

# Data analysis challenges in LISA inference

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11th LISA CosmoWG Workshop - Porto

2024/06/19

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# A comparison

A recipe for disaster

Ground based (2G)

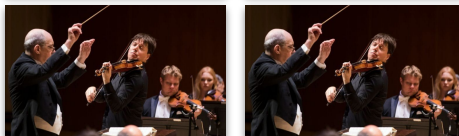


+



(+ noise)

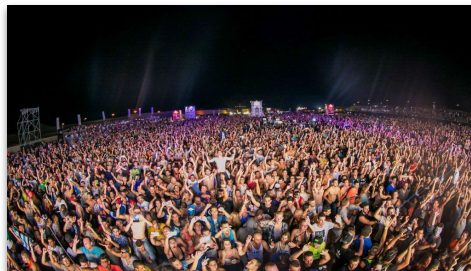
Space based



+

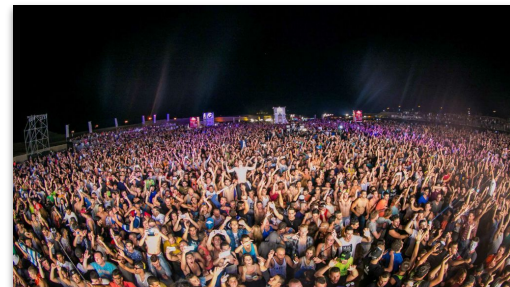


+



(+ noise)

Pulsar Timing Array



+

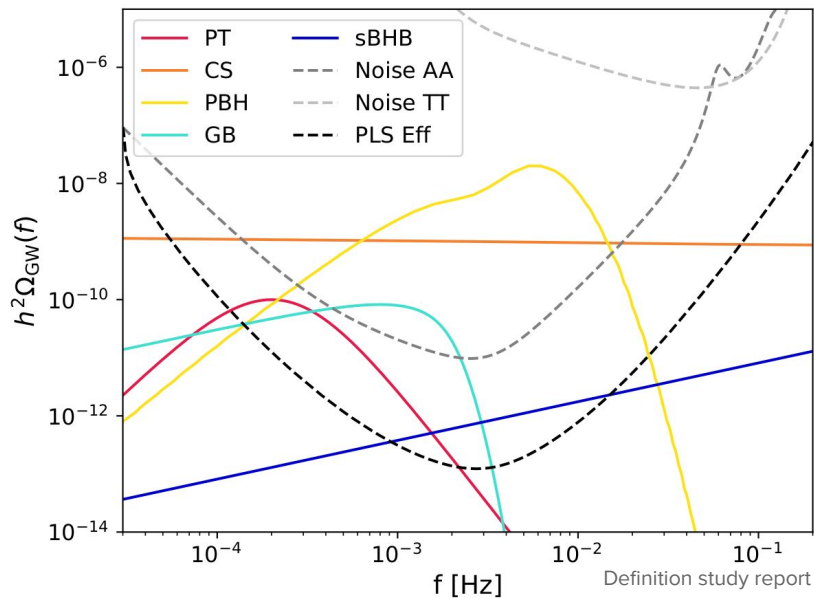


(+ noise)



# The upside down

e.g. Braglia+ 2406.10048



+



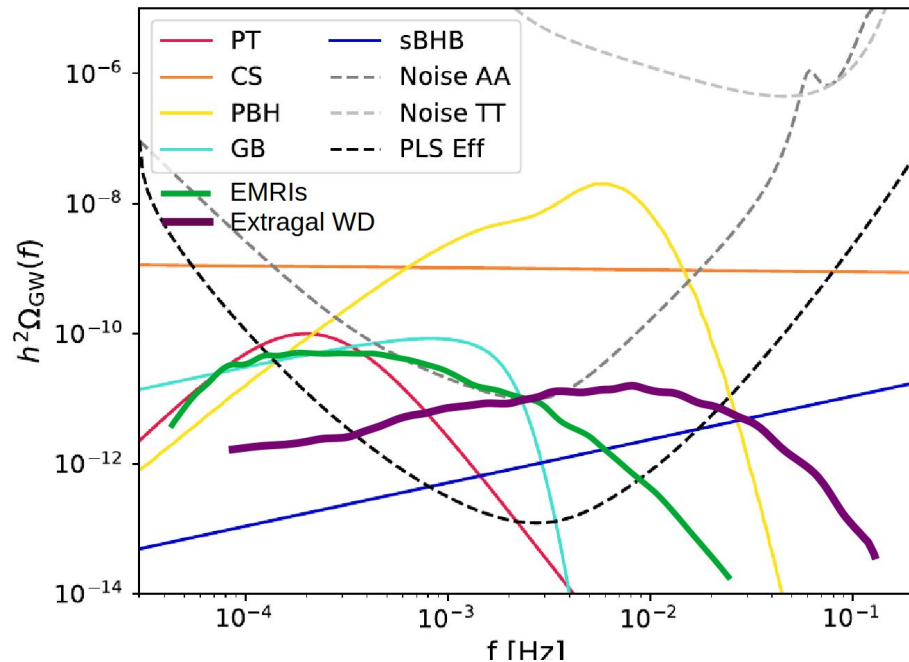
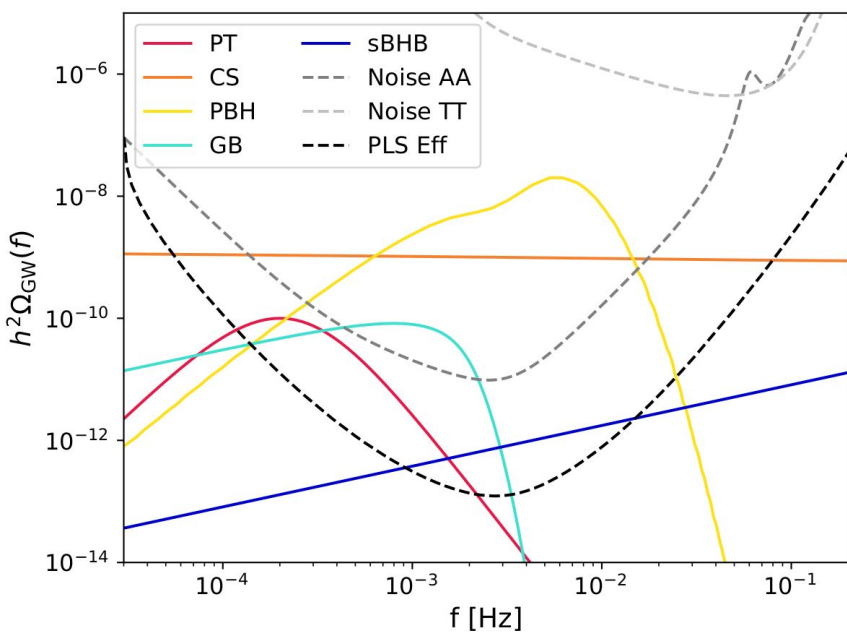
+



(+ noise)

