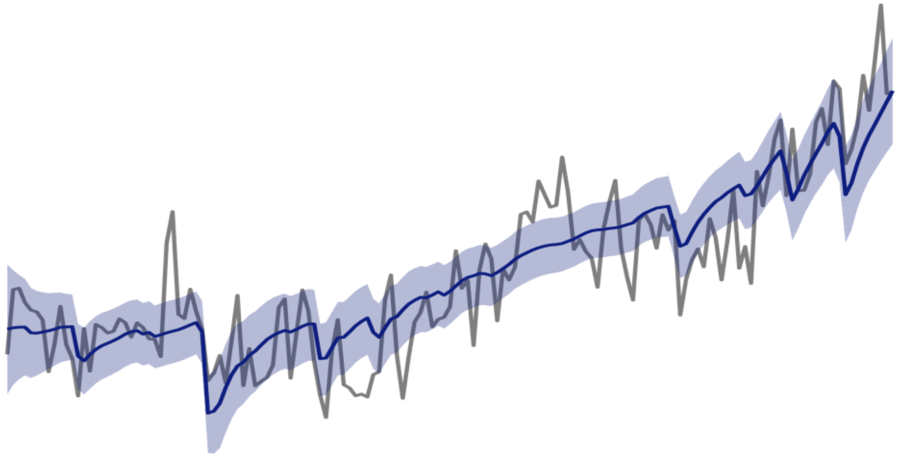
Emulating internal and external components of global temperature variability

Maybritt Schillinger, Beatrice Ellerhoff, Kira Rehfeld, Robert Scheichl



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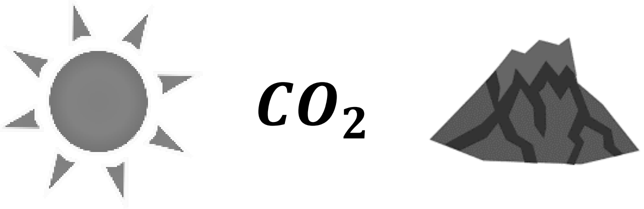
Temperature variability

Temperature variability
(observed / simulated)

