

# globalemu: Novel and robust emulation of 21-cm signals from the Epoch of Reionization

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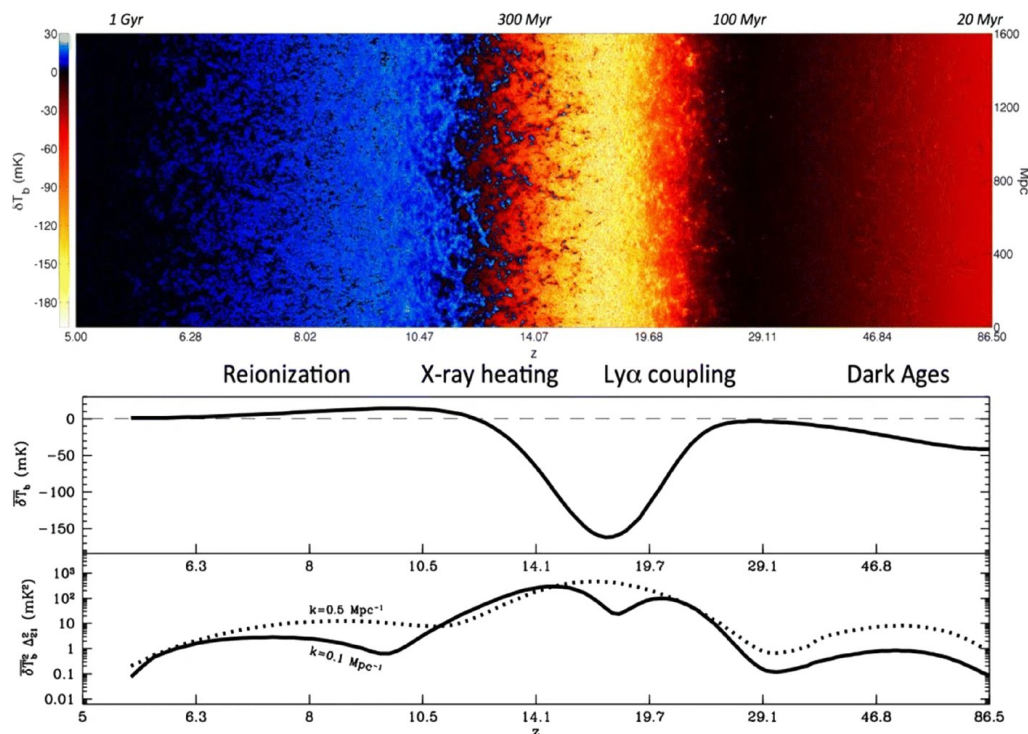
In collaboration with Will Handley, Anastasia Fialkov, Eloy de Lera Acedo and Kamran Javid



**EUROPEAN ASTRONOMICAL  
SOCIETY ANNUAL MEETING**



# 21-cm Cosmology and the SKA



**REACH, EDGES,  
SARAS, LEDA etc.**

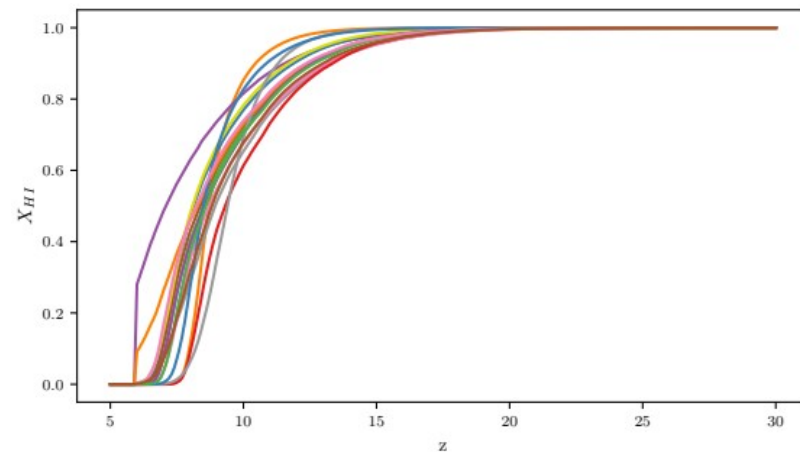
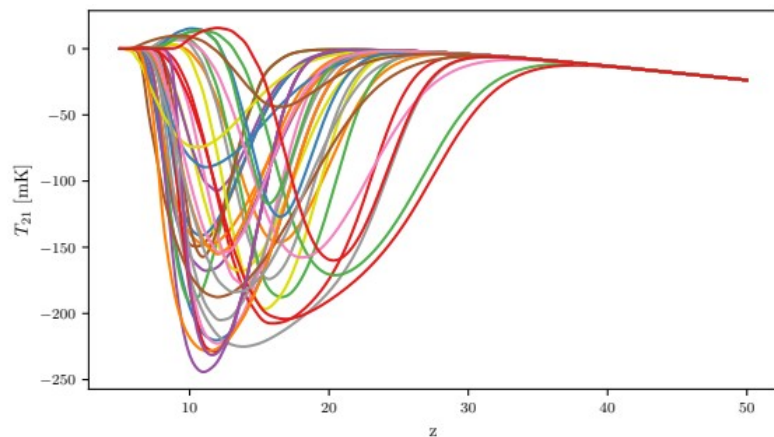
**SKA, HERA,  
MWA, LOFAR etc.**

