A WEAKLY PARAMETRIC APPROACH TO STOCHASTIC BACKGROUND IN LISA

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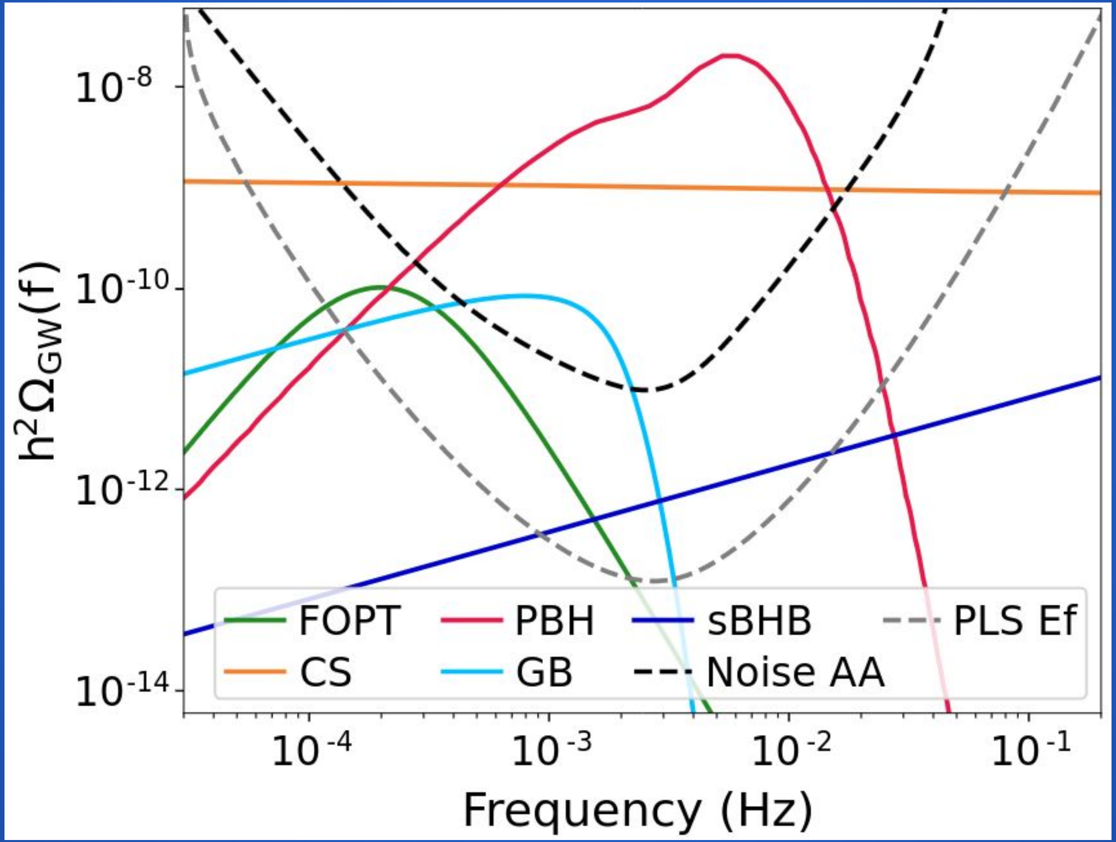
11th LISA CosWG - 19/6/2024

STOCHASTIC BACKGROUND IN LISA

LISA Definition Study Report



SEARCHING BACKGROUND IN LISA -CHALLENGES

NOISE SIGNAL

$$C(f) = S_n(f) + R(f)S_h(f)$$

SEARCHING BACKGROUND IN LISA -CHALLENGES

$$C(f) = S_n(f) + R(f)S_h(f)$$

- Non-Stationarity (gaps, glitches, ...)
- Noise Uncertainties
- Correlation between TDI channels
- likely non-existing null channel

SEARCHING BACKGROUND IN LISA -CHALLENGES

$$C(f) = S_n(f) + R(f) S_h(f)$$

- Non-stationarity, Anisotropy, Non-Gaussianity
- Overlapping signals
- Astrophysical Models depend on populations
- Cosmological Models depend on fundamental physics

SEARCHING BACKGROUND IN LISA - MODELS

NOISE \ SIGNAL	Template Based	Template Free
Template Based	Boileau 23 Adam 14	Caprini 19 Flauger 21
Template Free	Baghi 23 Muratore 23	?

