 21-cm as a benchmark
  - Galaxy SEDs
  - CMB Power Spectrum
  - Gravitational Wave Strains



Beam Induced Chromaticity

- We observe a weighted version of the sky and the weighting changes with frequency
- The structure can mimic or hide the 21-cm signal leading to false detections





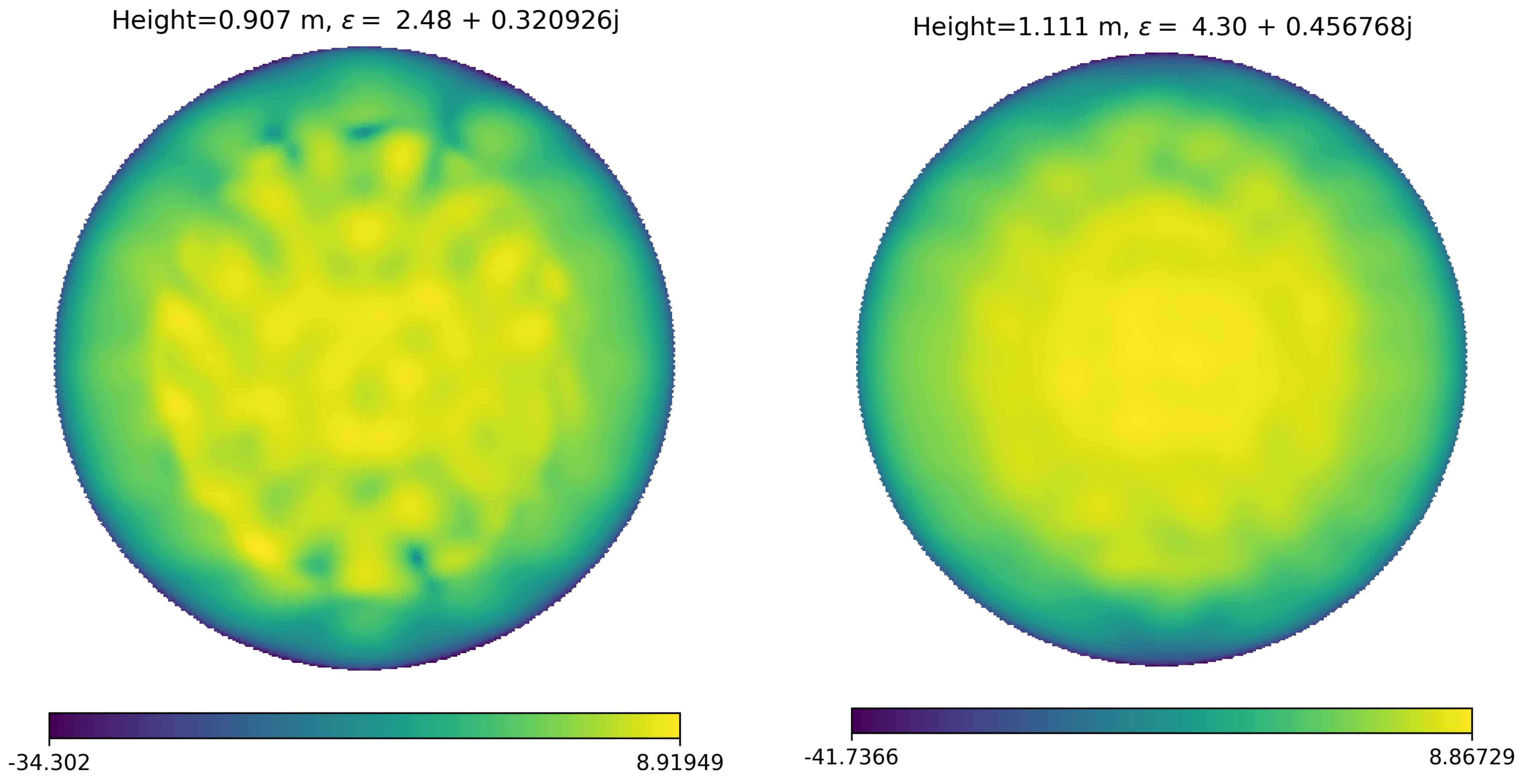
DiRAC RAC Grant: Emulating the REACH Beam

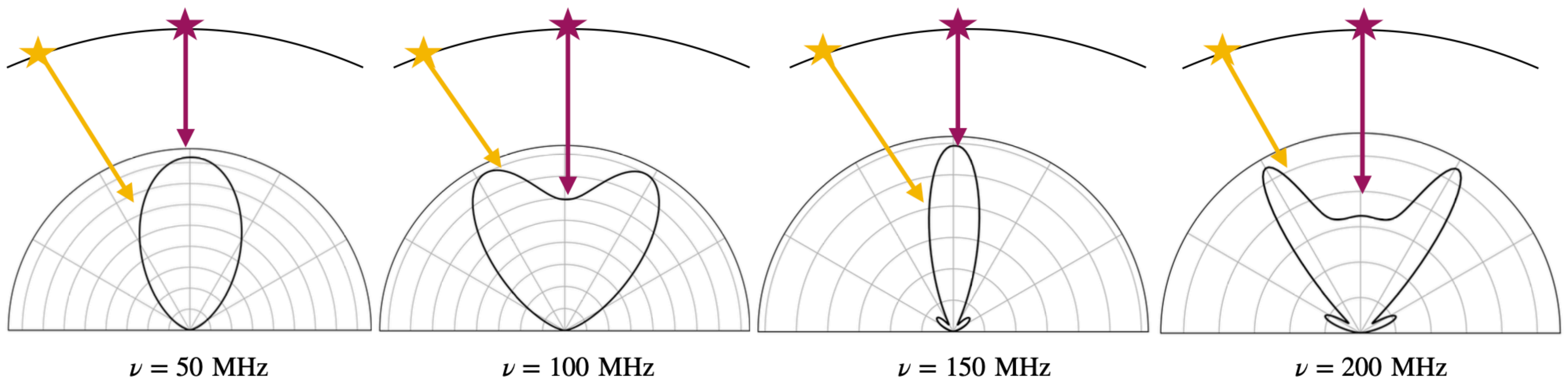
- I led and won a DiRAC RAC17 application to neural network emulators of the REACH beam pattern (3.22 Million CPU hrs)

- Rely on Electromagnetic simulations and assume absolute knowledge of the beam in the REACH analysis pipelines

- Likely to be construction errors and properties of the soil around the antenna change with time

- Goal to physically model the properties of the antenna and the impact of the environment alongside foregrounds and the 21cm signal

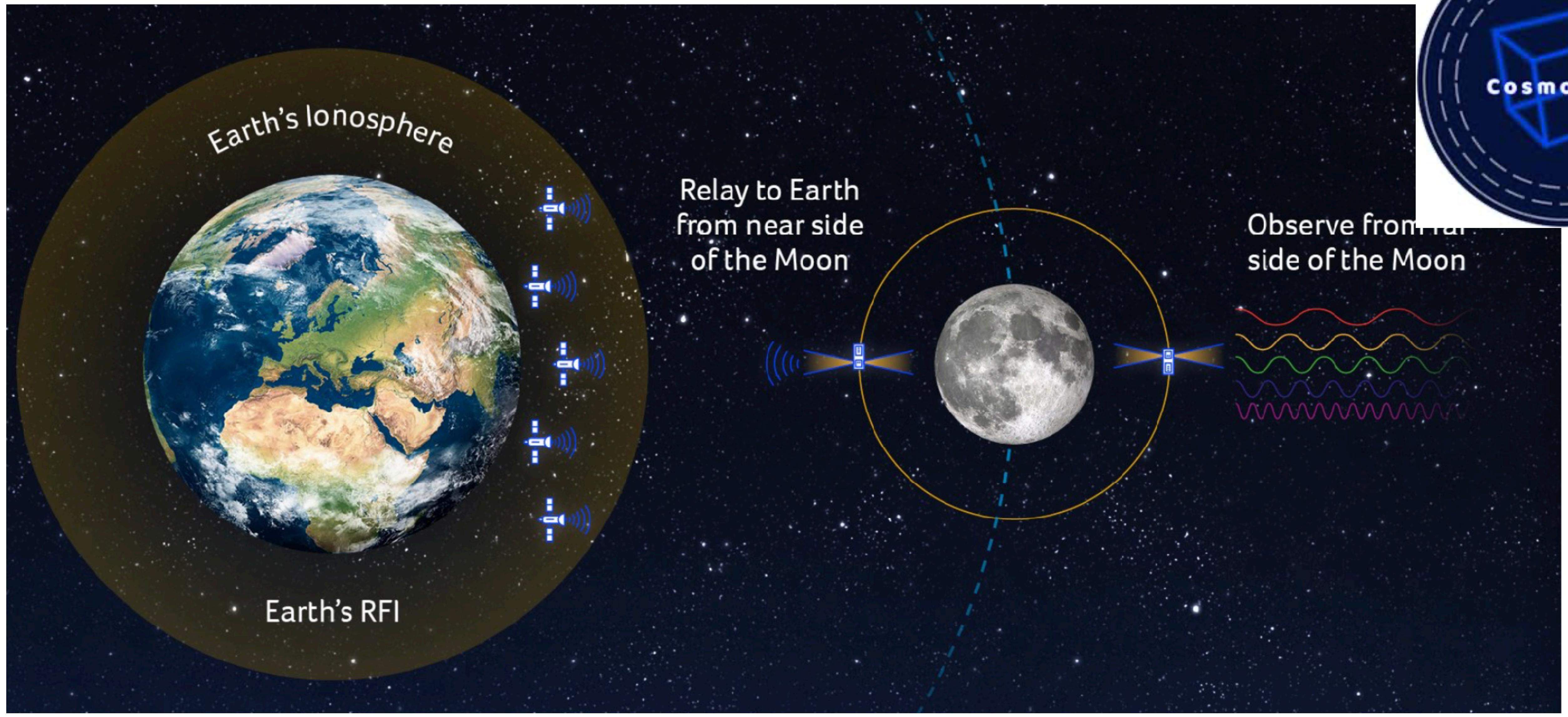


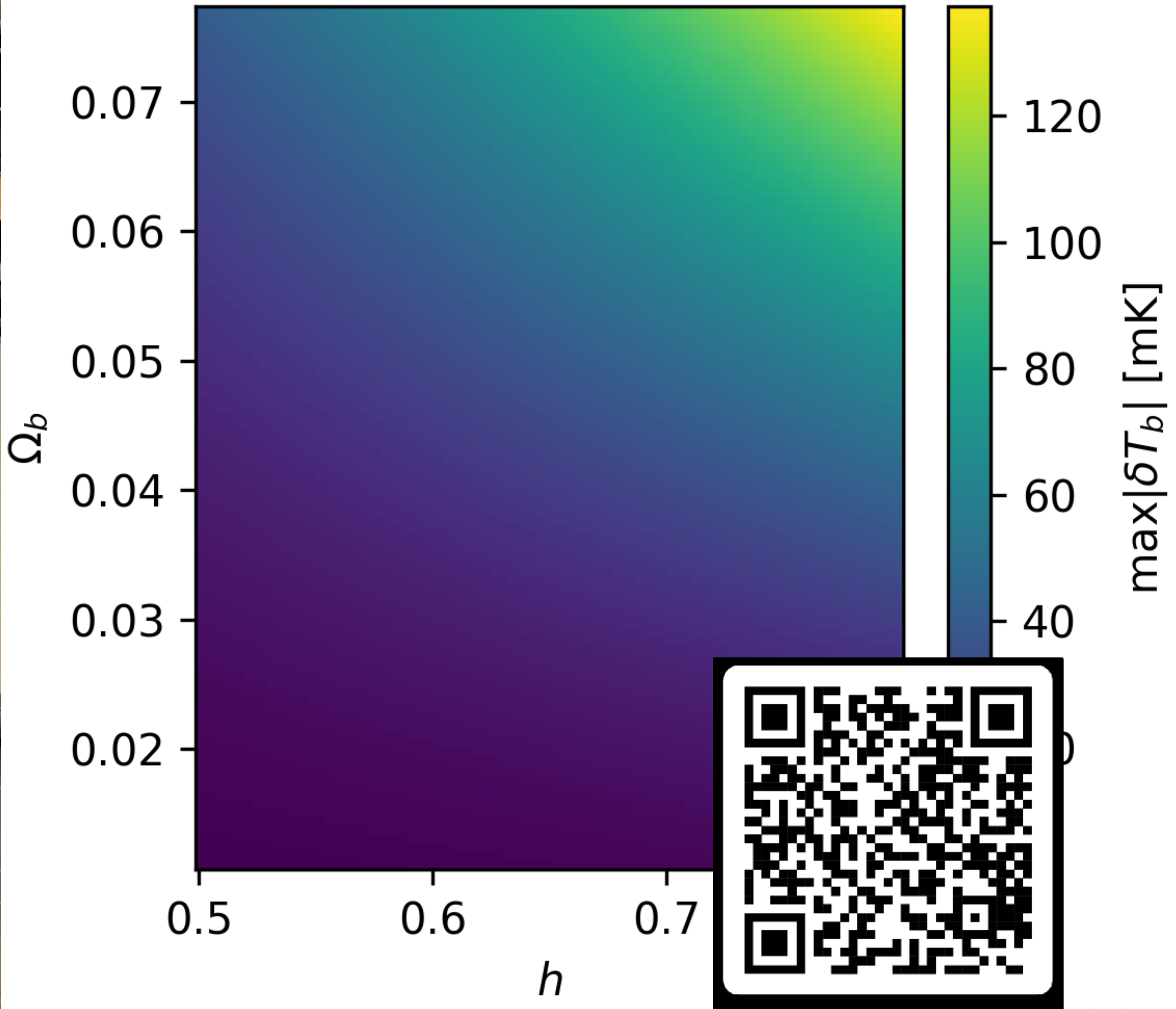


CosmoCube and the Dark Ages

CosmoCube

- CosmoCube aims to detect the dark ages 21-cm signal from the far side of the moon using a cubesat
- I am working on science forecasts
- Initial development funded by UKSA
- Applying for ESA Mini-Fast ($\lesssim 50$ €M; ≤ 5 yr to launch)
- Led by Cambridge, Portsmouth and RAL
- Mission paper submitted to Nature Astronomy





CosmoCube

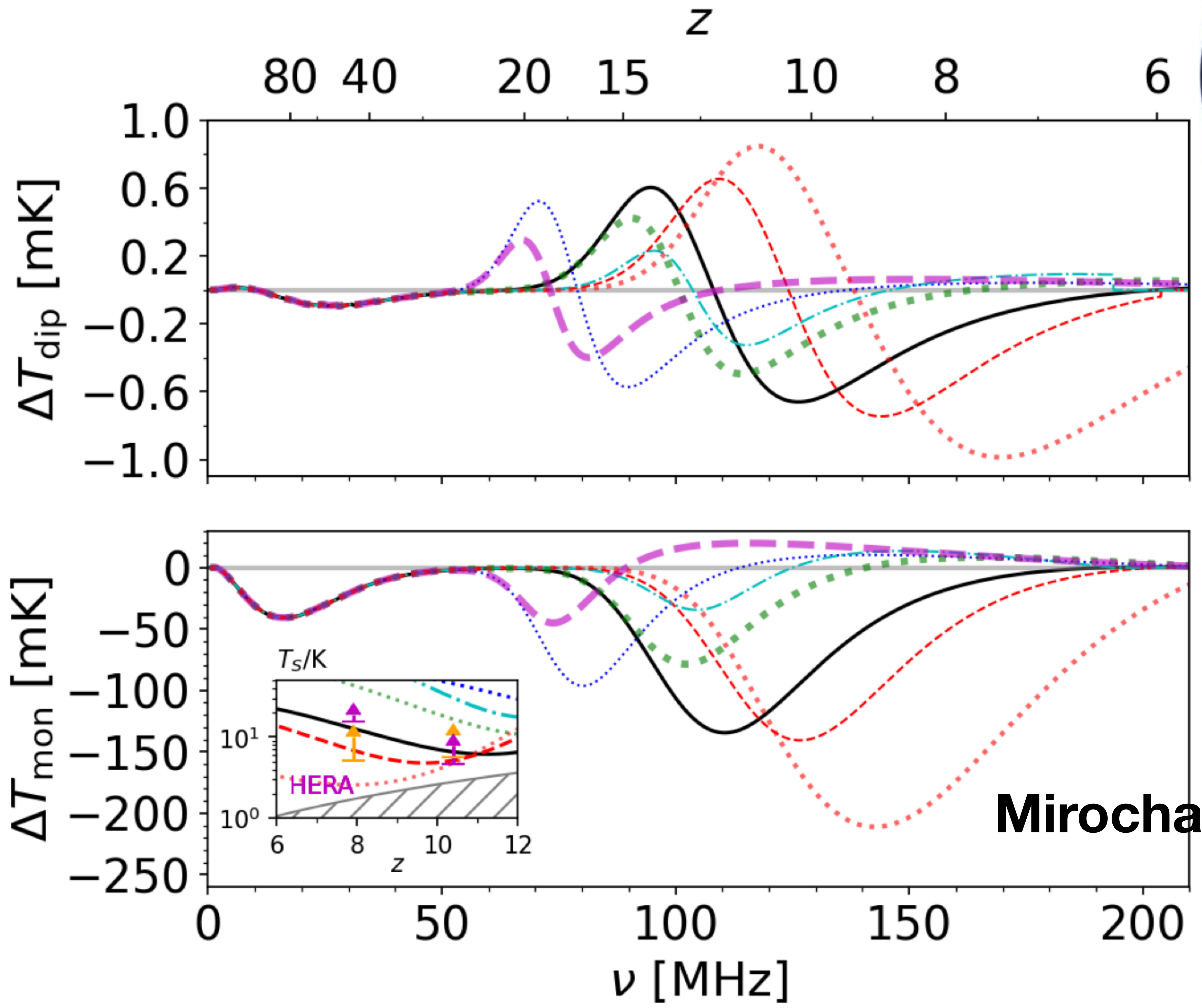
Dark Ages, tensions and synergies

- Working with colleagues at JPL to forecast joint constraints from CosmoCube and CHIC

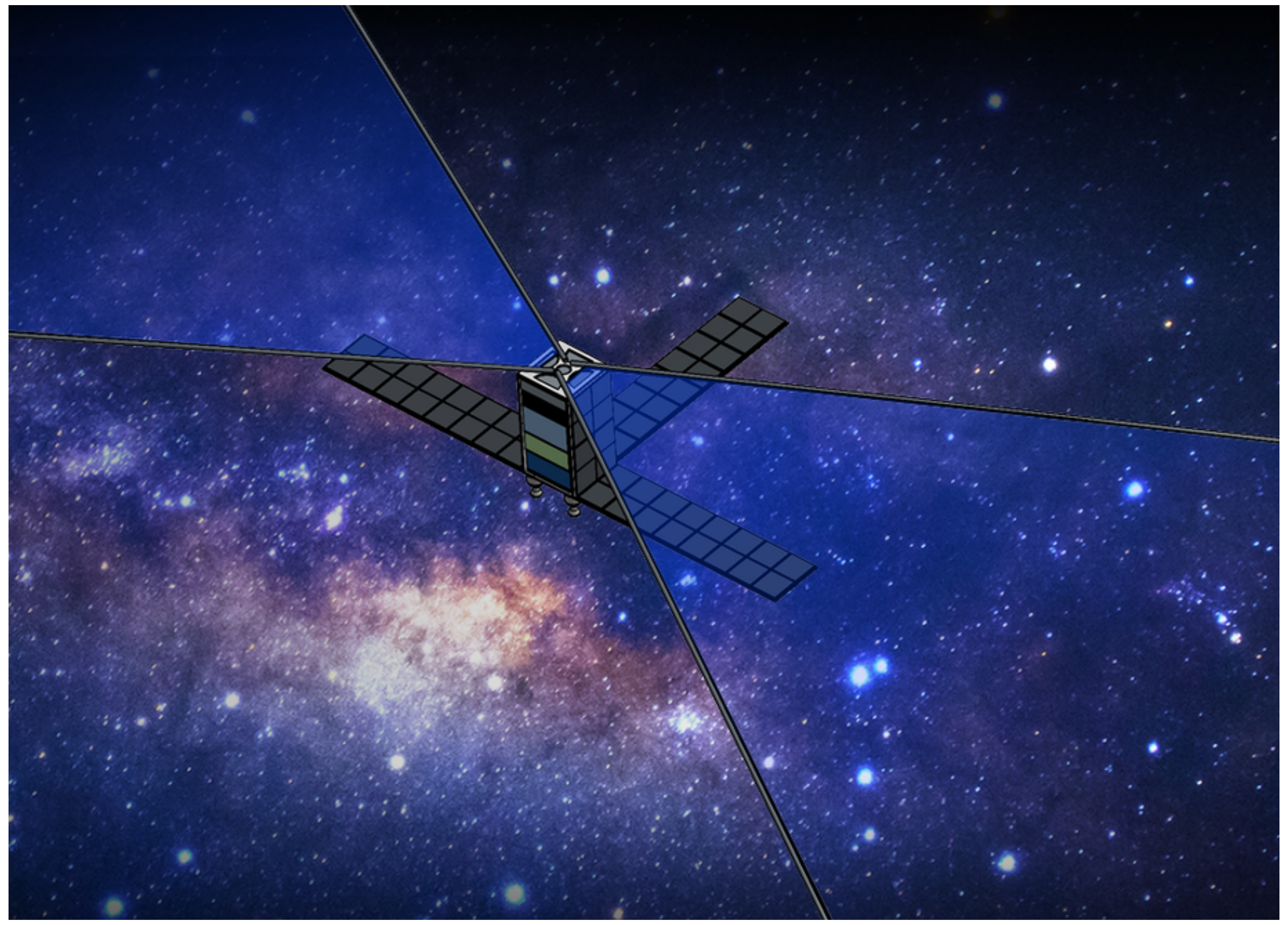
- CHIC is a proposal to measure the 21-cm dipole from lunar orbit

- I am leading the development of machine learning tools to assess concordance and tension between various instruments

- Particularly important if we want to comment on the Hubble tension



Mirocha et al 2024

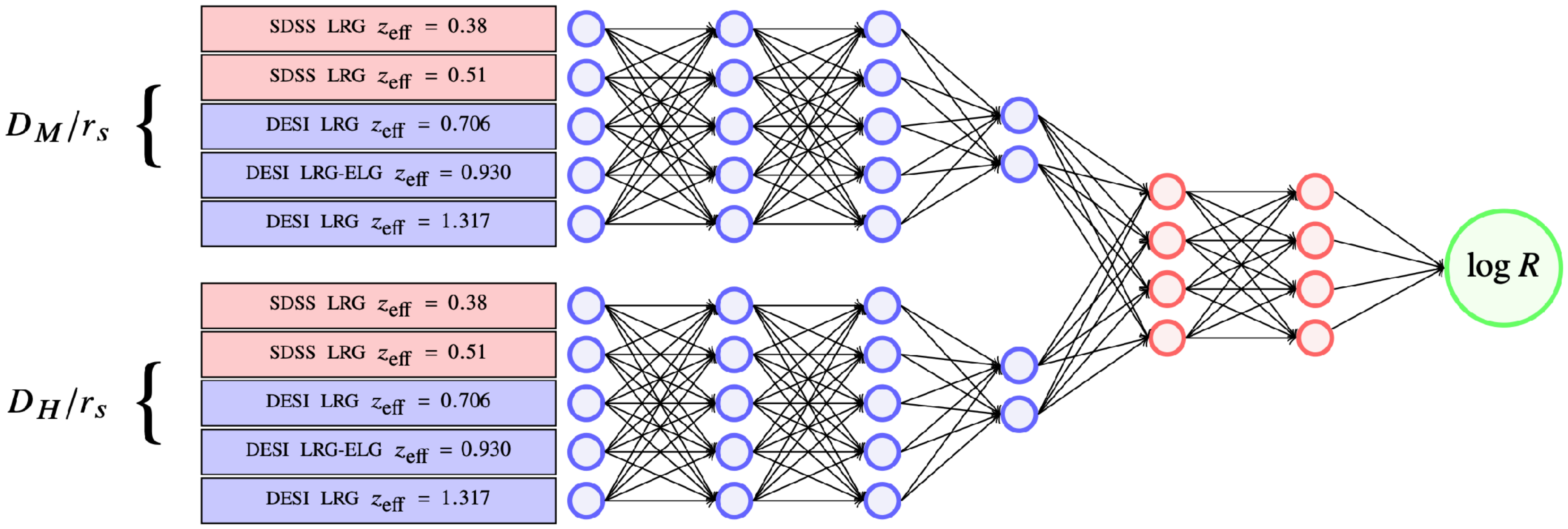


Dark Ages, tensions and synergies

- In Bevins et al 2025 I showed that you can use Neural Ratio Estimation to calibrate Bayesian tension statistics for particular model choices

- R can be thought of as how our confidence in dataset A has improved or not given data set B

- The tension statistic R has nice properties but very sensitive to the modelling choice



