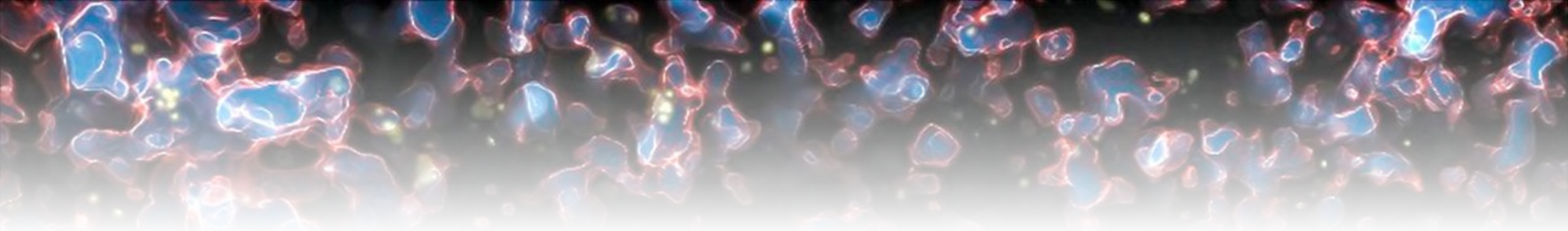
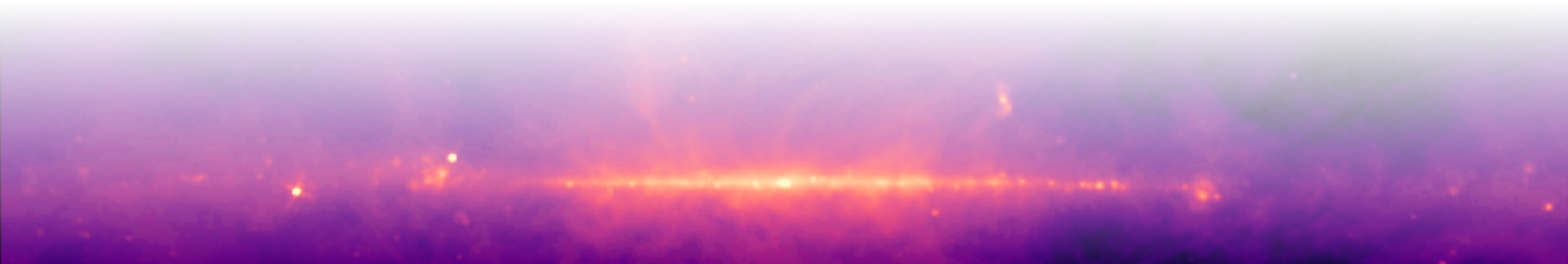


Revisiting Gaussian Process Foreground Subtraction for 21 cm Cosmology

Nick Kern
Pappalardo Postdoctoral Fellow
MIT Kavli Institute

Science at Low Frequencies VII
December 2, 2020



Revisiting the GPR technique

arXiv.org > astro-ph > arXiv:2010.15892

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Astrophysics > Cosmology and Nongalactic Astrophysics

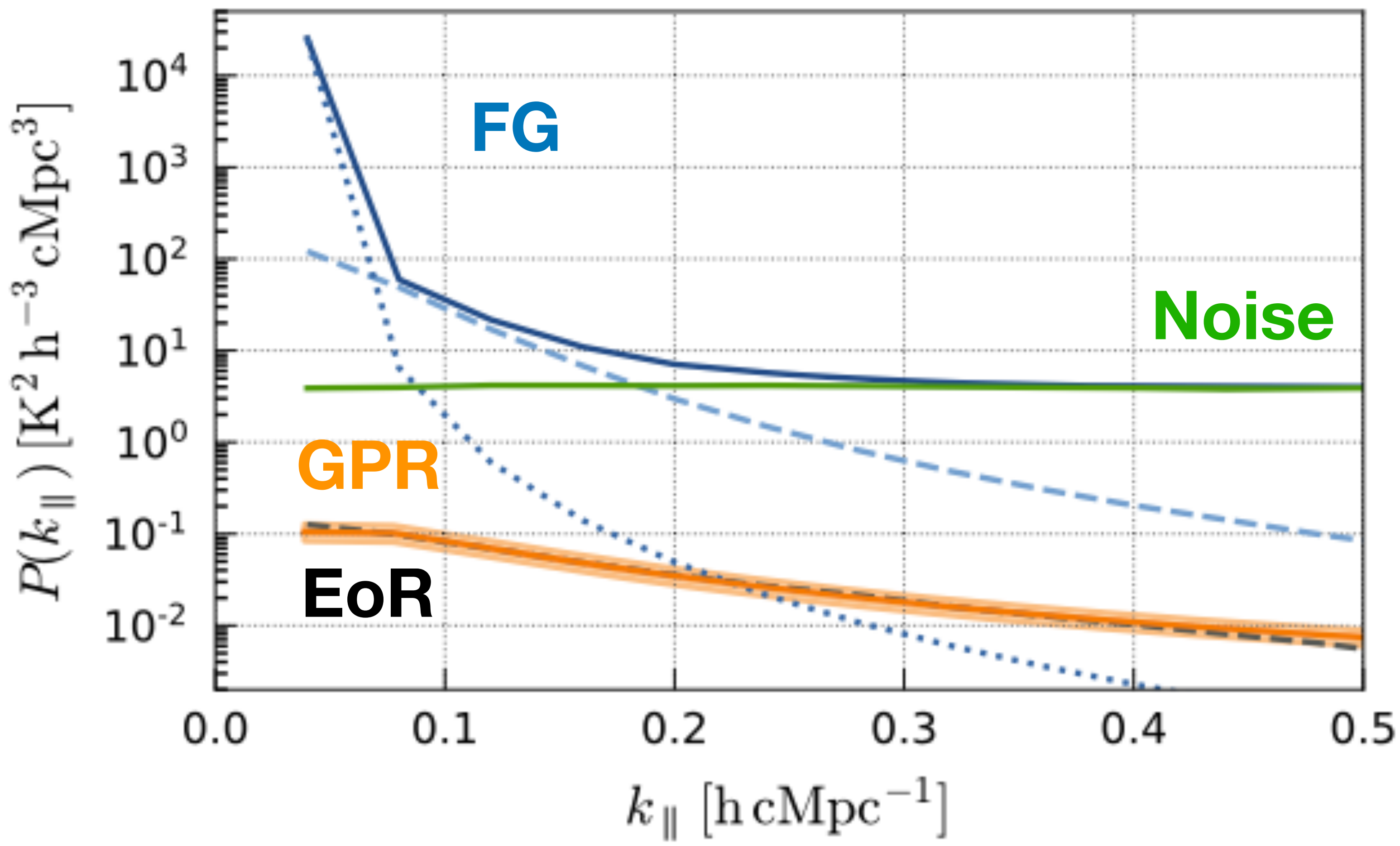
[Submitted on 29 Oct 2020]

Gaussian Process Foreground Subtraction and Power Spectrum Estimation for 21 cm Cosmology (GPR-FS)

Nicholas Kern, Adrian Liu

Gaussian process regression for FG subtraction (GPR-FS)

Promising technique for foreground subtraction

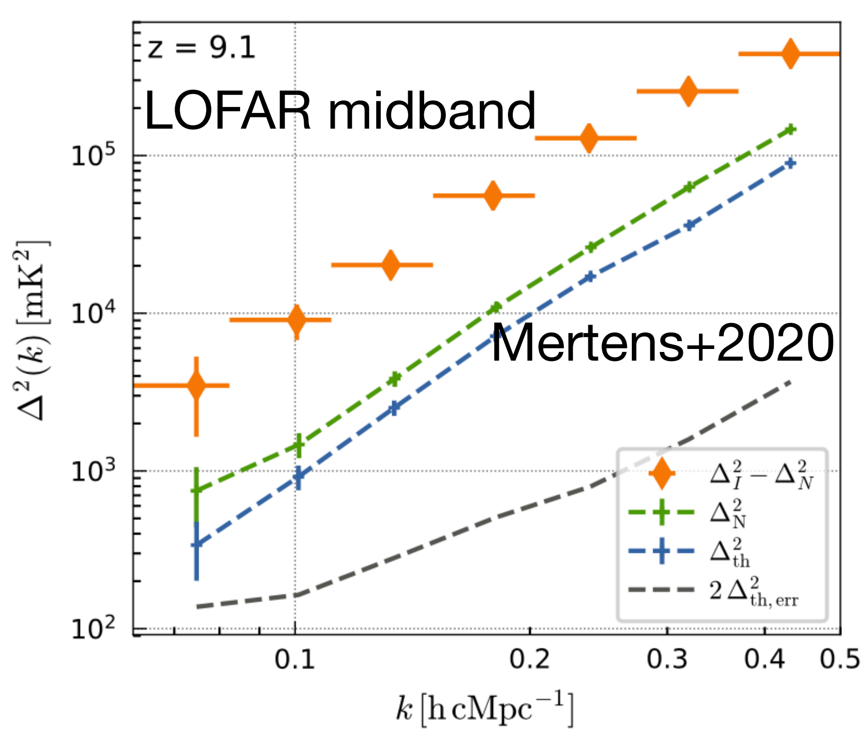


Mertens+2018

Gaussian process regression for FG subtraction (GPR-FS)