What do we propose?

SEARCHING BACKGROUND IN LISA - MODELS

NOISE \ SIGNAL	Template Based	Template Free
Template Based		
Template Free		

MODELLING WITH GP - PRELIMINARY ASSUMPTION

- Fourier Domain

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- ➔ Fourier Domain
- ➔ GENERATION 1.5 TDI (Unequal and constants LISA arms) and AET variables

MODELLING WITH GP - PRELIMINARY ASSUMPTION

- → Fourier Domain
- → GENERATION 1.5 TDI (Unequal and constants LISA arms) and AET variables
- → Whittle Likelihood

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- Gaussian, Isotropic and stationary SGWB

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- Model Signal and Noise strain:

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- Gaussian, Isotropic and stationary SGWB
- Model Signal and Noise strain:

  - We assume perfect knowledge of TDI transfer matrix (*)

$$S_{n,\alpha\beta}(f) = \frac{1}{2} S_n(f) M_{\alpha i,\mathrm{TDI}}(f) M^*_{i\beta,\mathrm{TDI}}(f)$$

*Note: OMS and Acceleration noise components have different transfer function

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$$S_{h,\alpha\beta}(f) = R_{\alpha\beta}(f) S_h(f)$$

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MODELLING WITH GP

We employ the expectation value of Gaussian Process to model the PSD

$$\mu(X_*|X) = \mu(X_*) + \Sigma(X_*, X)\Sigma(X, X)^{-1}(g(X) - \mu(X))$$

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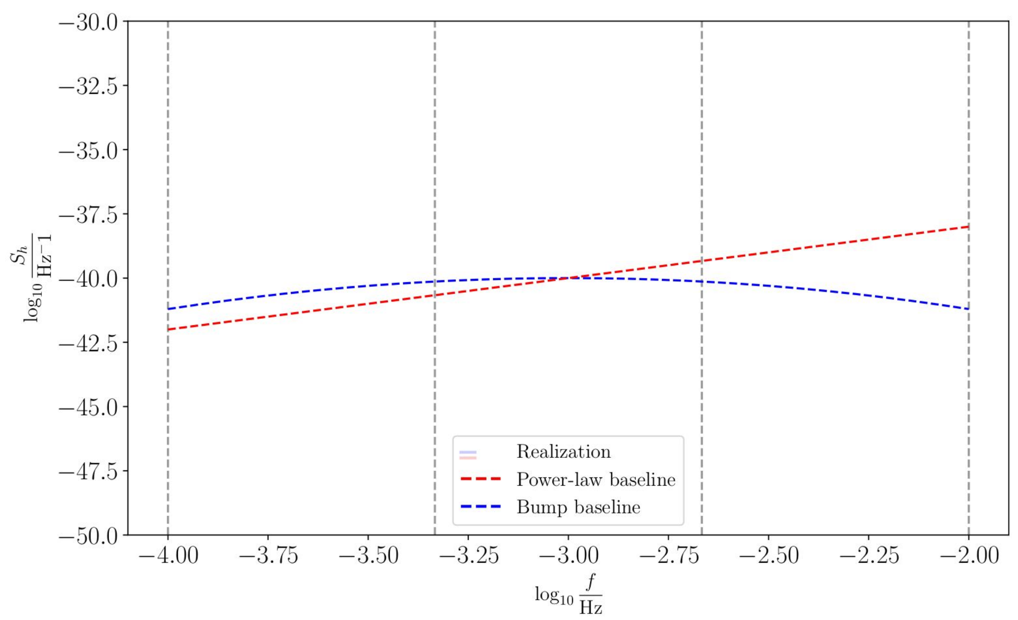
BASELINE