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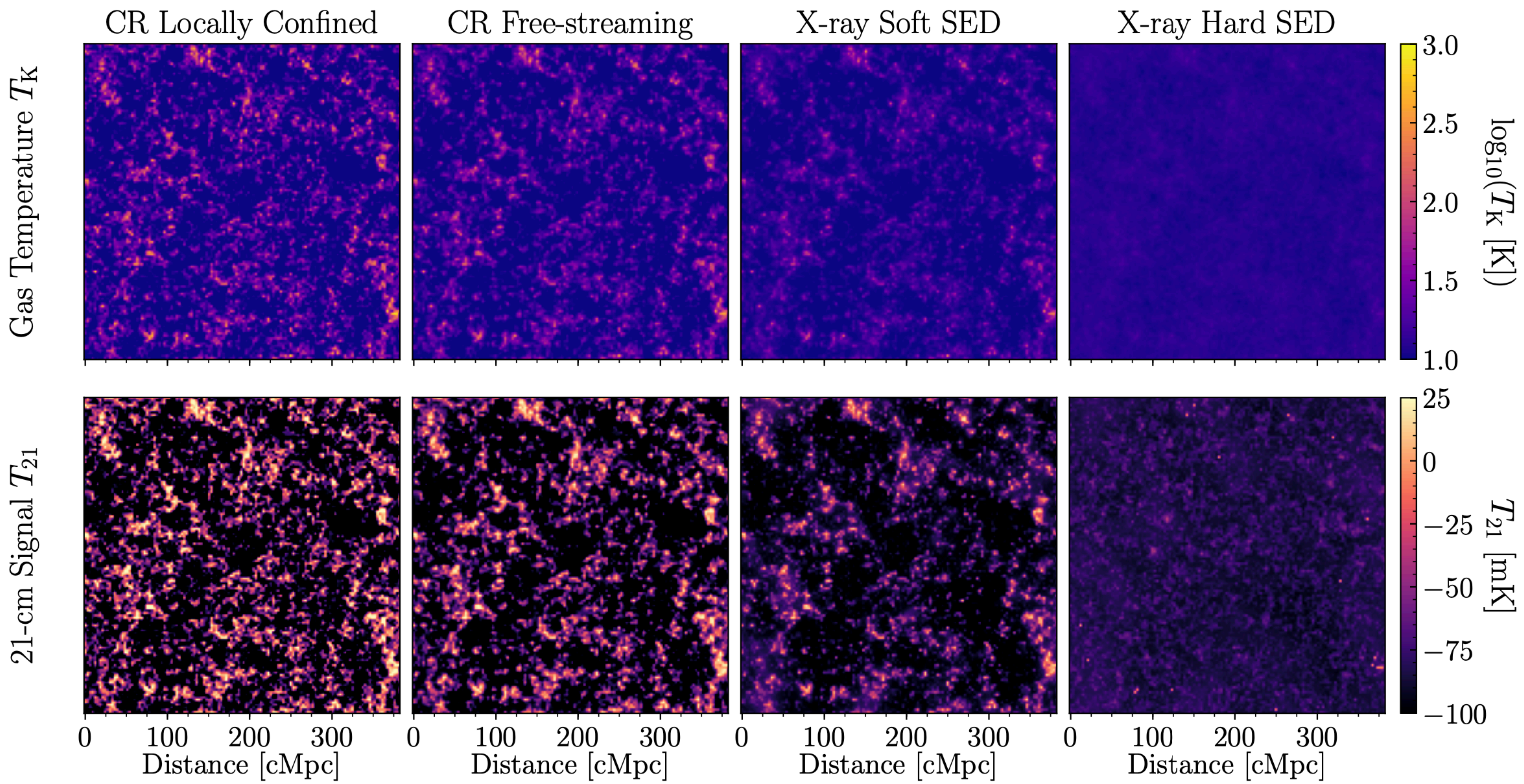
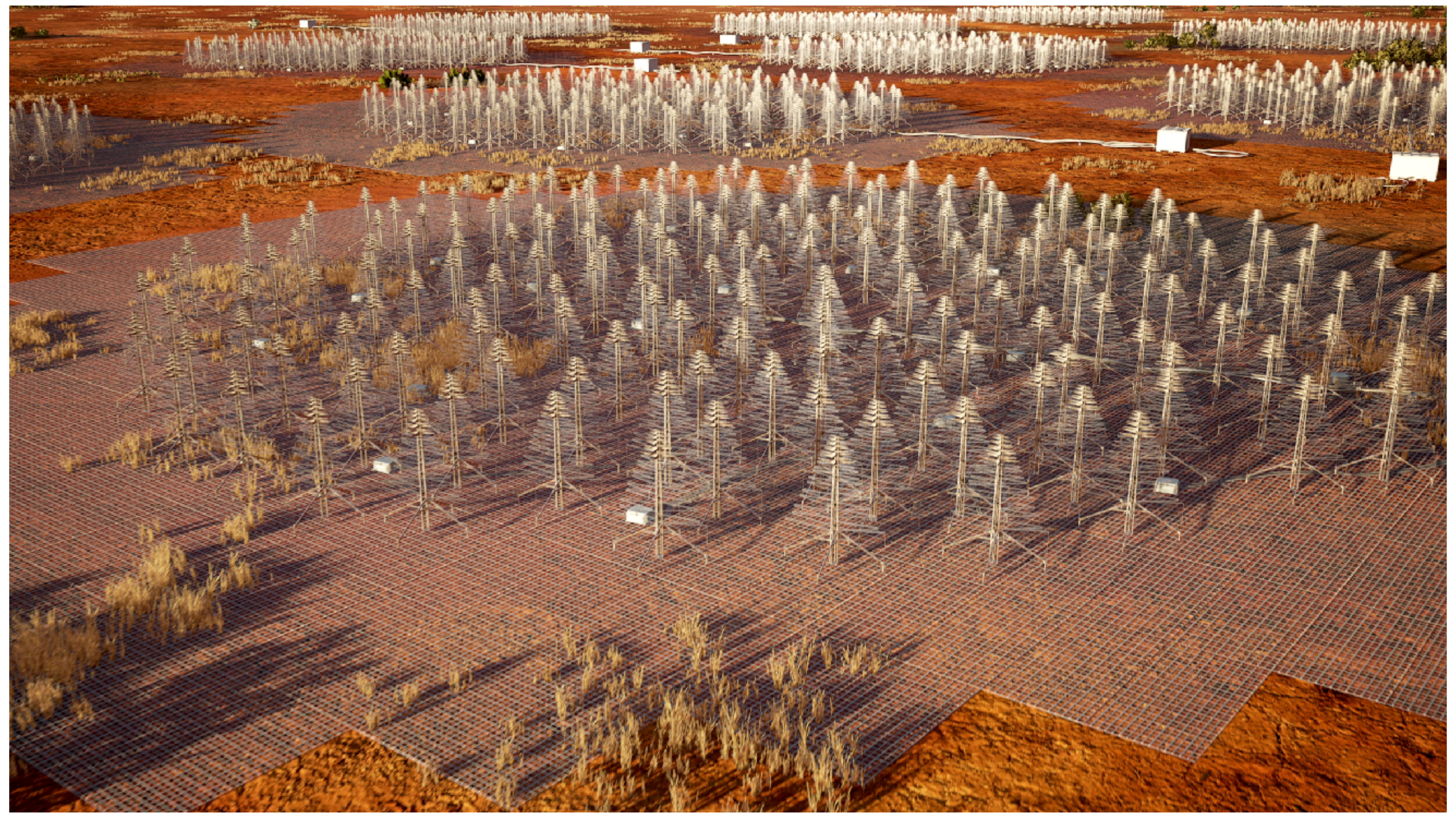
The SKA and the power spectrum

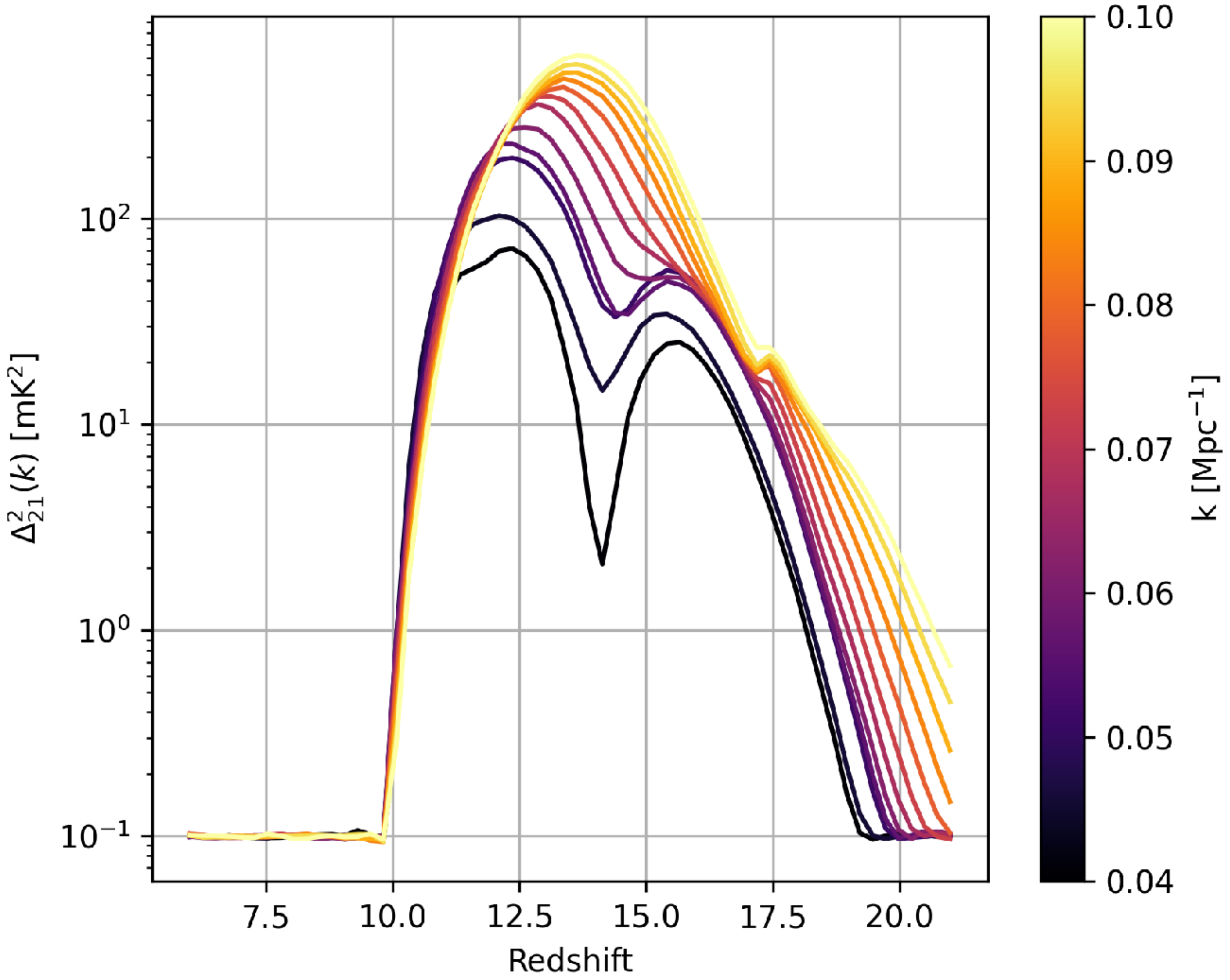
The SKA - Imagining the 21-cm signal



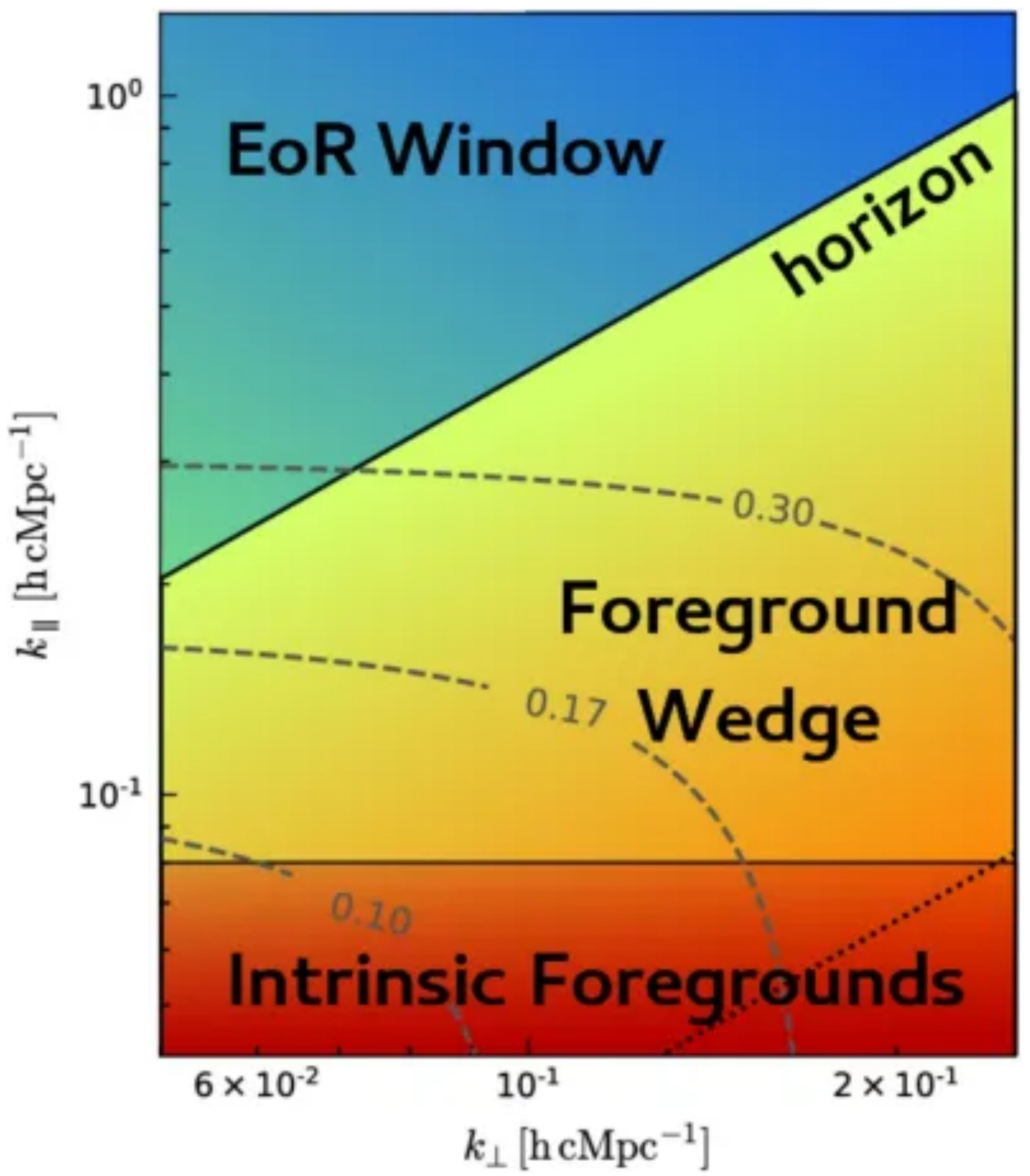
Gessey-Jones et al. 2023

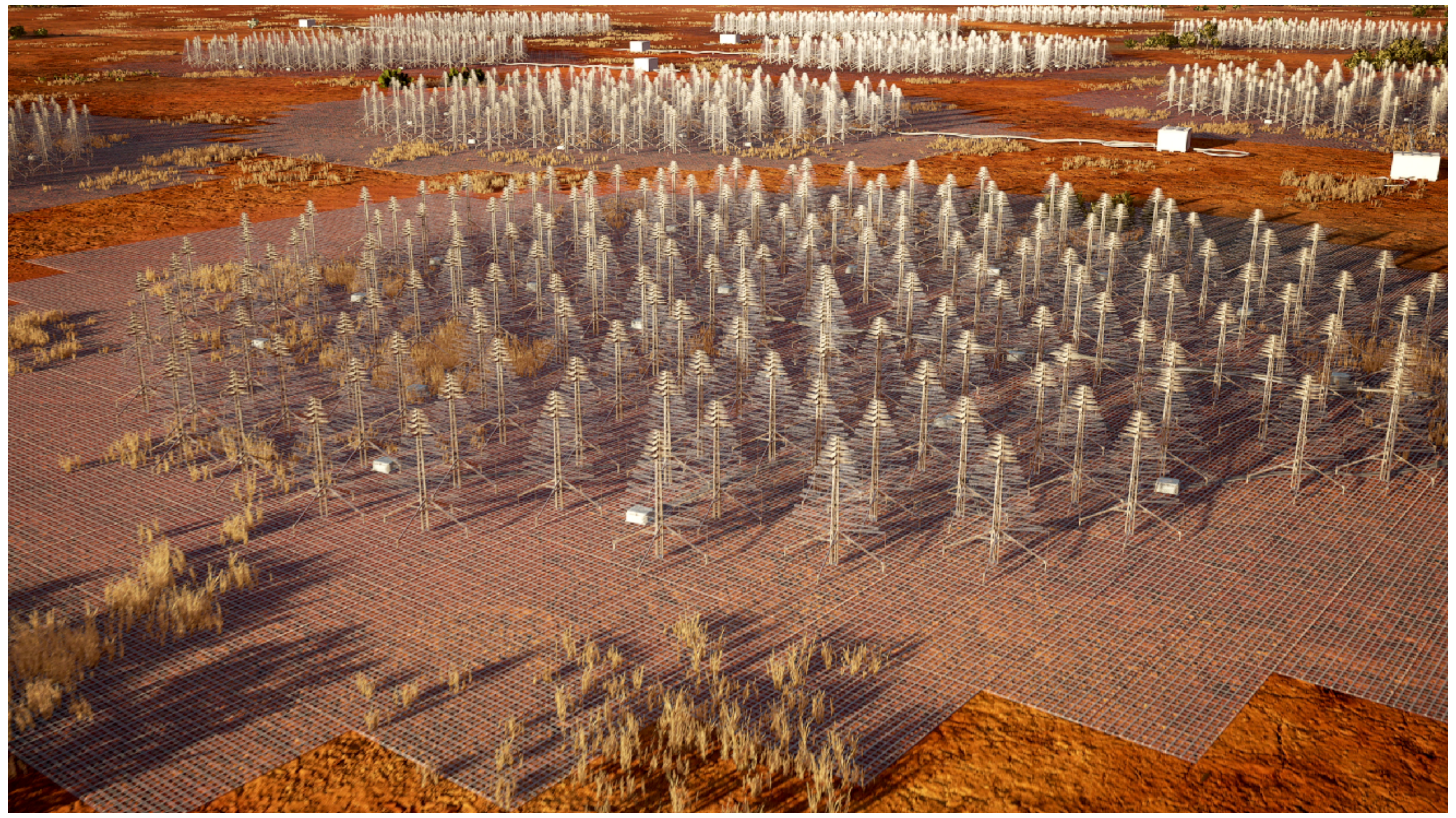


The SKA - 21-cm power spectrum



Breitman et al. 2023 21cmEMU





The SKA

- The SKA will revolutionise 21-cm Cosmology
- Larger redshift range than existing telescopes
- Larger collecting area and baselines
- Redundant baselines will help researchers isolate the instrumental effects
- Need to develop pipelines now to handle the unprecedented data rate
- Develop methods to handle instrumental systematics like mutual coupling
- Science data challenges

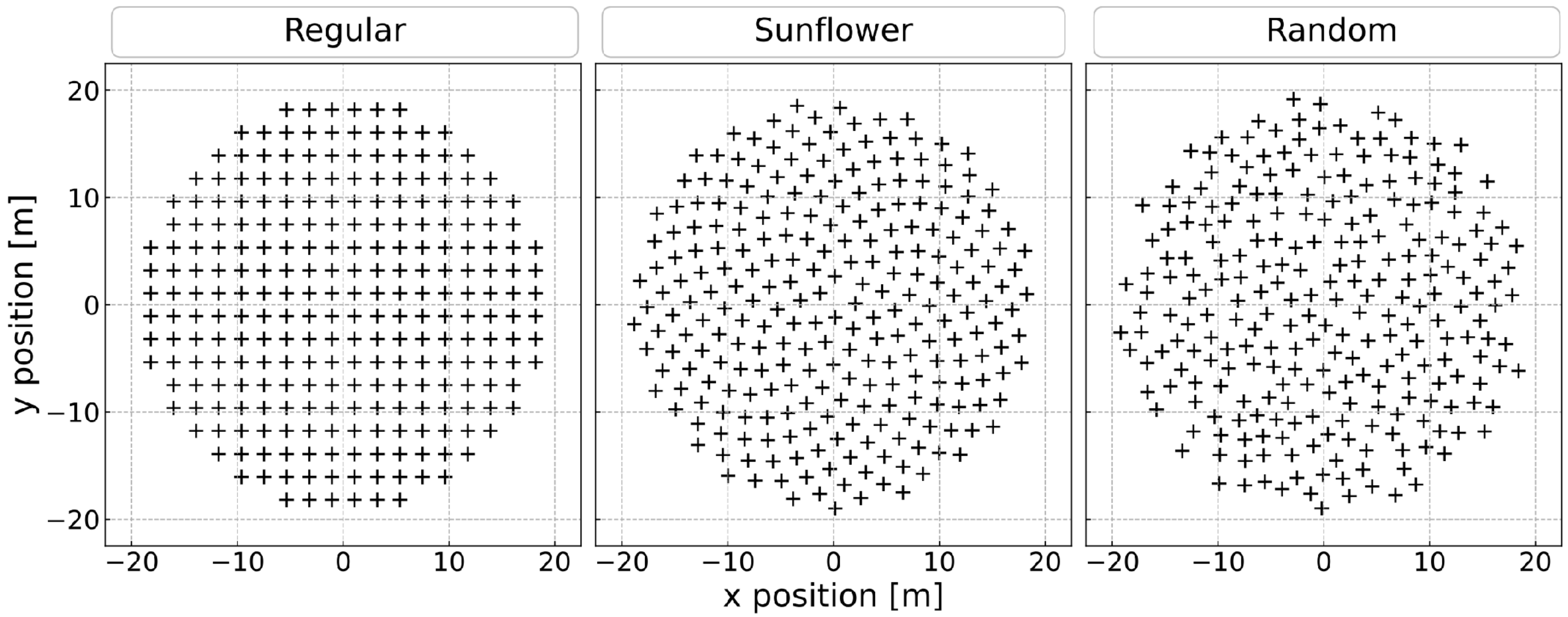
The SKA - Mutual Coupling

- To capture variations in the 21-cm power spectrum we need compact dense arrays of antennas

- Short baselines -> large angular scales -> small $k_\perp$ modes

- However in such arrays the antennas excite currents on each other

- This effects how each antenna sees the sky



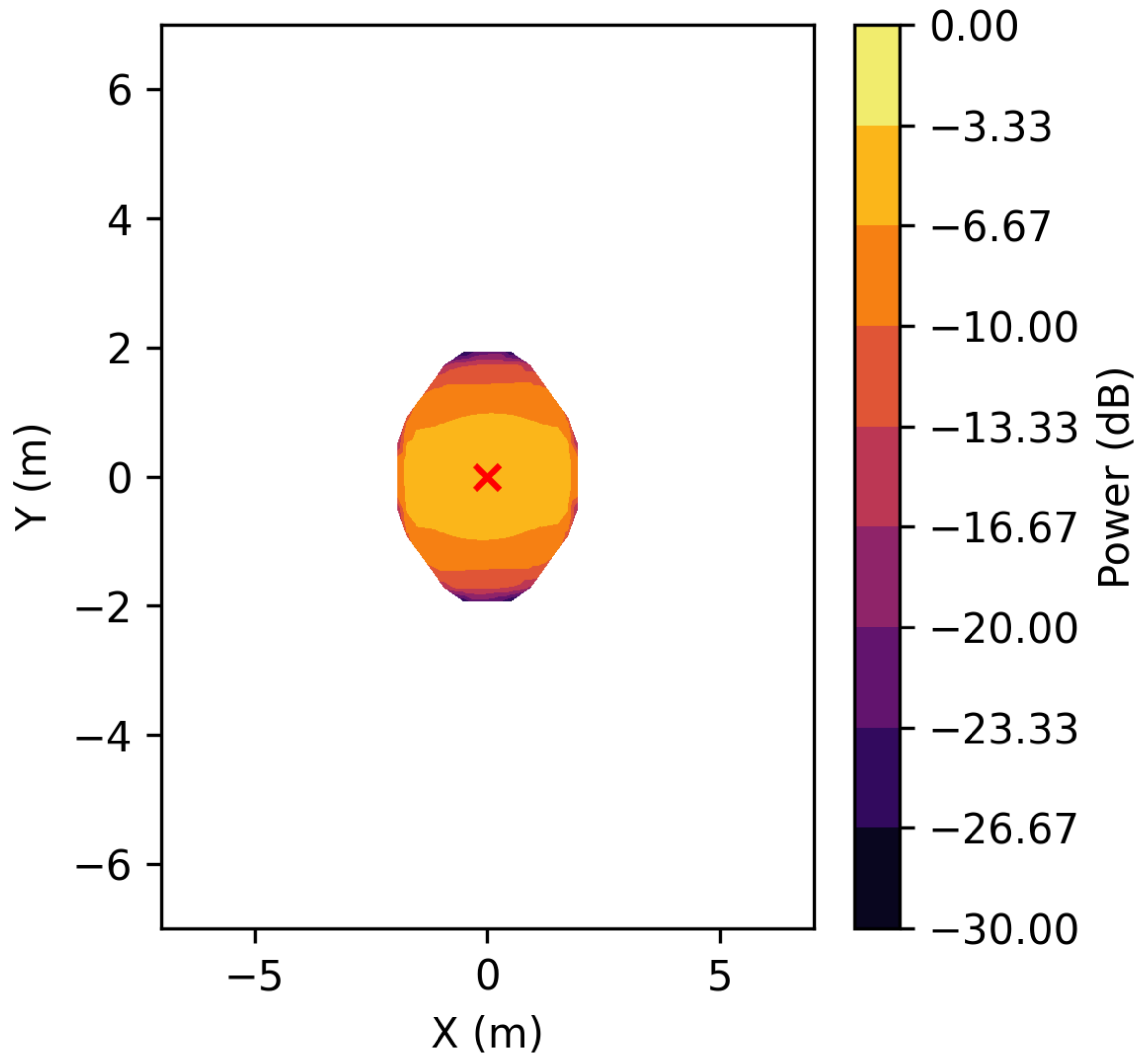
The SKA - Mutual Coupling

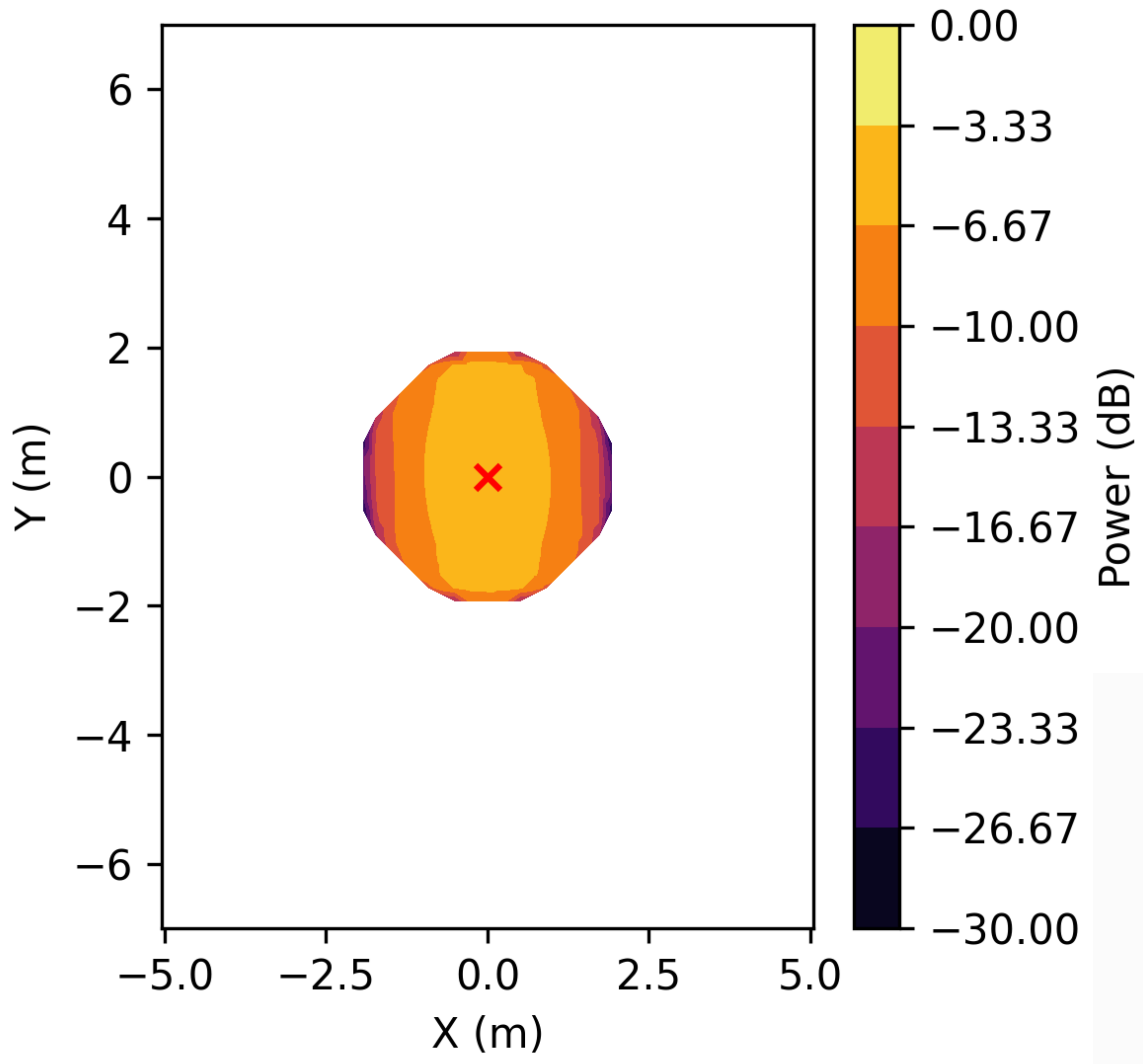
- Existing simulations are fast but they are not fast enough to put inside likelihood loops