Promising technique for foreground subtraction

Becoming more widely used in 21 cm analyses



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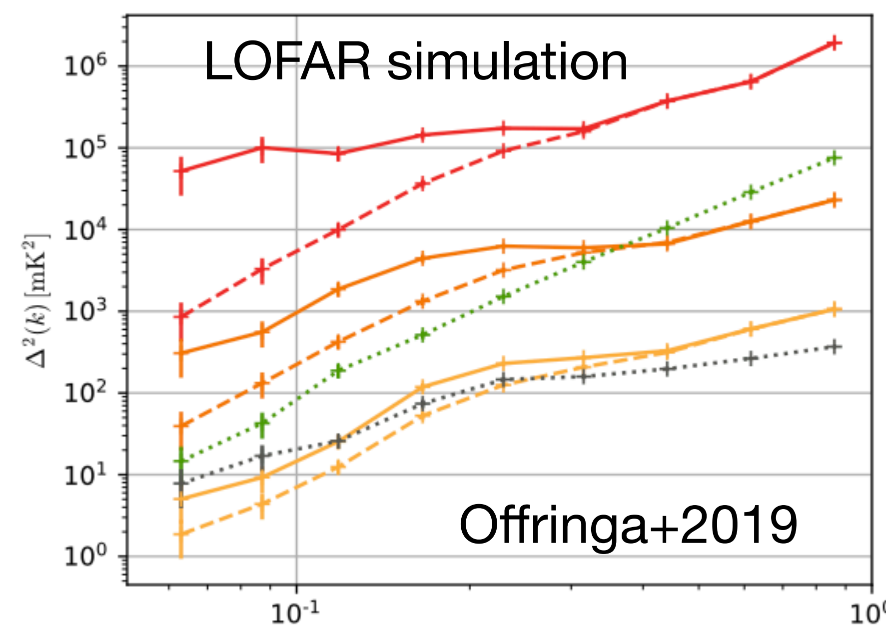

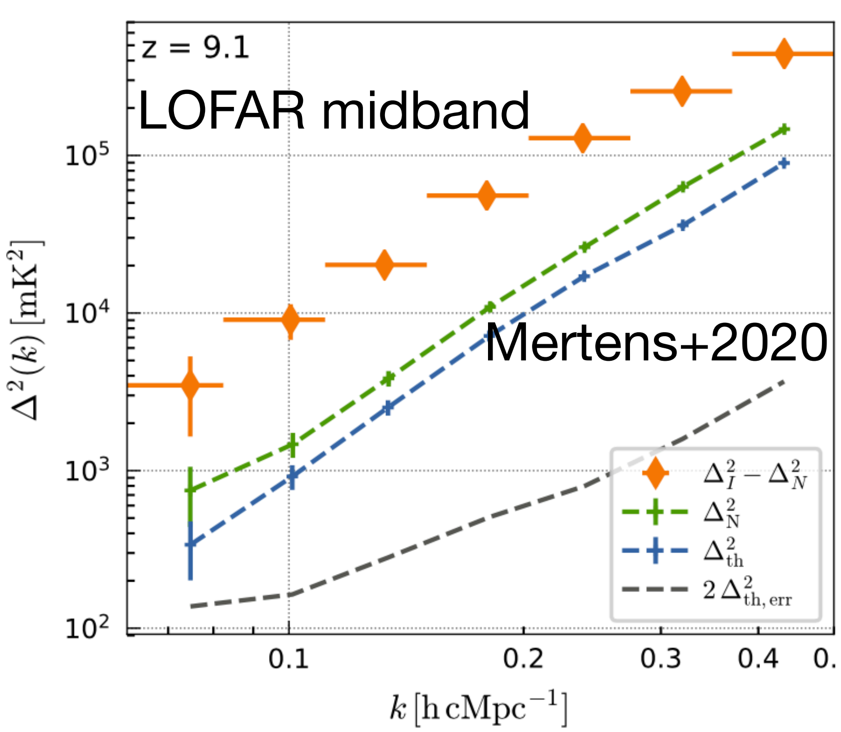

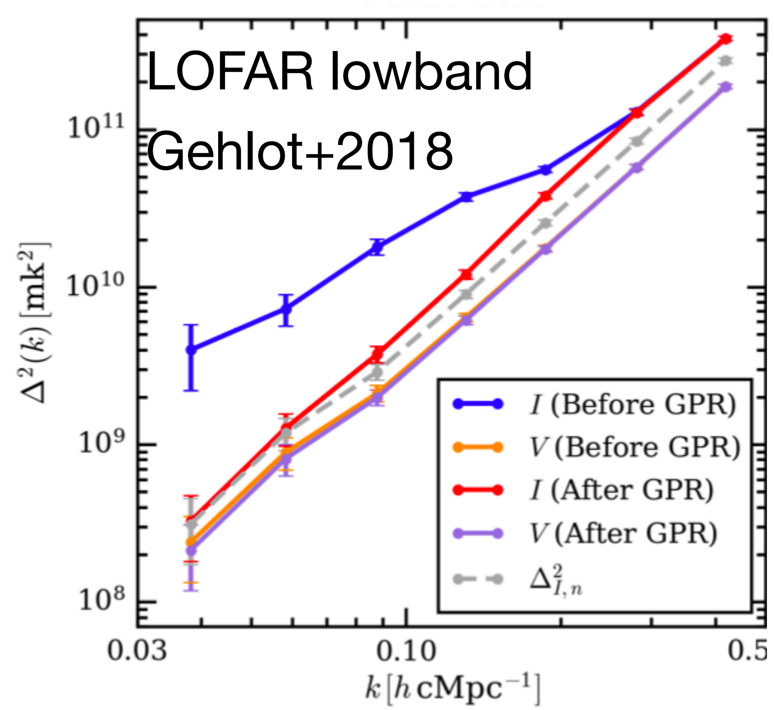

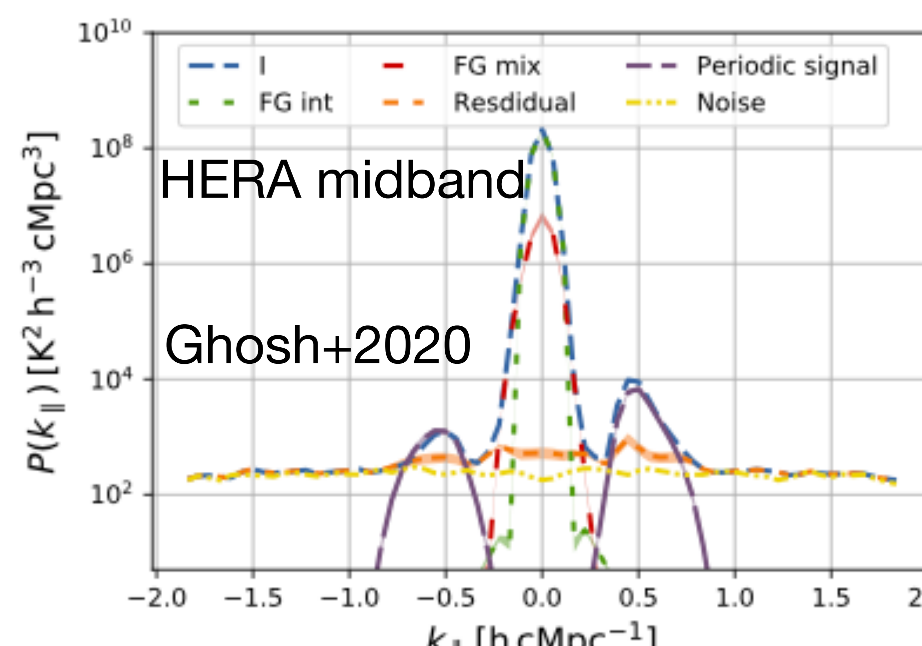

Gaussian process regression for FG subtraction (GPR-FS)

Promising technique for foreground subtraction

Becoming more widely
used in 21 cm analyses

Why is it so effective?
How does it compare to existing covariance-based techniques?

