



# Gaussian Process Regression: An Application in Radio Cosmology

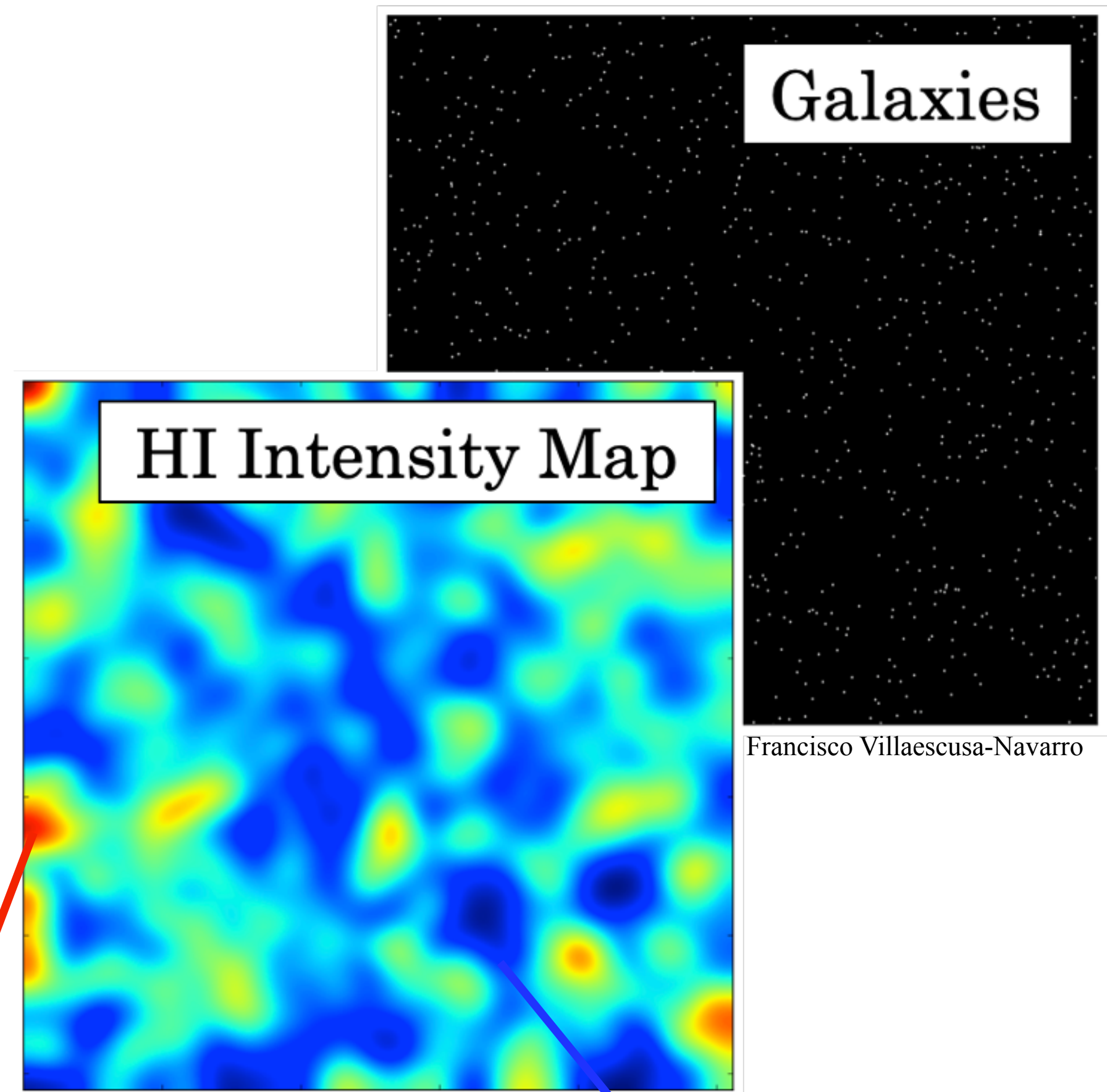
arXiv:2105.12665

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# HI intensity mapping

- Large-scale structure: how matter is clustered and structured on a large scale in our Universe
- After reionisation, most of the neutral hydrogen (HI) can be found in galaxies
  - HI is a good tracer of the large-scale structure
- Can quickly map **large** areas of the sky
- **But need to remove foregrounds!**



**Higher intensity**  
**= more HI present**  
**= more matter present**

**Lower intensity**  
**= less HI present**  
**= less matter present**

# Motivation

- **GPR** has already been applied as a foreground removal technique successfully in the context of the Epoch of Reionisation (see e.g. [Mertens et al. 2018](#) [arXiv:1711.10834] and public code [ps\\_eor<sup>1</sup>](#))
  - \* How does **GPR** perform in the case of low redshift, single-dish Intensity Mapping?
  - \* How does it compare to other methods e.g. PCA?
  - \* Could we use it for future surveys such as the SKA?