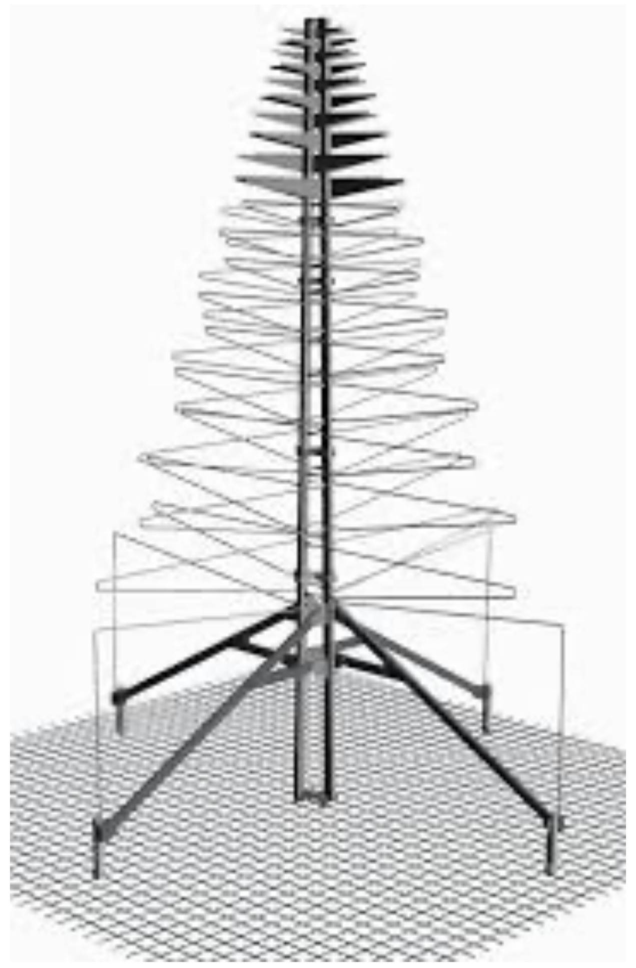
- Look again towards emulating the beam patterns

- Demonstrate with SKA antenna in small arrays

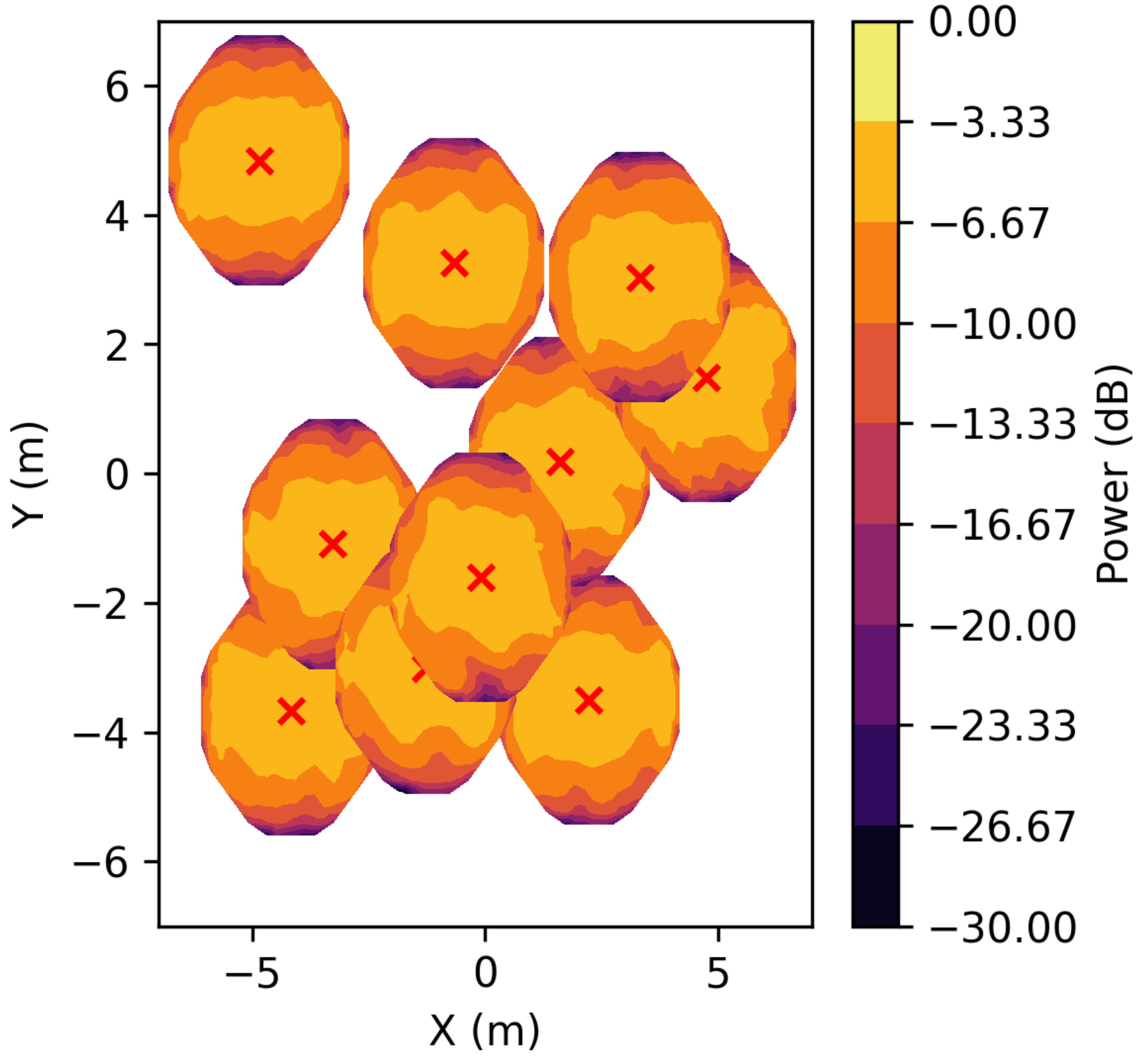
The SKA - Mutual Coupling

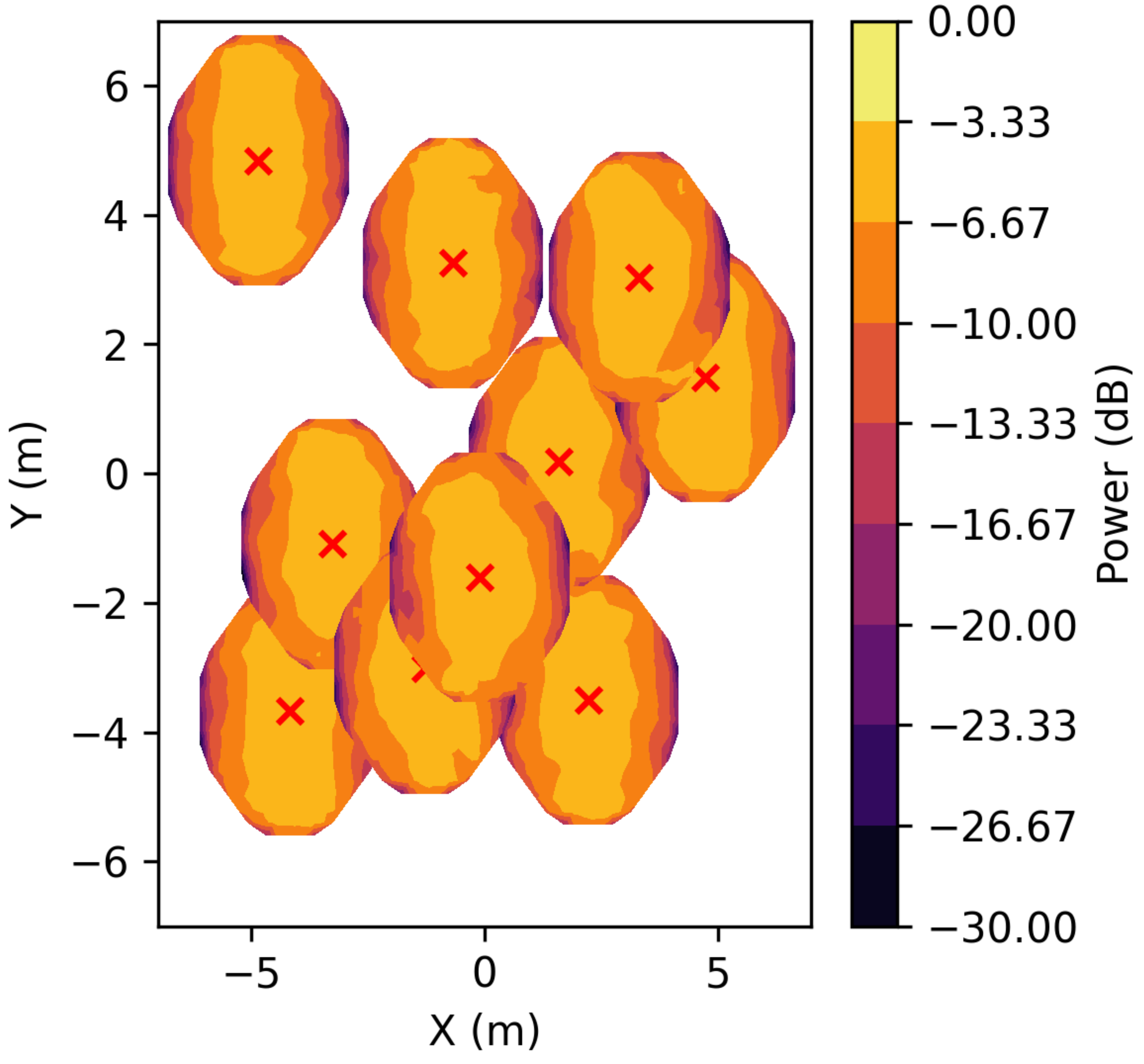






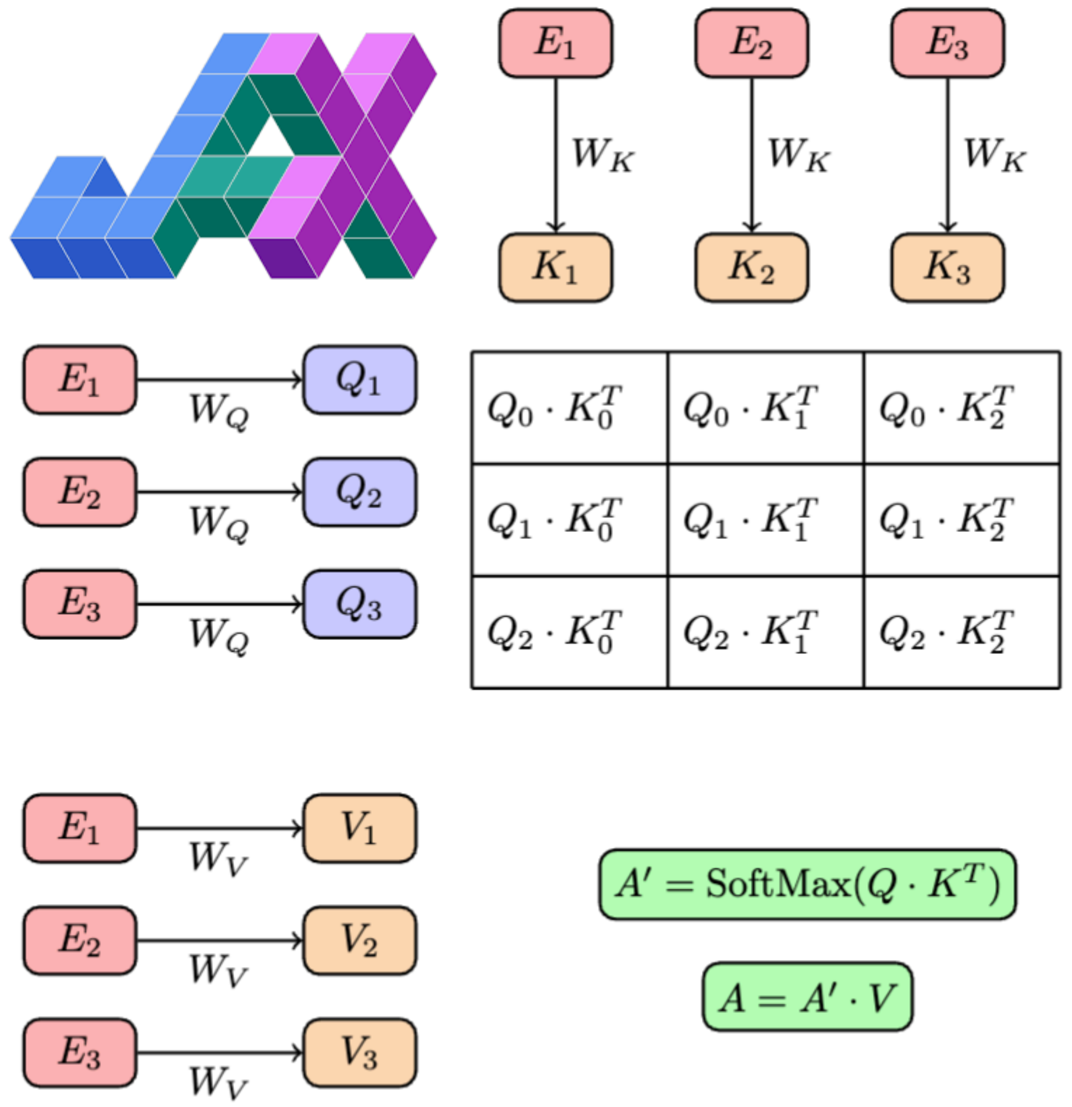
The SKA - Mutual Coupling

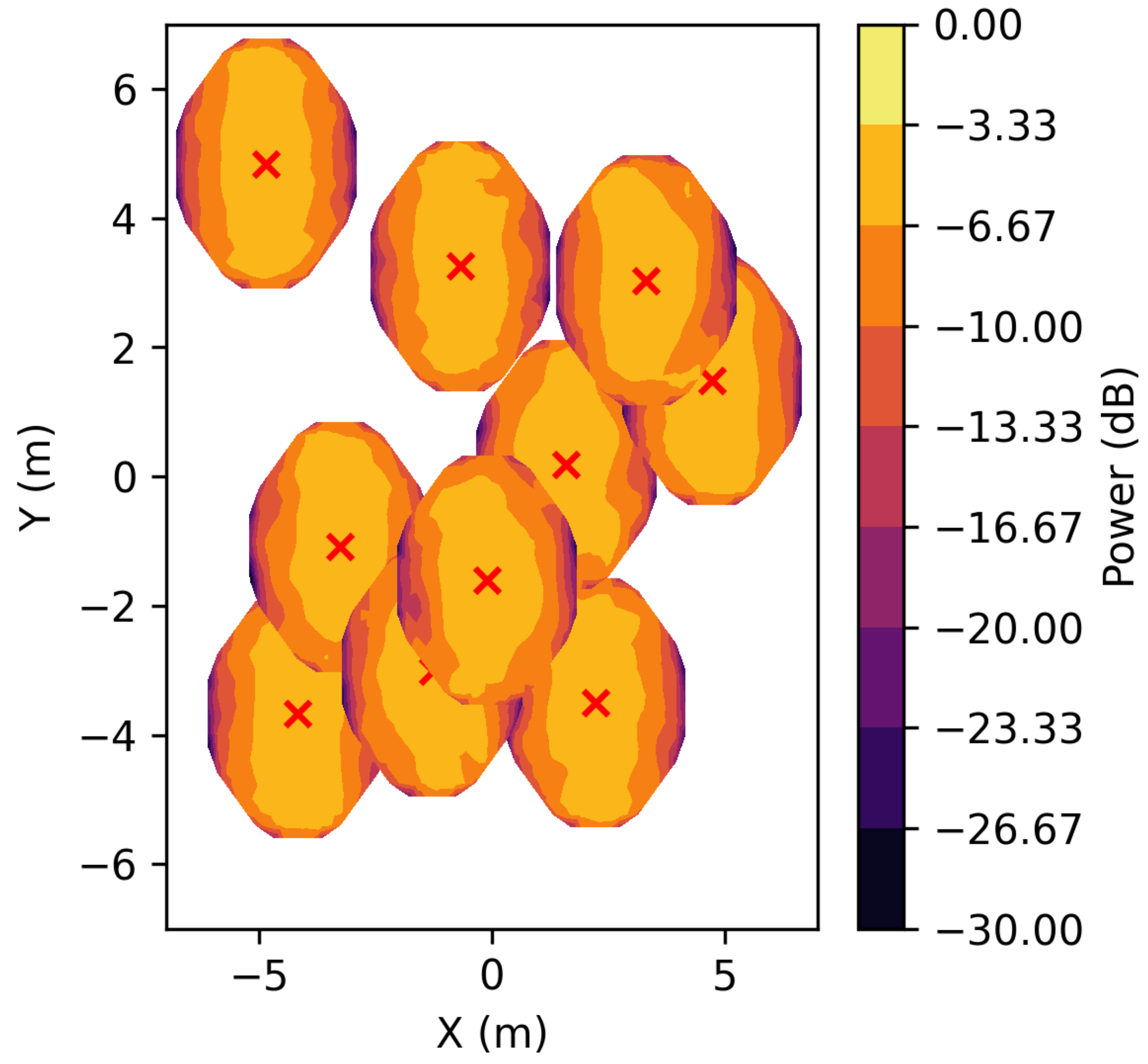


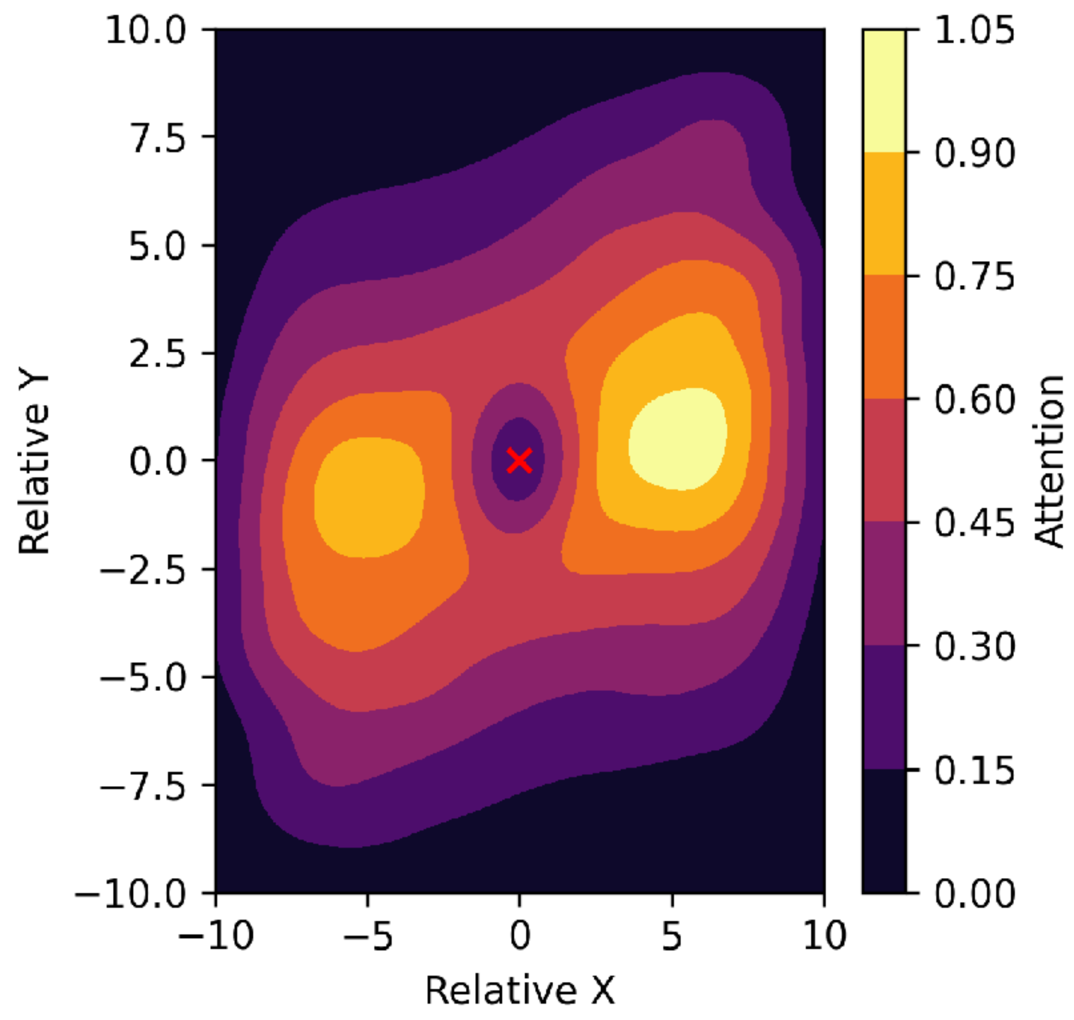


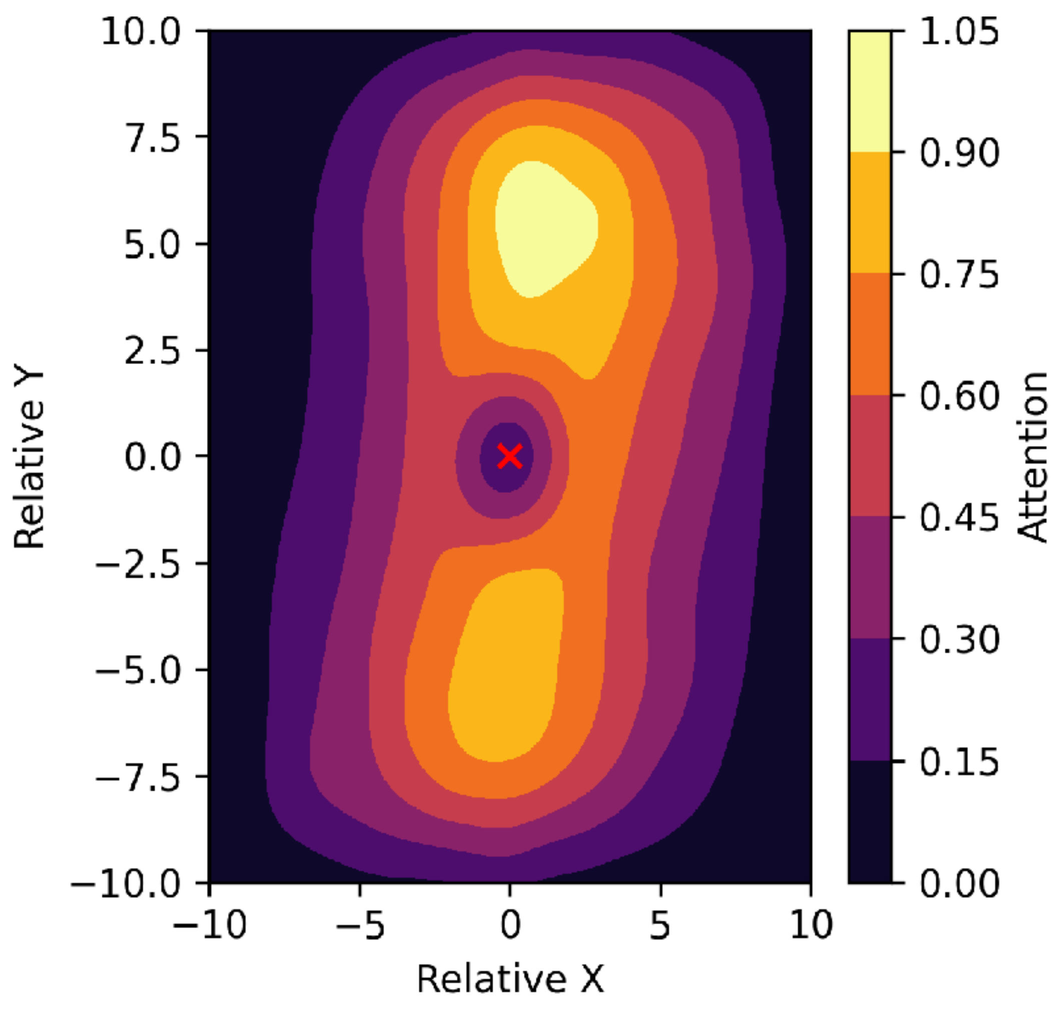
The SKA - Mutual Coupling

- Beam Pattern of each antenna is dependent on the relative positions of the antennas
- Need the network to learn the spatial relationships between antennas
- Attention mechanism to encode or embed the relative importance of each antenna in predicting beams
- The same technology as used in LLMs but here rather than tokens being words they are the (x, y) coordinates of antennas