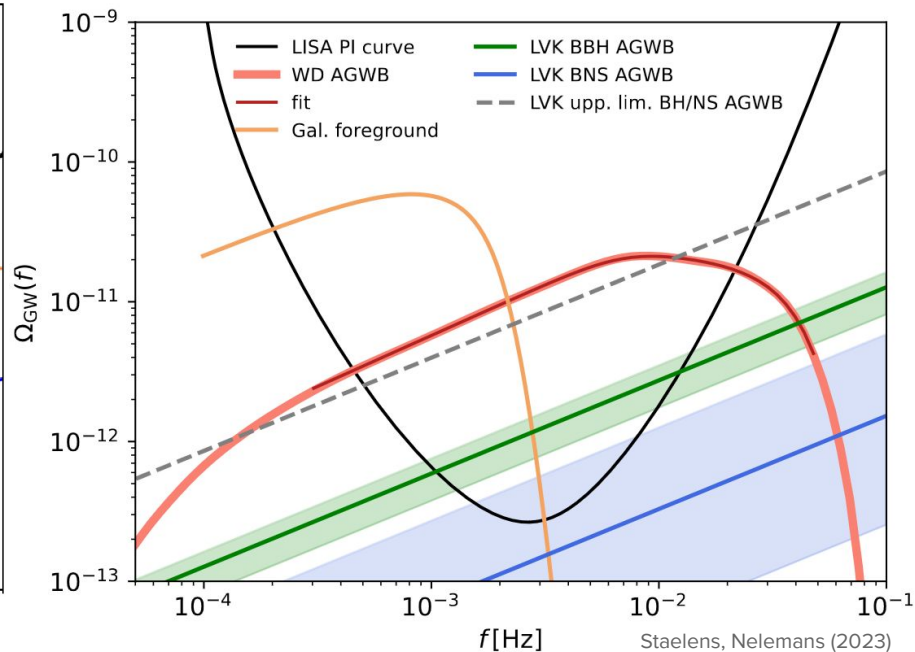
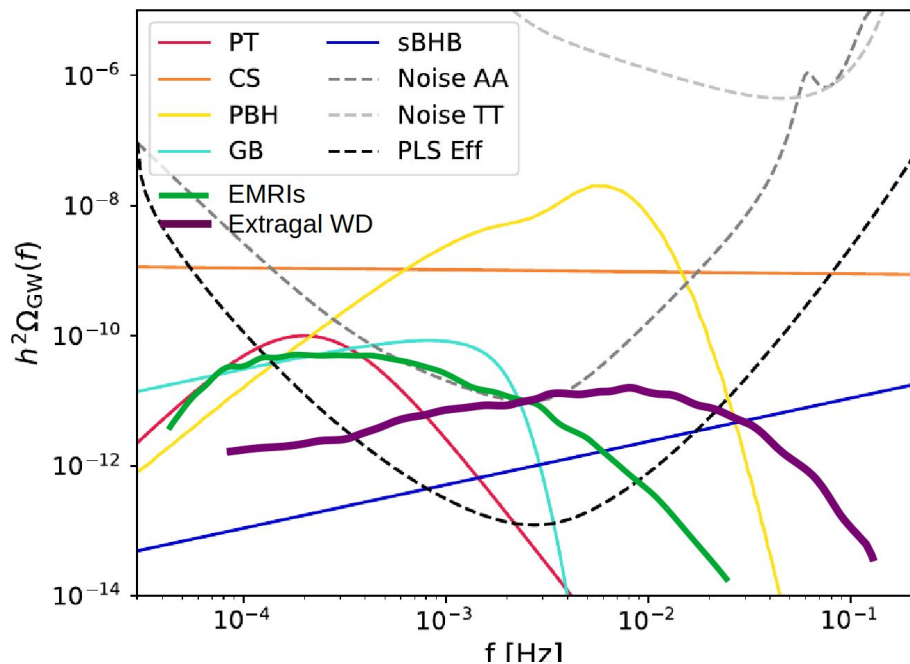
# Find the differences

Ready for mixtures?



# Find the differences

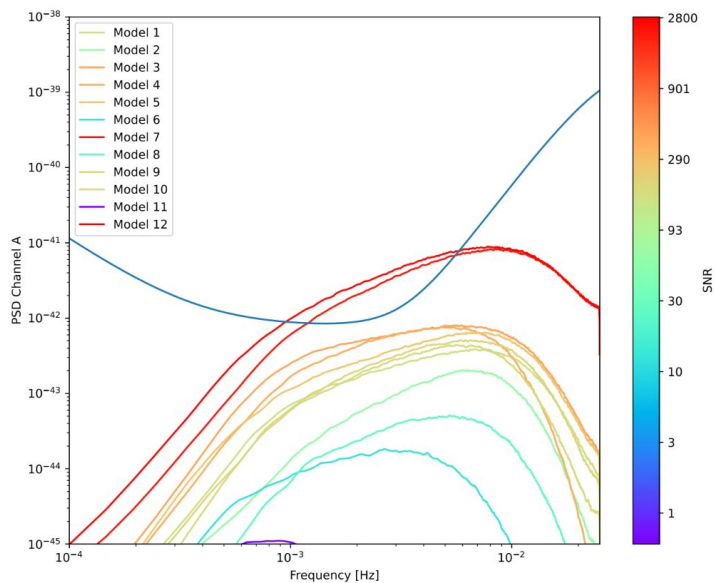
Ready for mixtures?