SKA-like  
simulations

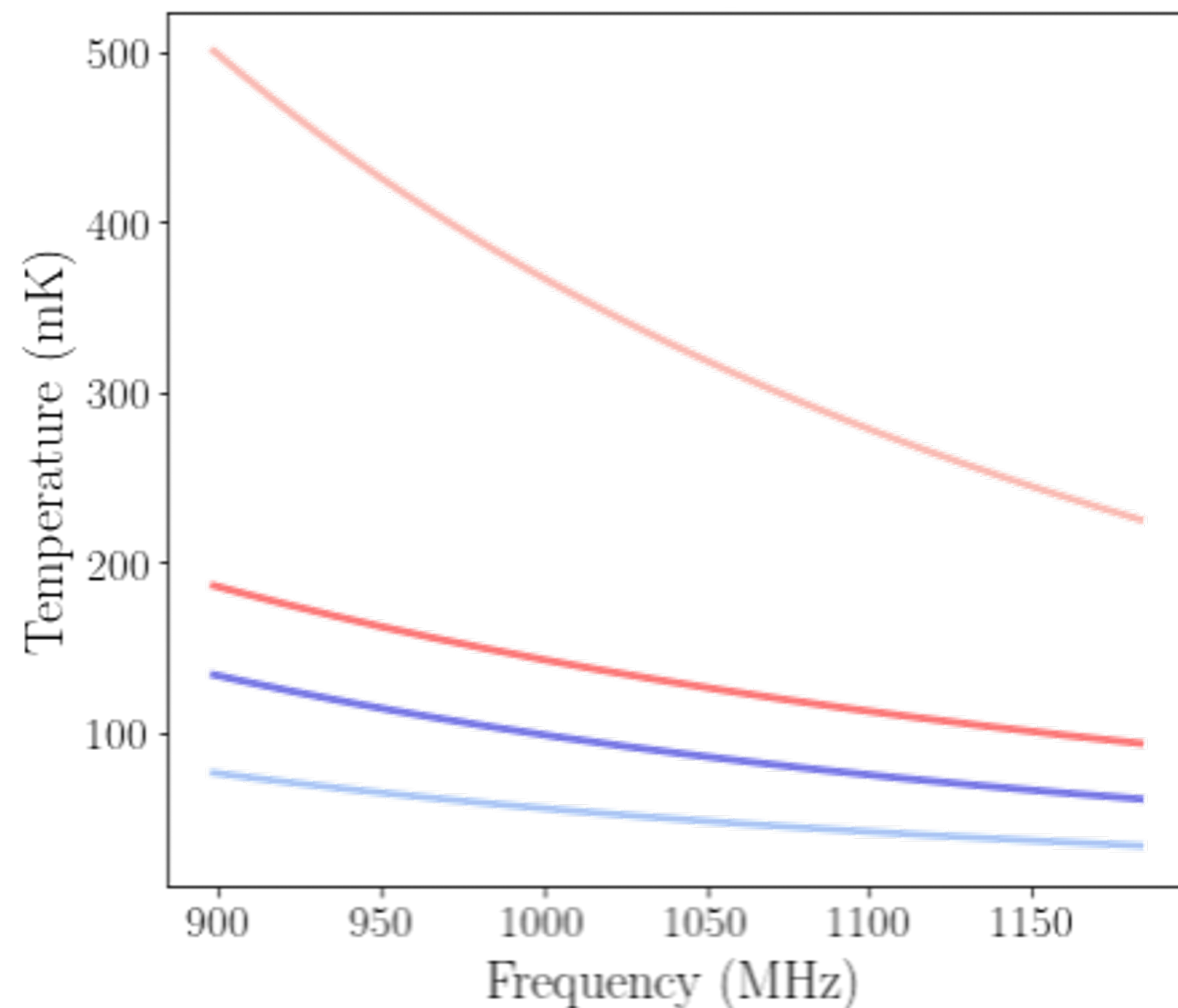
**Assume our data, and each of its  
components (foreground, HI, noise) is a  
Gaussian process**