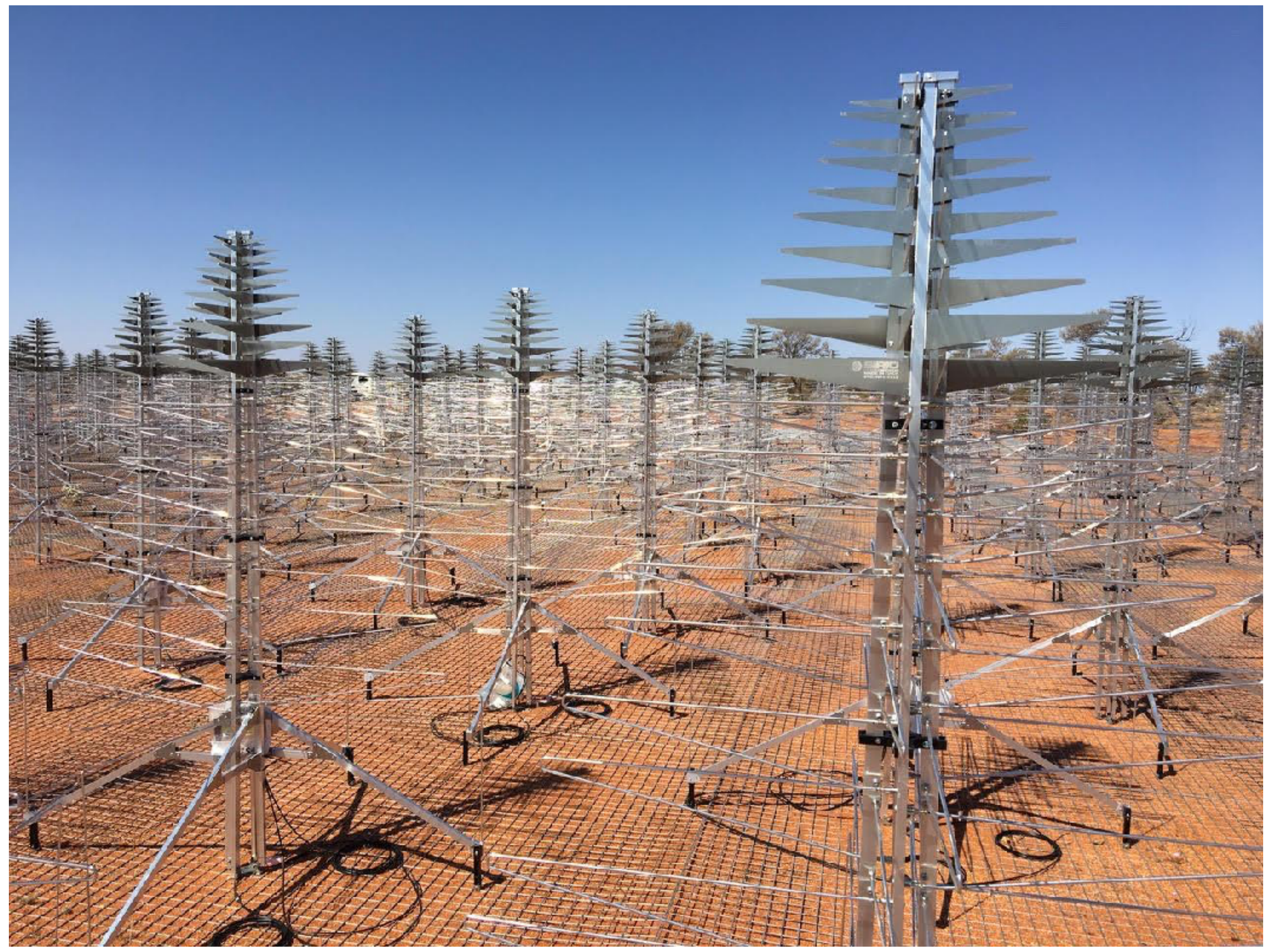




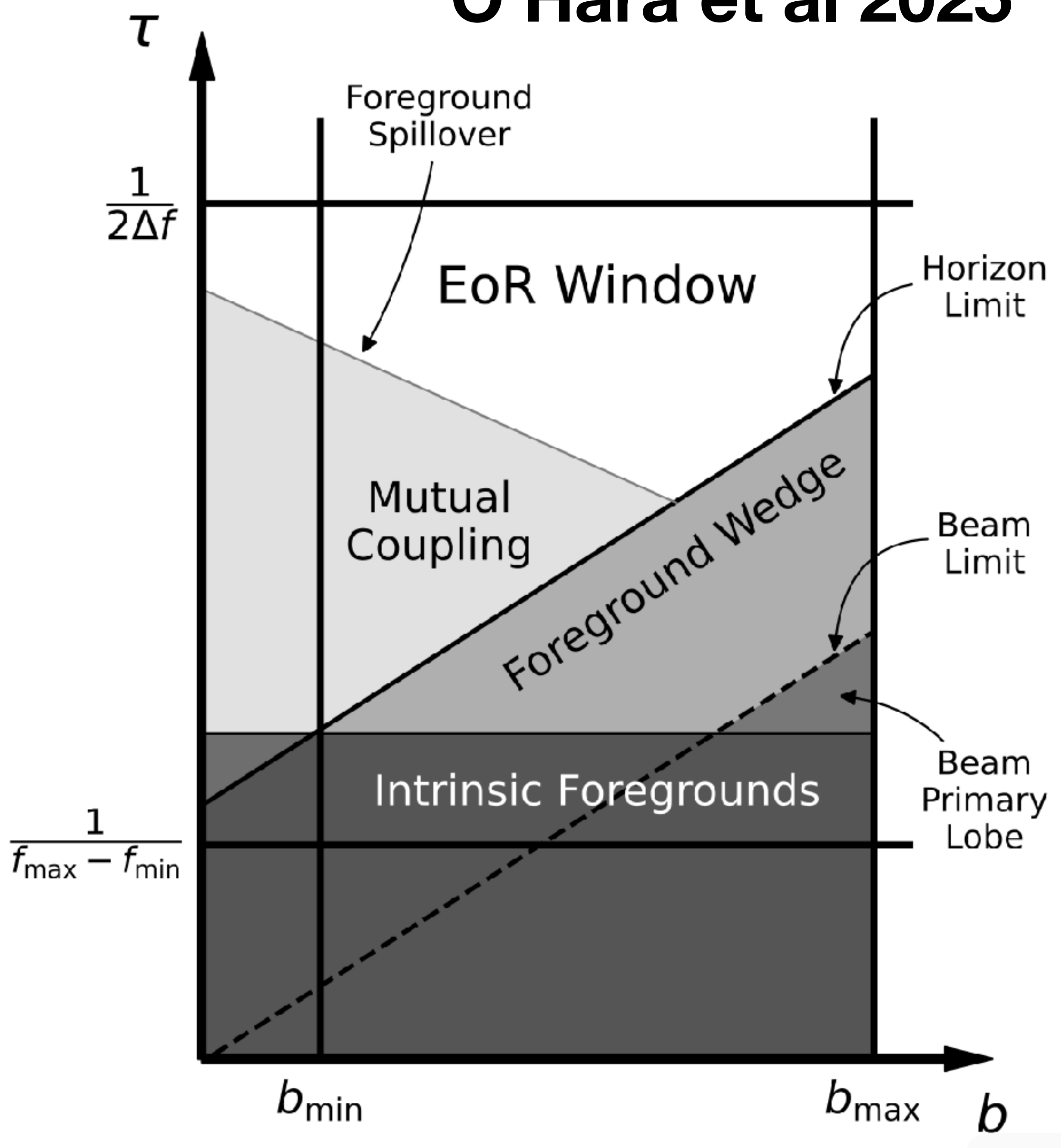


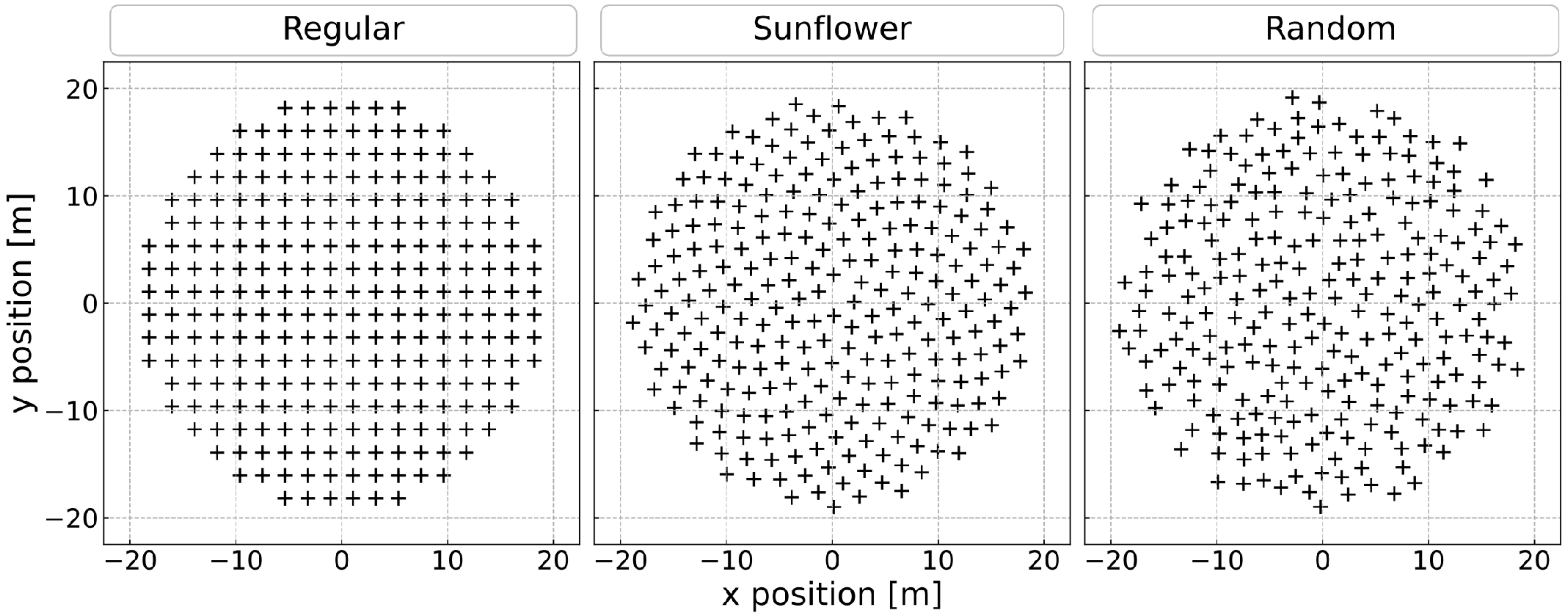
The SKA - Mutual Coupling

- Forward model mutual coupling with the foreground and 21-cm signal
- This will help clean data revealing the 21-cm signal
- Can use it to design array layouts the minimise the impact of mutual coupling while still achieving their science goals



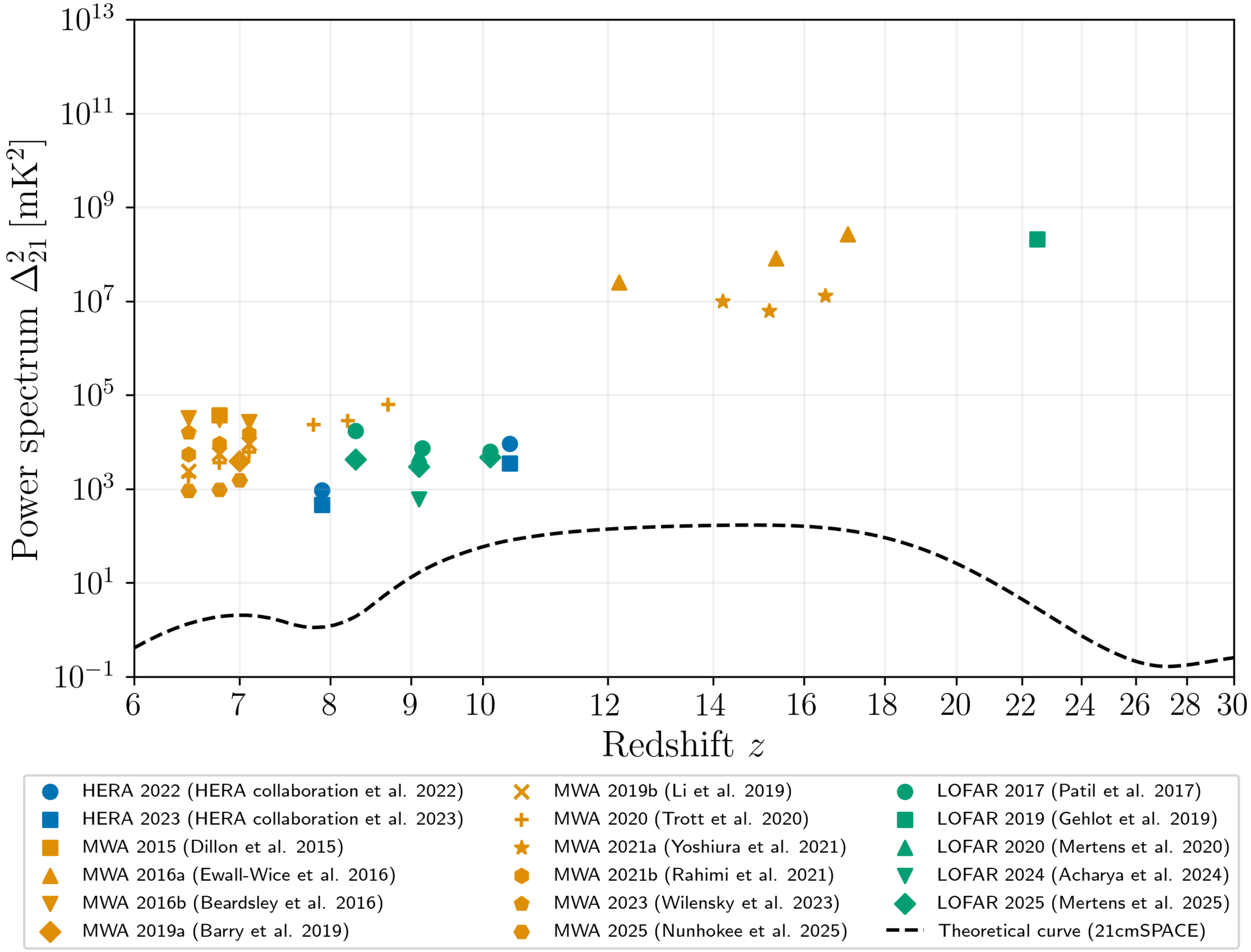
O’Hara et al 2025



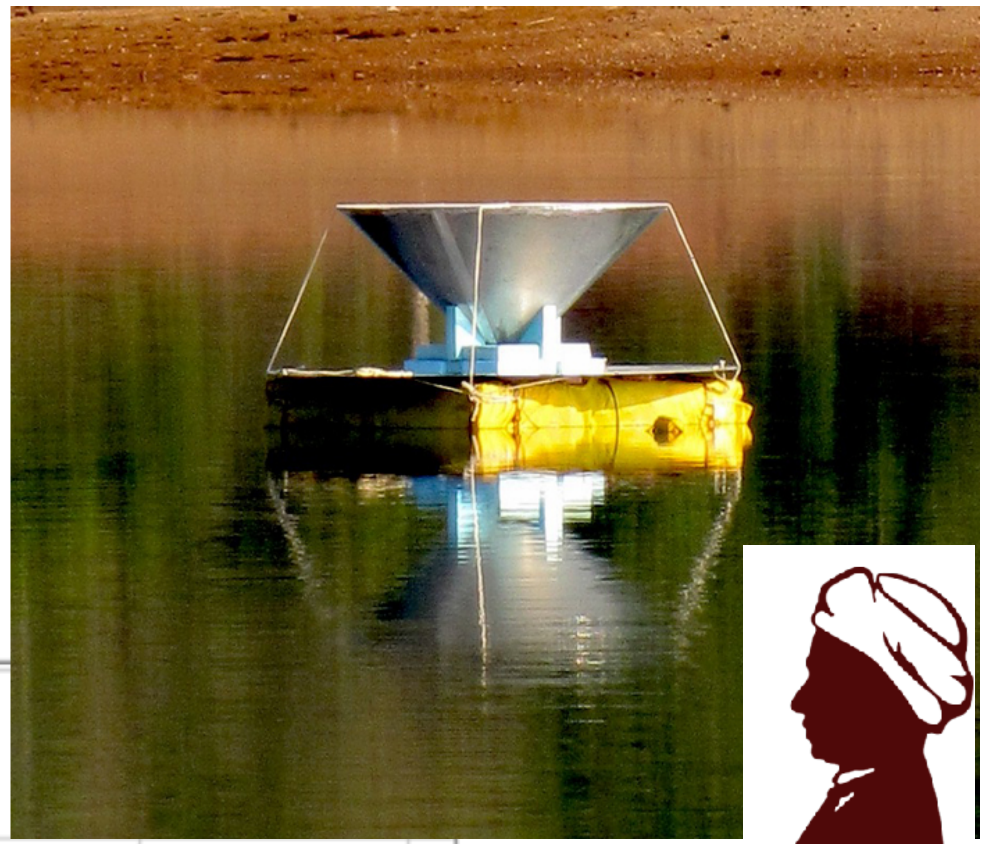


Constraining the physics of the early universe

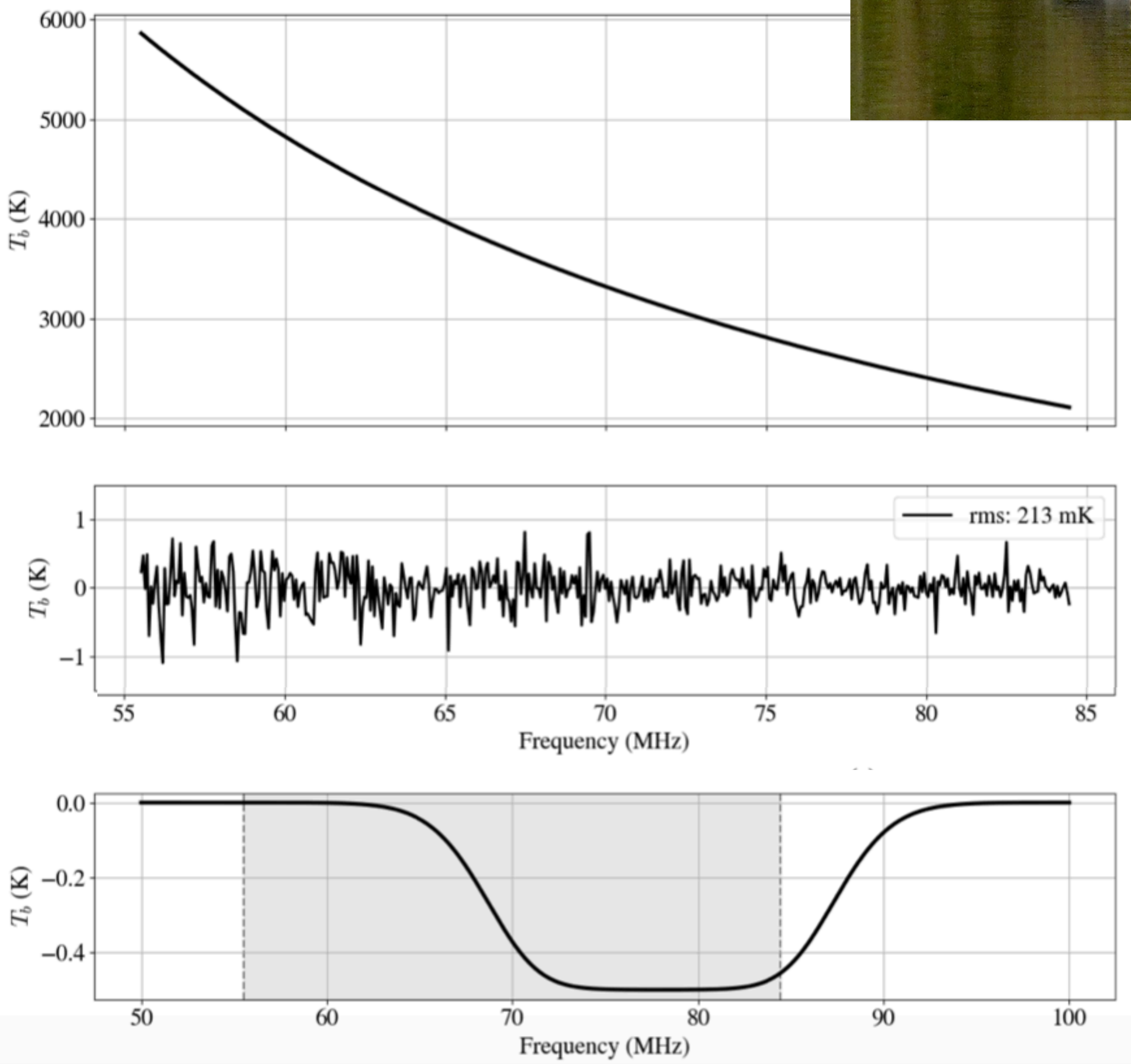
Power Spectrum Upper Limits



SARAS3

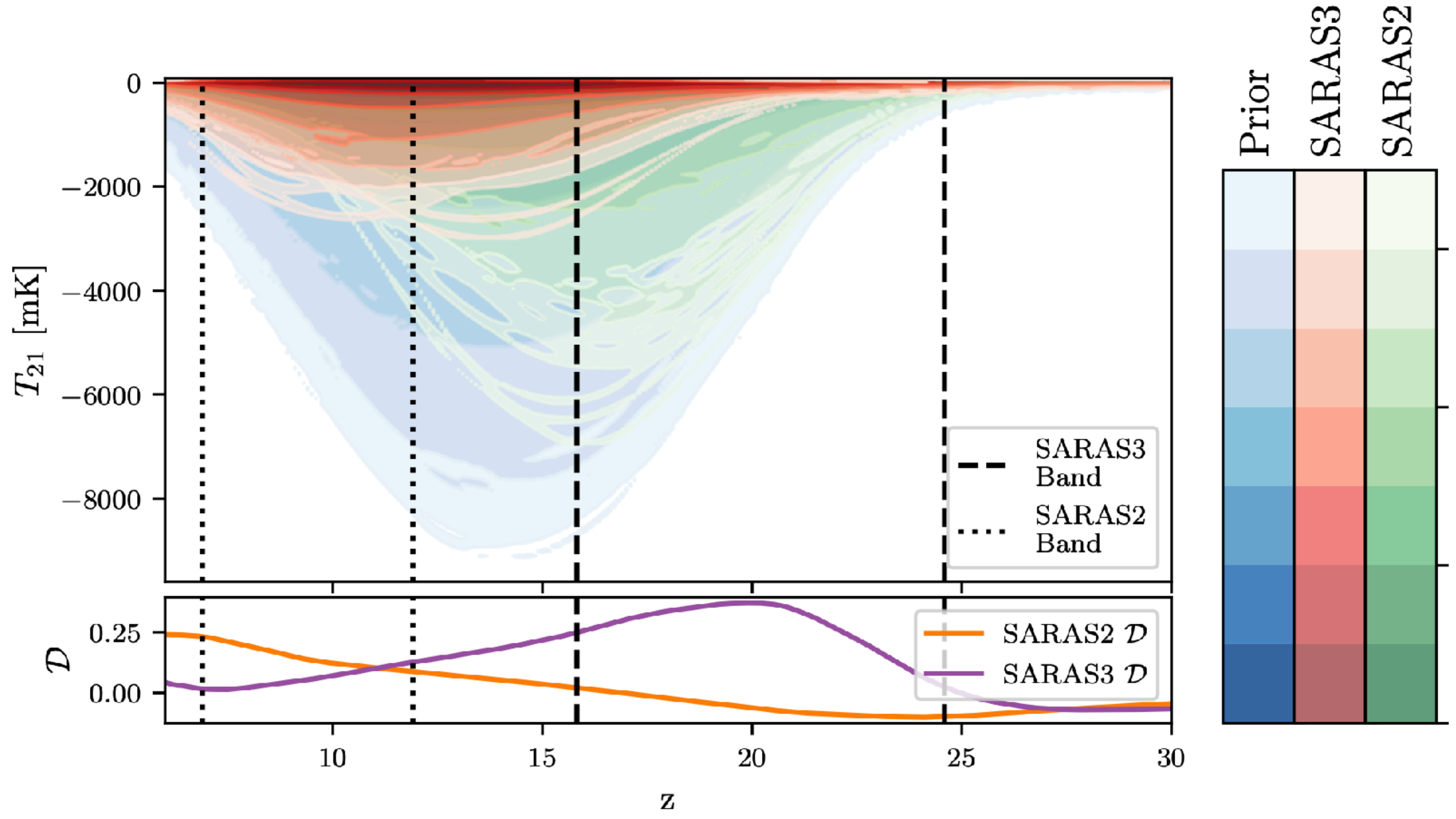


- SARAS3 recently disputed the EDGES detection at 95% confidence [Singh et al. 2021]
- Very different to the EDGES instrument
- No evidence for the EDGES signal in their data
- Use the data as an upper limit on the magnitude of the 21-cm signal after removing a model for the foregrounds



Constraining the properties of the infant universe

- Bevins et al. 2022 MNRAS - SARAS2 in a Bayesian framework
- Bevins et al. 2022 Nature Astronomy - Analysed SARAS3 data
- Placed constraints on the magnitude of the 21-cm signal
- Using emulators for inference on physical signals
- Setting the standard for inference in the field