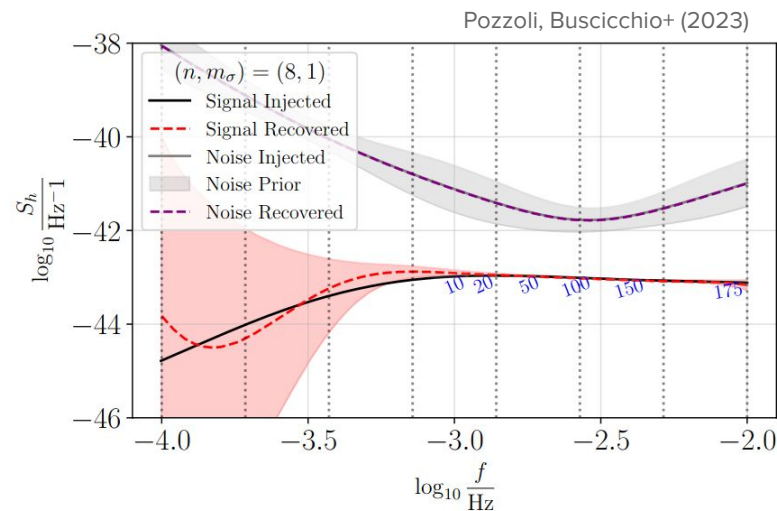
Collaborative effort is ongoing... 5

# EMRI foregrounds

## In unknown noise



Pozzoli, Babak+ 2023

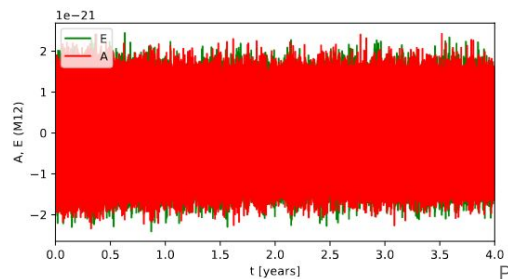
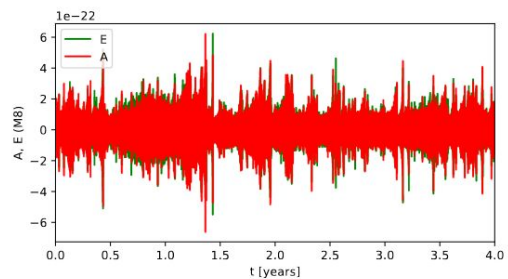
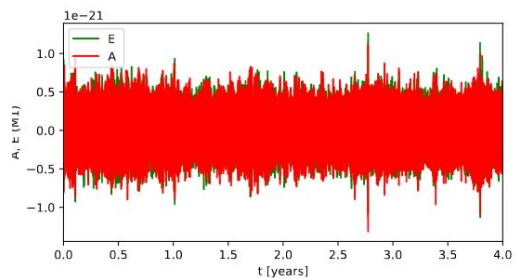


Pozzoli, Buscicchio+ (2023)

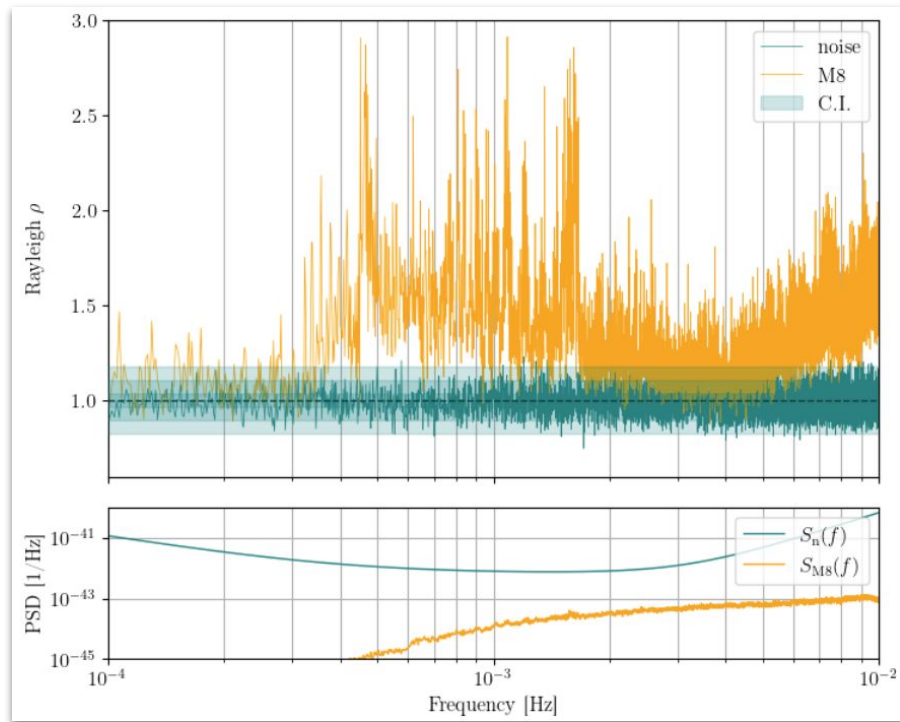
- Suitable for known & unknown global spectral shape
- Suitable for narrow spectral features
- Suitable for evidence-driven adaptive refinement

# EMRI foregrounds

## Stationary?



Piarulli, Buscicchio+ 2024



Non-stationary

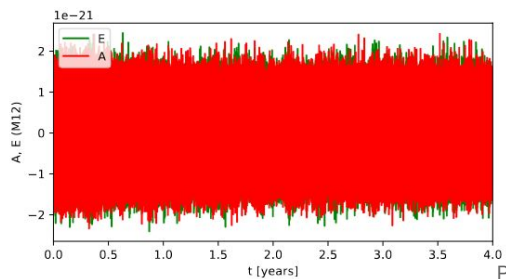
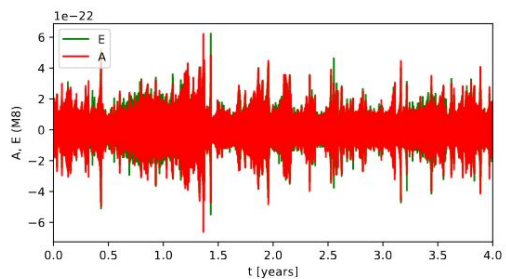
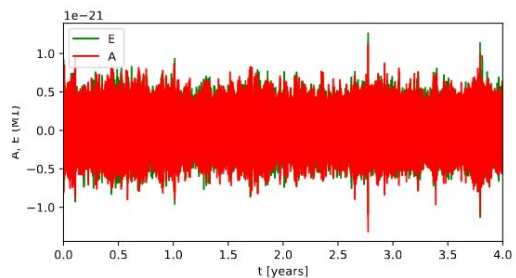
Gaussian