# Our data's covariance function:

$$K = K_{\text{fg}} + K_{21} + K_{\text{noise}}$$

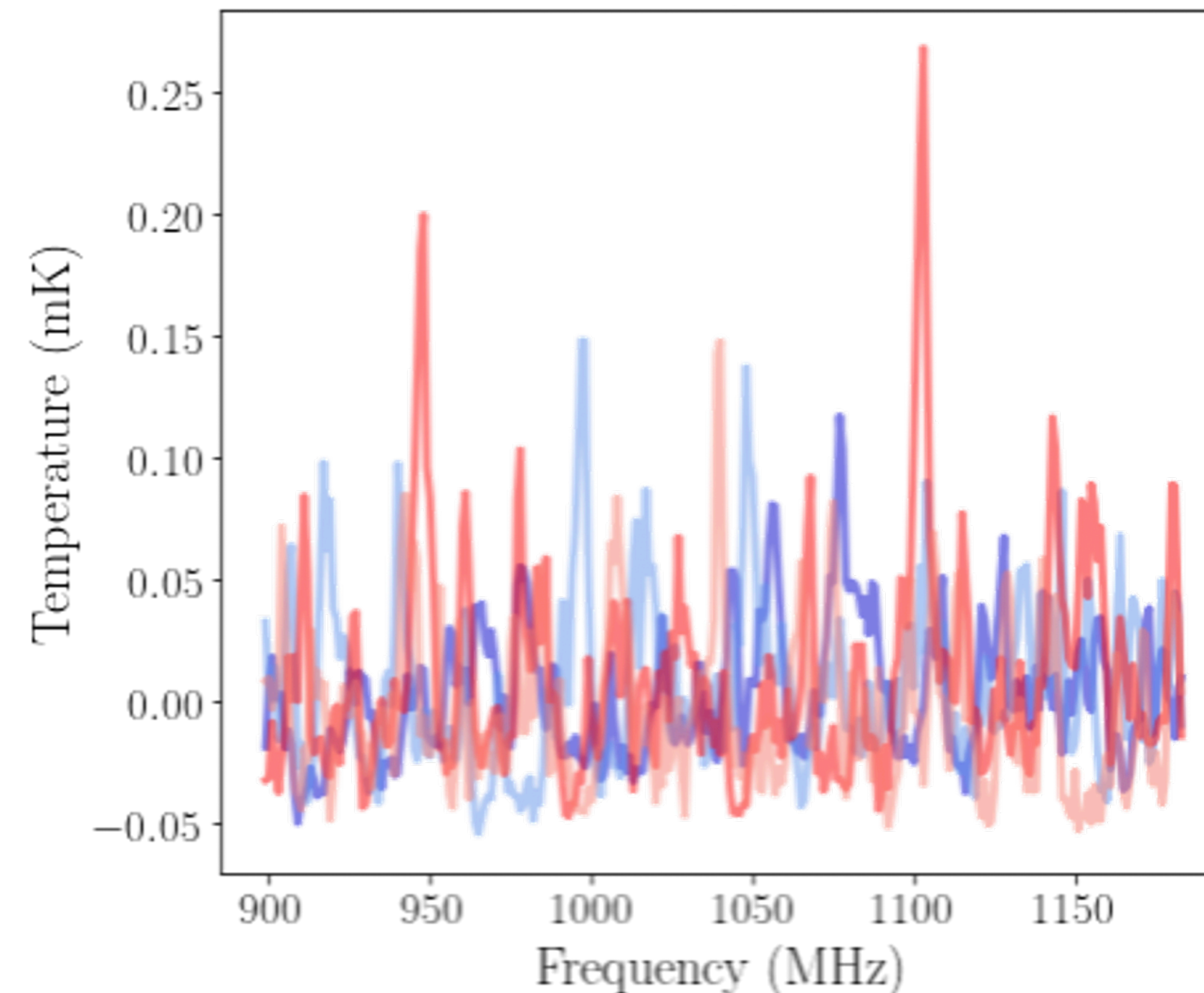
## Smooth foregrounds $K_{\text{fg}}$

- Correlated in frequency