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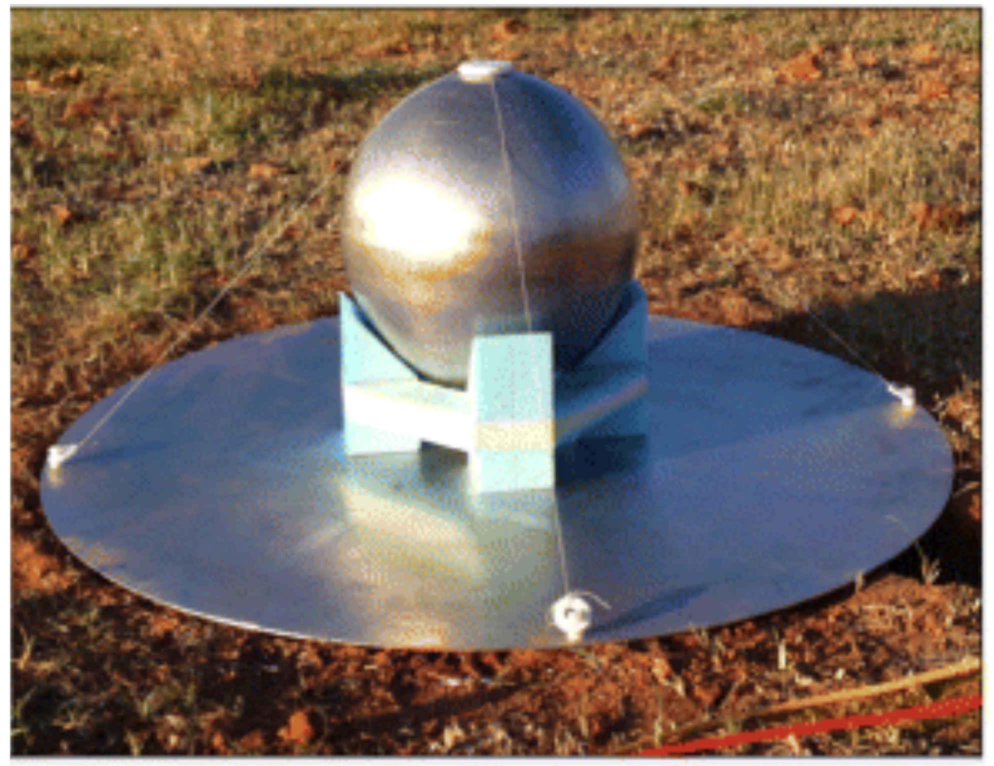
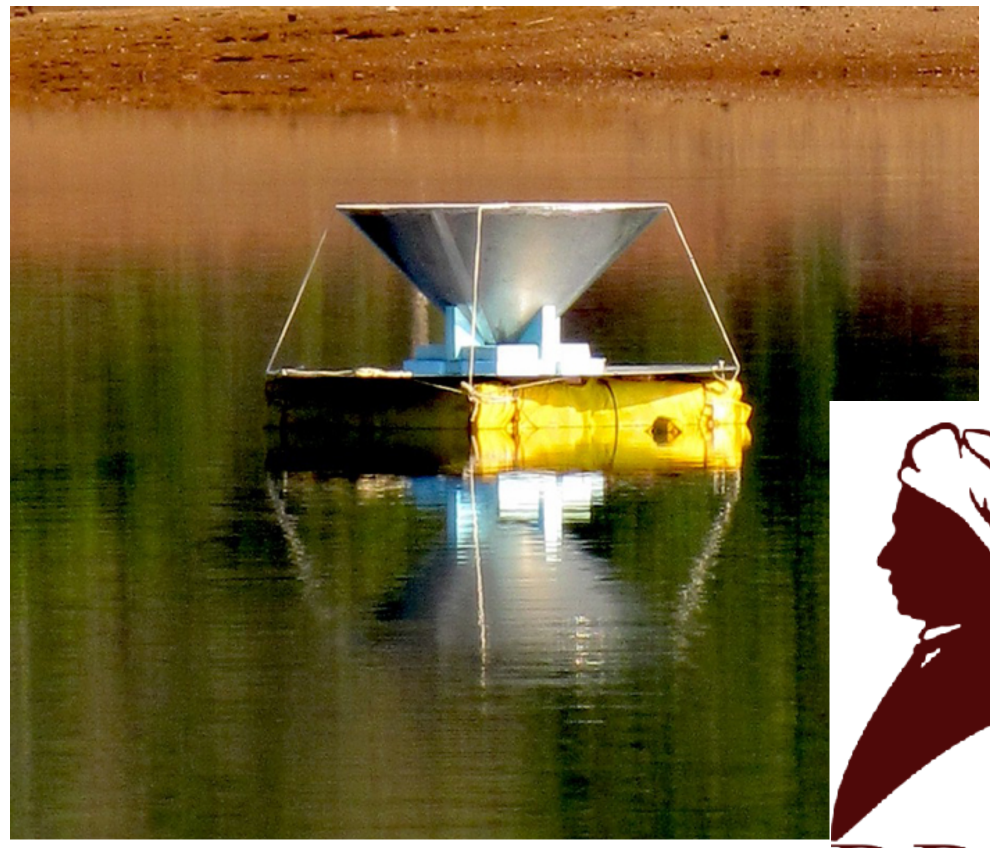
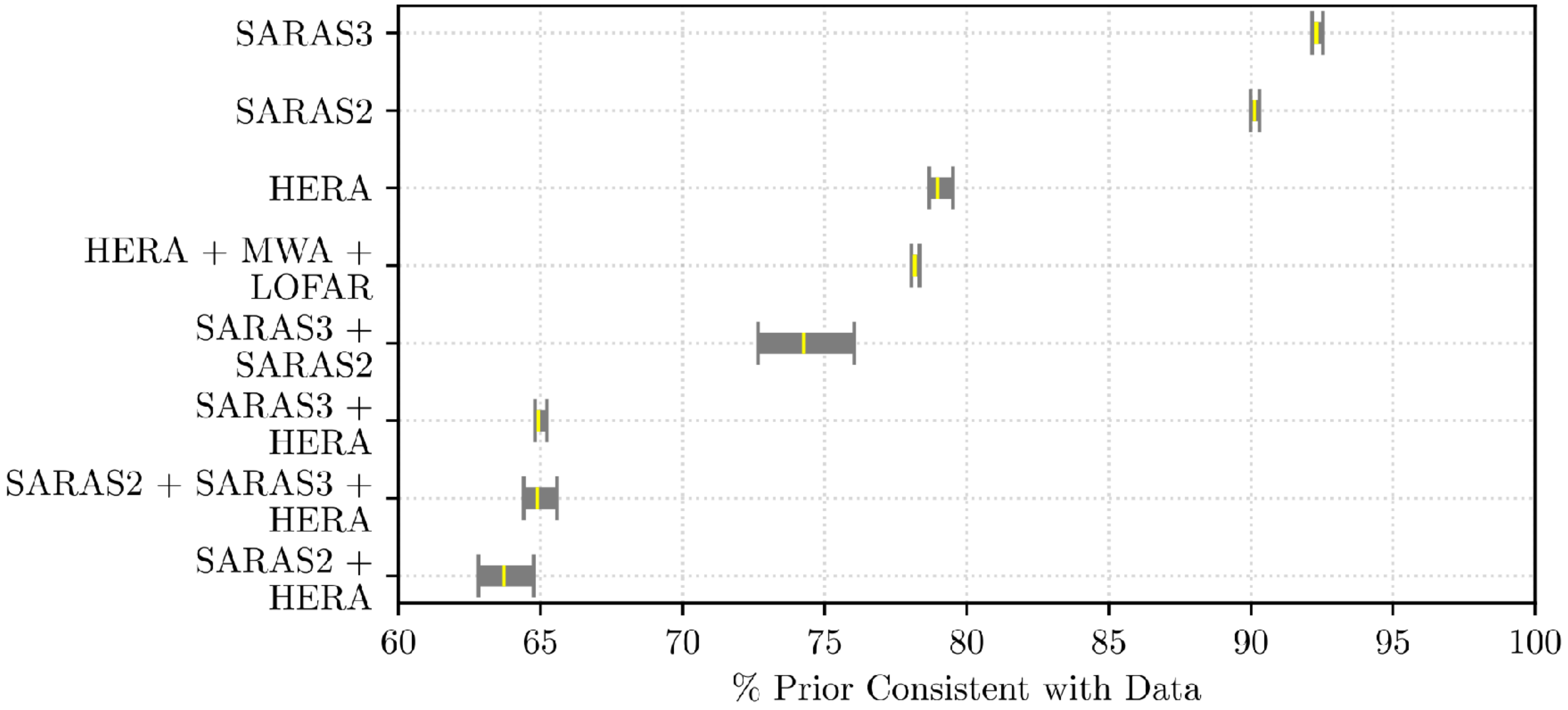




Constraining the properties of the infant universe

- Bevins et al 2024 MNRAS - jointly analysed SARAS2, SARAS3, HERA, LOFAR and MWA data
- First joint analysis of sky-averaged 21-cm experiments and power spectrum observations
- Constrained contribution of high redshift galaxies to the radio background and X-ray heating



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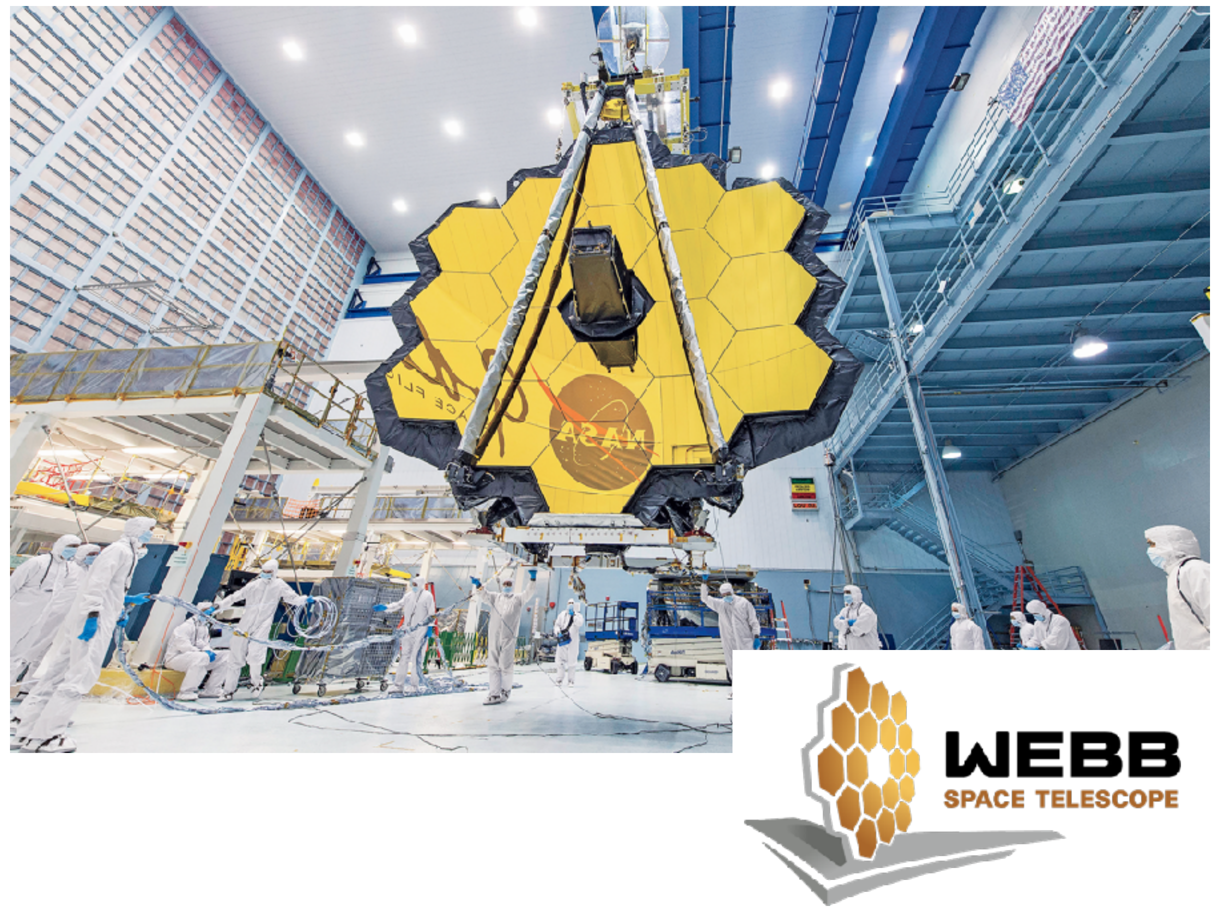
MWA MURCHISON WIDEFIELD ARRAY

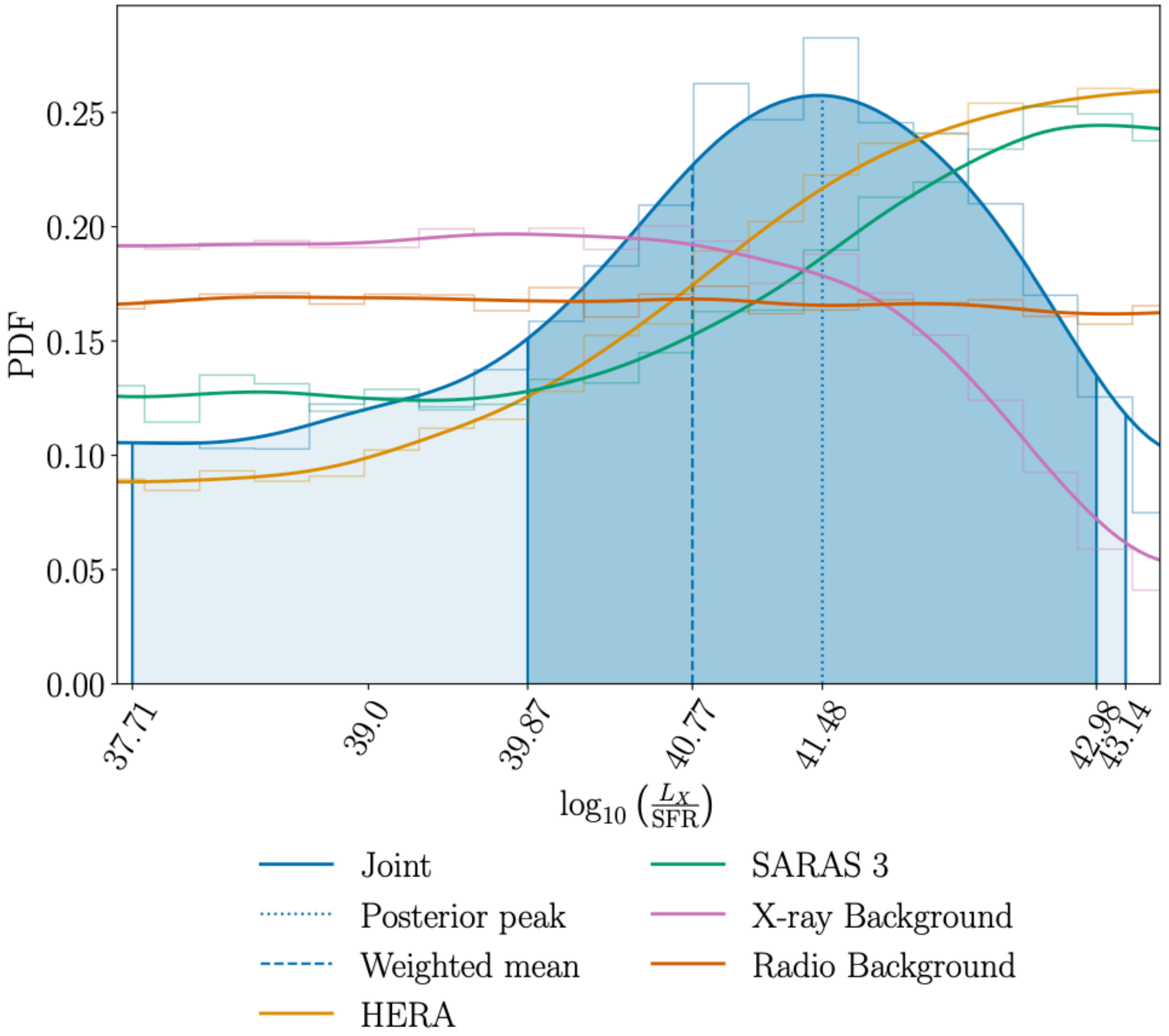
LOFAR

Constraining the properties of the infant universe



- Pochinda, Gessey-Jones, Bevins et al. 2024 MNRAS - X-ray and Radio Background observations

- Dhandha, Gessey-Jones, Bevins et al. 2025 MNRAS - UVLF observations from JWST

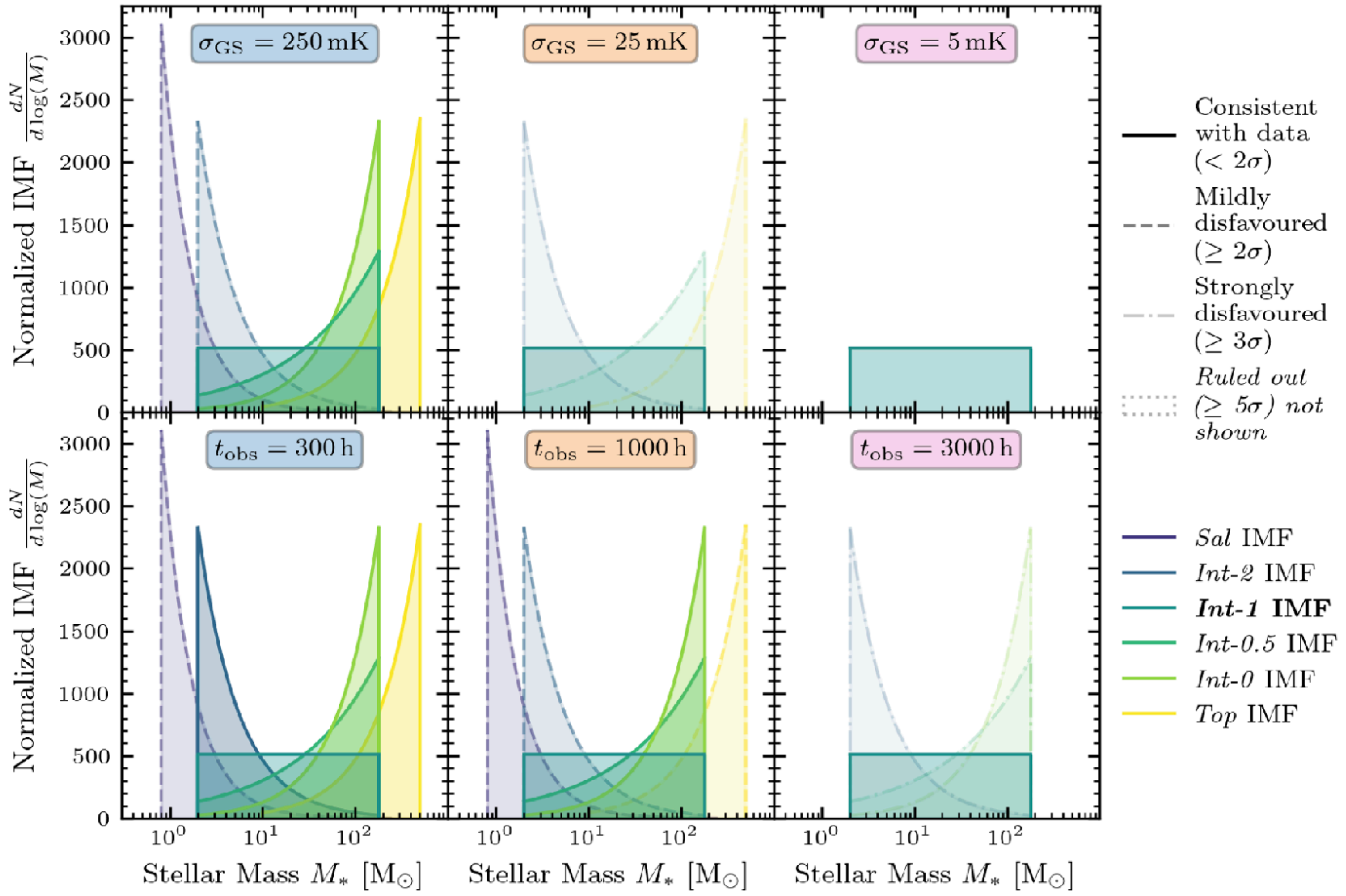


Constraining the properties of the infant universe

- Gessey-Jones, Pochinda, Bevins et al. 2024 MNRAS - Cosmic strings as a source of excess radio background
- Sims, Bevins et al. 2025 MNRAS - Lyman line and CMB observables
- Gessey-Jones, Sartorio, Bevins et al. 2025 Nature Astronomy - Forecast constraints of REACH and the SKA on the Population III IMF

REACH

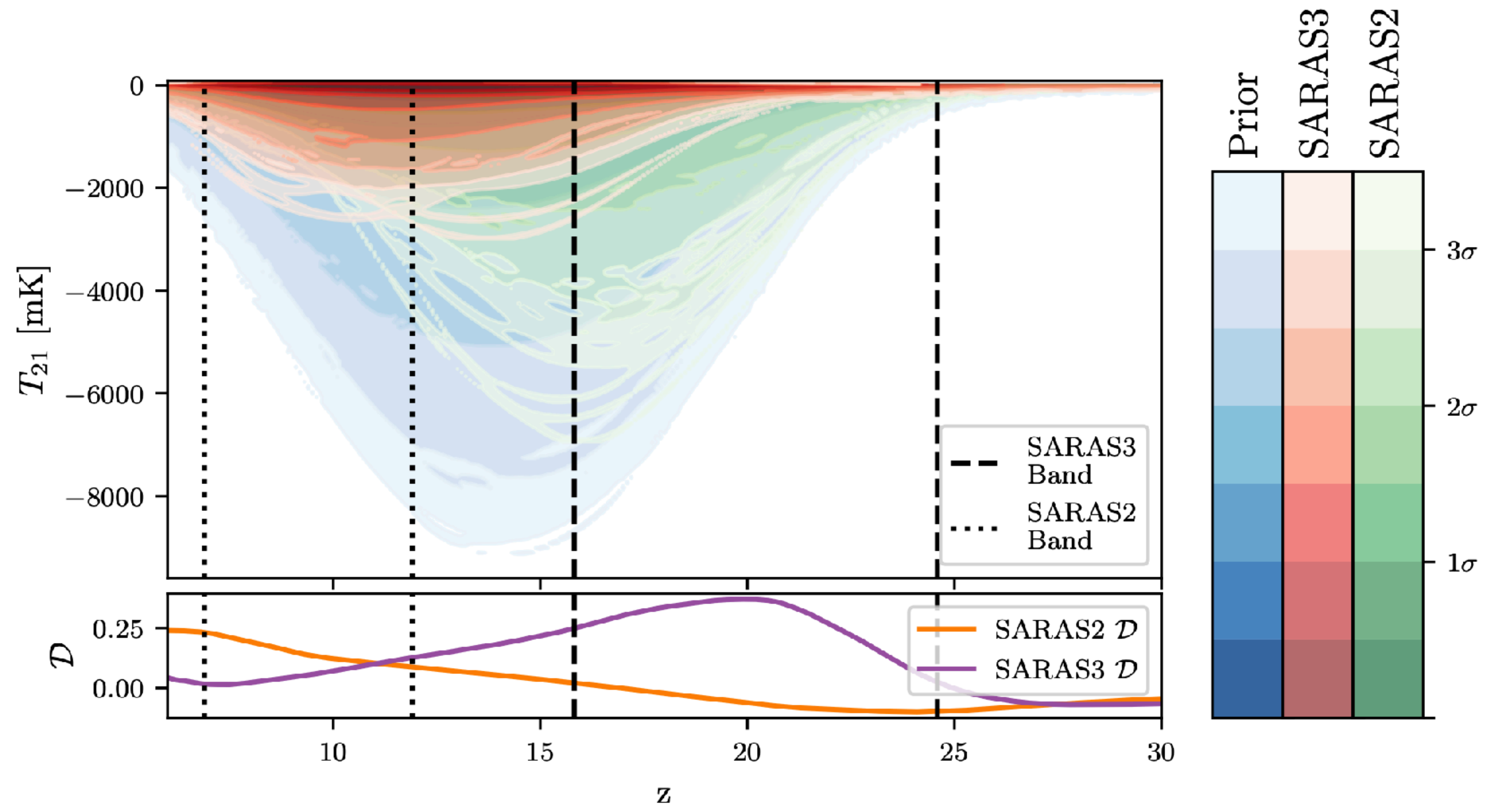
SKAO

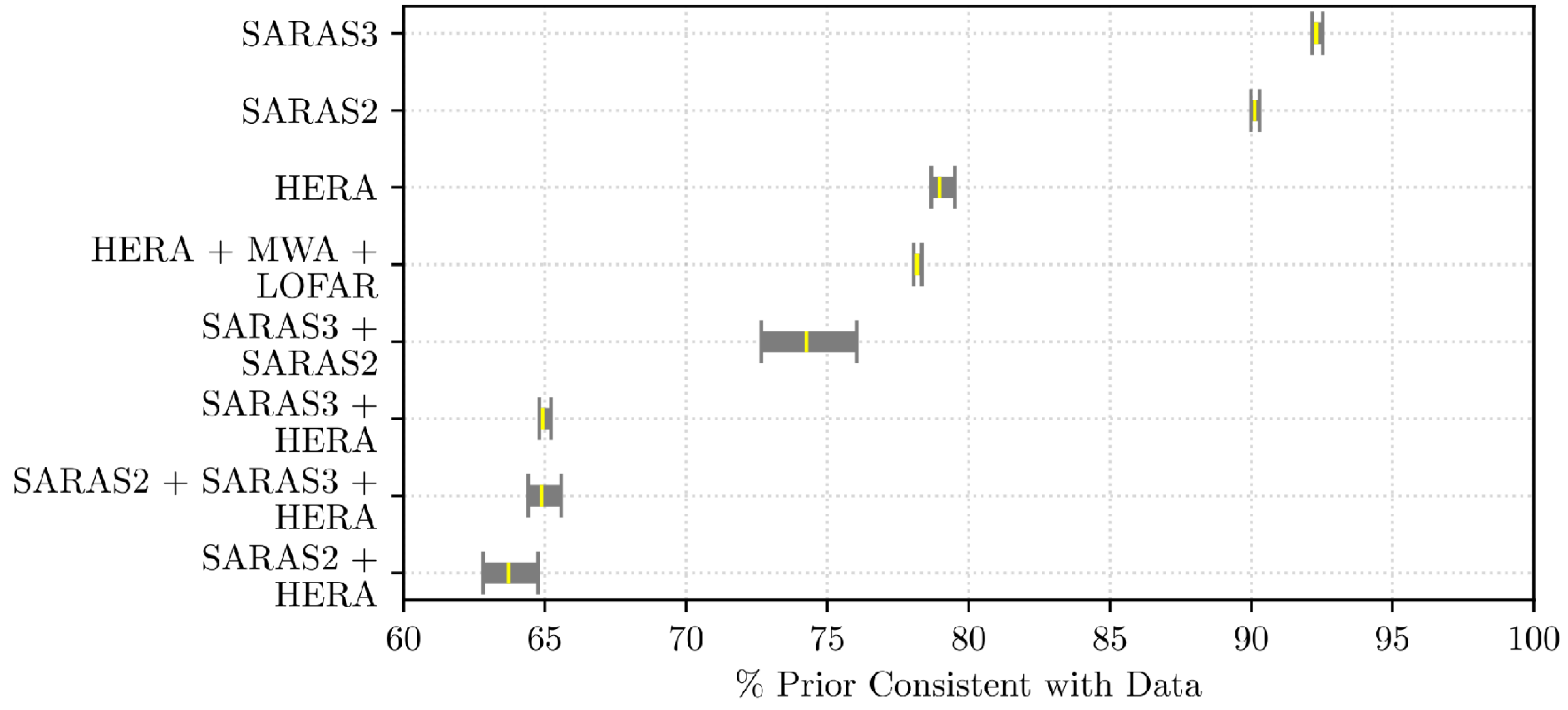


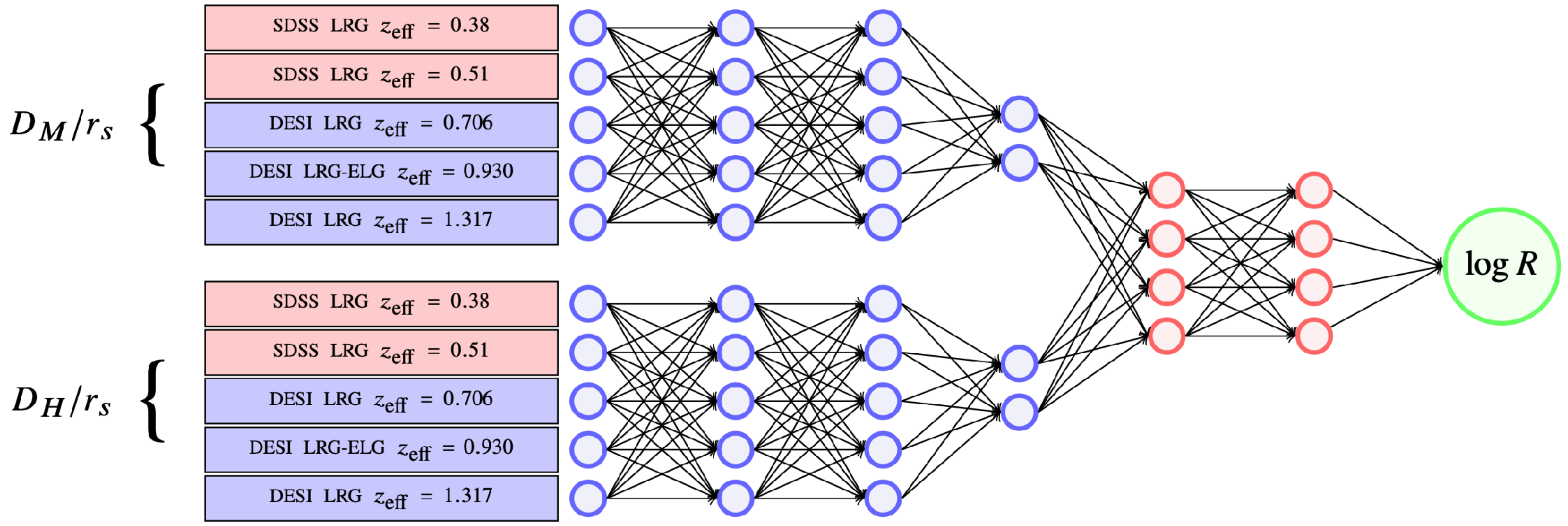
Summary and Conclusions

My Research

- My research connects theory, instrumentation and data analysis to extract scientific value from 21-cm observations
- Put some of the first constraints on the properties of early galaxies with the SARAS3 data
- Performed the first joint analysis between power spectrum and sky-averaged data
- Defined the state of the art machine learning enhanced inference pipelines that are now widely used in the field