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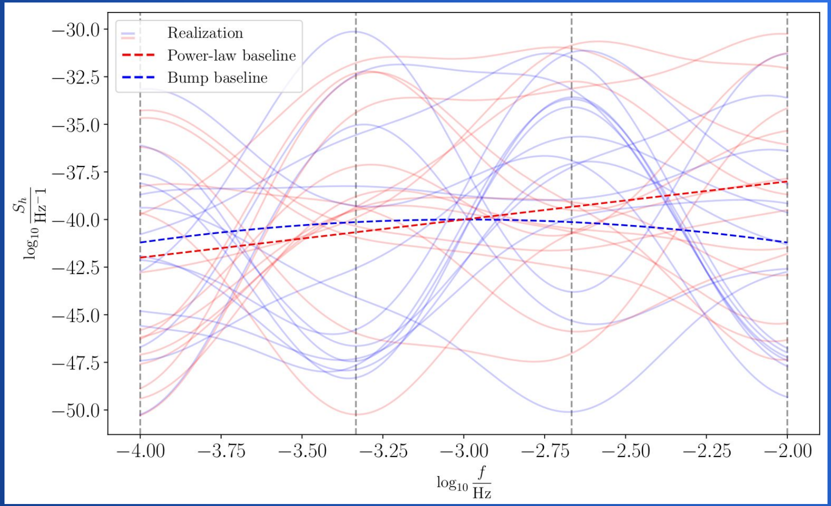
DEVIATION FROM THE BASELINE AT KNOTS

where

$$\Sigma_{ij}^{RBF}(X, Y) = k_{RBF}(x_i, y_j) = \exp(-\frac{|x_i - y_j|^2}{2\sigma^2})$$



MODELLING WITH GP

We employ the expectation value of Gaussian Process (EGP) to model the PSD

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BASELINE

DEVIATION FROM THE BASELINE AT KNOTS

The model depends on 2 hyperparameters:
- the number of knots
- kernel lengthscale

MODELLING WITH GP

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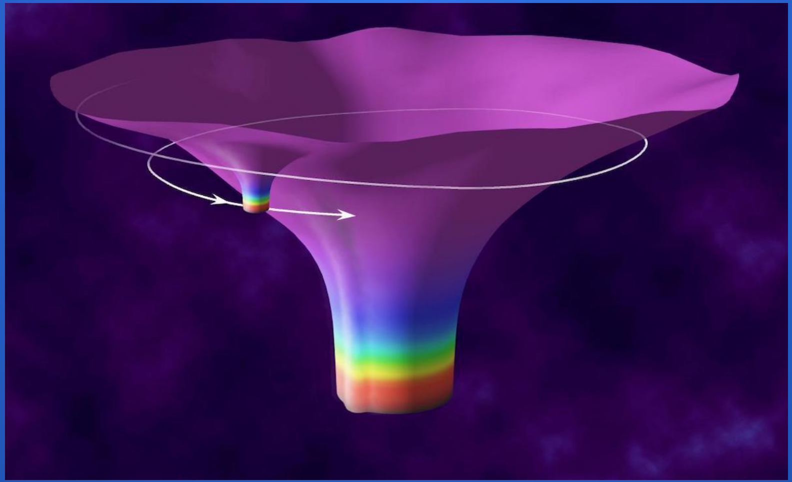
$$\mu(X_*|X) = \mu(X_*) + \Sigma(X_*, X)\Sigma(X, X)^{-1}(g(X) - \mu(X))$$

SIGNAL with power-law as baseline

NOISE with fixed baseline at SciRD level

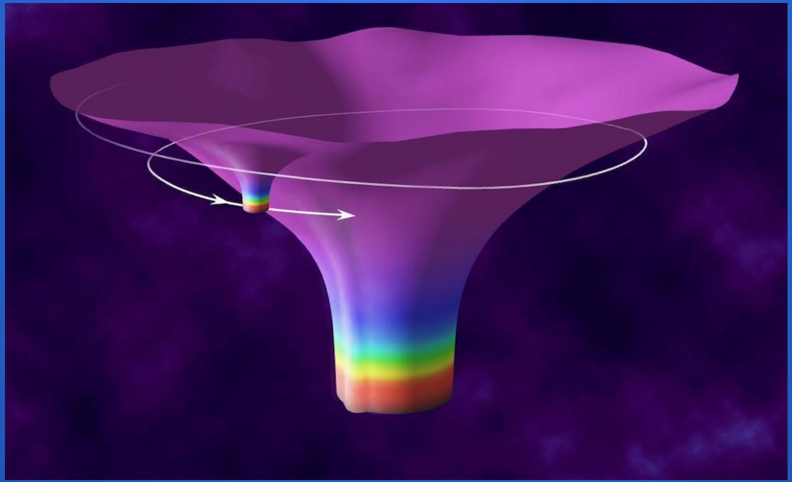
*Number of knots can be different for noise and signal