- High amplitude
- Overall smooth in frequency



## 21cm signal $K_{21}$

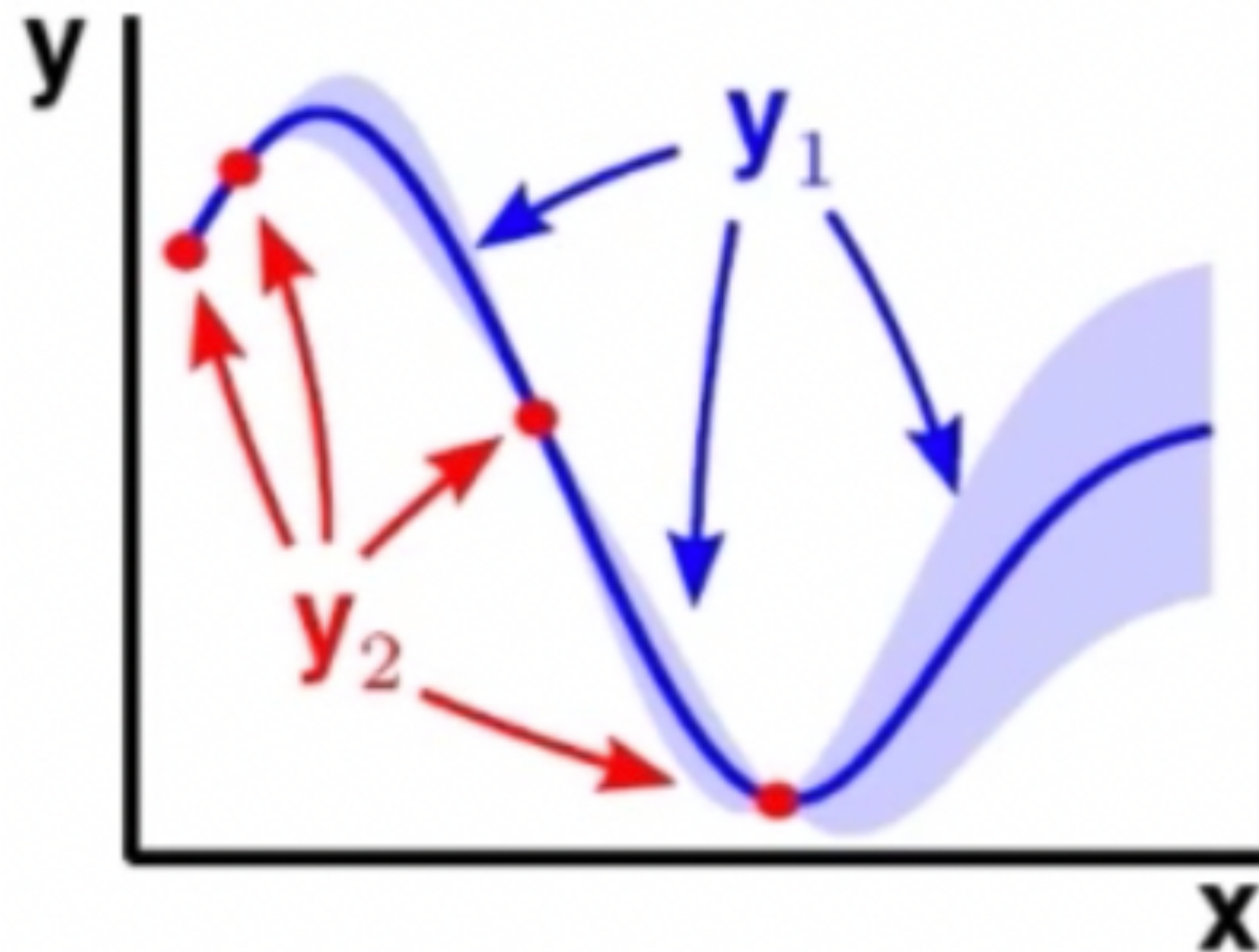
- Not correlated in frequency
- Small amplitude
- Not smooth in frequency