Deterministic

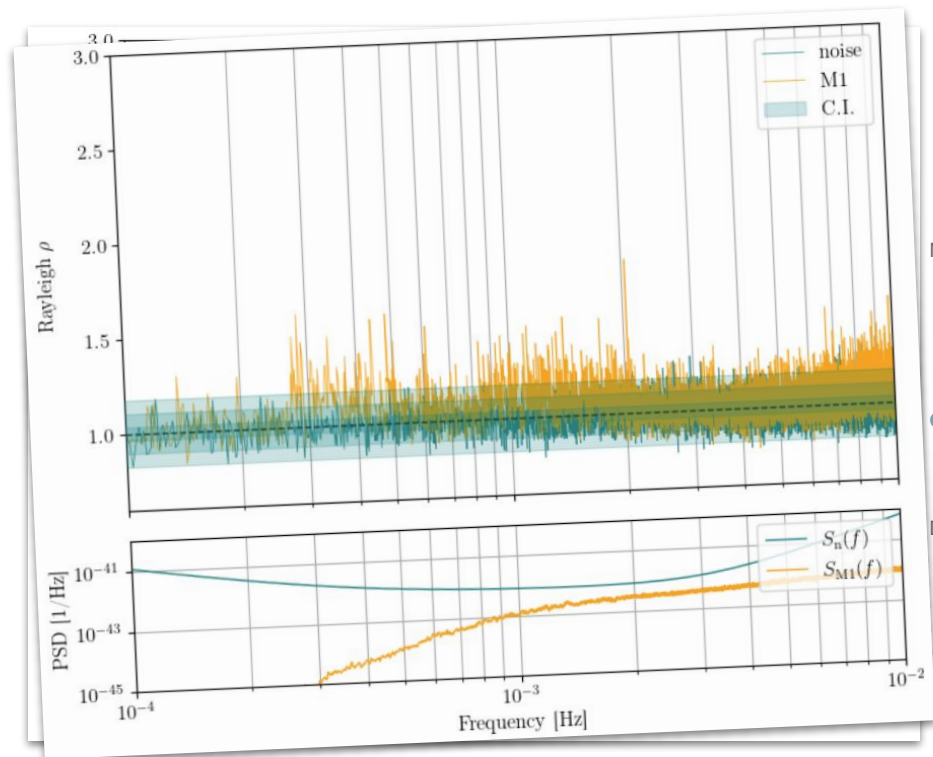
Piarulli, Buscicchio+ 2024

# EMRI foregrounds

## Stationary?



Piarulli, Buscicchio+ 2024



Non-stationary



Gaussian



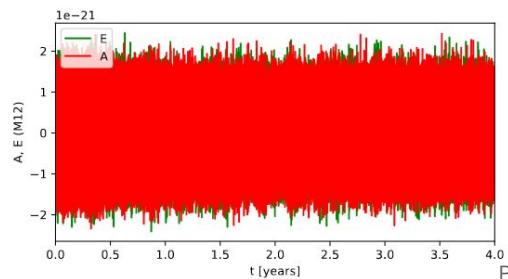
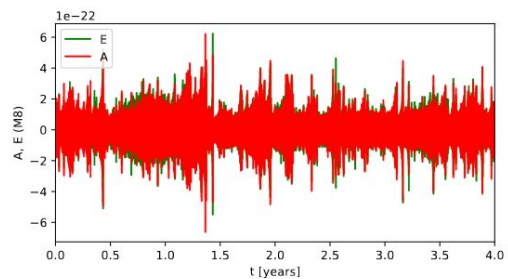
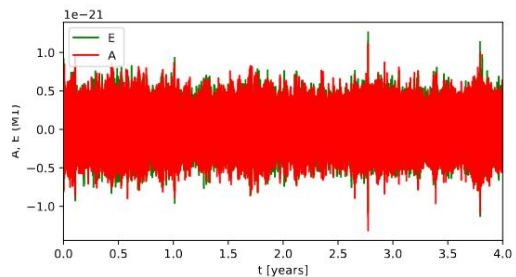
Deterministic

Piarulli, Buscicchio+ 2024

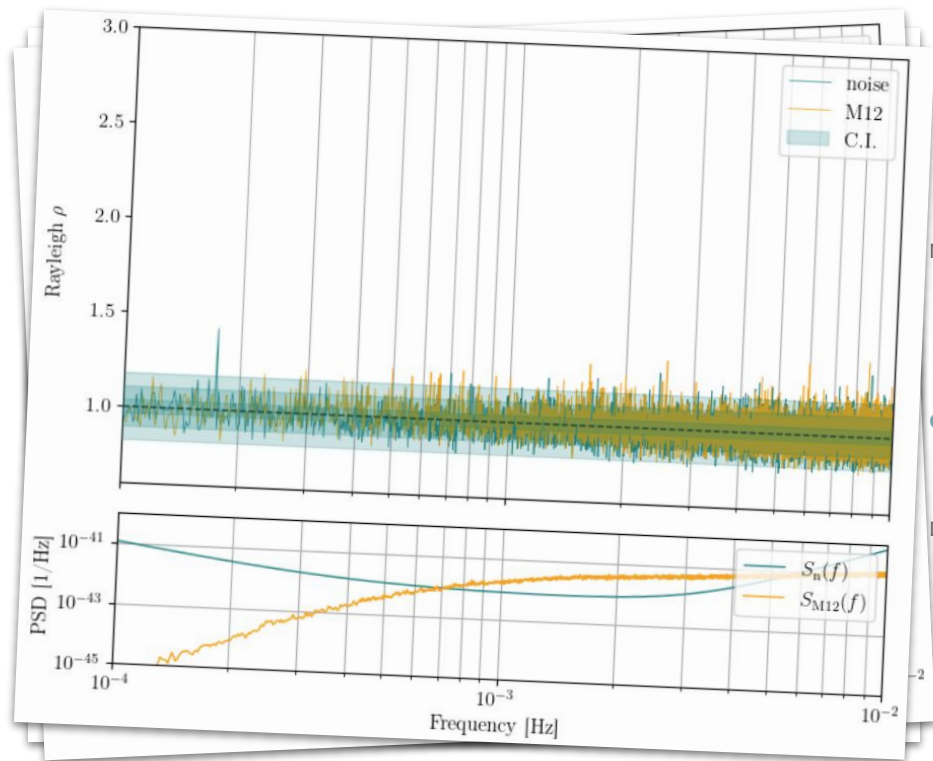


# EMRI foregrounds

## Stationary?



Piarulli, Buscicchio+ 2024

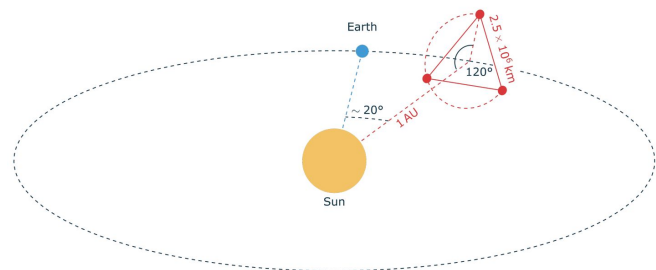


Piarulli, Buscicchio+ 2024

Non-stationary  
↑  
Gaussian  
↓  
Deterministic

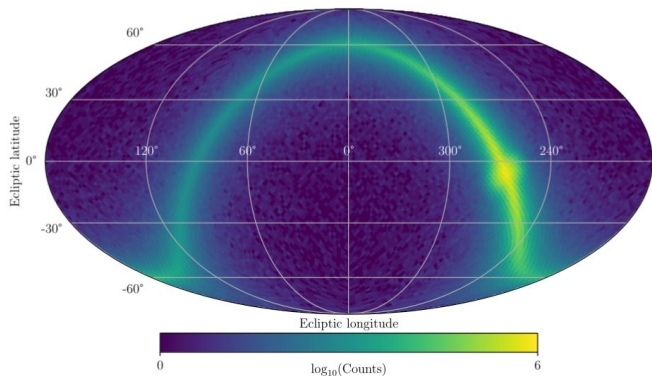
# DWD foreground

## Cyclostationary



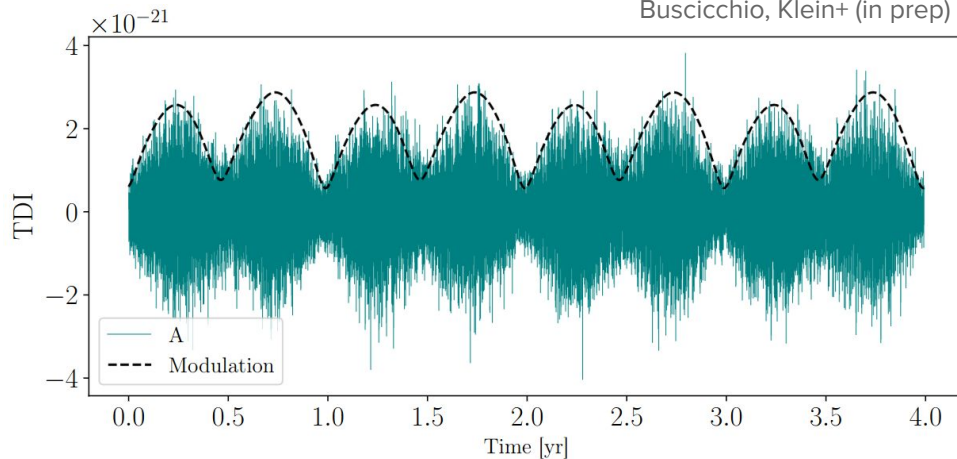
+

=



$$1/T_{\text{mission}} \leq 2/T_{\text{orb}} \ll f_s \ll 1/\Delta t$$

Buscicchio, Klein+ (in prep)