GPR-FS: How it works

Condition the joint density on the data

$$f|d \sim \mathcal{N}\left(\mathrm{E}[f], \mathrm{Cov}[f]\right)$$

$$\mathrm{E}[f] = C_{\mathrm{fg}} C^{-1} d$$

Gaussian Processes for Machine Learning
Rasmussen & Williams 2006

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$$r = d - \mathrm{E}[f]$$

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Form the residual!

$$r = d - \mathrm{E}[f]$$

$$r = (I - C_{\mathrm{fg}} C^{-1}) d$$

$$r = R_{\mathrm{GPR-FS}} d$$

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Rasmussen & Williams 2006

Inverse covariance weighting and the OQE

A general quadratic estimator (QE) of the power spectrum

Inverse covariance weighting and the OQE

A general quadratic estimator (QE) of the power spectrum

$$d = \begin{bmatrix} d_{\nu_1} \\ d_{\nu_2} \\ \vdots \end{bmatrix}$$

$$\hat{q}_\alpha = d^T R^T C_{,\alpha} R d$$

Fourier transform operator

weighting matrix

Tegmark+97, Liu+2011

Inverse covariance weighting and the OQE

A general quadratic estimator (QE) of the power spectrum

$$d = \begin{bmatrix} d_{\nu_1} \\ d_{\nu_2} \\ \vdots \end{bmatrix} \qquad \hat{q}_\alpha = d^T R^T C_{,\alpha} R d$$

Fourier transform operator

weighting matrix

The optimal quadratic estimator (OQE)

$$R = C^{-1}$$

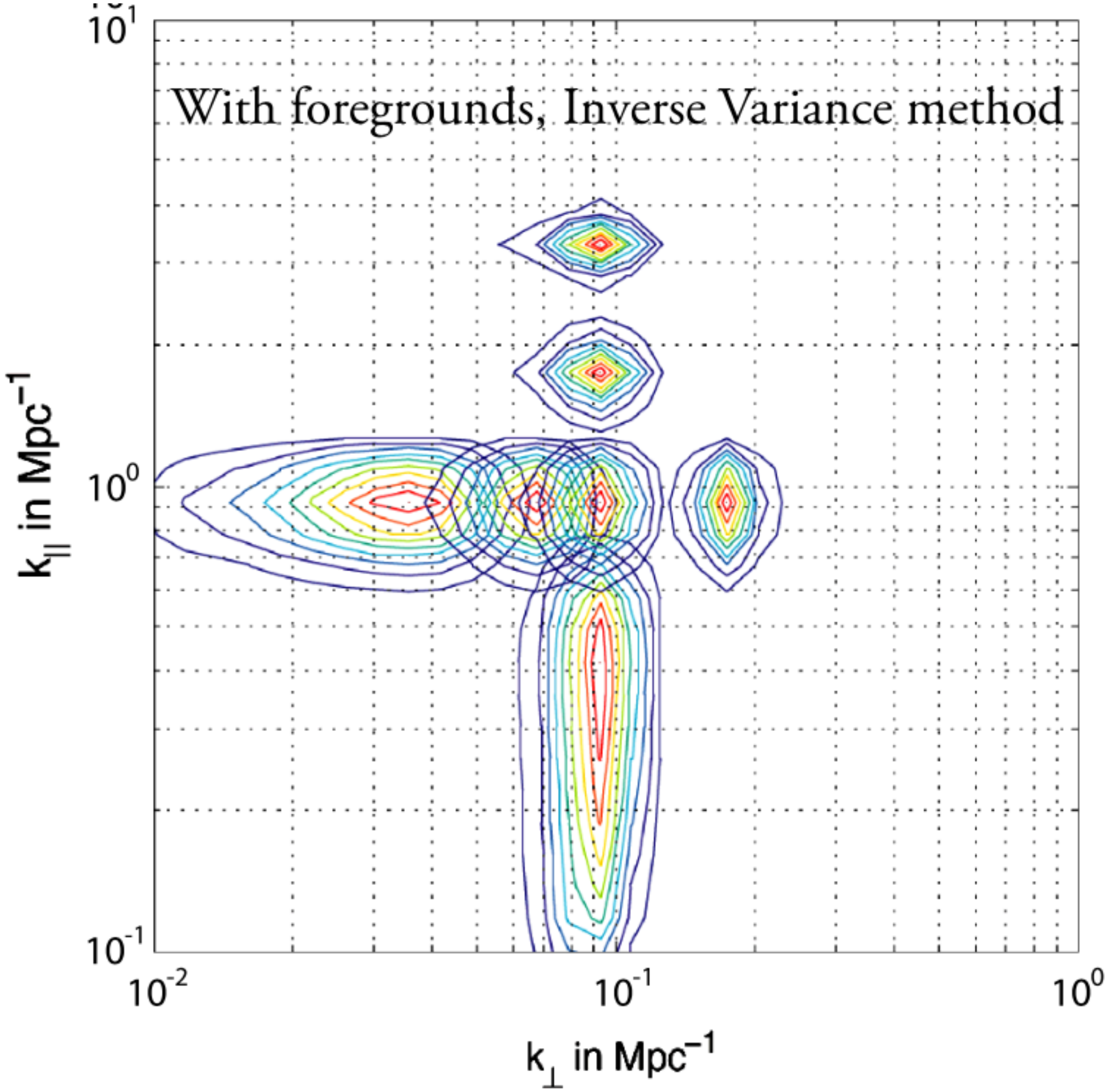
$$C = C_{\rm fg} + C_{\rm s} + C_{\rm n}$$

Tegmark+97, Liu+2011

The OQE for 21 cm: caveats

1. Window functions can be non-trivial!

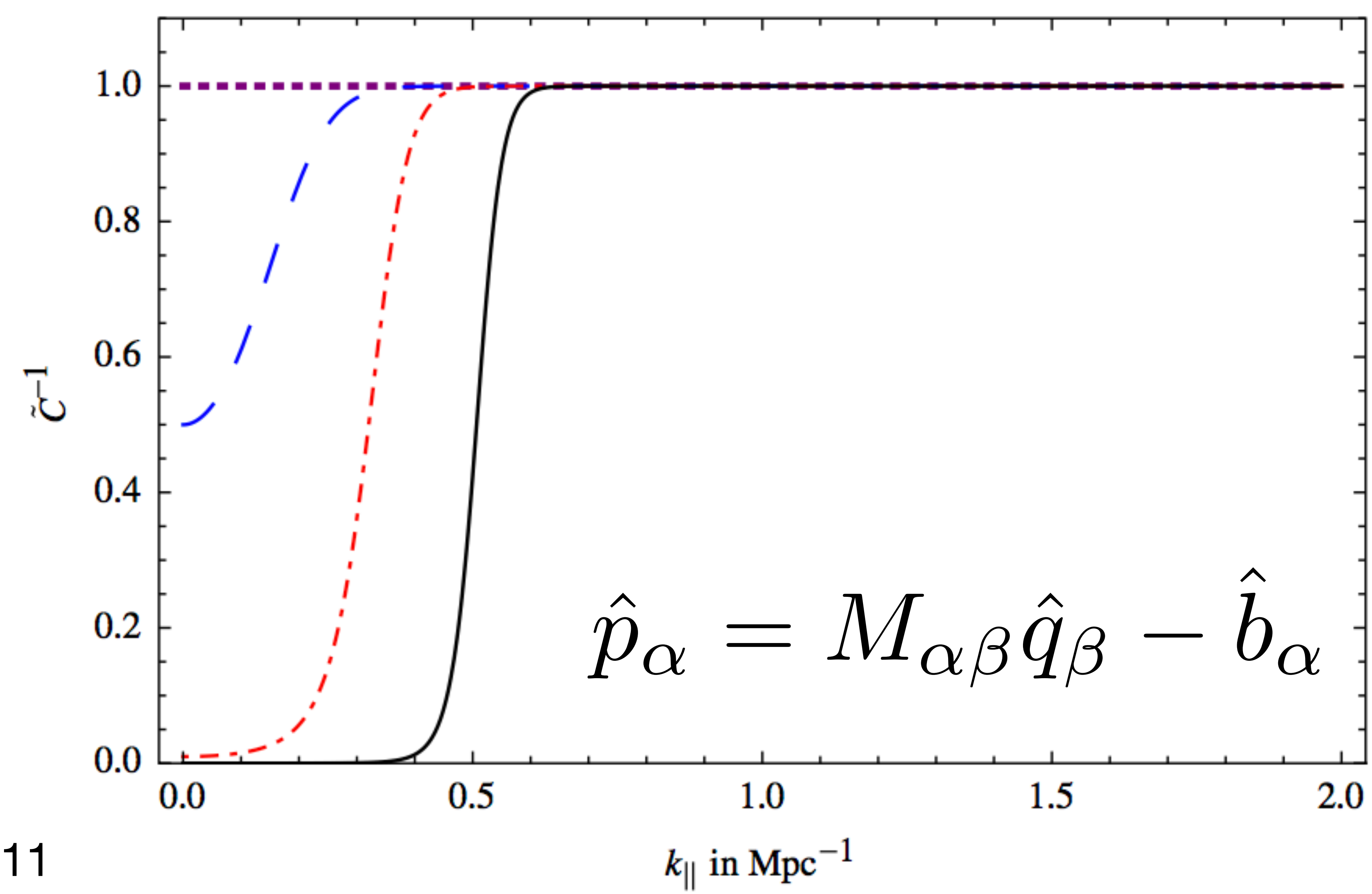
$$\langle \hat{p} \rangle = W p_{\mathrm{true}}$$