Koopmans, L.V.E., Barkana, R., Bentum, M. et al. Exp Astron 51, 1641–1676 (2021).

# Why are we interested in signal emulators?



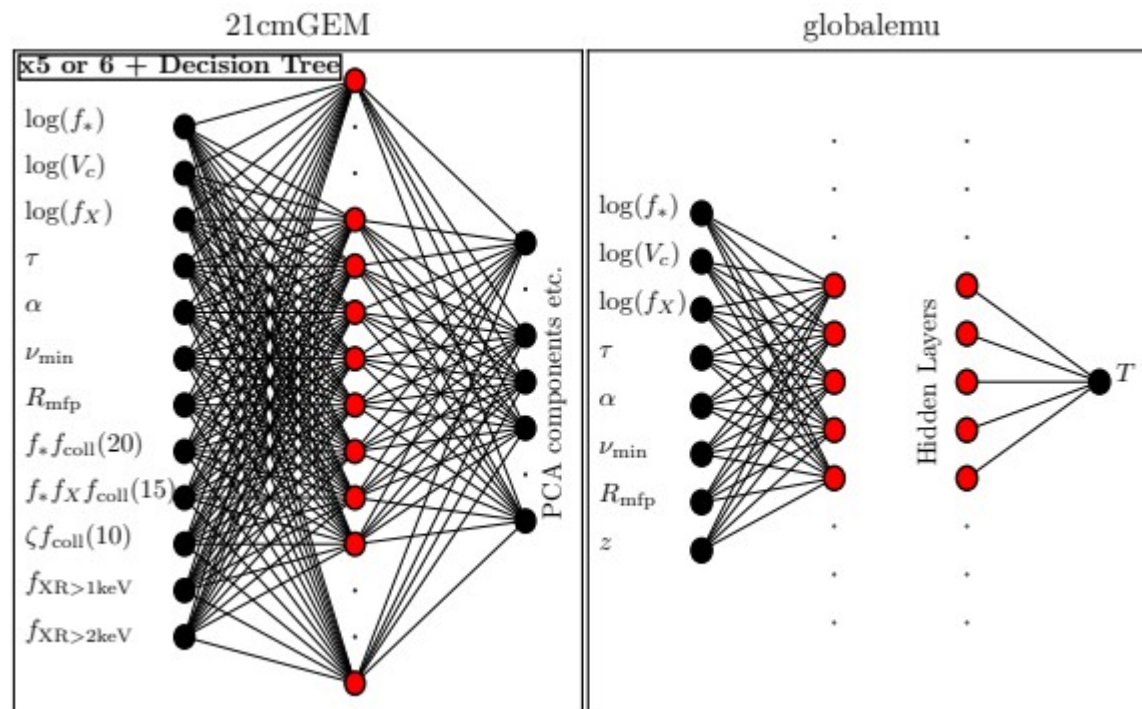
- Need a quick method to generate physical signal models to fit to our data
- Full semi numerical simulations take of order ~hrs
- Neural network emulators produce signals ~ms