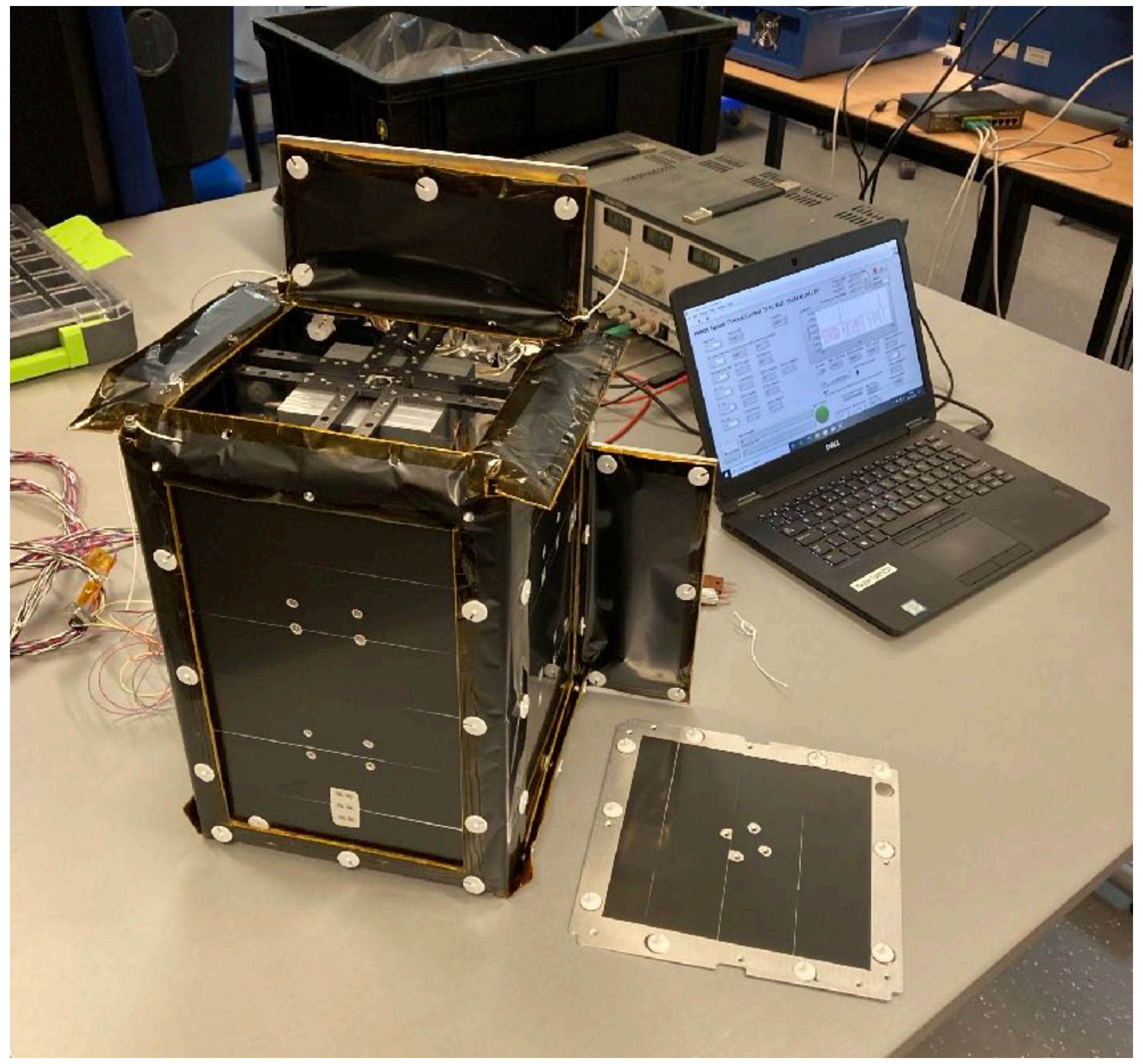


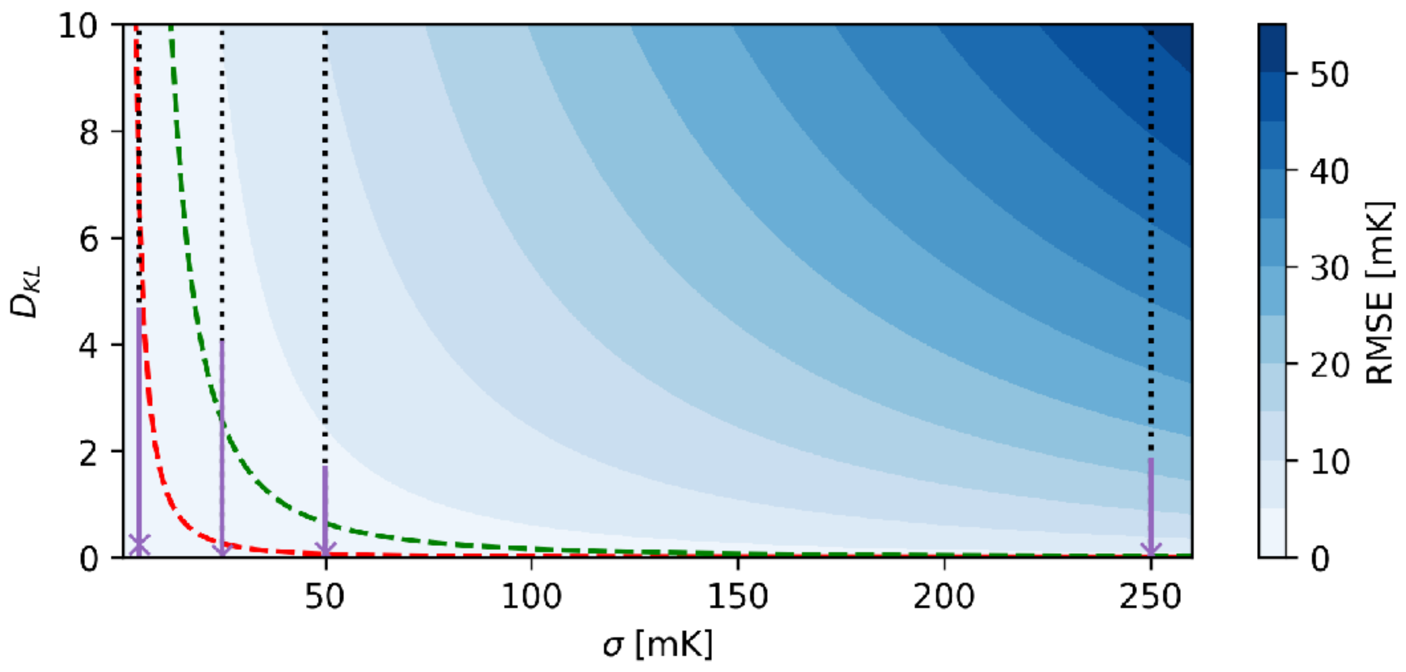


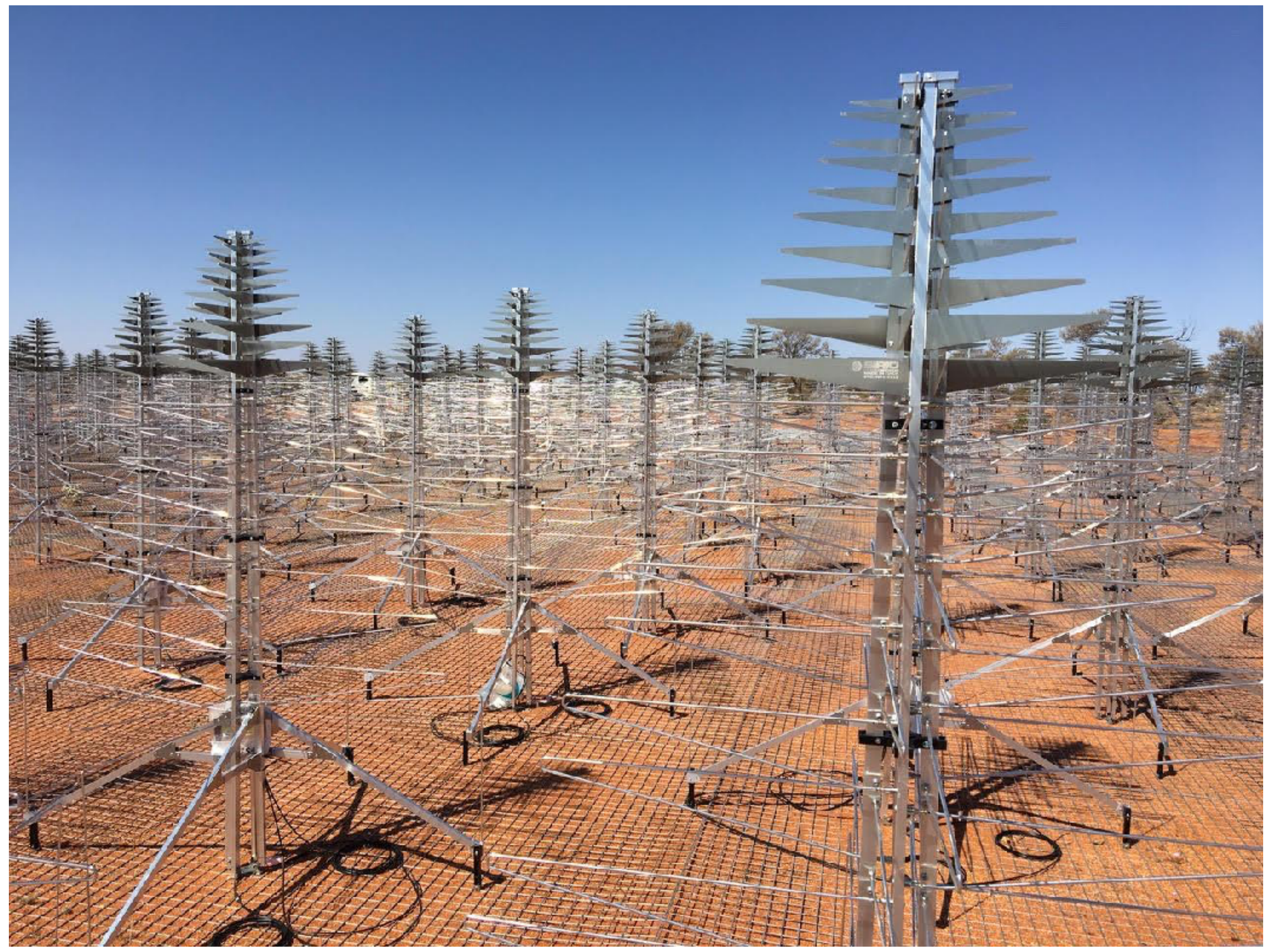


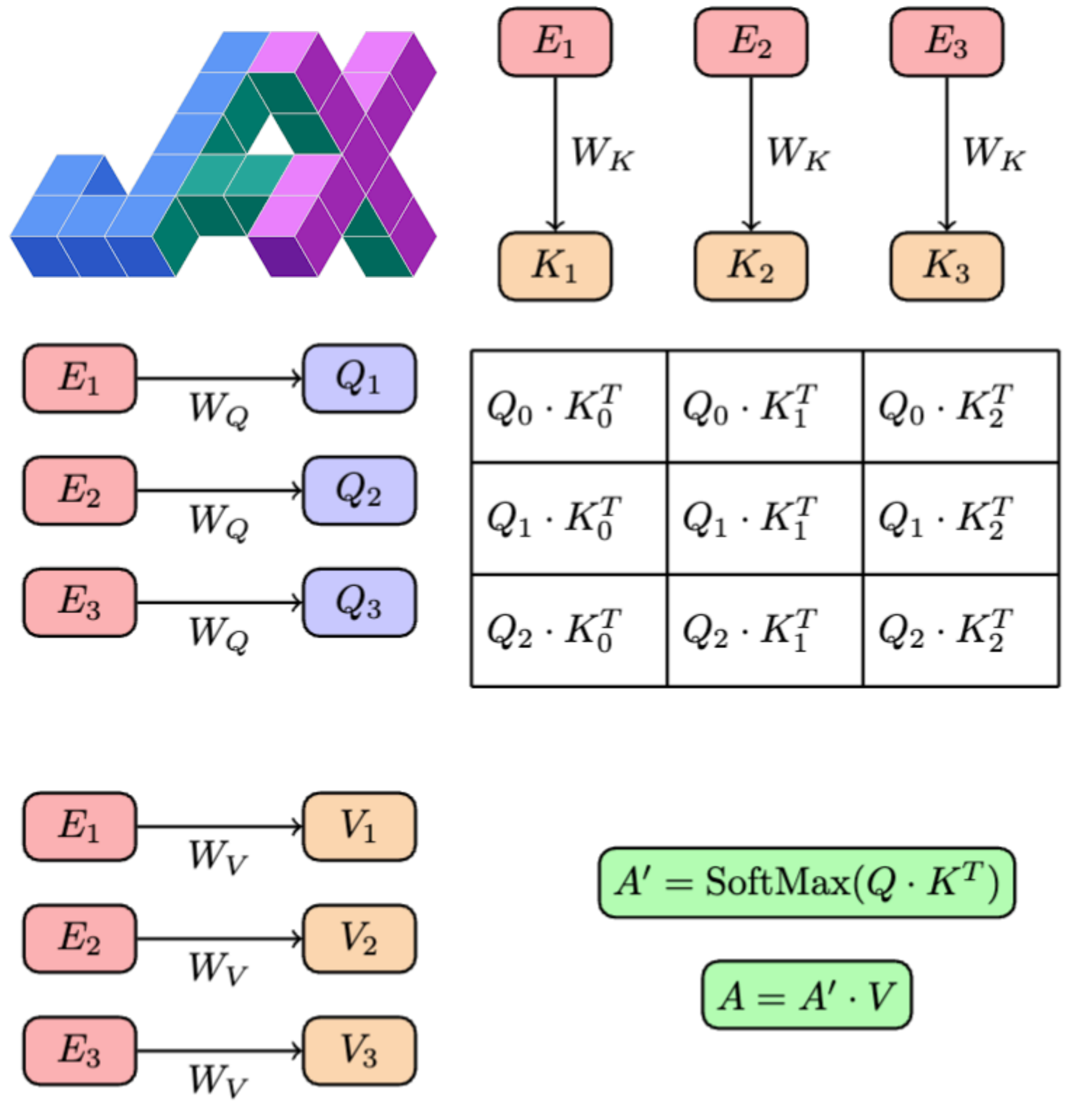
The future

- Addressing the physical modelling of antenna beam patterns in 21-cm Cosmology
- Building machine learning tools to model instrumental effects like mutual coupling and help calibrate REACH
- Building the next generation of neural network emulators for cosmology and astrophysics
- Working on forecasts for future instruments including CosmoCube, CHIC and the SKA

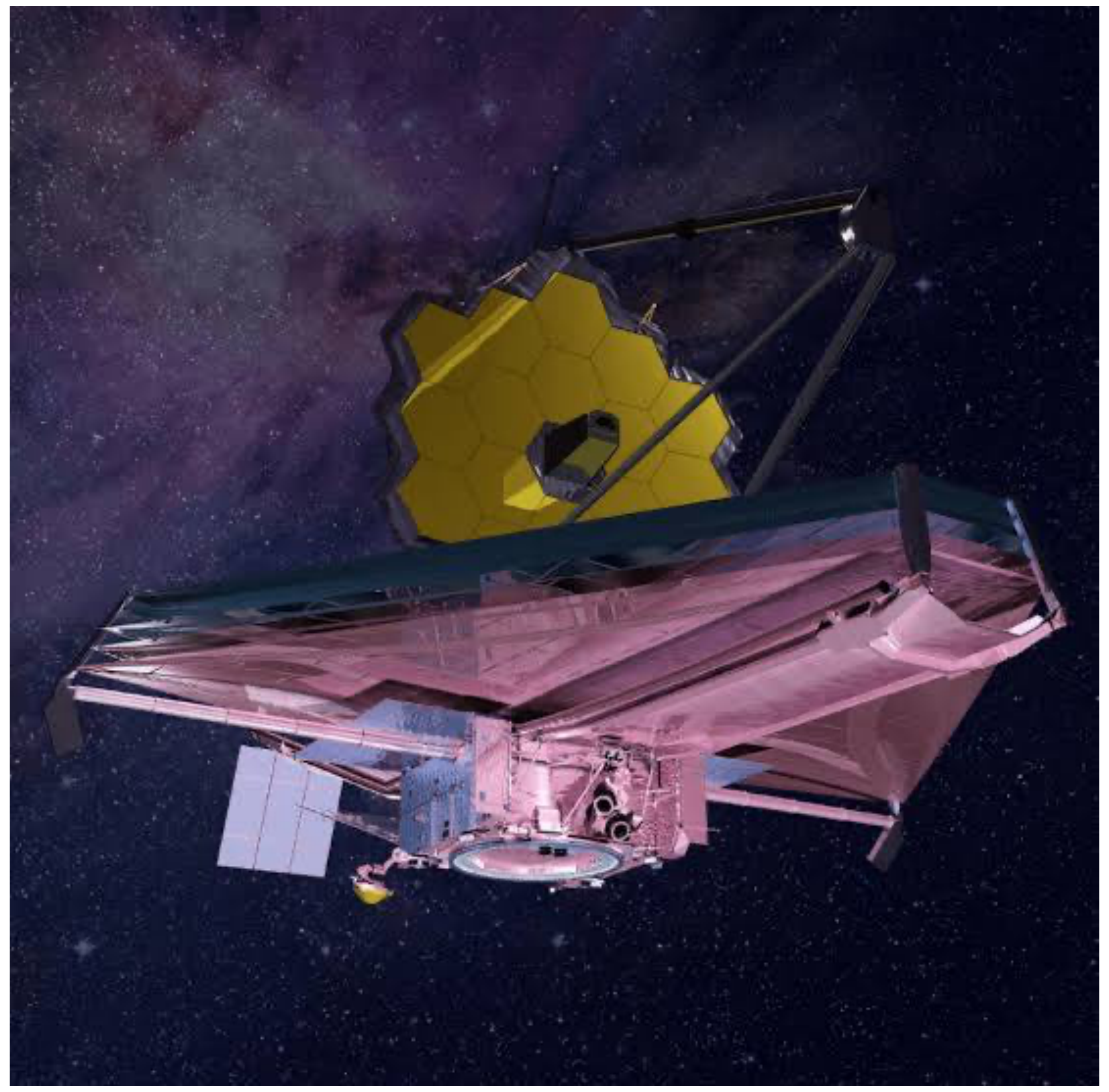


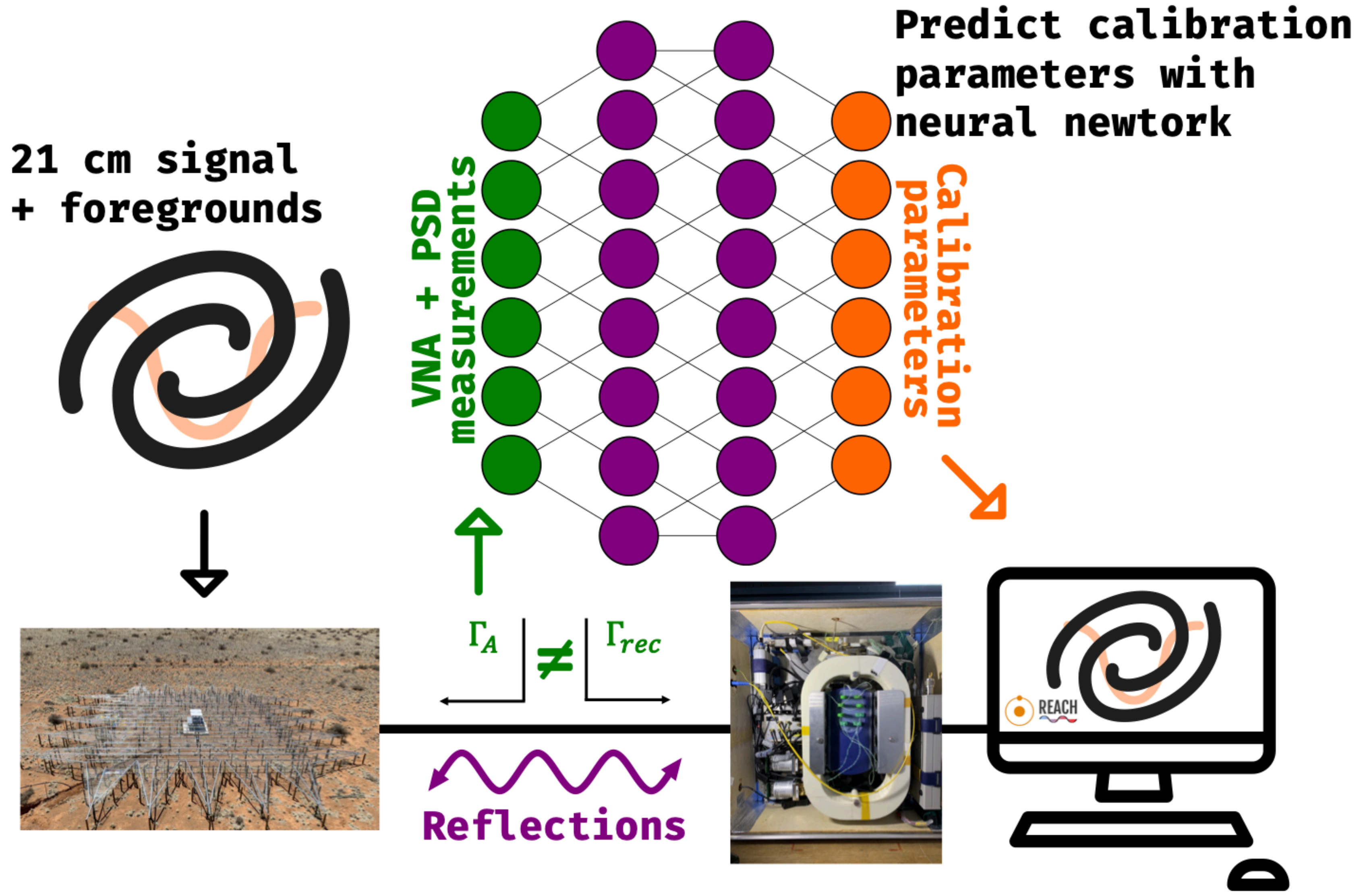


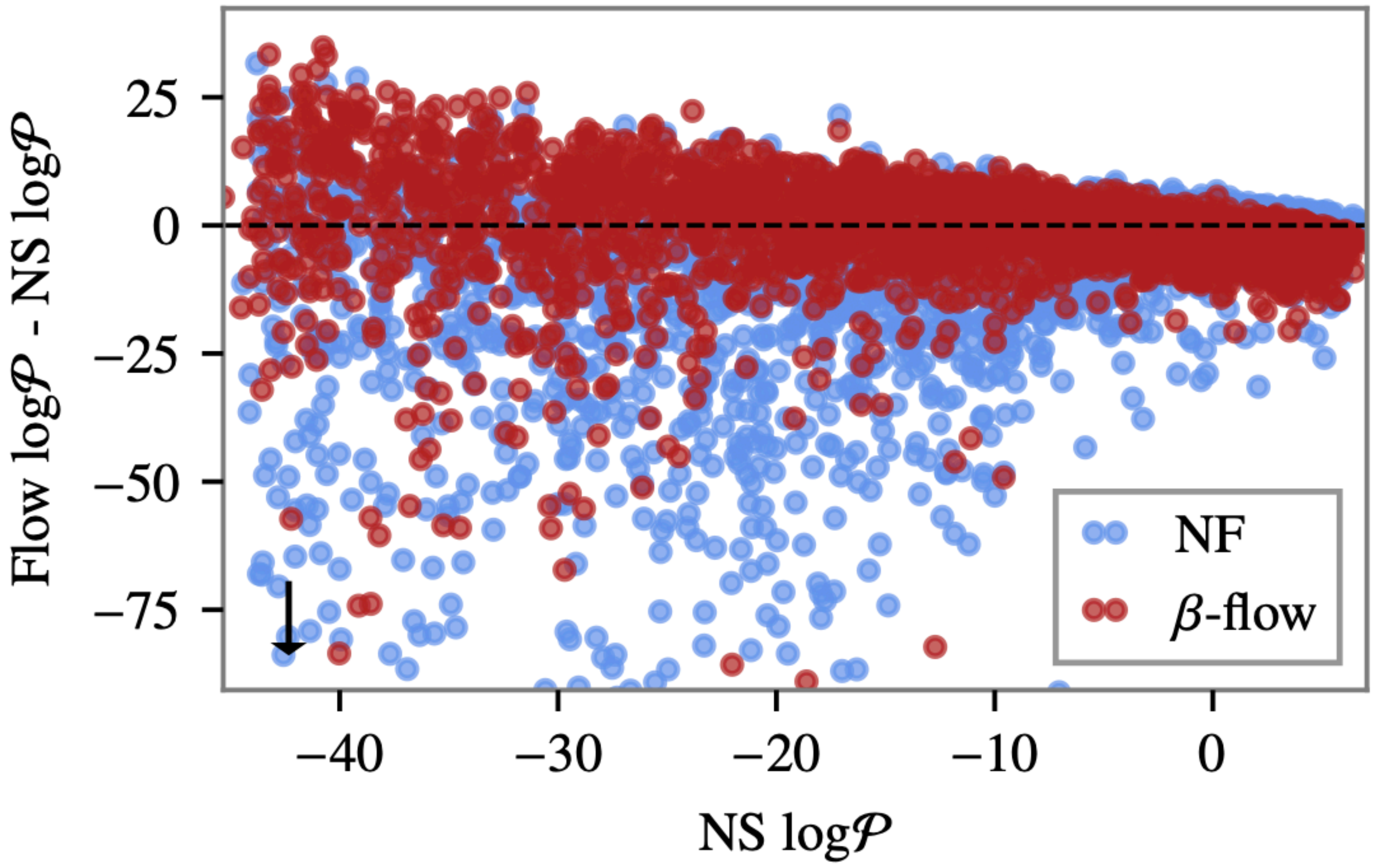


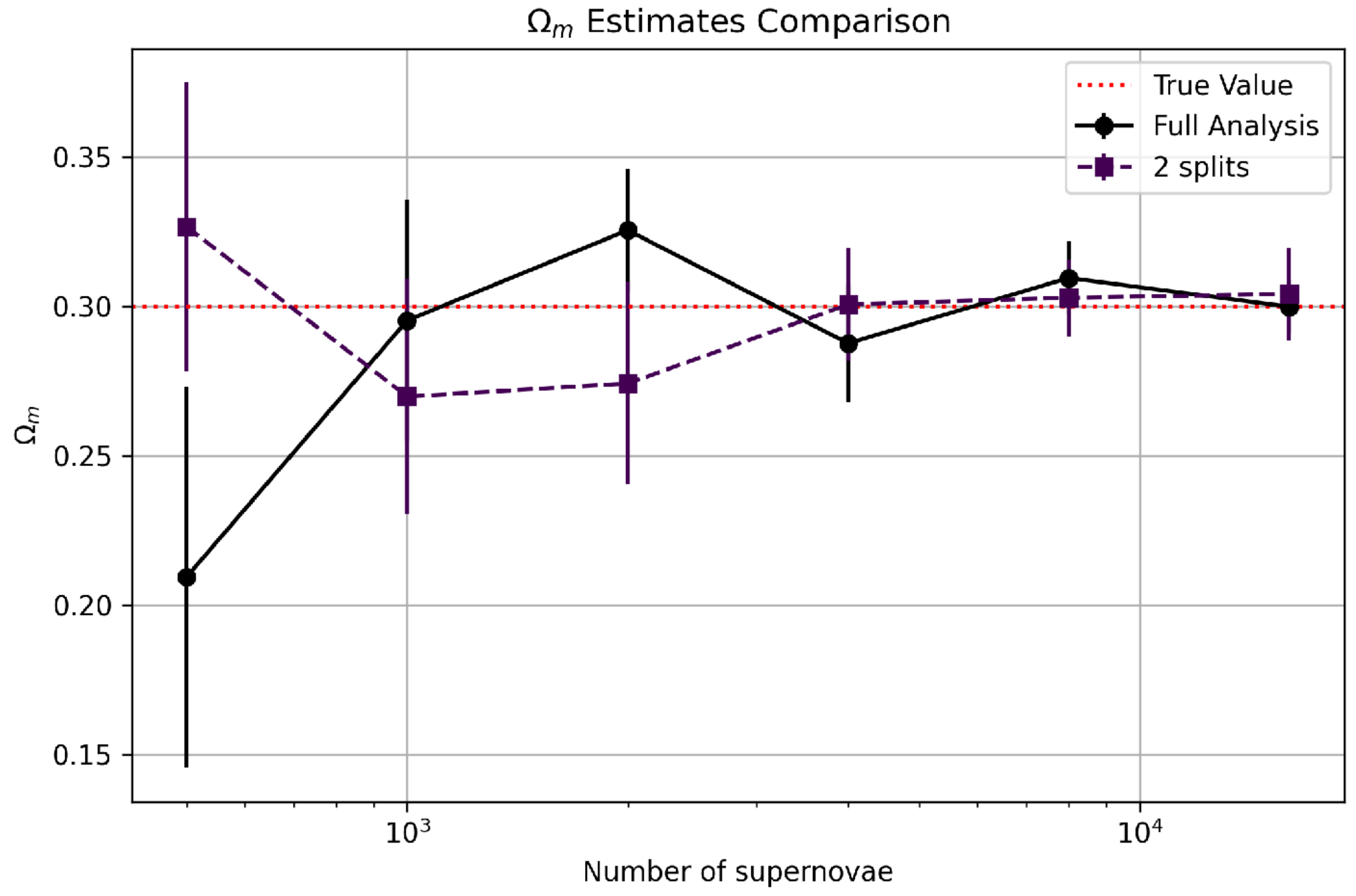


What did I not cover?