RESULTS - APPLICATION TO EMRI



RESULTS - APPLICATION TO EMRI

- The largest majority of EMRIs will be undetectable → Possible SGWB



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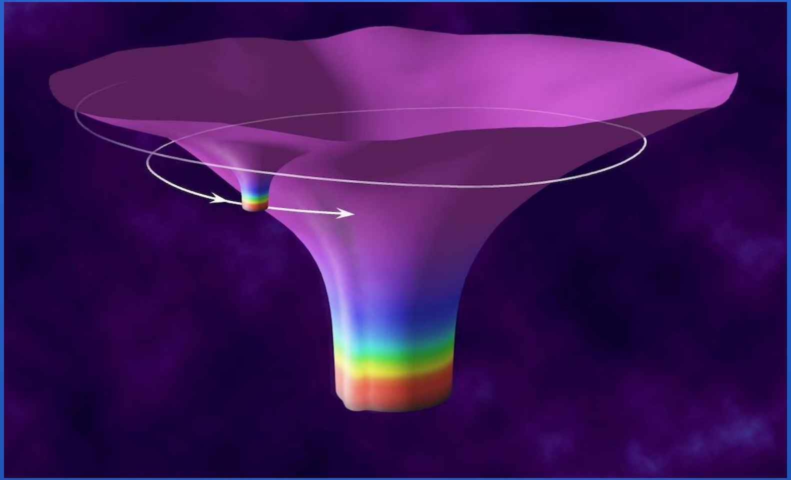
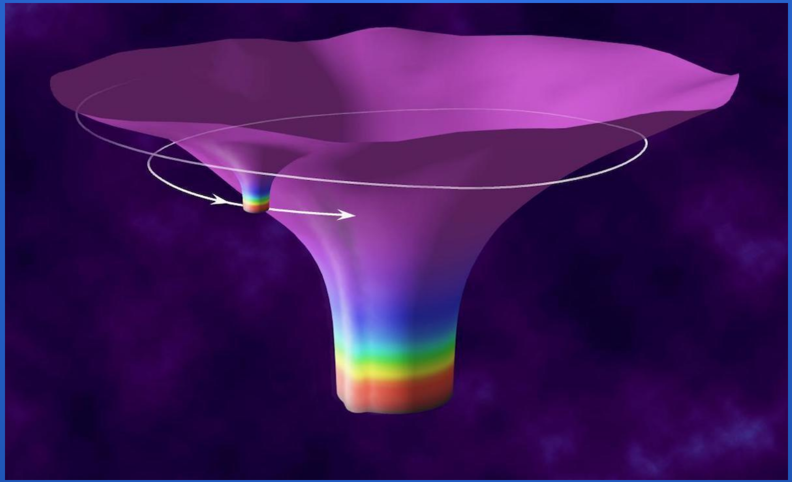
- EMRI are extremely complex objects, both for the GW waveform and population



RESULTS - APPLICATION TO EMRI

- The largest majority of EMRIs will be undetectable → Possible SGWB
- EMRI are extremely complex objects, both for the GW waveform and population
- A lot of uncertainties in the SGWB