# What is different about *globalemu*?



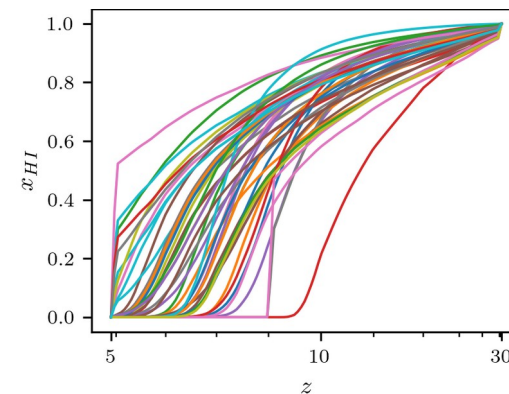
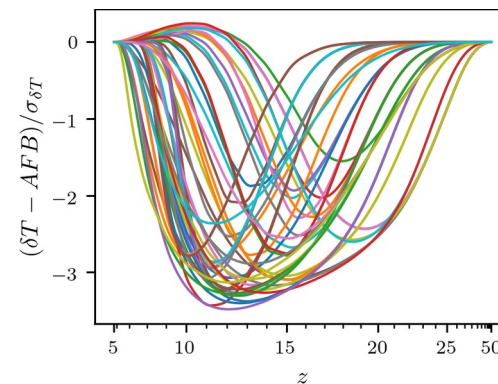
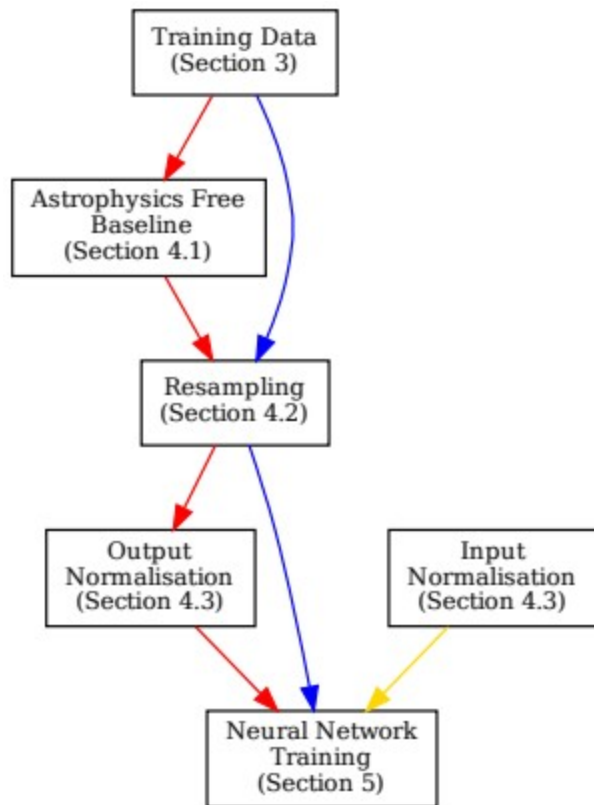
- Redshift as an input
- One simple and small neural network that we can make vectorised calls to
- Train and test on the same dataset for comparison



# Physically Motivated Preprocessing



- Lots of details in the paper
- Subtract astrophysics free structure at high redshift and add it back in later
- Resample signals to capture regions of high variation

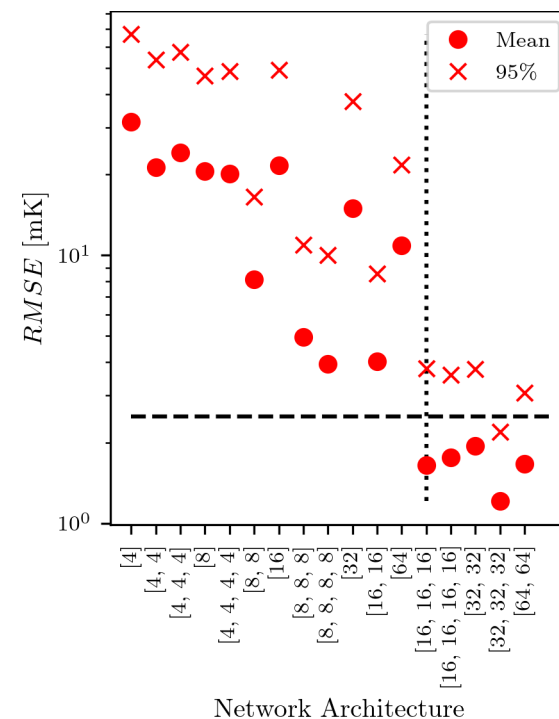




# Neural Network Specifics



- Practical decisions about our required accuracy based on the expected noise in the REACH experiment
- Loss function and optimizer