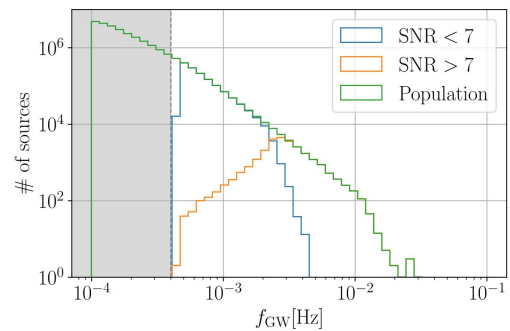
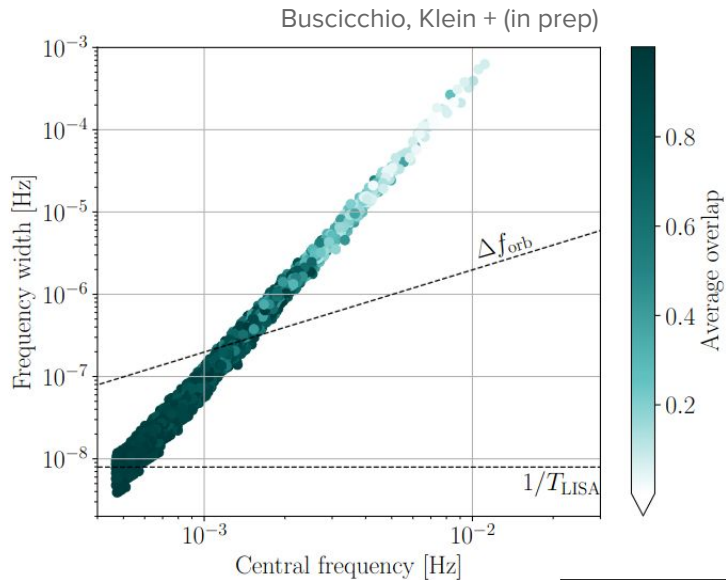
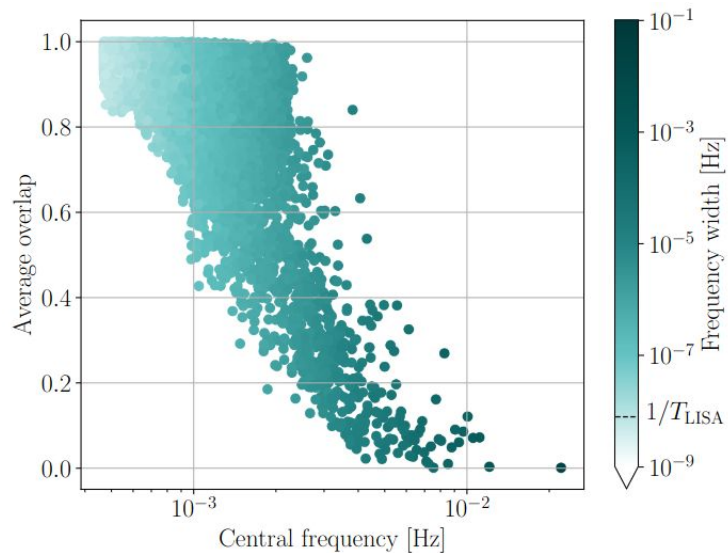


$$\mathcal{C}(f, f') = \sum_{n=-\infty}^{\infty} \gamma_n |\mathbf{J}| \delta \left( f - f' + \frac{n}{T_l} \right) \mathcal{S} \left( \frac{f + f'}{2} \right)$$

Sidenote: Time-domain windowing and gaps have similar effect **10**

# DWD foreground

## Cyclostationary

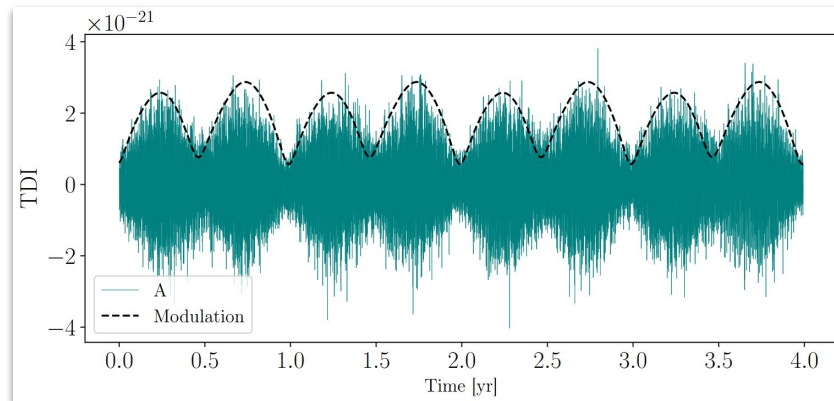


# DWD foreground

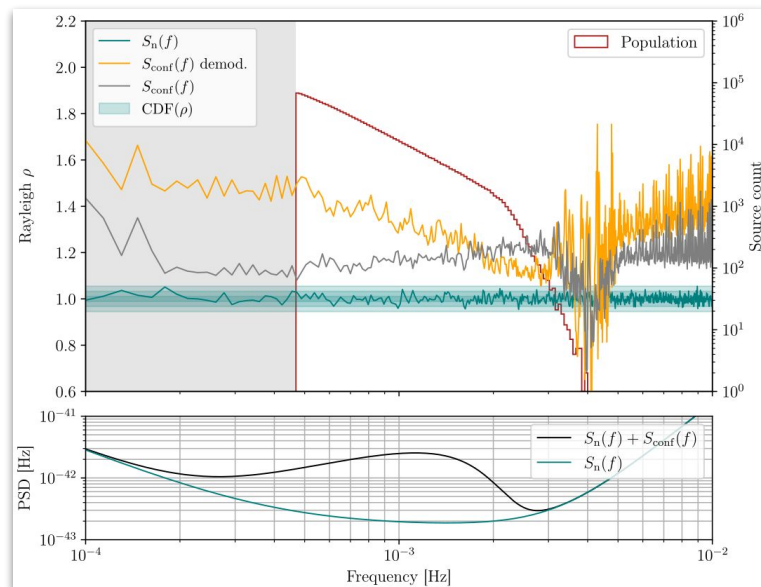
## Cyclostationarity

Heavy-tailed likelihoods for the characterization of stochastic gravitational wave background signals