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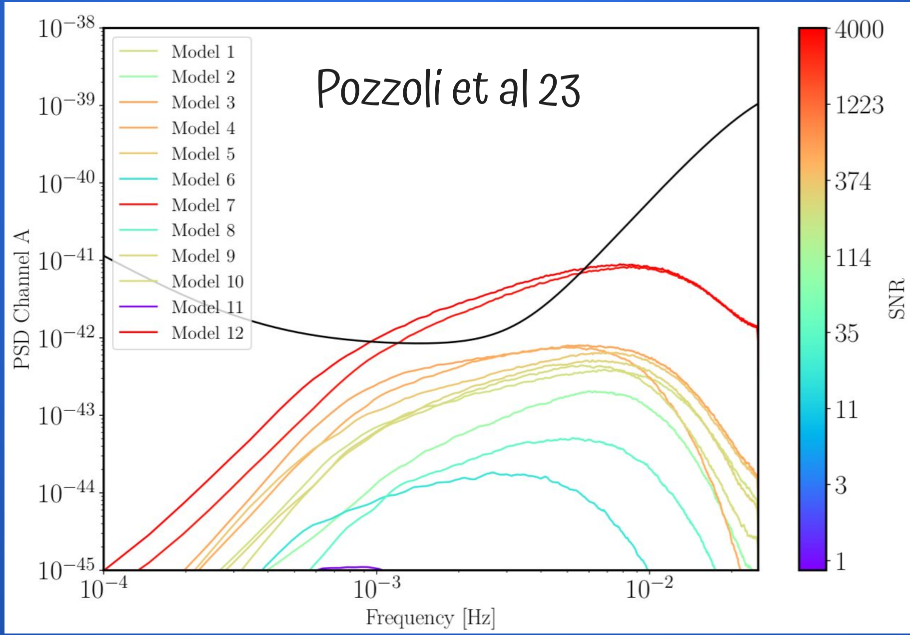
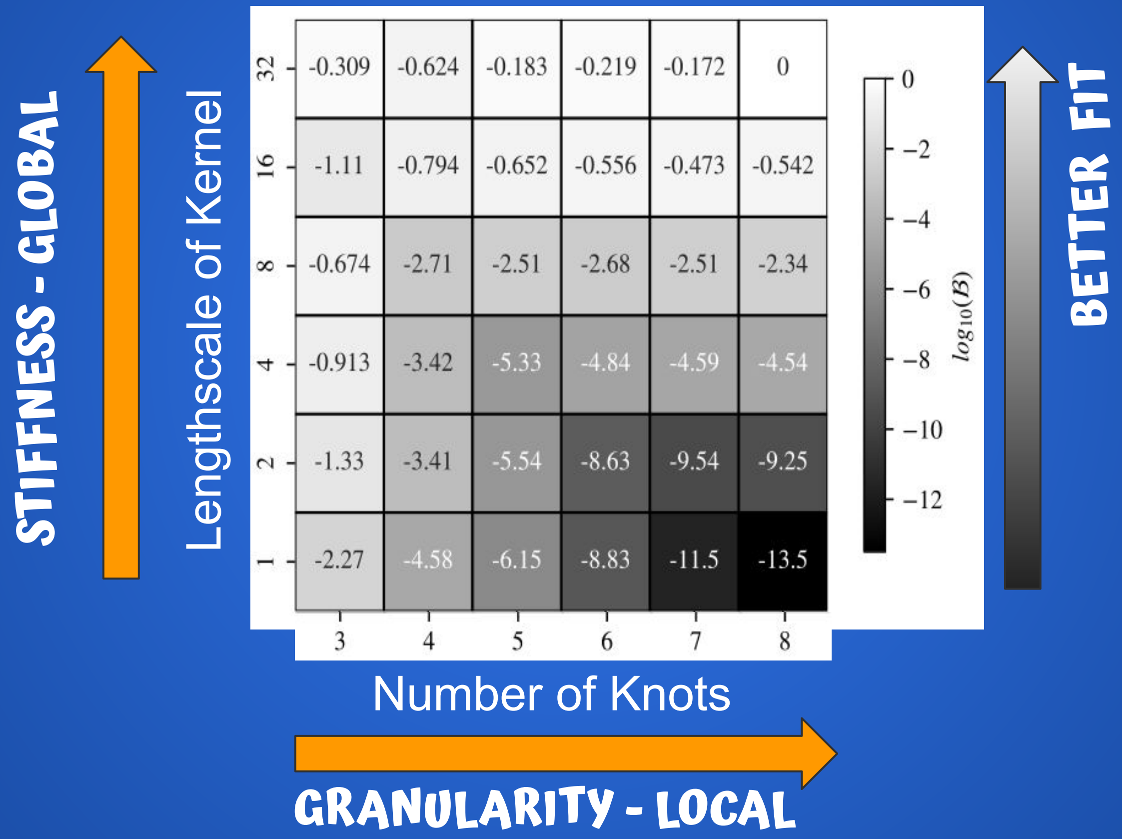


RESULTS - APPLICATION TO EMRI

→ Free Template algorithm is necessary to study this kind of SGWB

- We inject noise + EMRI realization M1 from Pozzoli et al 23
- We recover noise with EGP using 3 knots
- We recover signal exploring different combination of hyperparameters