Liu+2011

The OQE for 21 cm: caveats

2. Inverse covariance is a “high-pass filter”, requires normalization



Liu+2011

The OQE for 21 cm: caveats

3. Residual bias subtraction is tricky

$$\hat{p}_\alpha = M_{\alpha\beta}\hat{q}_\beta - \hat{b}_\alpha$$

$$\hat{b}_\alpha = \mathrm{tr}[(N + C_{\mathrm{fg}})M_{\alpha\beta}C_{,\beta}]$$

need to know this very accurately

Dillon+2014

GPR-FS and the OQE

How does GPR-FS relate to the OQE?

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$$C^{-1} = [C_{\mathrm{n}} + C_{\mathrm{HI}}]^{-1}(I - C_{\mathrm{fg}} C^{-1})$$

GPR-FS and the OQE

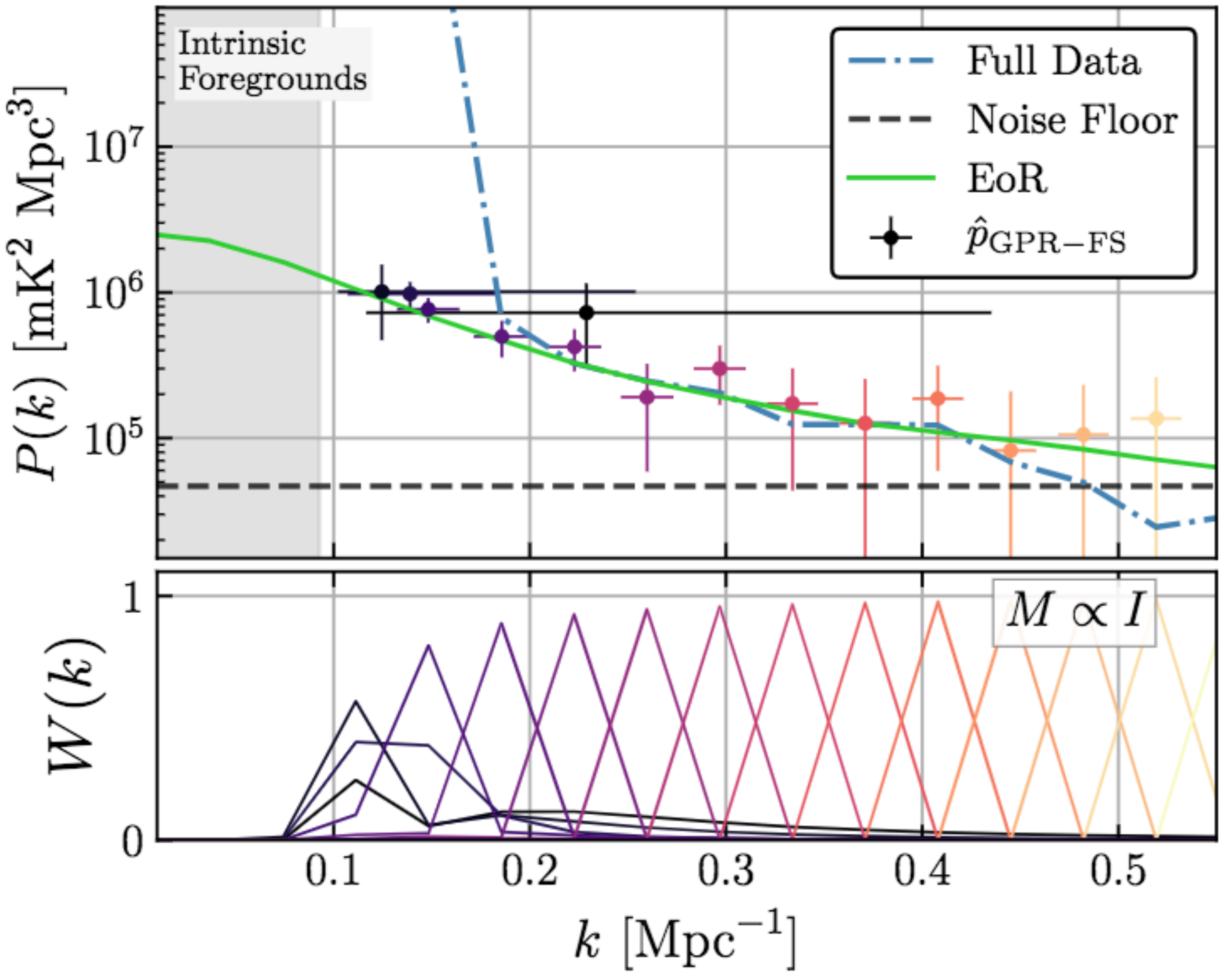
How does GPR-FS relate to the OQE?