Karnesis, Buscicchio+ (in prep)



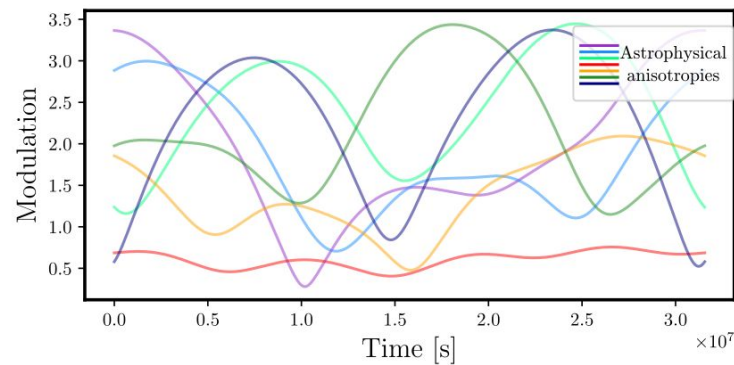
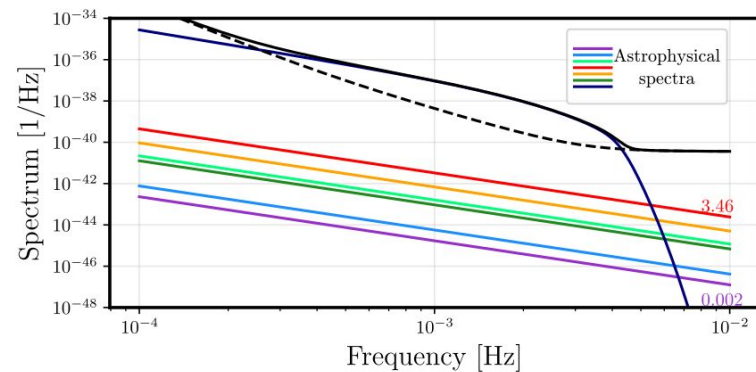
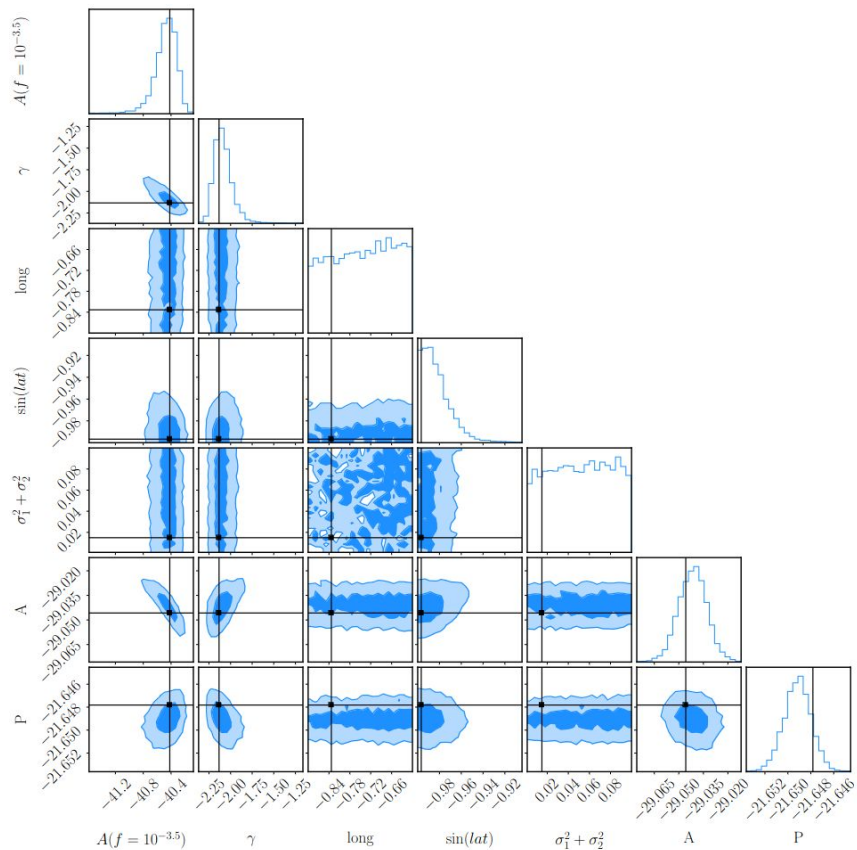
Buscicchio, Klein+ (in prep)





# Cyclostationary spectra

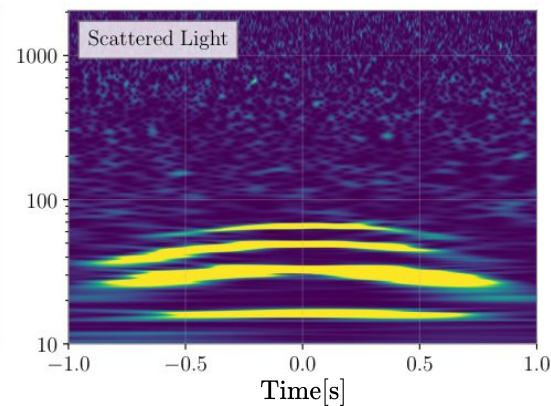
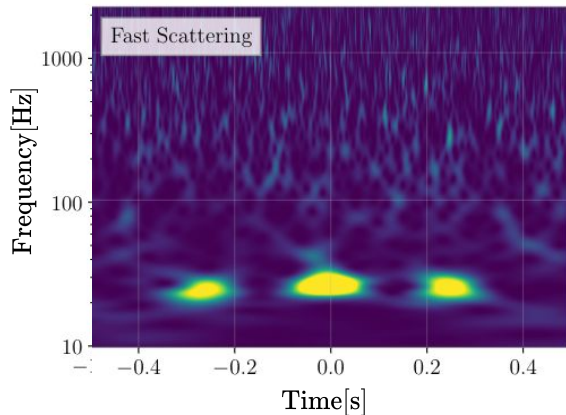
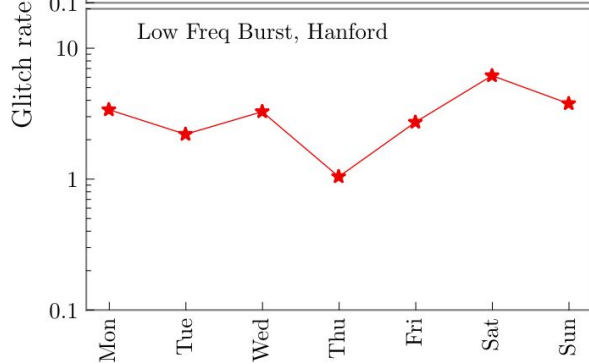
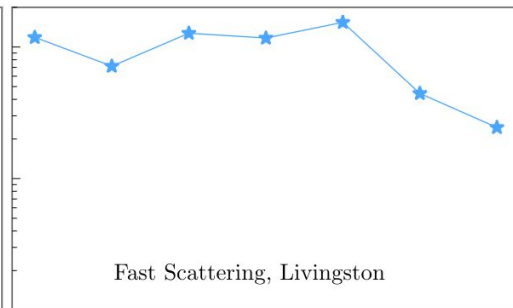
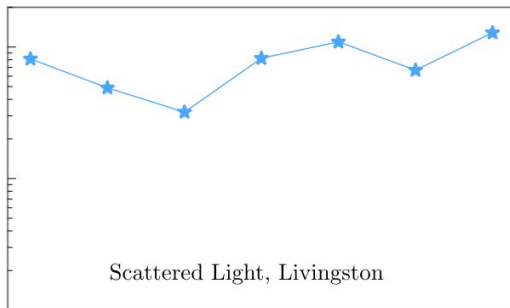
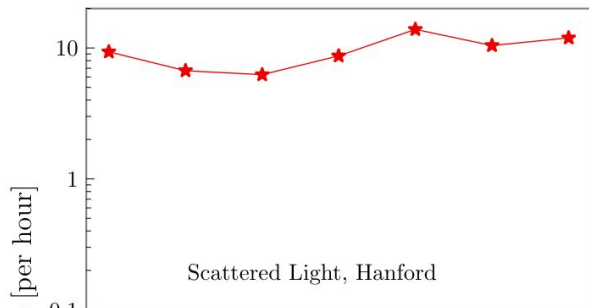
## An intermediate step