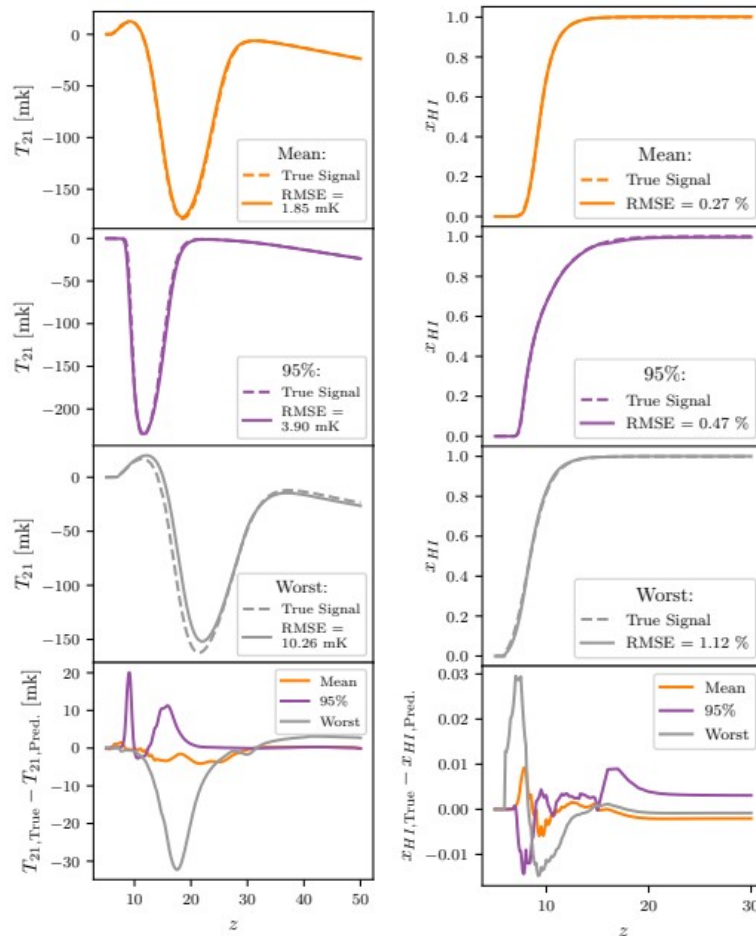


# Results



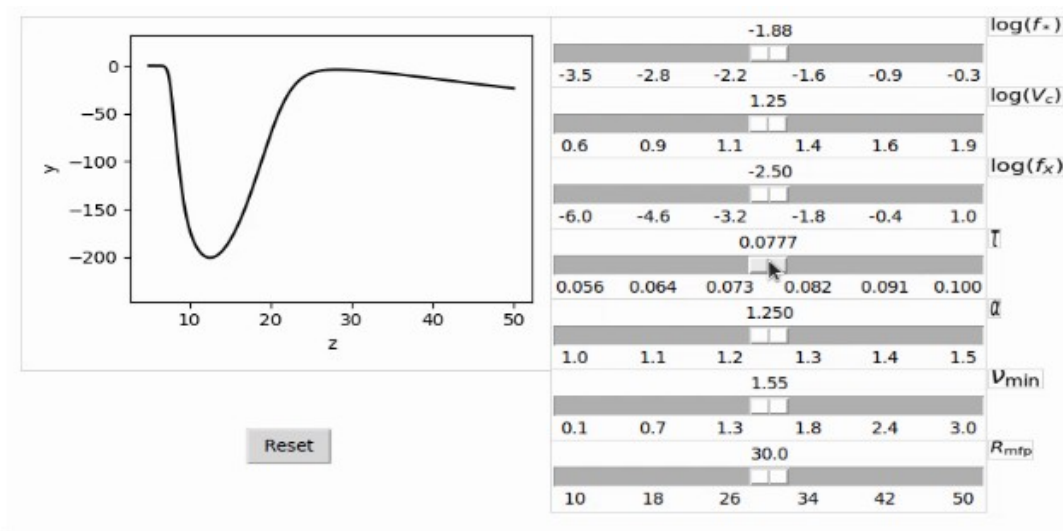
For the global signal:

- ***globalemu***:
  - Max Normalised RMSE = 6.32 %
  - Emulation time: 1.3 ms
- ***21cmGEM***:
  - Max Normalised RMSE = 10.55 %
  - Emulation time: 133 ms



# Accessible and Adaptable

- Pip installable and fully documented
- Available on github with some trained models
- Emulator GUI