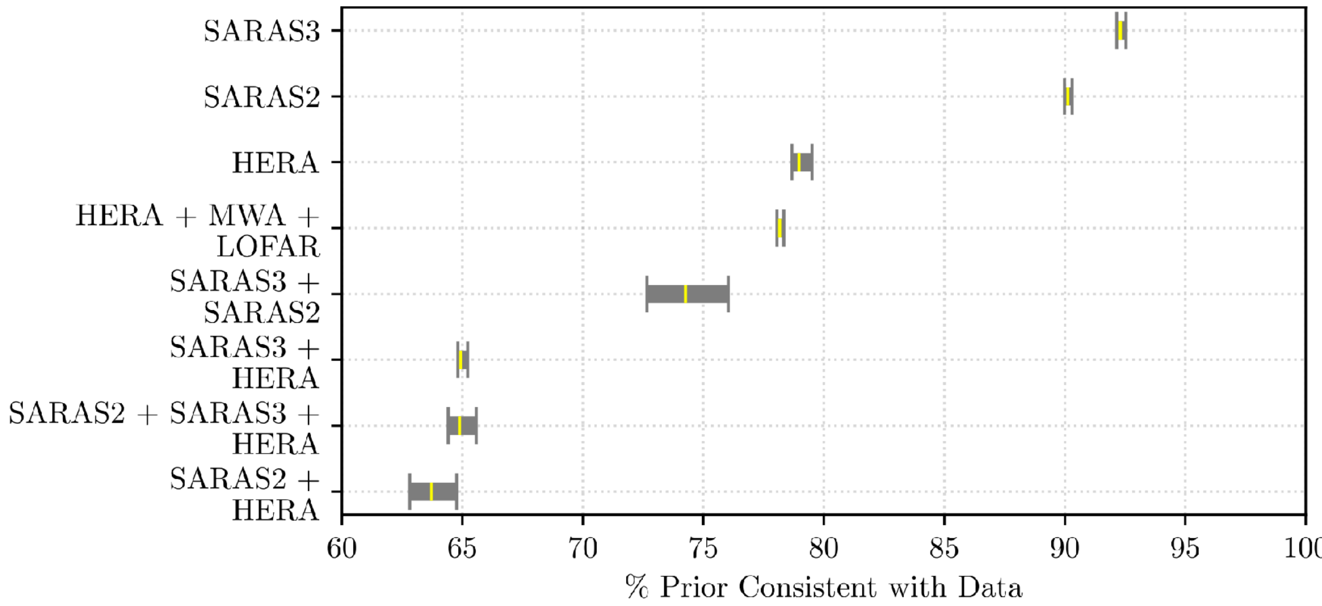




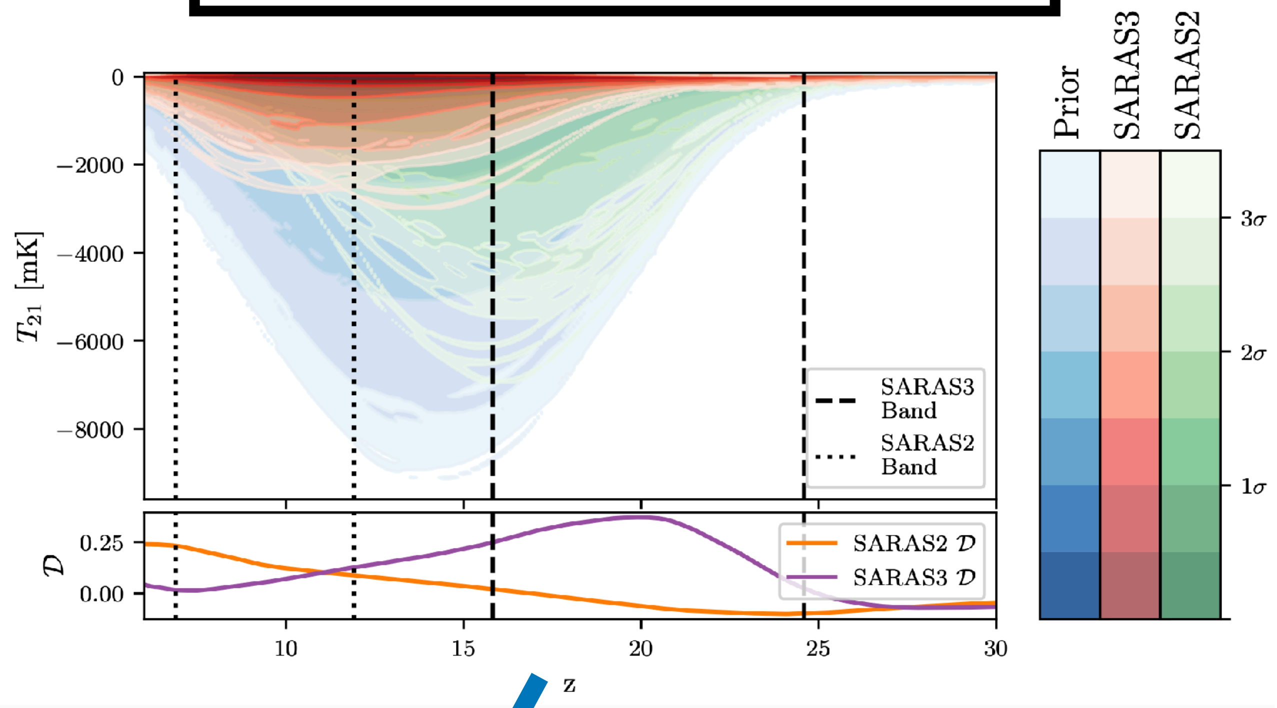
The Pillars of Modern Cosmology

Instrumentation

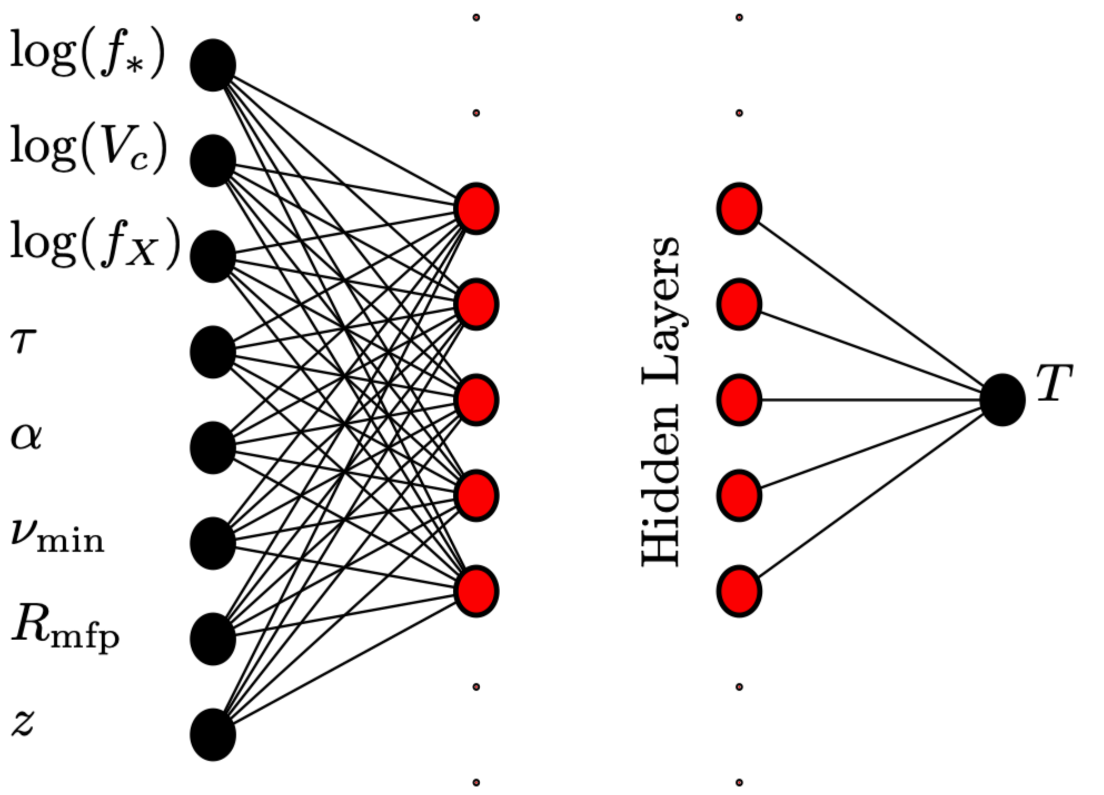
Data Analysis



Theory



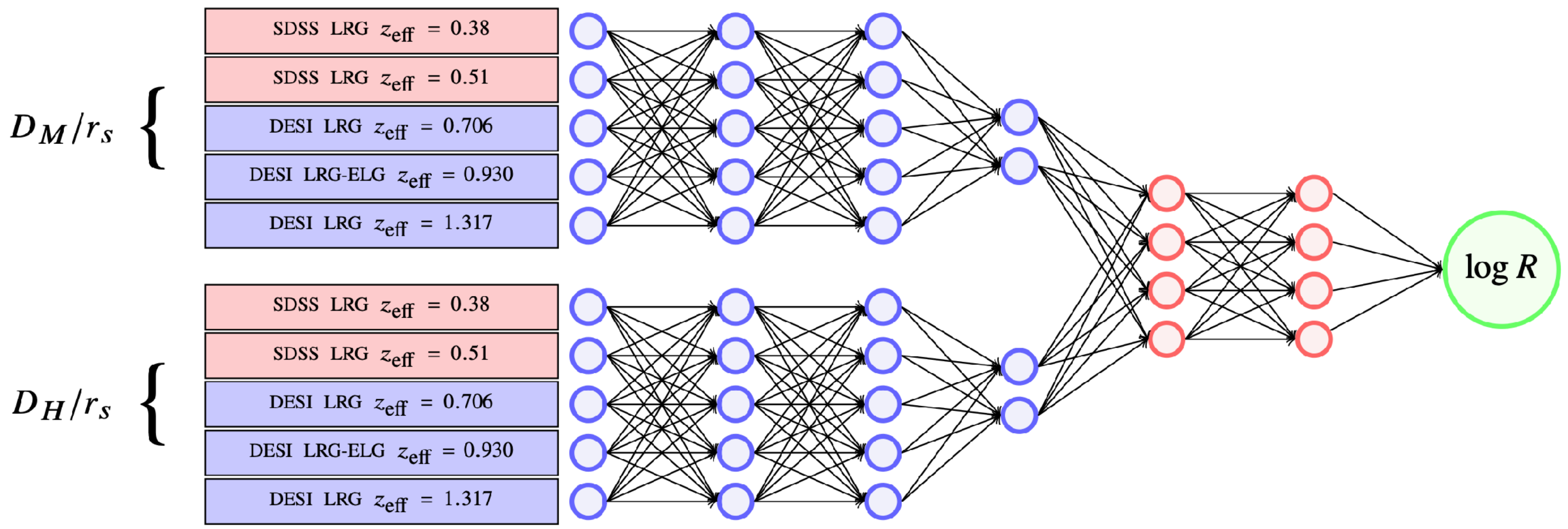
Machine Learning

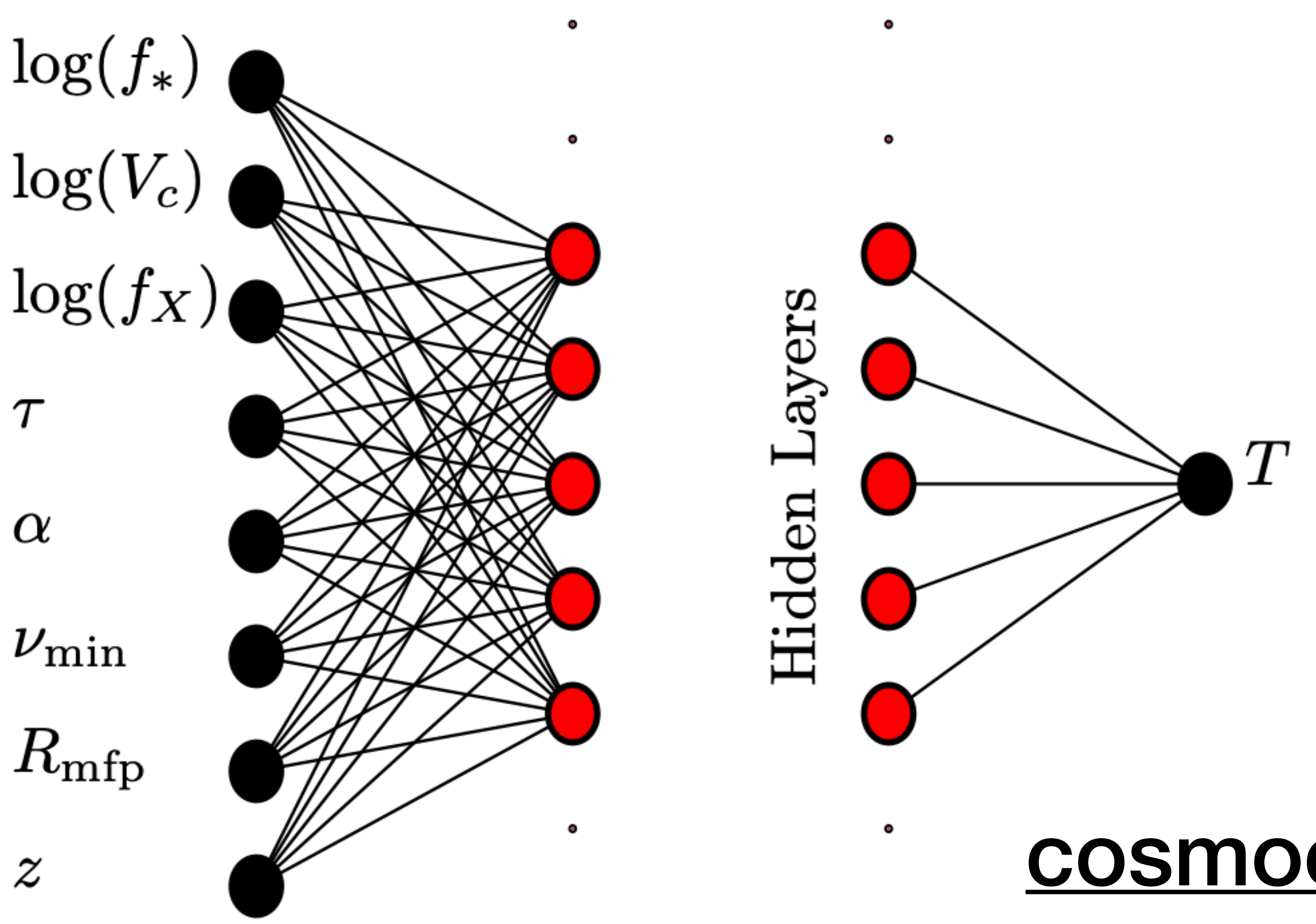


SKAO

Learning the infant universe

- 21-cm Cosmology has the potential to unlock a previously unseen epoch in the Universe’s history
- My research is pioneering applications of machine learning to 21-cm cosmology and beyond
- Machine learning offers a powerful, expressive and computationally efficient solution for various forward modelling problems
- Demonstrated the power of synergetic analysis and led the way for joint analysis in the field of 21-cm Cosmology



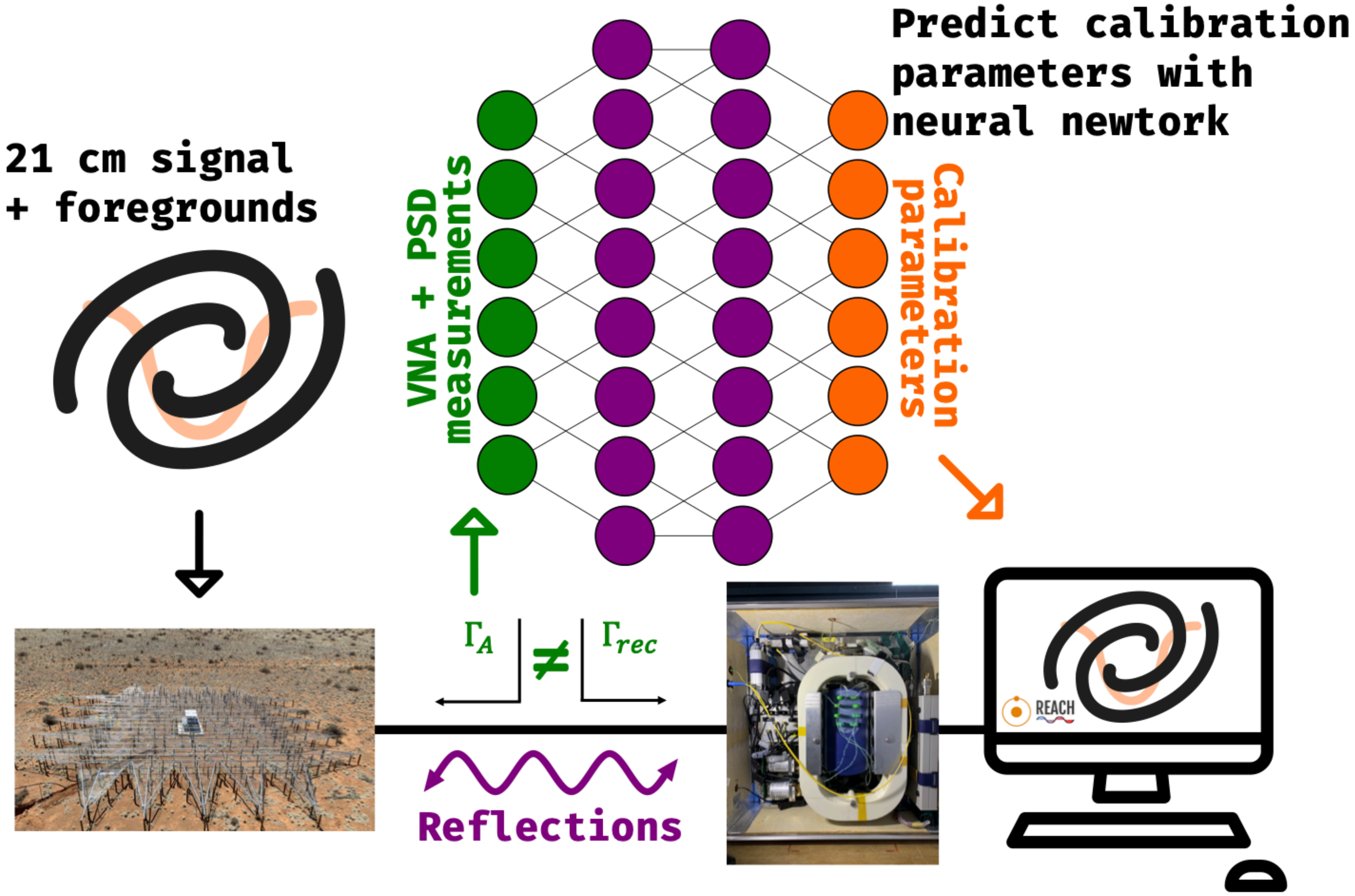


cosmocube.net
reachtelescope.org
harrybevins.co.uk
github.com/htjb

Additional Slides

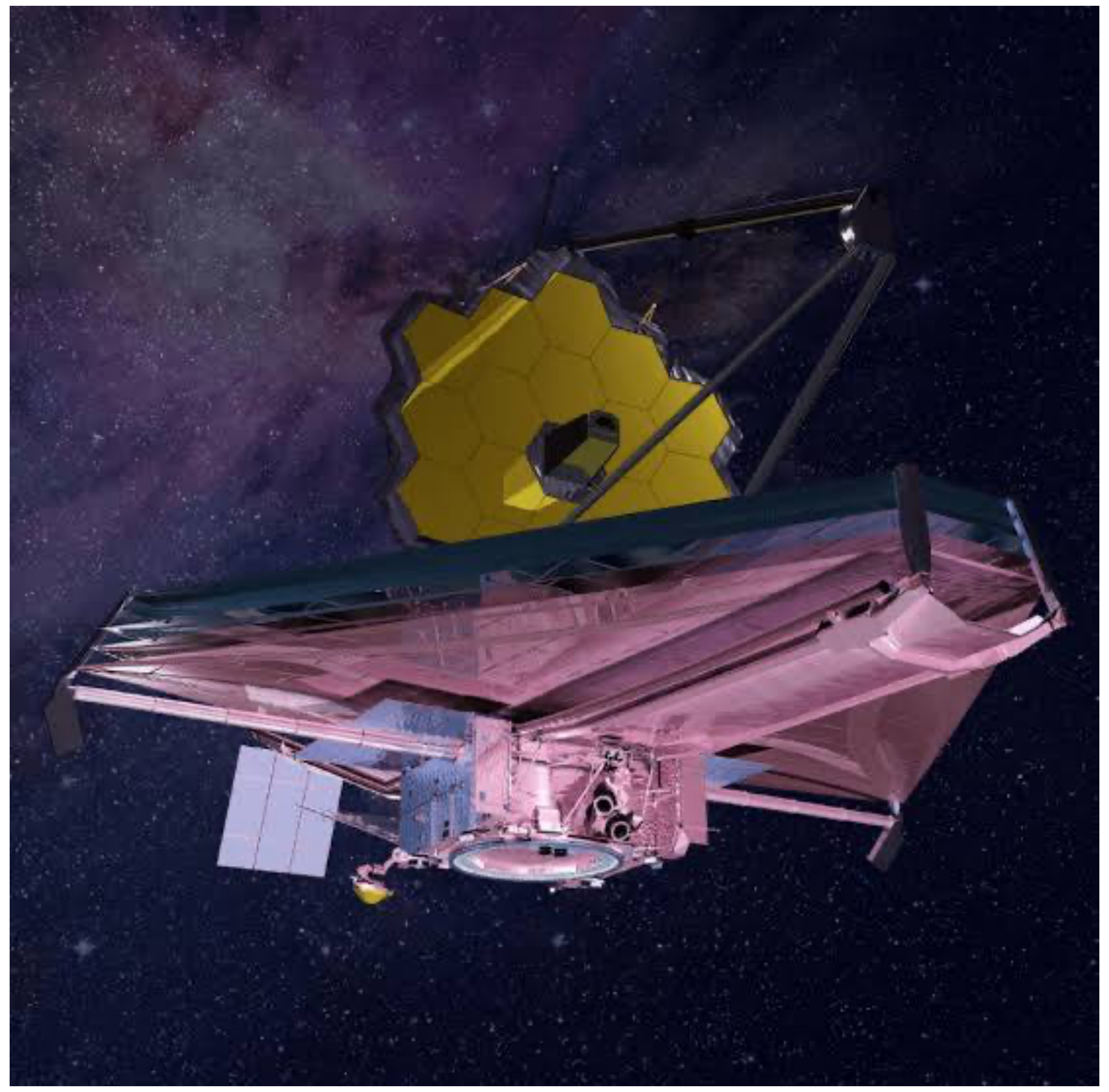
Calibrating REACH with Machine Learning

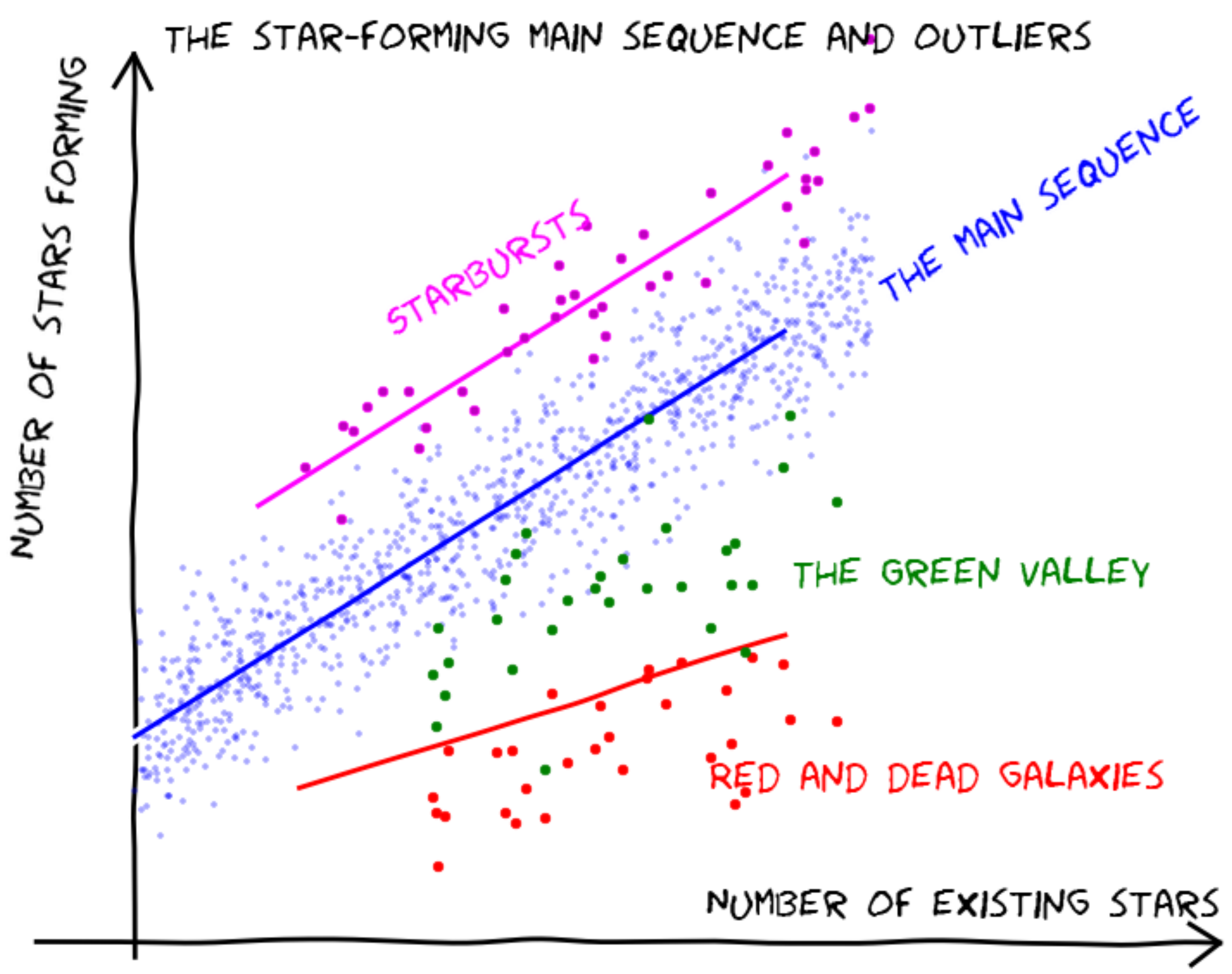
- I pushed for the application of machine learning to calibration of REACH
- Currently supervising a PhD student Sam Leeney working on this
- Correcting for electronics in the receiver chain
- Use the observations of internal references as training data to learn the properties of the system
- Compliments more traditional approaches