$$C^{-1} = [C_{\rm n} + C_{\rm HI}]^{-1}(I - C_{\rm fg}C^{-1})$$

$$R_{\rm OQE} = [C_{\rm n} + C_{\rm HI}]^{-1} R_{\rm GPR-FS}$$

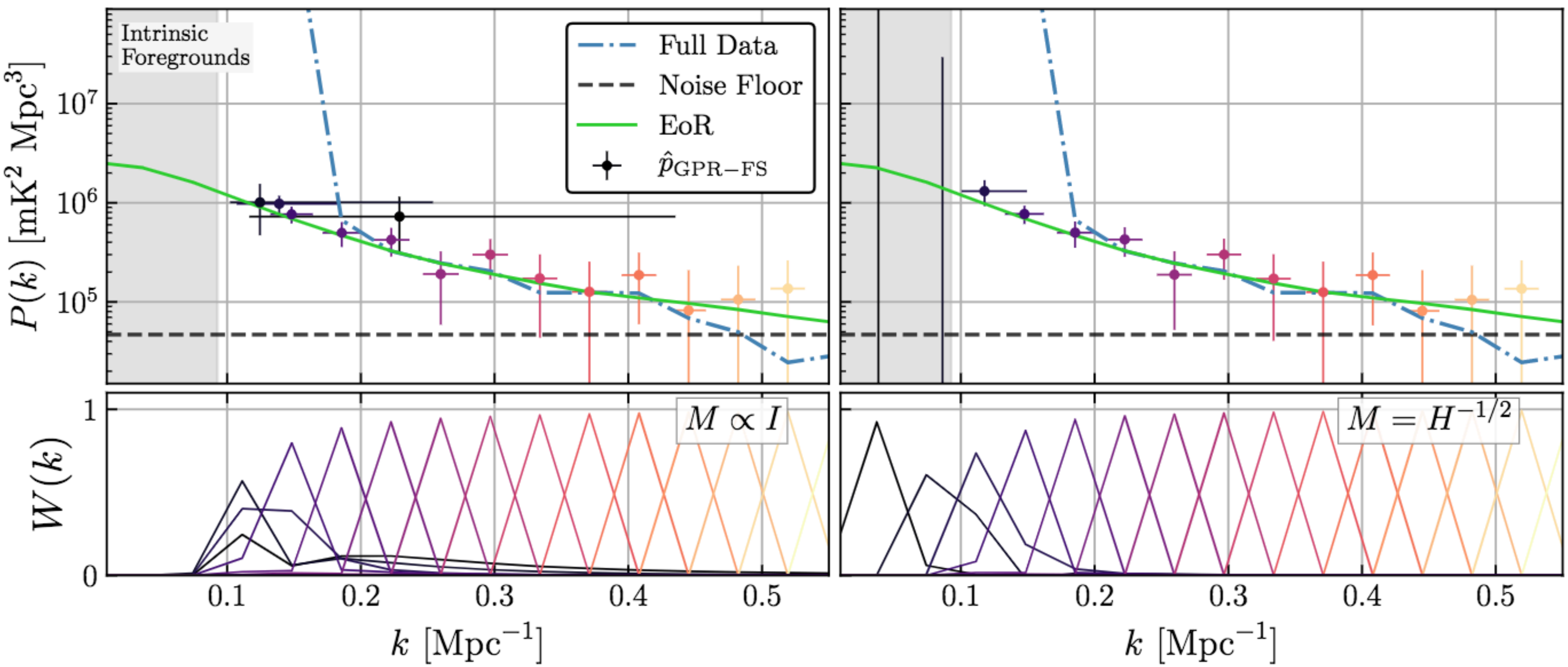
GPR-FS on mock data

Mapping the window functions

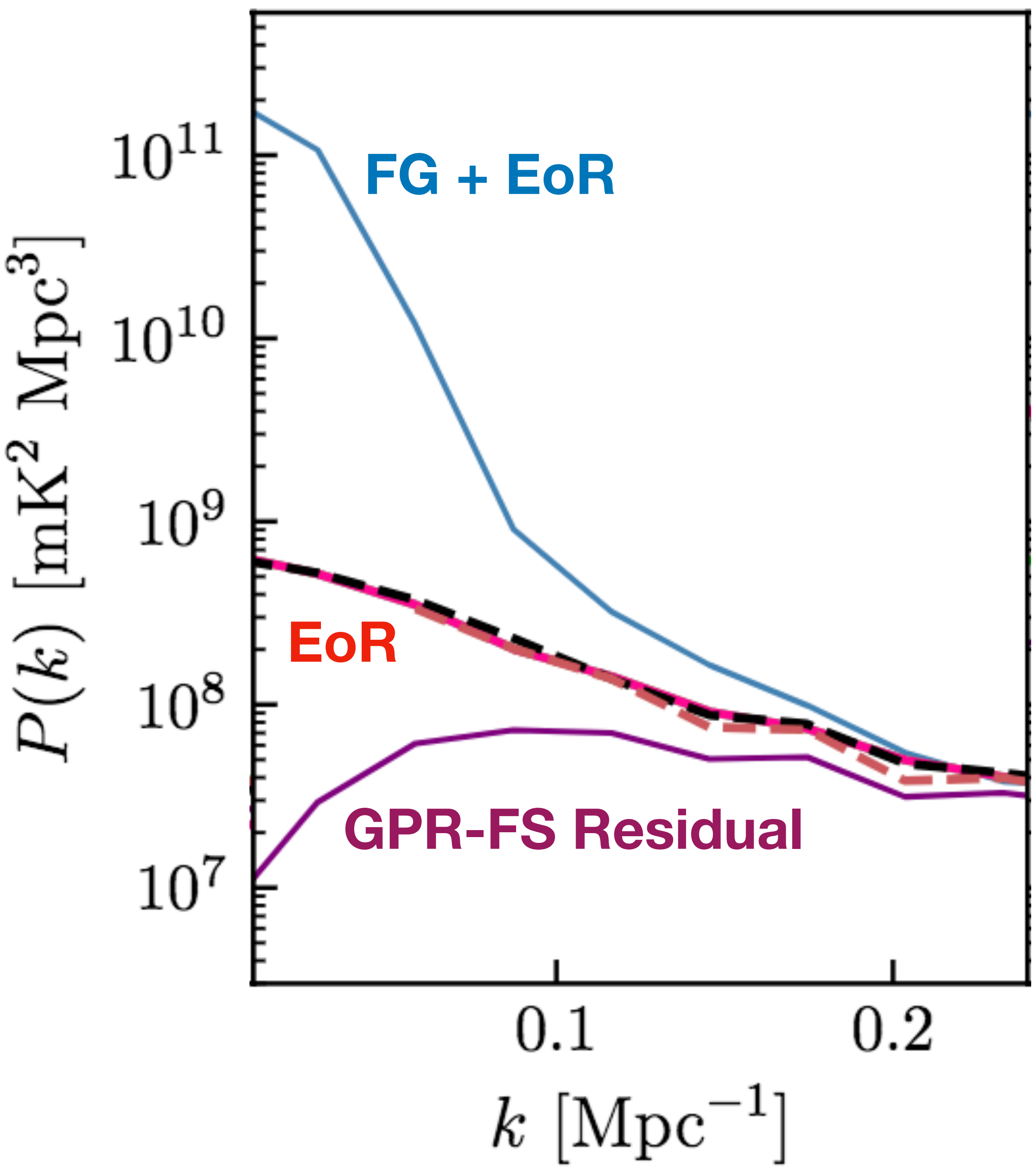


GPR-FS on mock data

Mapping the window functions



GPR-FS *requires* normalization



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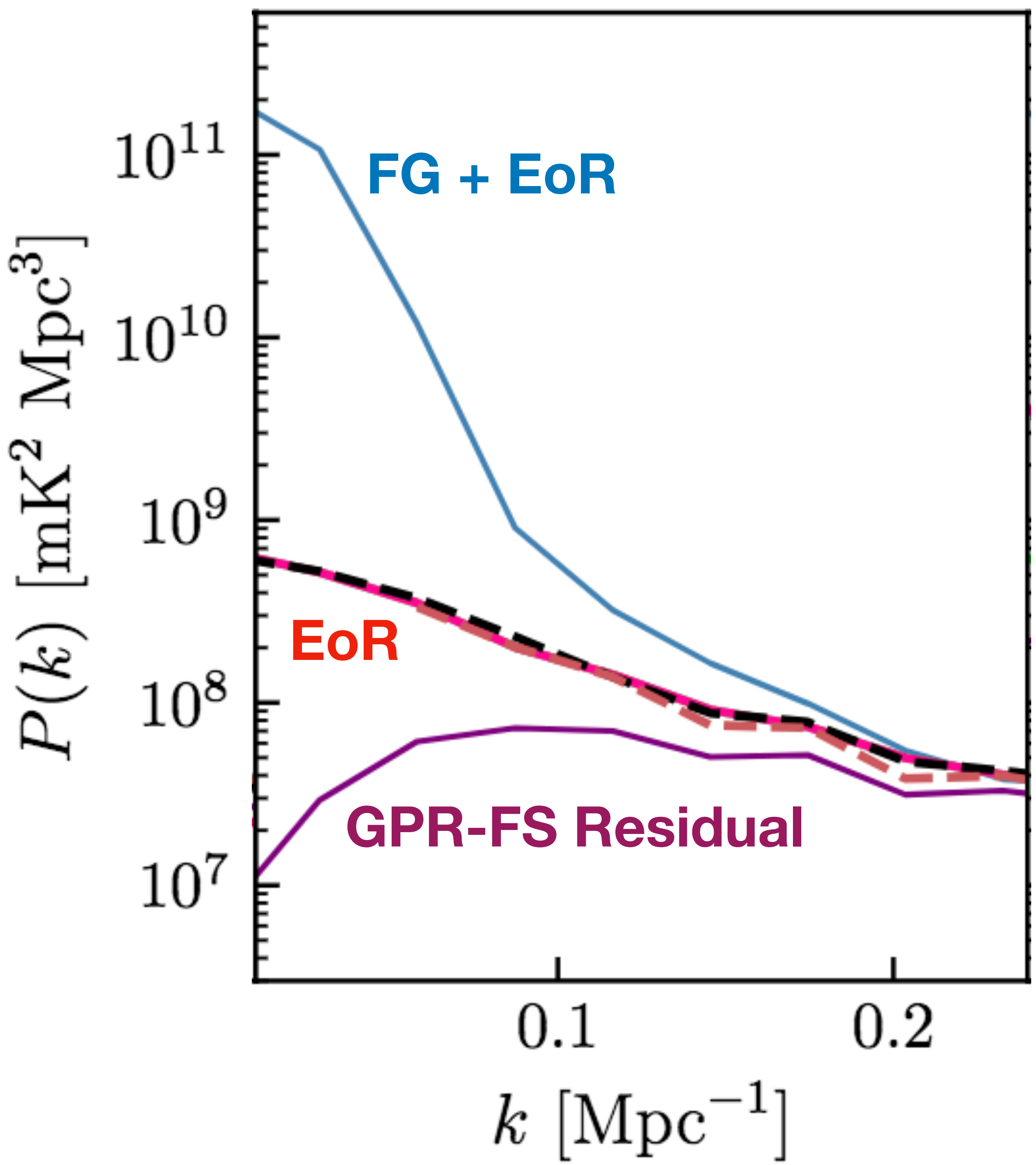