# The junkyard

## A quick digression

Glanzer+ (2023)

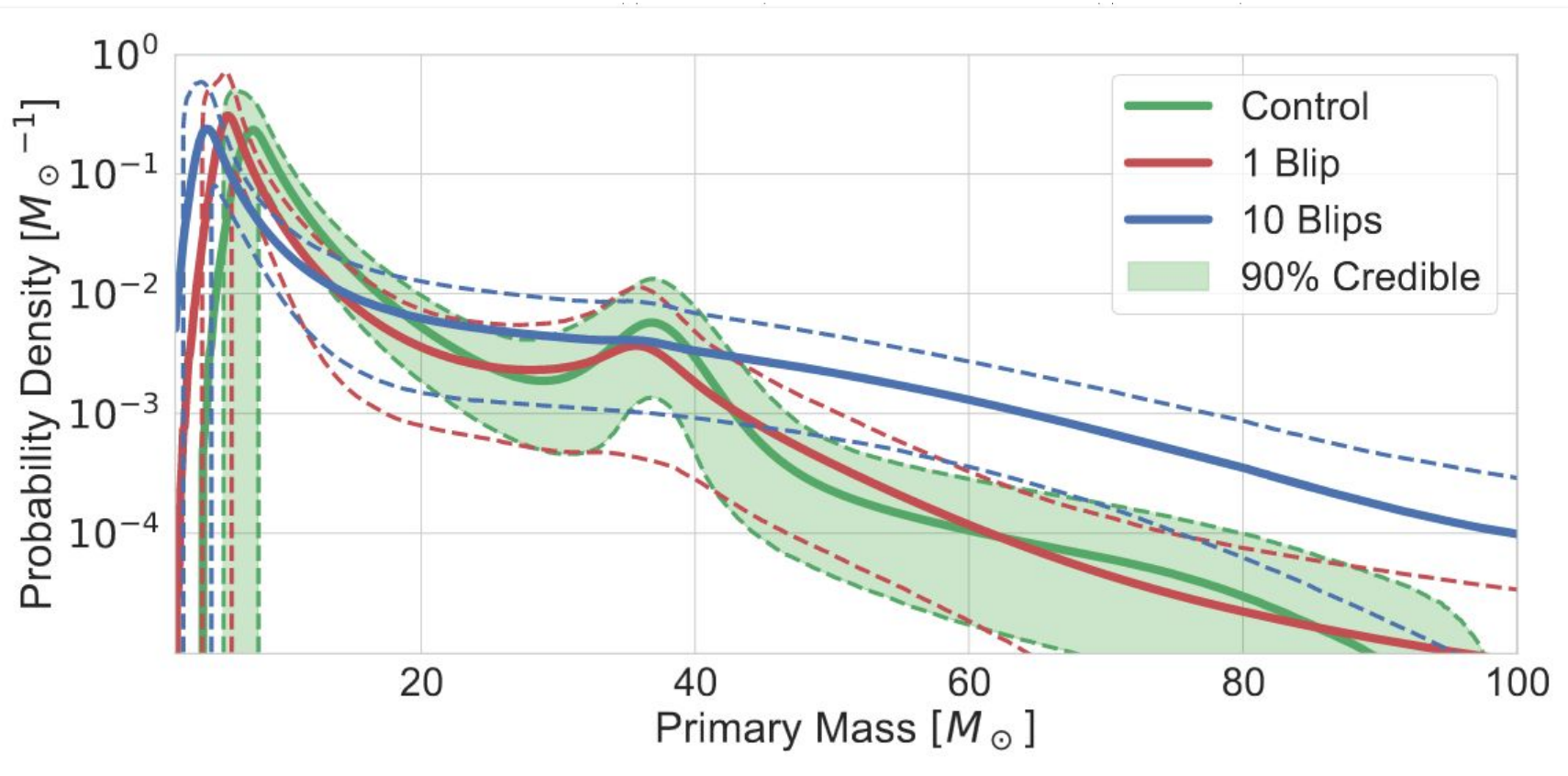


Any plan for gating in LISA? Line notching?

# The junkyard

Why important?

Heinzel+ (2023)





**Thanks!**  
**Questions?**





# Backup slides

# Cyclostationarity

## The key ingredient

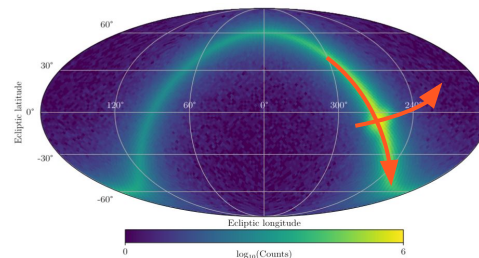
Pozzoli, Buscicchio+ (in prep)

$$\int_{\mathbb{R}} d\theta_N \int_{\mathbb{R}} d\phi_N p(\theta_N, \phi_N) e^{in\theta_N} e^{im\phi_N} = \exp \left[ -\frac{1}{4} (m^2 + n^2) \sigma_+^2 + \frac{1}{4} (m^2 - n^2) \sigma_{-,c}^2 + \frac{mn}{2} \sigma_{-,s}^2 \right] e^{in\theta_M} e^{im\phi_M}$$