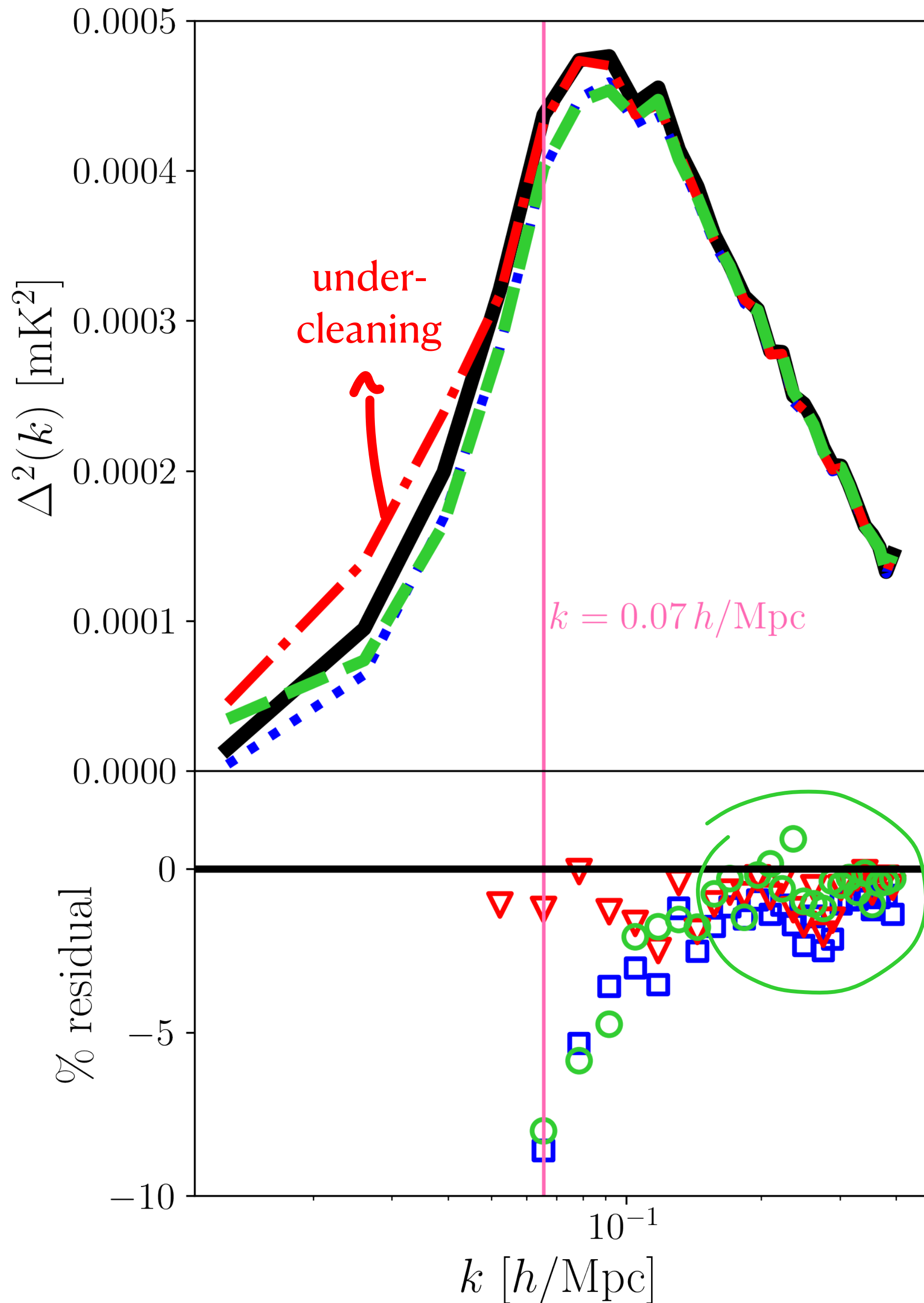
# Foreground removal

How does **GPR** remove foregrounds? By predicting them!