$$\hat{p}_\alpha = M_{\alpha\beta}\hat{q}_\beta - \hat{b}_\alpha$$

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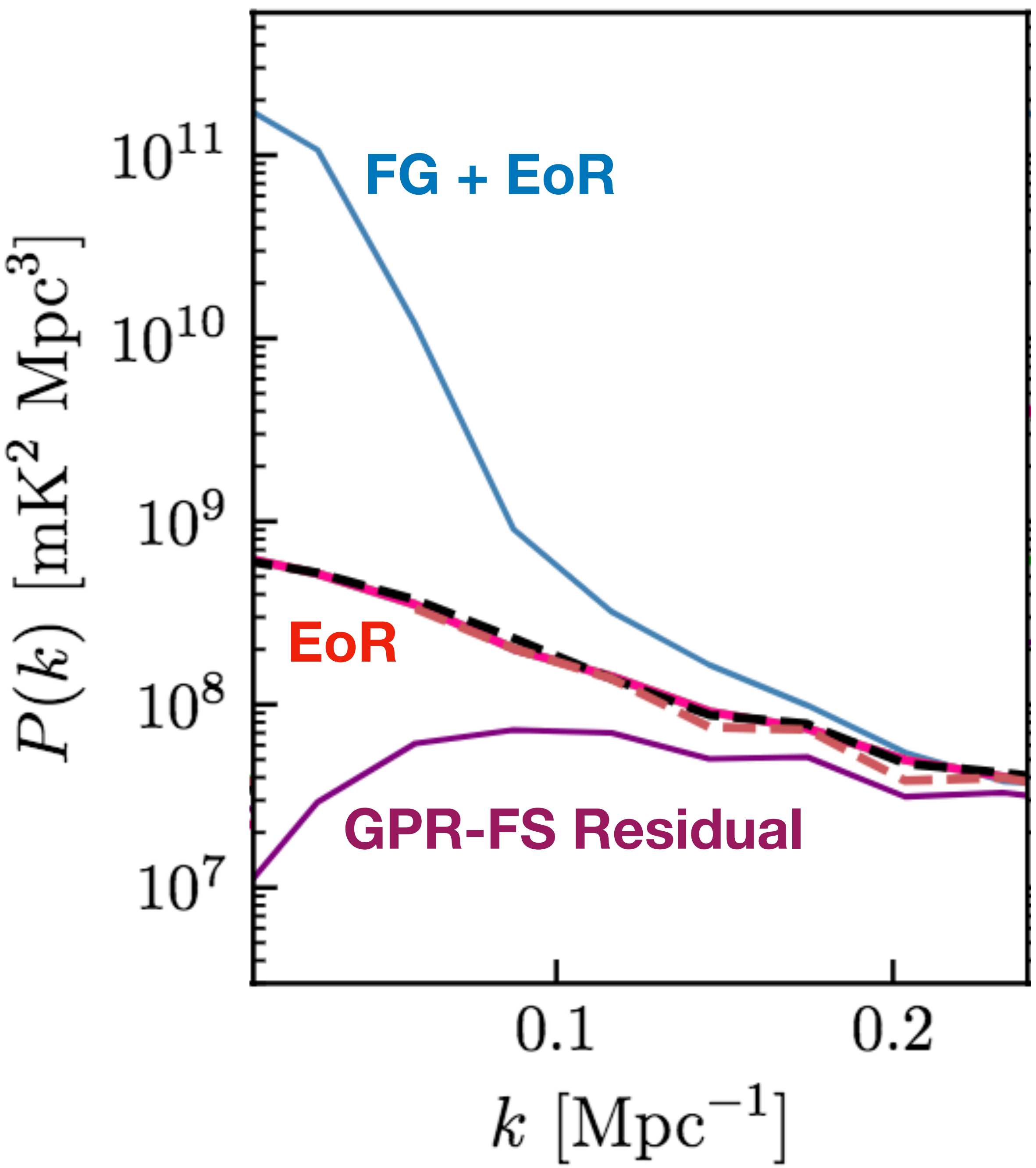