$$\sigma_+^2 = \sigma_1^2 + \sigma_2^2,$$

$$\sigma_{-,c}^2 = (\sigma_1^2 - \sigma_2^2) \cos 2\beta,$$

$$\sigma_{-,s}^2 = (\sigma_1^2 - \sigma_2^2) \sin 2\beta.$$

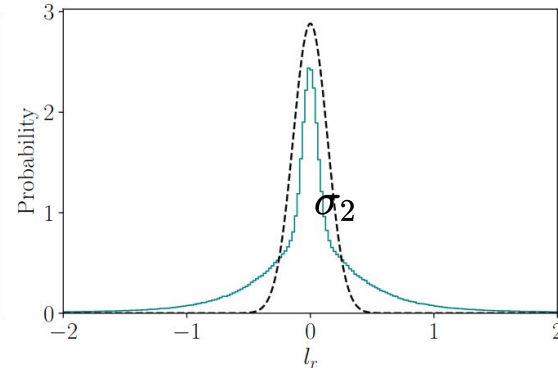
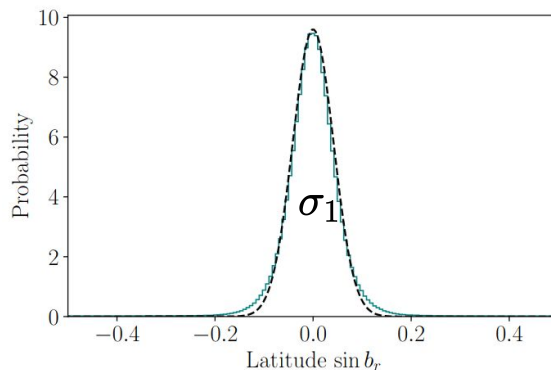


$$\phi_X(t) = E [e^{itX}]$$

### Characteristic function over integers!

- exists analytical for many probability distributions
- closed upon mixing

Smoothly interpolates pixel and spherical harmonics decomposition



# Non-gaussian SGWB

Draw the line where you need to



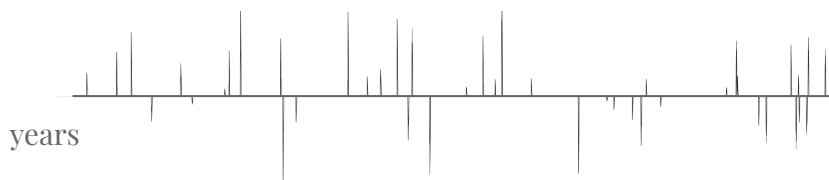
Is it stochastic?

Individual event  
param. est.



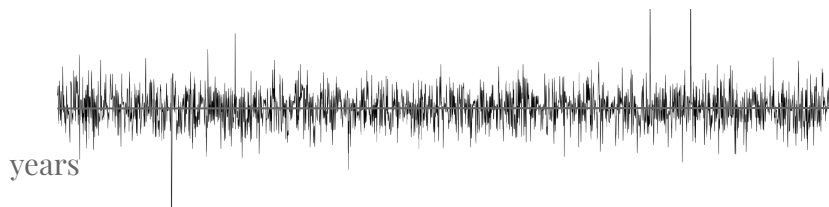
Is it stochastic?

Overlapping event  
param. est.



Is it deterministic?

Non-Gaussian  
param. est.



Is it deterministic?

Gaussian SGWB  
param. est.

# A different perspective

Campbell processes (Van Kampen 1981)

$$H_1 : s = n + g + h$$

$$H_0 : s = n$$

$$h^A(t) = \sum_{\sigma=1}^N u^A(t - \tau_{\sigma}; \theta_{\sigma})$$

Data model

$$s_i^A = g_i^A + h_i^A + n_i^A$$



Where do you draw the line?  
Confusion noise





# Non-gaussian SGWB

## An effective theory: Part 1

$$\hat{Y}(s) = \frac{1}{2} [\check{C}_g]_{ij}^{AB} \mathbf{s}_i^A \mathbf{s}_j^B + \chi h \sum_{n=1}^{\infty} \frac{1}{n!} \check{\Gamma}_{i_1 \dots i_n}^{A_1 \dots A_n} \mathbf{s}_{i_1}^{A_1} \dots \mathbf{s}_{i_n}^{A_n}$$

Buscicchio, Ain+ (2022)

Free field

Interactions

Nothing more than  
**population model**

Vertices

$$\Gamma^{A_1 \dots A_n}(t_1, \dots, t_n) = \rho \int \left\langle \prod_{k=1}^n u^{A_k}(t - t_k; \hat{\theta}) \right\rangle_{\hat{\theta}} dt$$

Extremely fast to evaluate

# Non-gaussian SGWB

## An effective theory: Part 1

$$\hat{Y}(s) = \frac{1}{2} [\check{C}_g]_{ij}^{AB} s_i^A s_j^B + \chi h \sum_{n=1}^{\infty} \frac{1}{n!} \check{\Gamma}_{i_1 \dots i_n}^{A_1 \dots A_n} s_{i_1}^{A_1} \dots s_{i_n}^{A_n}$$

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Extremely fast to evaluate

Generating functional of  
connected diagrams

$$W[J] = \langle e^{iJ_{A_k} u^{A_k}} \rangle$$

One current per detector

# Non-gaussian SGWB

## An effective theory: Part 1

$$\hat{Y}(s) = \frac{1}{2} [\check{C}_g]_{ij}^{AB} s_i^A s_j^B + \chi h \sum_{n=1}^{\infty} \frac{1}{n!} \check{\Gamma}_{i_1 \dots i_n}^{A_1 \dots A_n} s_{i_1}^{A_1} \dots s_{i_n}^{A_n}$$

Buscicchio, Ain+ (2022)

Free field

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Nothing more than  
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Vertices

$$\Gamma^{A_1 \dots A_n}(t_1, \dots, t_n) = \rho \int \left\langle \prod_{k=1}^n u^{A_k}(t - t_k; \hat{\theta}) \right\rangle_{\hat{\theta}} dt$$

Extremely fast to evaluate

Generating functional of  
connected diagrams

$$W[J] = \langle e^{iJ_{A_k} u^{A_k}} \rangle$$

One current per detector

**Unfortunately: if the noise hypothesis is not under control (you cannot switch off the SGWB), poor performances.**



# Non-gaussian SGWB

## An effective theory: Part 2

Ballelli, Buscicchio+ (2023)

**Theorem III.1.** For a given statistics  $\mathcal{S}(u^1, \dots, u^{N_D})$ , where  $u^A = h^A + n^A$ , if  $n^A$  are statistically independent stochastic variables (i.e., the noise in our context) with non-zero even momenta and zero odd momenta, we consider the formal Taylor expansion in powers of  $u^A$ . A modified statistics where under  $\mathcal{H}_0$  terms with non-zero expectation values are canceled while preserving others is

$$\mathcal{S}_s(u^1, \dots, u^{N_D}) = \mathcal{S}(u^1, \dots, u^{N_D}) + \frac{1}{N_D} \sum_{\epsilon_1=-1,1} \dots \sum_{\epsilon_{N_D}=-1,1} \mathcal{S}(\epsilon_1 u^1, \dots, \epsilon_{N_D} u^{N_D}) . \quad (28)$$

Robust to noise mismodelling