Now we have: our data ( $d$ ), and its best fitting covariance function  
 $\left(K = K_{\text{fg}} + K_{21} + K_{\text{noise}}\right)$ . We can use this to *predict what the foregrounds look like in our frequency range*:

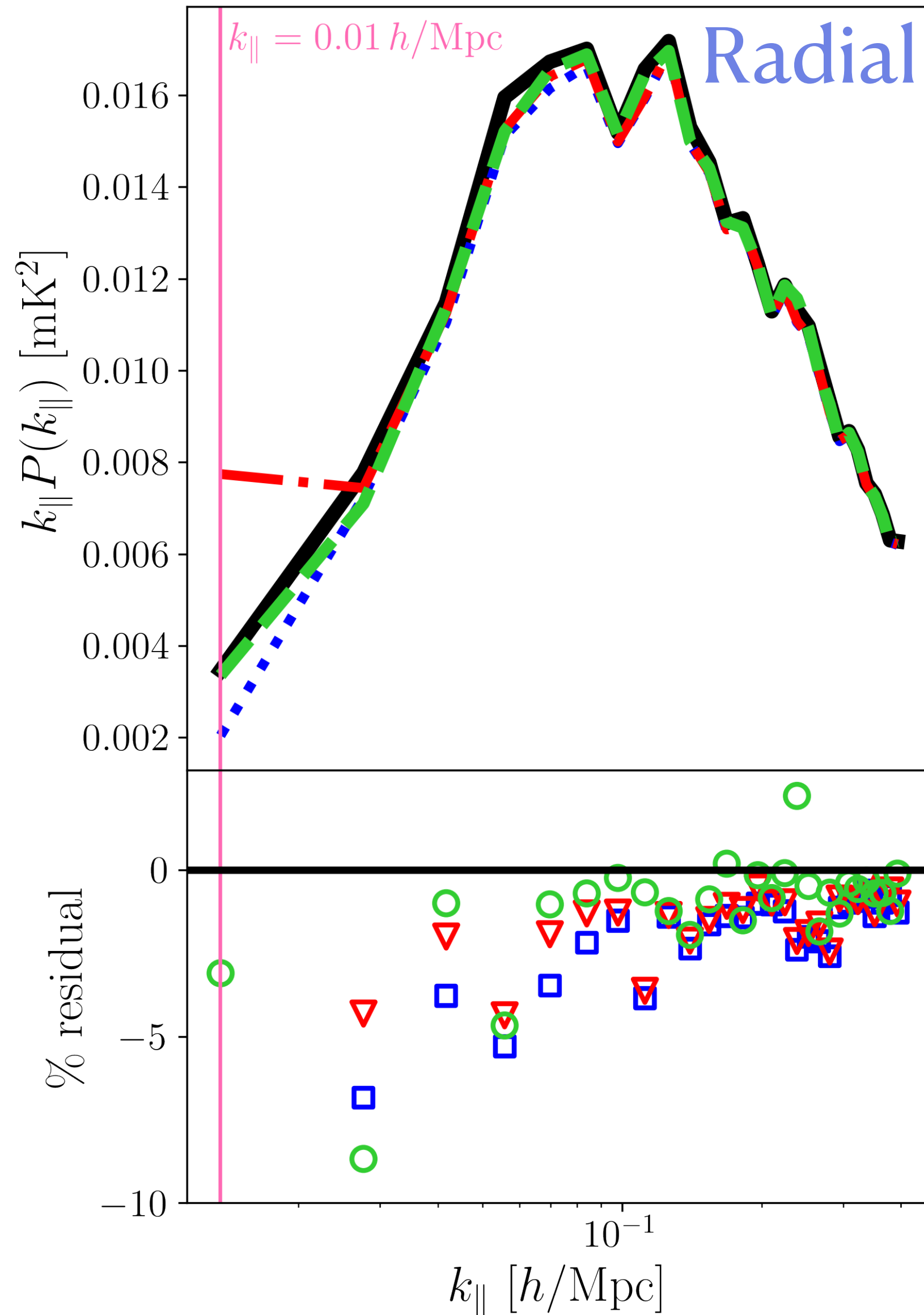


# Results



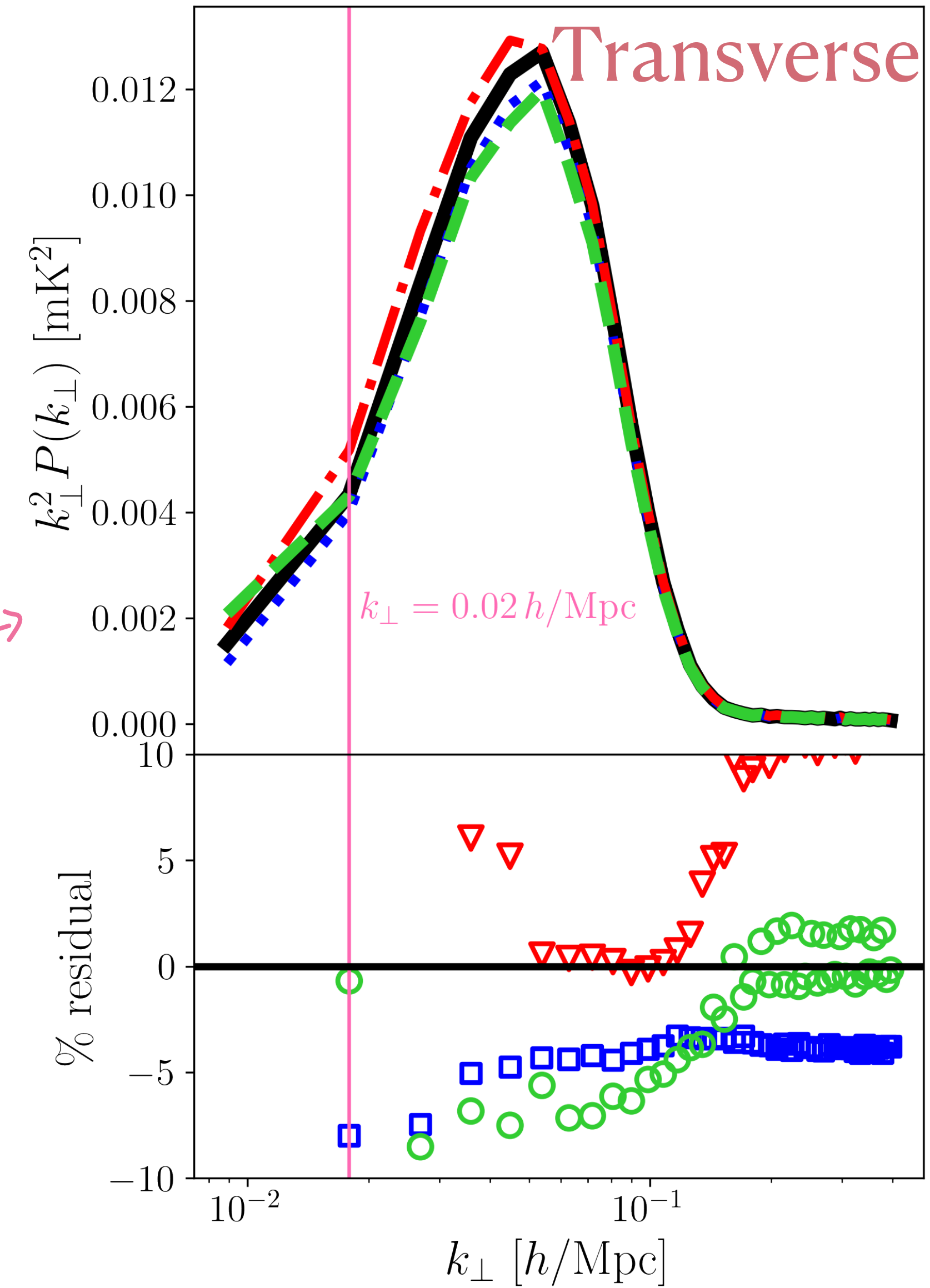
- True HI power spectrum is the black solid line, *what we want to recover*
- **GPR** results are in **green**
- PCA results are in **red** ( $N_{\text{fg}} = 2$ ) and **blue** ( $N_{\text{fg}} = 3$ )
- Bottom panel shows percentage residual difference from truth

# Results



- Very good
  - **GPR** is better than PCA on all scales
  - **GPR** recovers the full range of the radial power spectrum within 10% residual
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- Less good
  - **GPR** better on small scales where beam dominates
  - **GPR** cannot recover full range of transverse power spectrum within 10% residual

**GPR is better in the radial direction**





# Key takeaways

- *It is possible to run **GPR** for foreground removal technique in the case of single-dish, low redshift HI intensity mapping*
- **GPR** performs better than PCA on small scales
- **GPR** performs better in the radial direction than in the transverse direction
- For PCA, we constantly needed to change  $N_{fg}$  depending on bandwidth size, missing channels, including polarisation, etc.
  - **GPR does not require this fine tuning, it finds the best fitting covariance model given the data**
- Our code is available at [github.com/paulassoares/gpr4im](https://github.com/paulassoares/gpr4im)