RESULTS - APPLICATION TO EMRI



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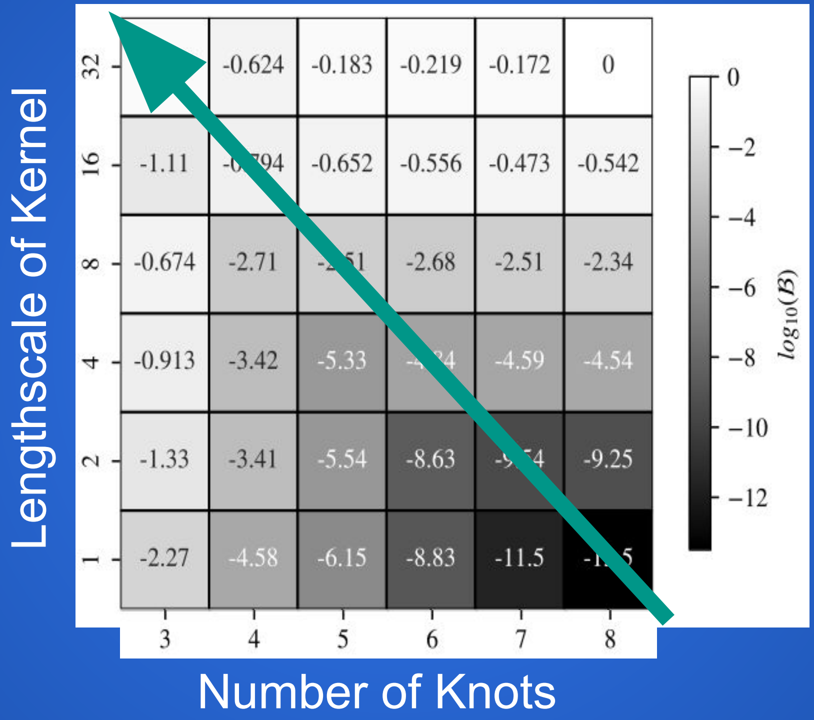
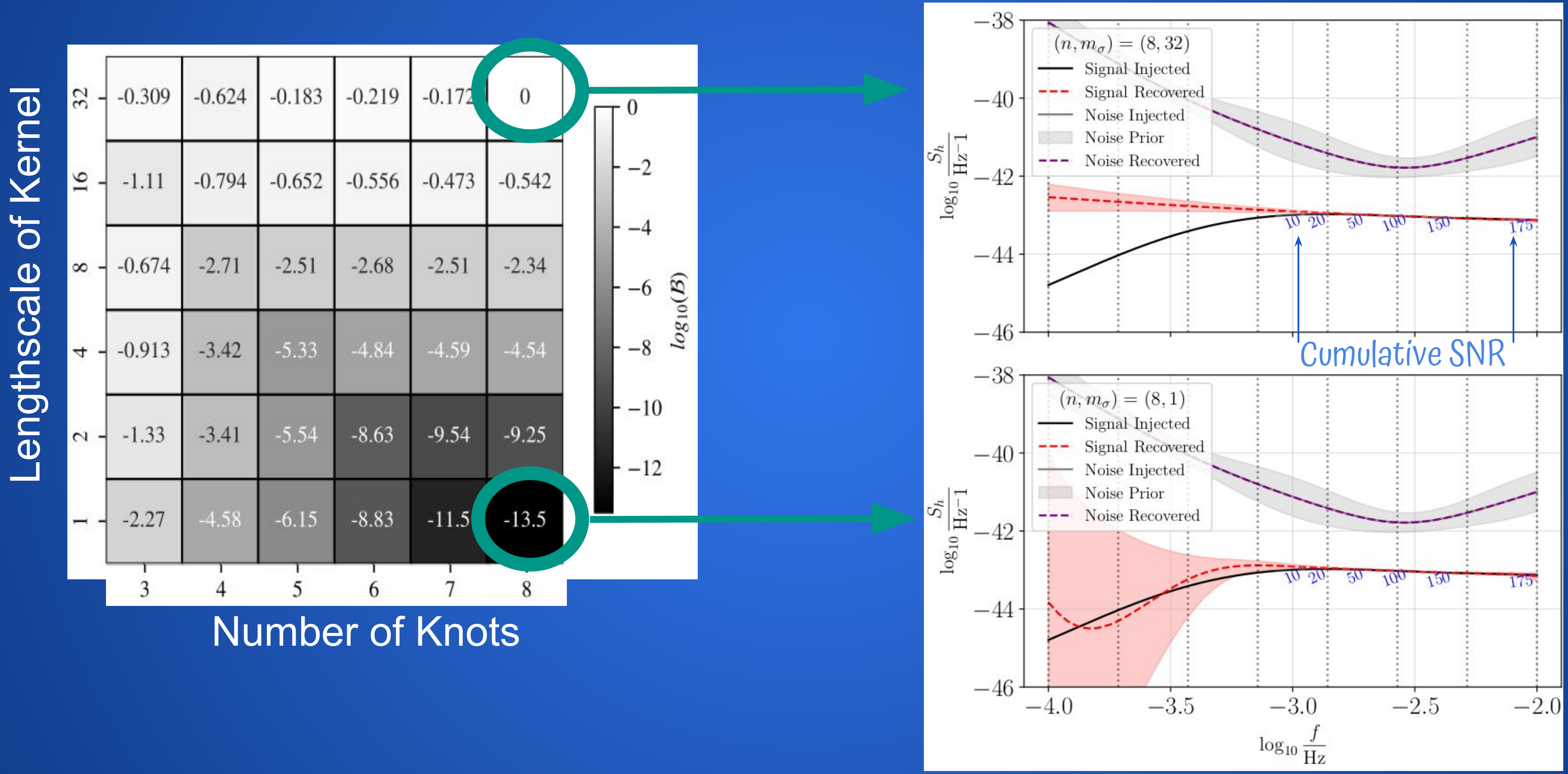