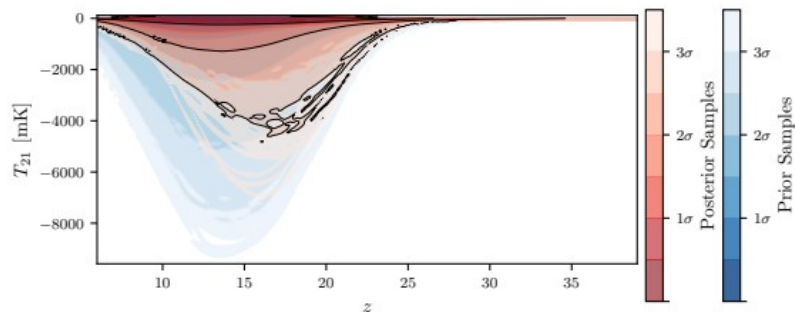
```
1 import numpy as np
2 from globalemu.preprocess import process
3 from globalemu.network import nn
4 import tensorflow as tf
5 import matplotlib.pyplot as plt
6
7 tf.random.set_seed(1420.4)
8
9 data_dir = 'data/'
10 base_dir = 'saved_model/'
11 z = np.arange(5, 50.1, 0.1)
12
13 process('full', z, base_dir=base_dir, data_location=data_dir)
14
15 nn(batch_size=len(z), epochs=500, base_dir=base_dir, layer_sizes=[16]*4)
16
17 from globalemu.eval import evaluate
18
19 predictor = evaluate(base_dir=base_dir)
20
21 parameters = np.loadtxt(data_dir + 'test_data.txt')
22 labels = np.loadtxt(data_dir + 'test_labels.txt')
23
24 signals, z = predictor(parameters)
25
26 [plt.plot(z, signals[i]) for i in range(len(signals))]
27 plt.show()
```



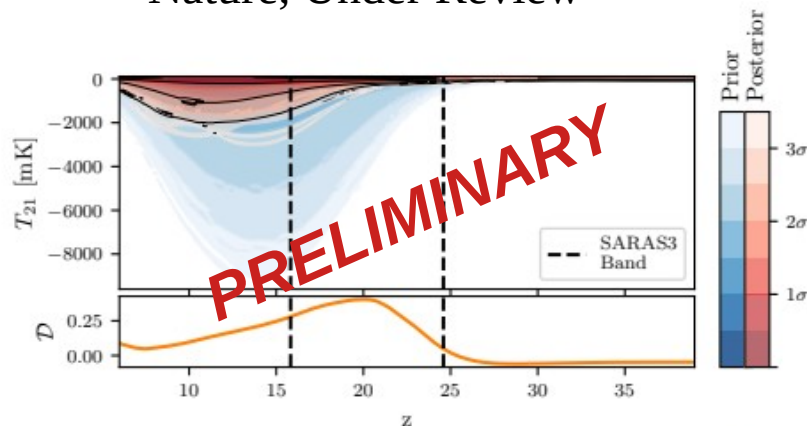


SARAS2:

<https://doi.org/10.1093/mnras/stac1158>



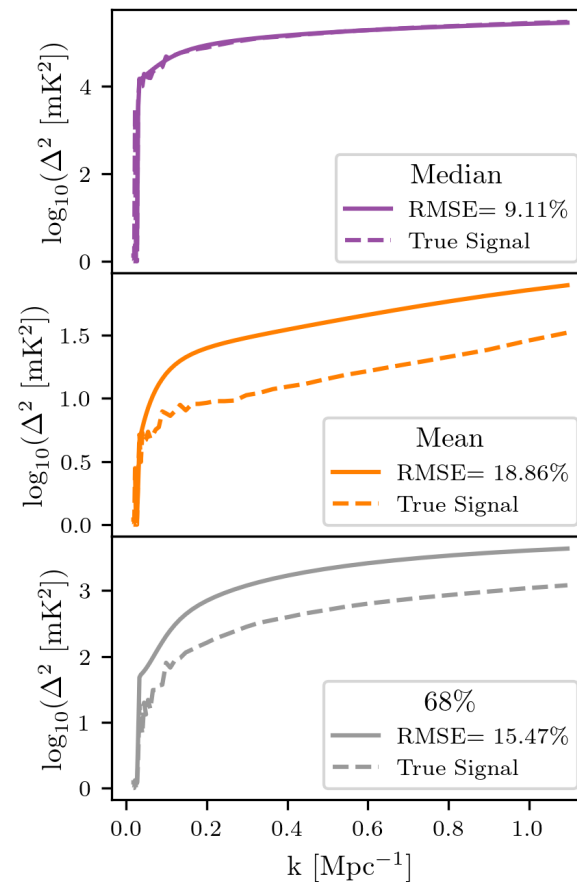
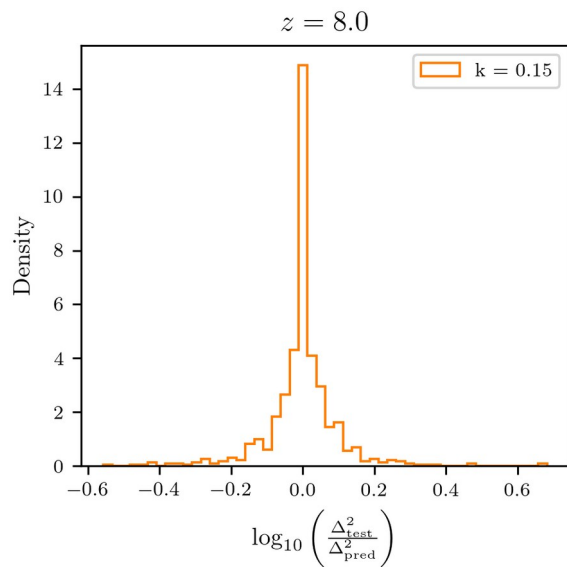
SARAS3: Submitted to  
Nature, Under Review



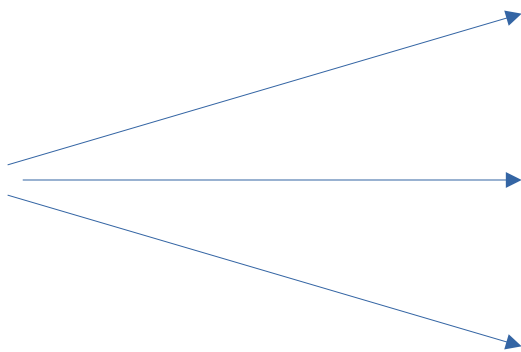
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## Not just a global signal emulator...

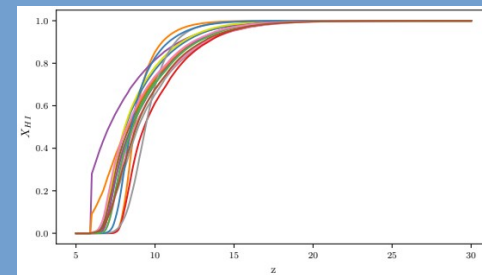
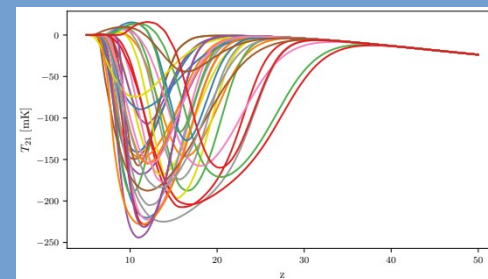
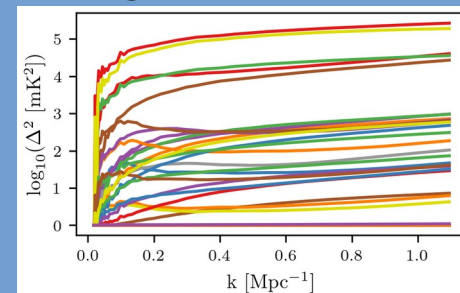
- Training on some excess radio background power spectrum models and assessing at  $z=8$  and  $k=0.15$
- Comparable accuracy to emulator used for recent HERA analysis ( $z=7.8$ ,  $k=0.13$ )



# Why is this important for the SKA?



## *globalemu*



- globalemu is your one stop shop for accurate and fast 21-cm signal emulation
- For the global signal we see a factor of approximately two improvement in emulation accuracy and a factor of 102 improvement in emulation time
- For the power spectrum we see a comparable level of accuracy with the emulator used in the recent HERA analysis

**globalemu paper:** <https://doi.org/10.1093/mnras/stab2737>

**globalemu in action (fitting SARAS2 data):**  
<https://doi.org/10.1093/mnras/stac1158>

**github:** <https://github.com/htjb/globalemu>