$$\hat{p}_\alpha = M_{\alpha\beta}\hat{q}_\beta - \hat{b}_\alpha$$

Recognized by Mertens+2020, but treated differently

The LOFAR GPR-FS pipeline

LOFAR normalizes their post GPR-FS data with a **bias correction**

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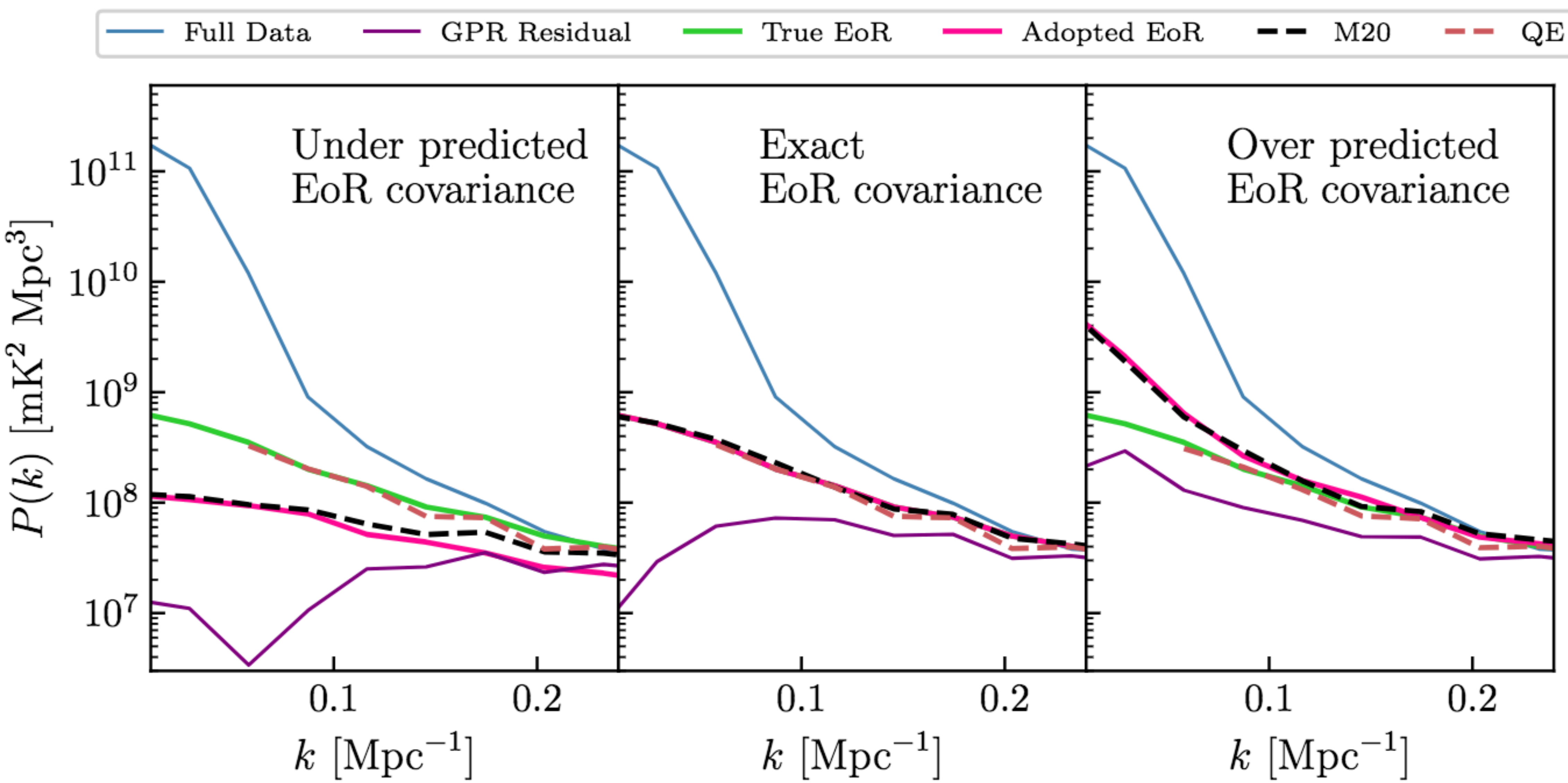
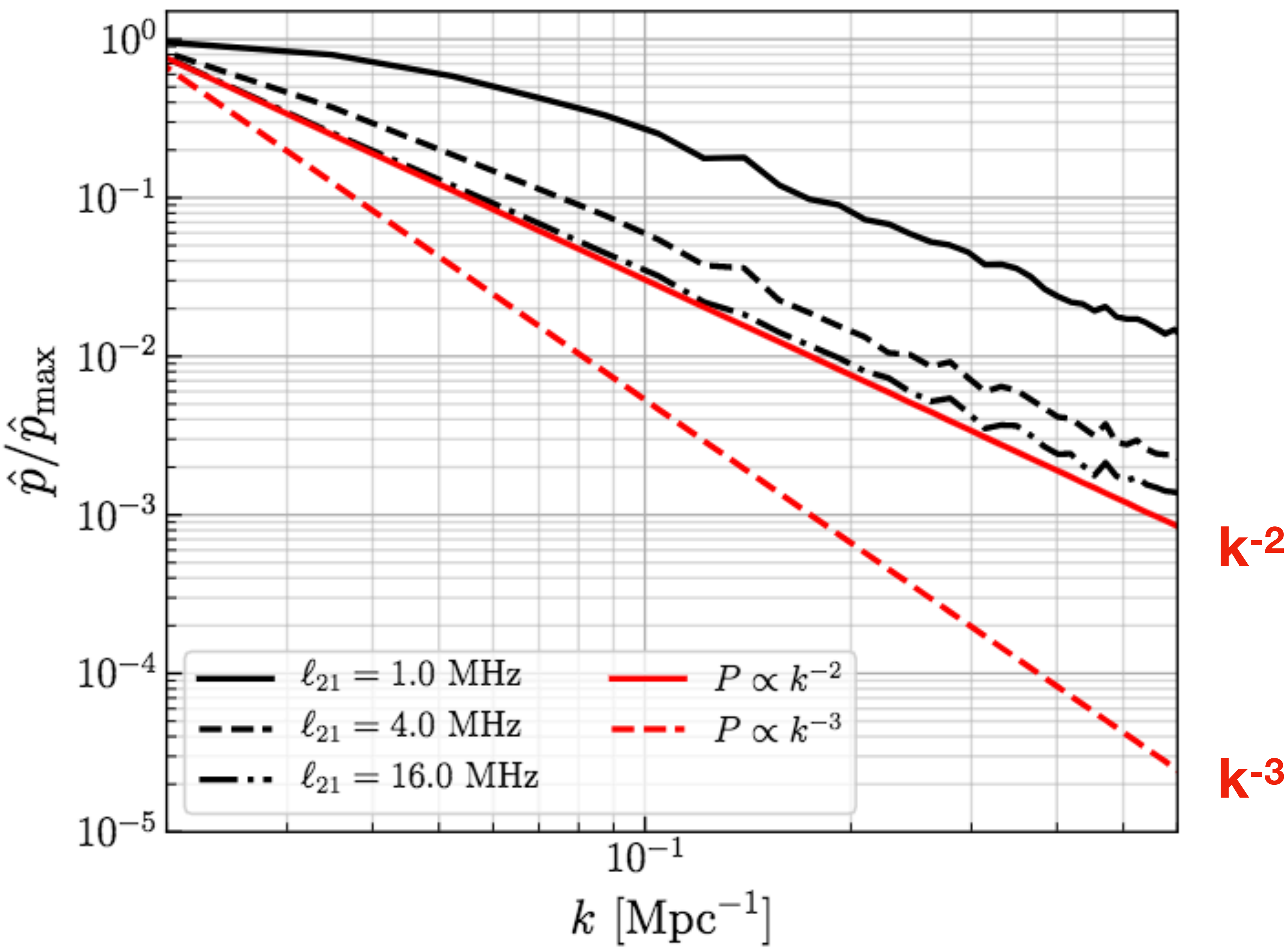
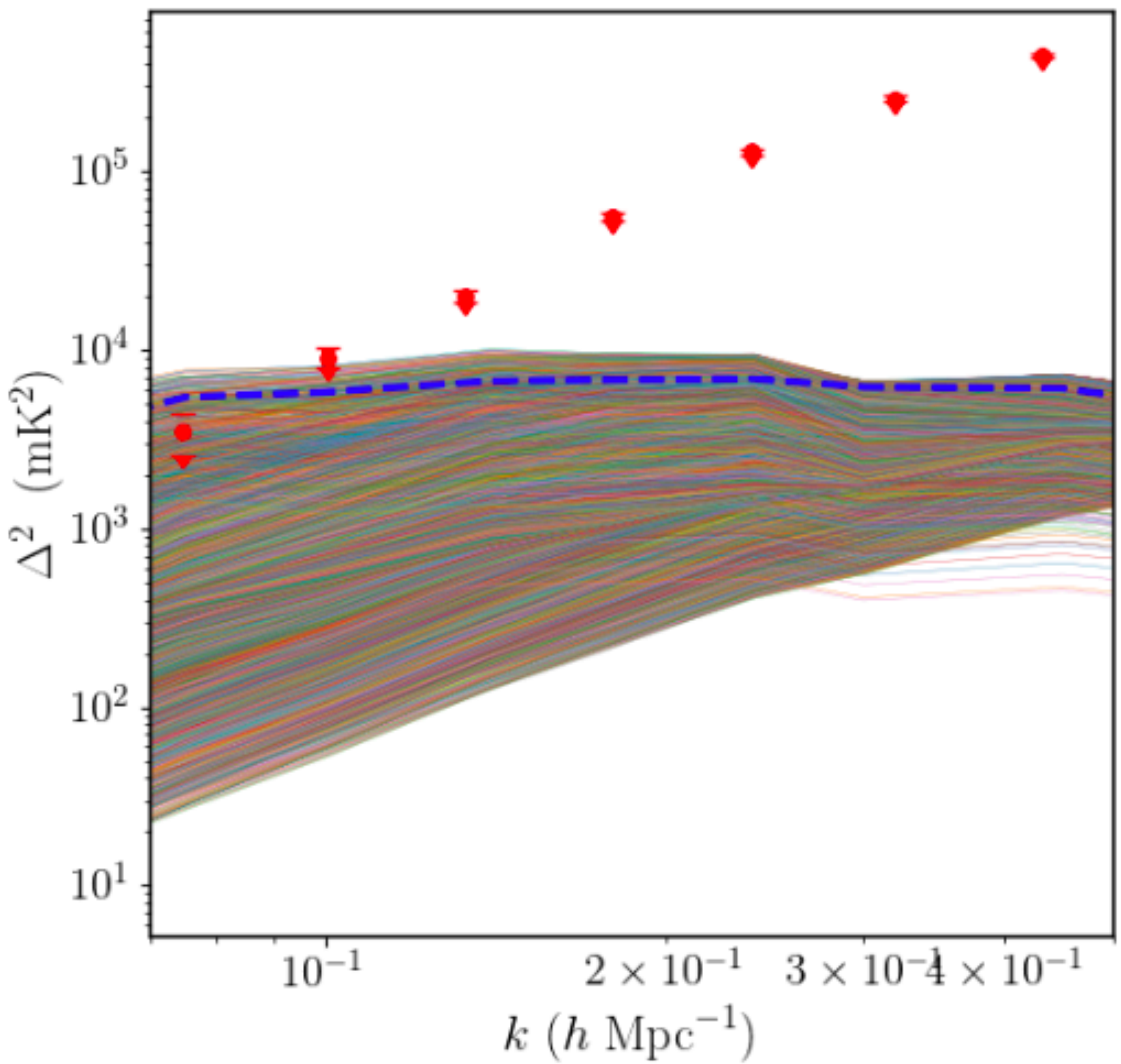
LOFAR normalizes their post GPR-FS data with a **bias correction**