RESULTS - APPLICATION TO EMRI



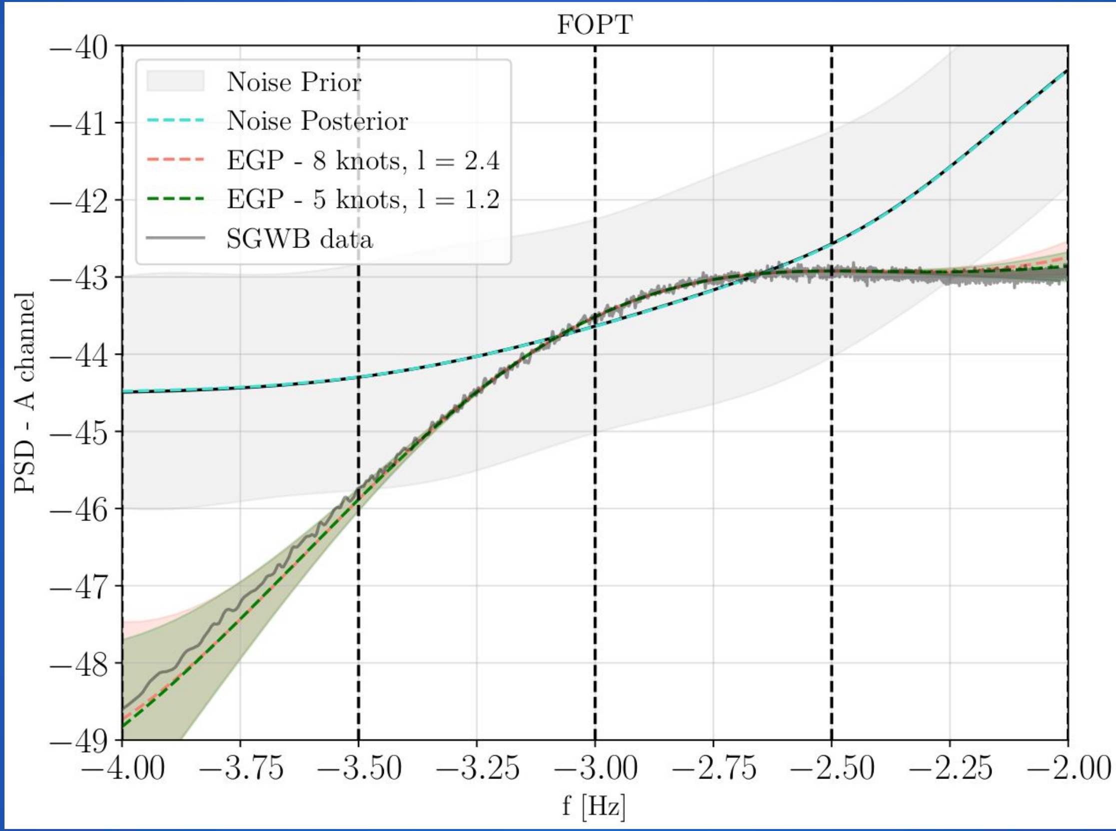
CONCLUSIONS & OUTLOOKS

In this work, we introduce a new flexible method for the simultaneous inference of SGWB and LISA noise.