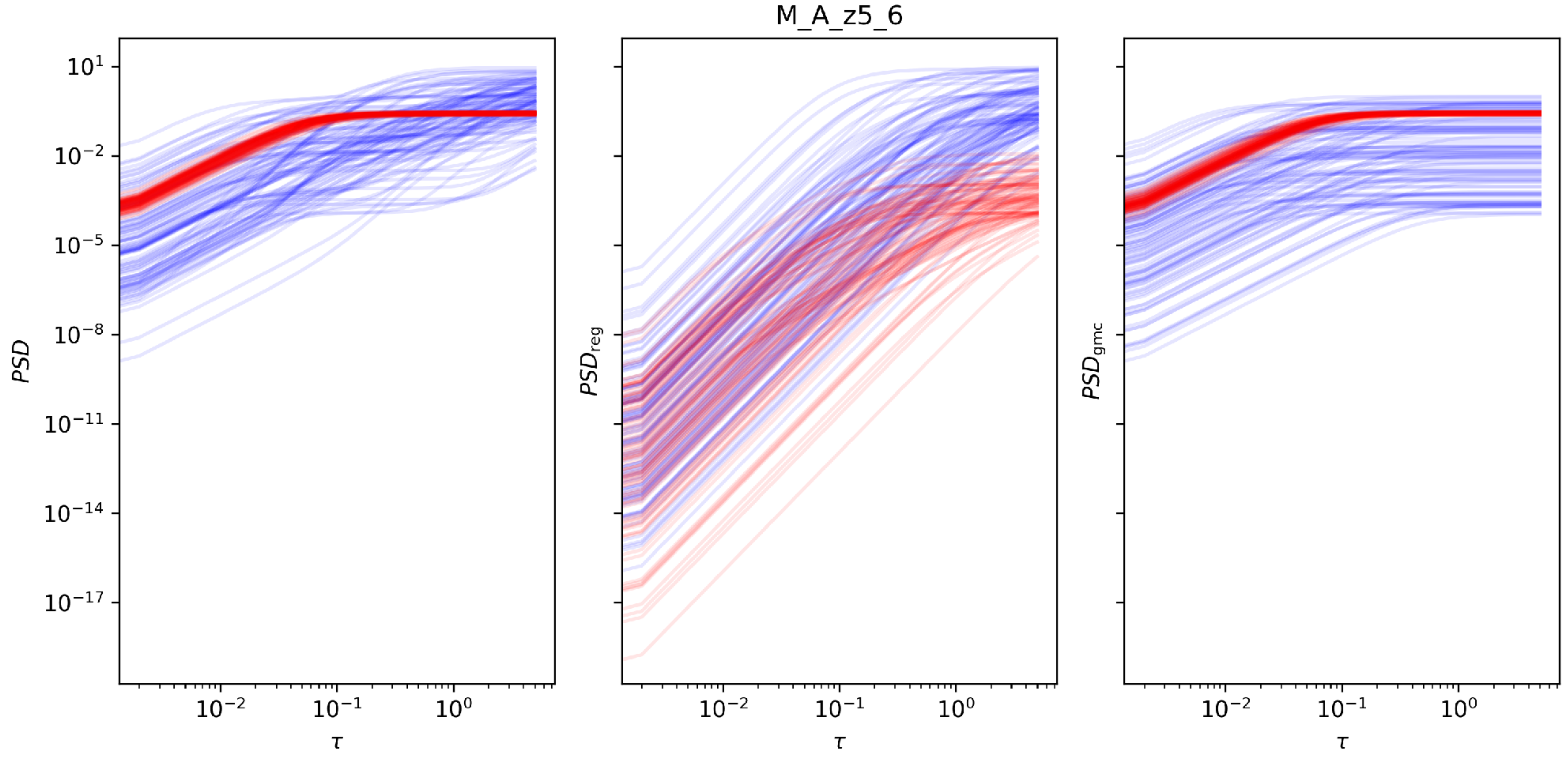


Connecting with JWST

- JWST offers a few of some of the first galaxies and exotic objects to form in the universe history
- We can use observations of main sequence galaxies to constrain the star formation rate properties of the population
- Currently analysing NIRCam data with LBI and SBI techniques with Sandro Tacchella and Charlotte Simmonds
- In practice these constraints can be used to inform 21-cm simulations

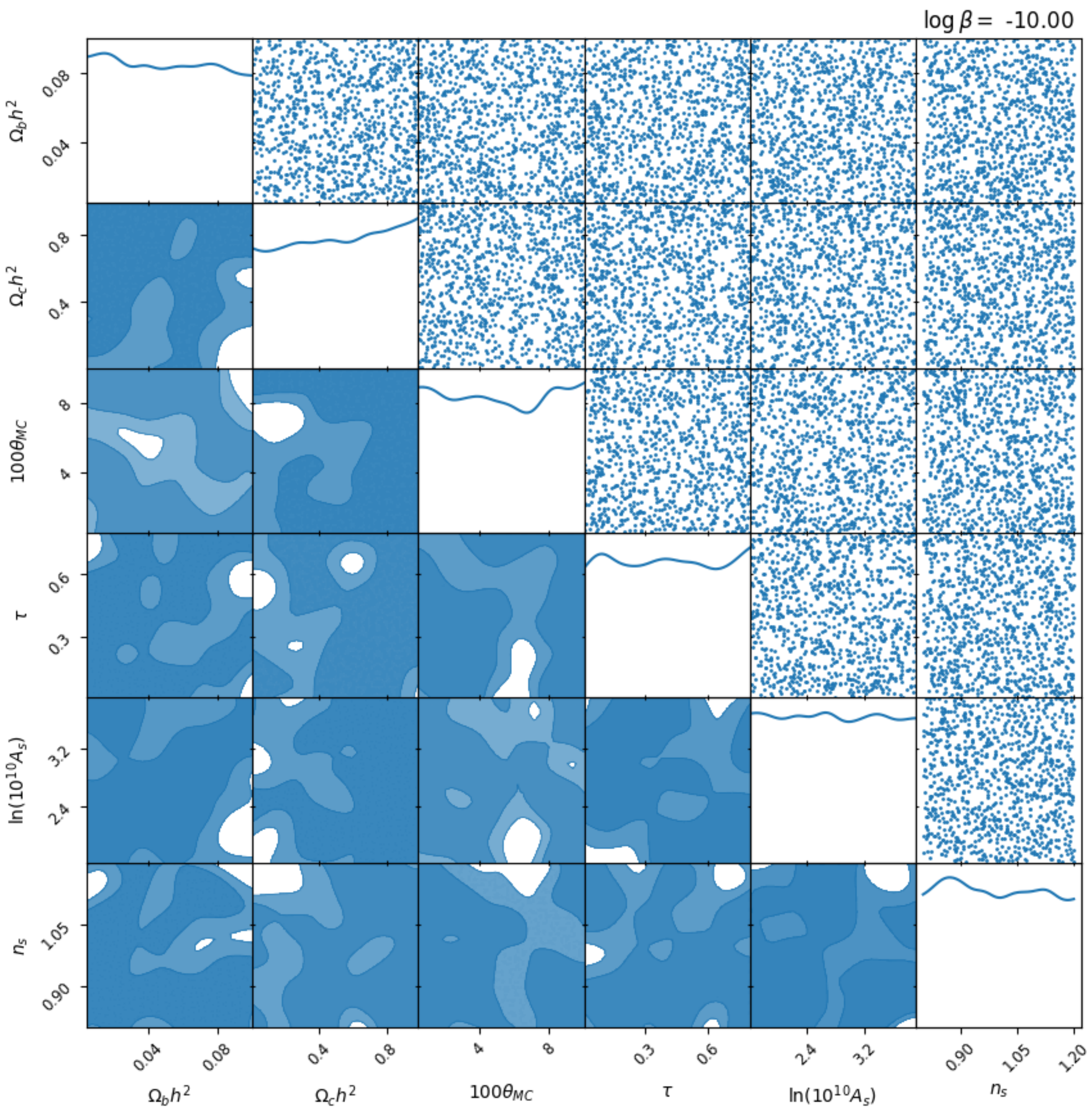






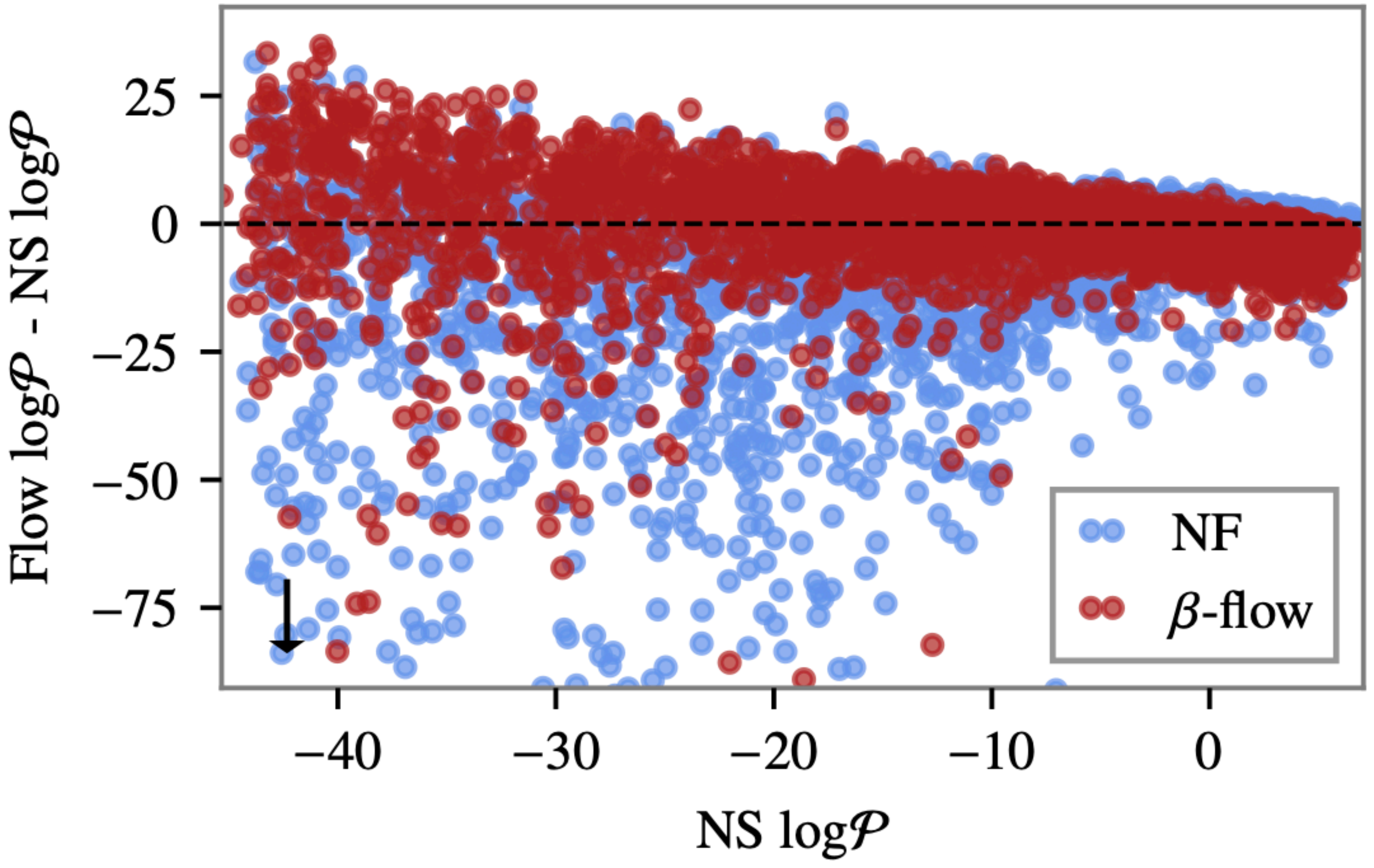
Machine Learning enhanced inference - β Flows

- Developed a novel framework for training density estimation tools
- Typically train these density estimation tools on posterior samples
- But some sampling algorithms give us samples on the way from the prior to the posterior
- Demonstrated that we can use these intermediary samples to improve performance of density estimators



Machine Learning enhanced inference - β Flows

- β-flows essentially allow you to generate samples anywhere between the prior and posterior
- β is an inverse temperature
- Worked with Metha Prathaban and Will Handley on applying β-flows to speed up inference on simulated gravitational waves and real data
- Use β-flows to define an adaptive prior
- Potential applications beyond astrophysics



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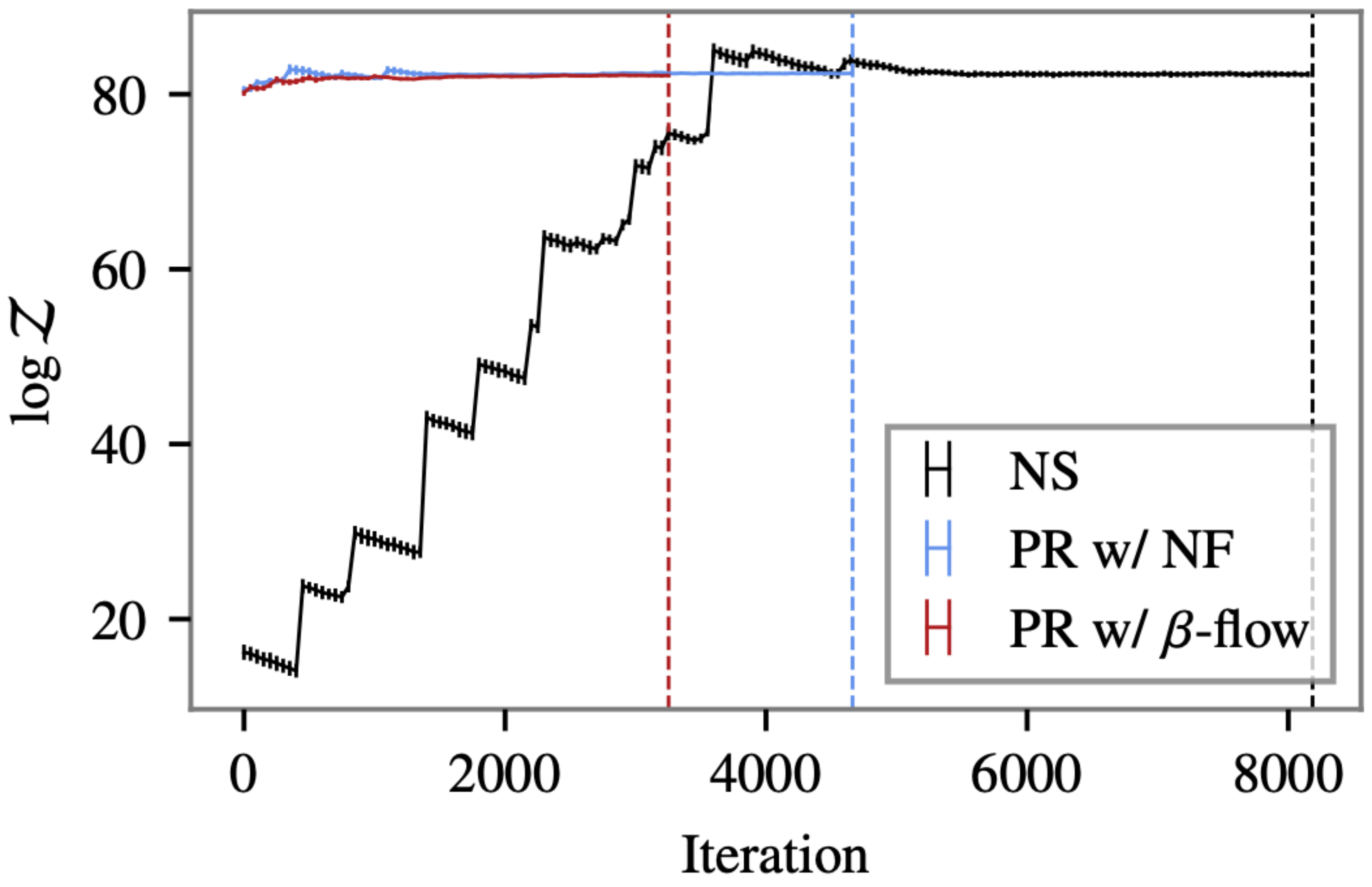
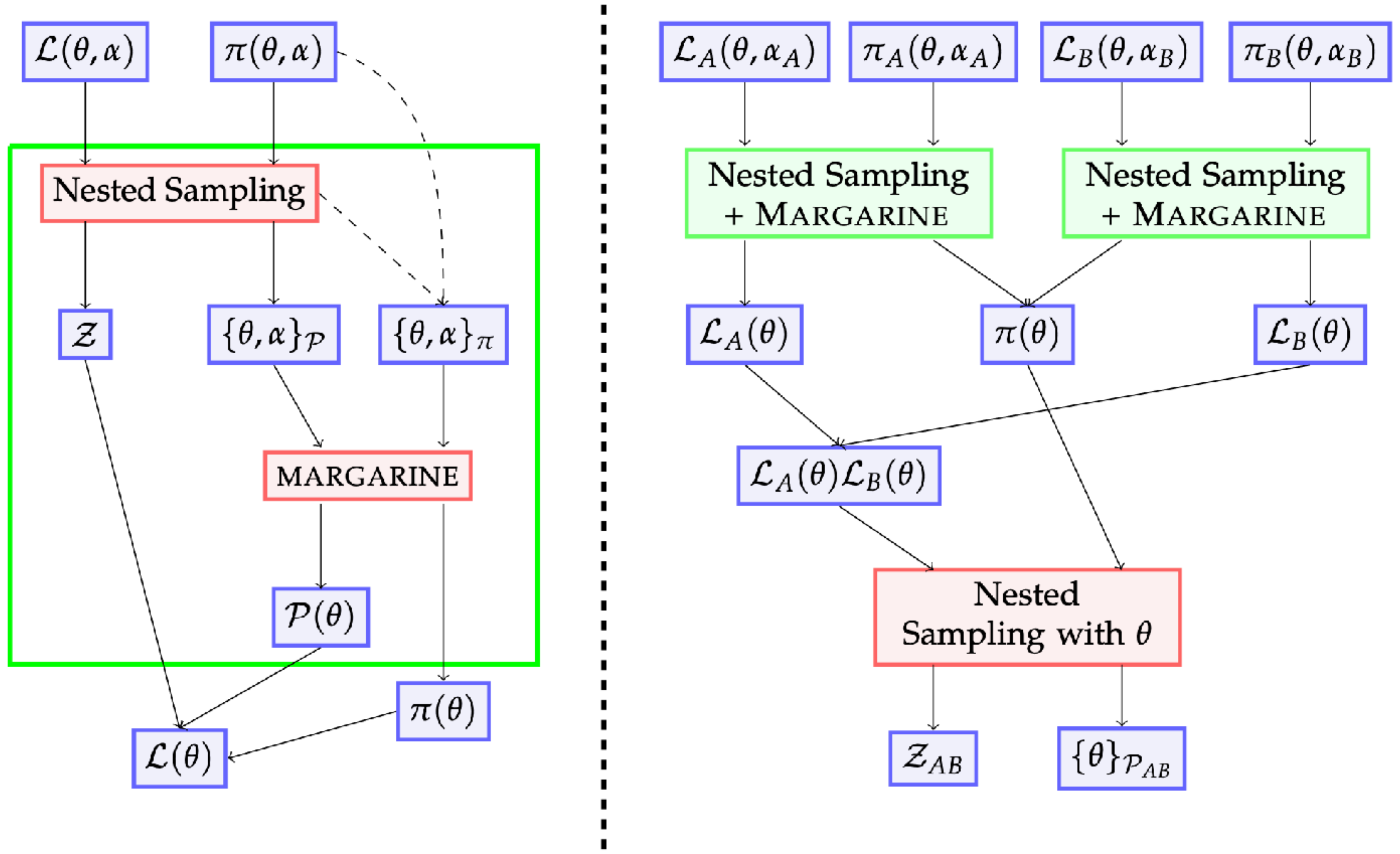


Machine Learning enhanced inference - Supernova

- To extract cosmology from supernova catalogues we have to model the light curves from thousands of individual objects and account for instrumental effects
- Each object constraints the cosmological parameters we are interested in but the surveys have their own nuisance parameters
- Very computational expensive high dimensional space to sample and explore!
- Proposed a divide and conquer approach to reduce the dimensionality of the problem using Normalising Flows [Bevins et al. 2022]



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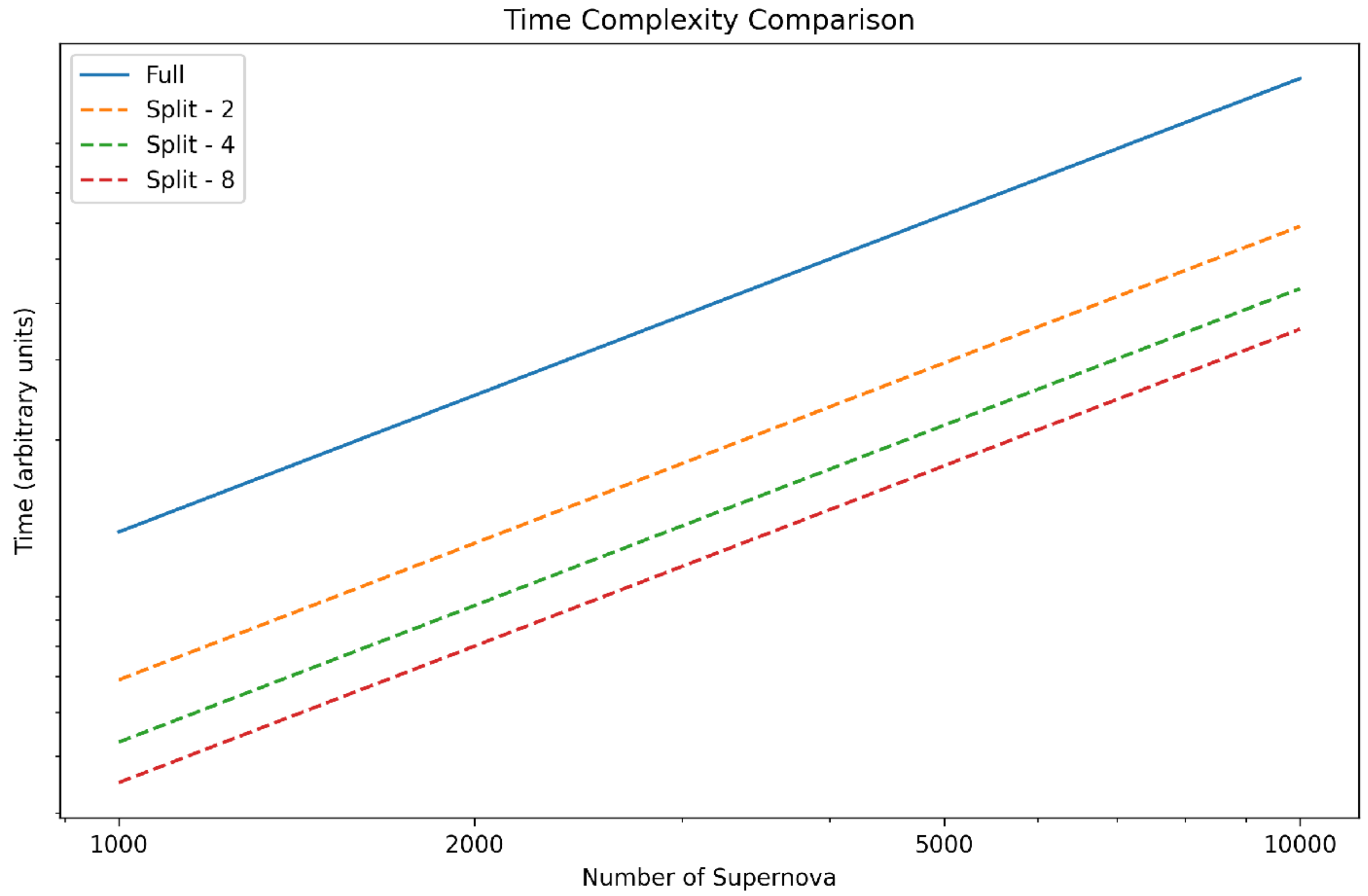

Machine Learning enhanced inference - Supernova

- Worked with Lehan Li and Kaisey Mandel on a proof of concept as Part III project

- Simulate a catalogue of N supernova with observed magnitudes m_B and some scatter $\sigma_i^m \sim \mathcal{N}(0,\sigma_i)$

- Want to infer cosmology given

$$m_i^B + \sigma_i^m = \mu(z_i; \Omega_m, w) + M_0$$

- Total parameter set$\theta = \{\Omega_m, w, \{\sigma_i\}^{N_{\text{survey}}}\}$

- Showed that by analysing surveys individually and combining the cosmological constraints in a post processing step with normalising flows we can significantly speed up the analysis