Results only as good as the EoR model



May be an oversight for ruling out certain models



Ruling out these kinds of models may be problematic

$$P(k) \propto k^{-3}\Delta^2$$

Ghara+2020
but also Greig+2020, Mondal+2020

LOFAR results do acknowledge this

- Test a few different covariance models before settling on an exponential EoR covariance

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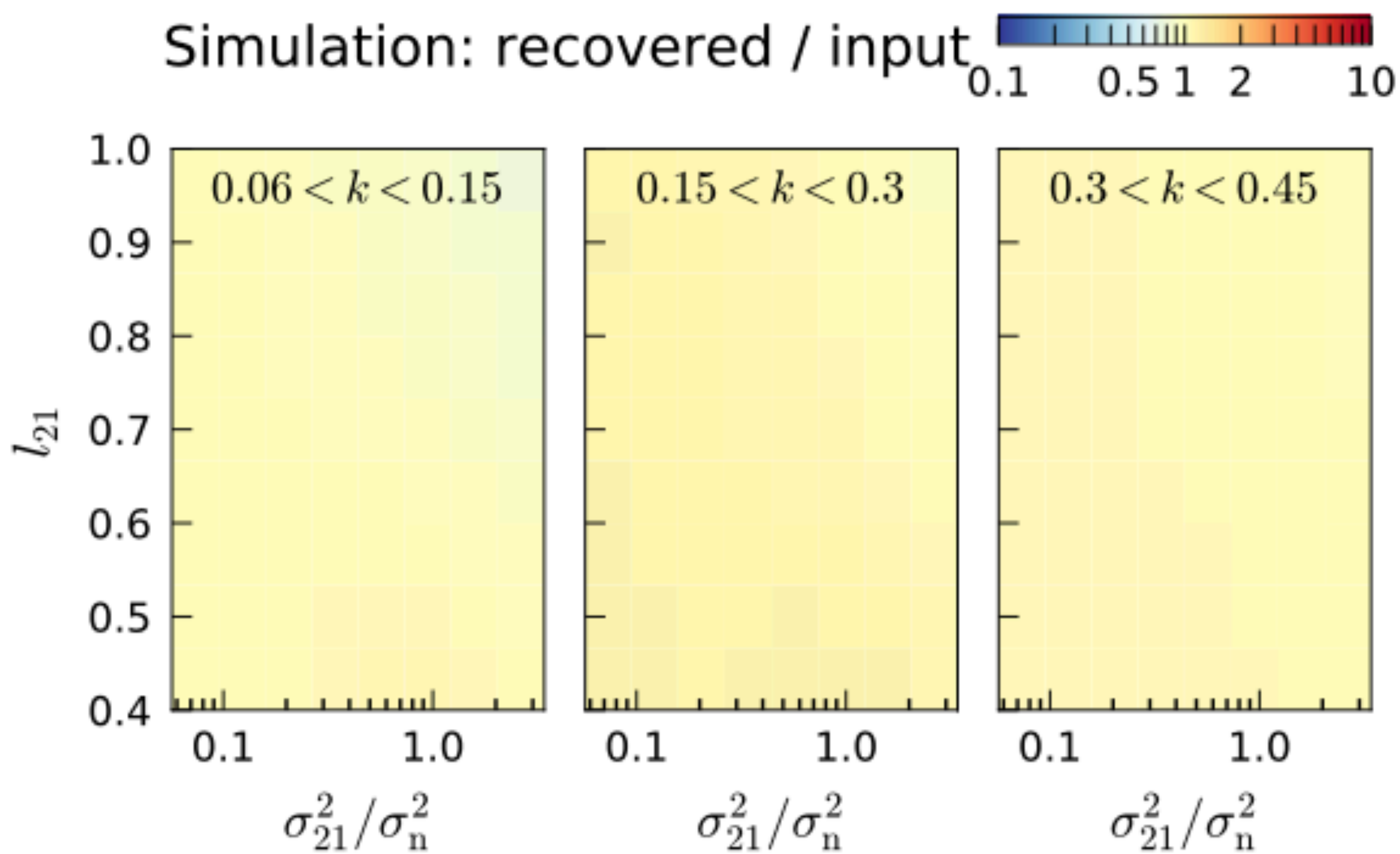
- Test a few different covariance models before settling on an exponential EoR covariance

- Simulated power spectrum recovery tests



Mertens+2020

Summary

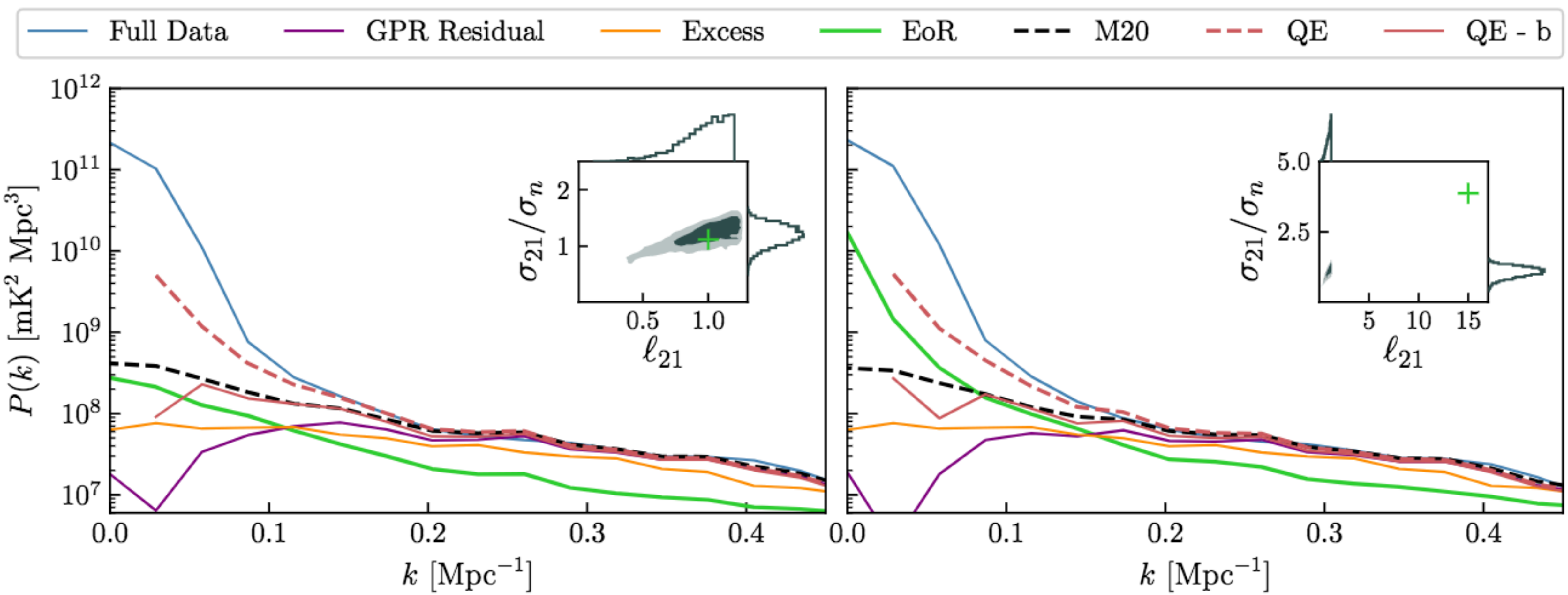
1. Gaussian process foreground subtraction is closely related to inverse covariance weighting

2. Window functions important for low k recovery

3. Current LOFAR estimator is particularly sensitive to a mismatched EoR covariance

Questions? Let's chat on the SALF slack! (@nkern)

Signal Recovery Test I: Impact of prior



Signal Recovery Test II: Tone injection