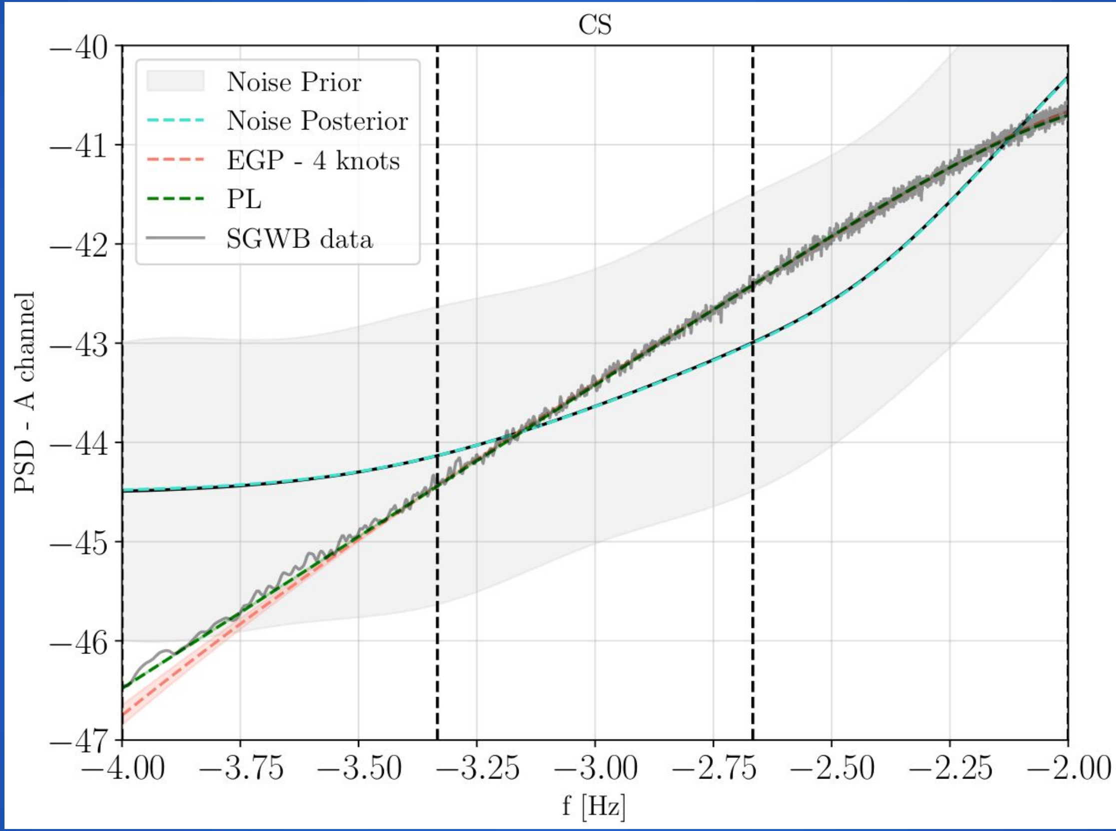
FUTURE EXTENSIONS:

- Multiple Backgrounds Injection
- Include correlation terms in TDI matrix
- Transdimensional Sampler
- Non-Stationary Signal (e.g., MW Foreground)

THANK YOU!



FOPT
Noise Prior
Noise Posterior
EGP - 8 knots, l = 2.4
EGP - 5 knots, l = 1.2
SGWB data
PSD - A channel
f [Hz]
−40
−41
−42
−43
−44
−45
−46
−47
−48
−49
−4.00
−3.75
−3.50
−3.25
−3.00
−2.75
−2.50
−2.25
−2.00


CS
Noise Prior
Noise Posterior
EGP - 4 knots
PL
SGWB data
PSD - A channel
f [Hz]
−40
−41
−42
−43
−44
−45
−46
−47
−4.00
−3.75
−3.50
−3.25
−3.00
−2.75
−2.50
−2.25
−2.00

$$C(f, f') = \sum_{n=-8}^{n=8} B_n S_h \left(\frac{f' + f}{2} \right) \delta \left(f - f' + \frac{n}{T} \right)$$