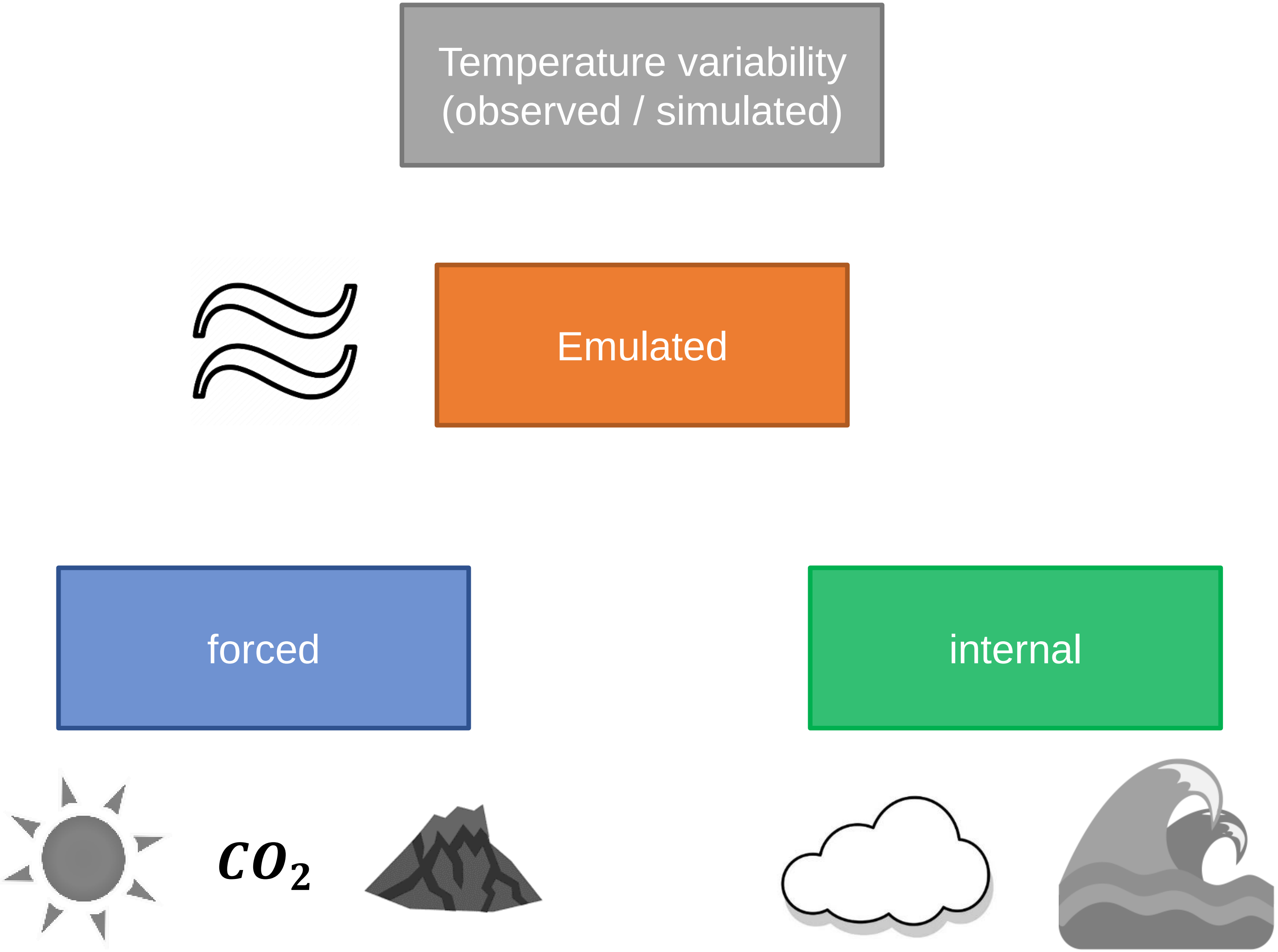
forced

internal



CO_2

Temperature variability



Temperature variability (observed / simulated)

≈

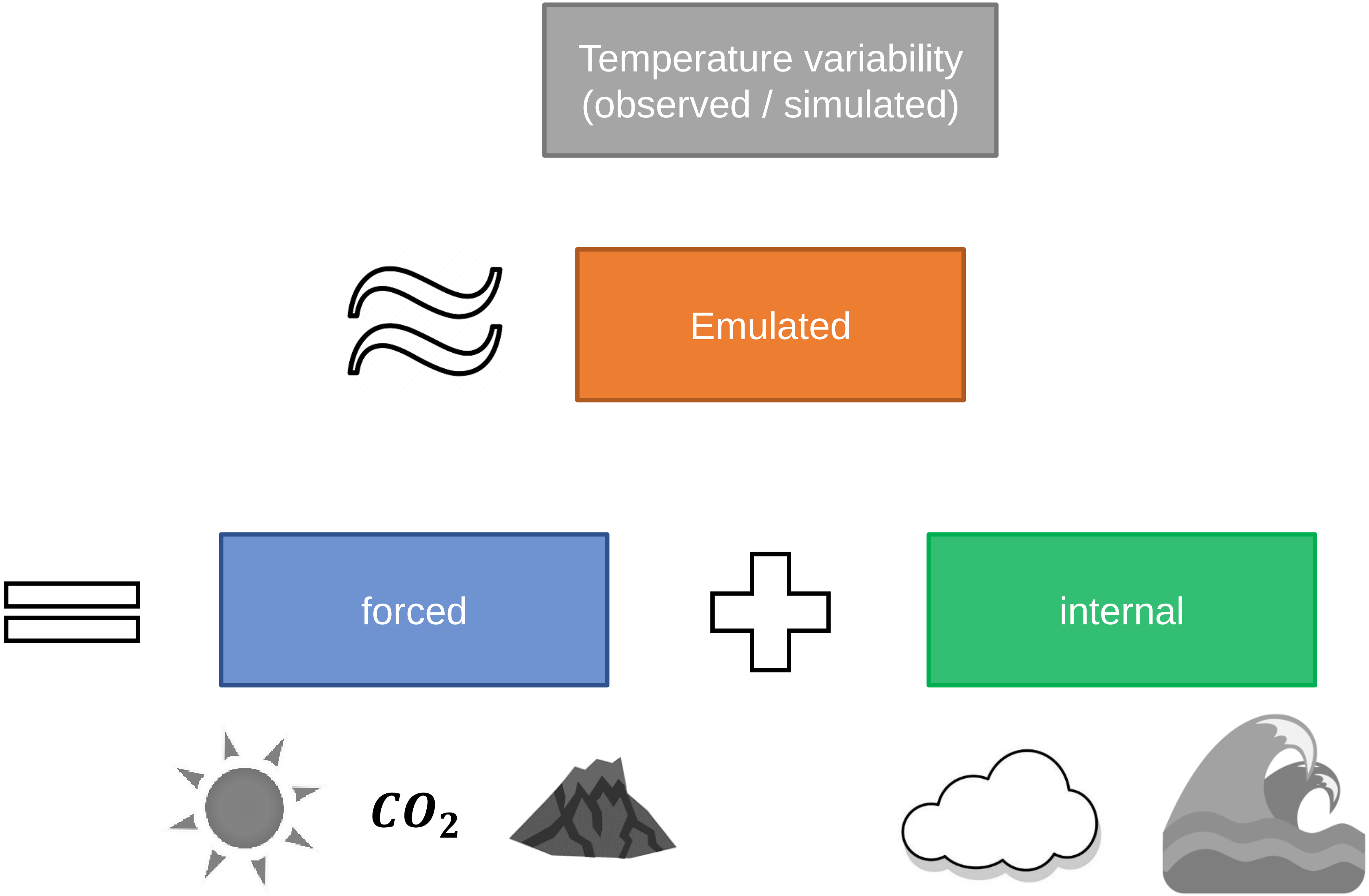
Emulated

forced

internal

CO_2

Temperature variability



Temperature variability (observed / simulated)

≈ Emulated

= forced + internal

CO_2

Separating forced from internal variability

1

Linear stochastic EBM

$$T(t) = forced + internal$$

Data

temperature

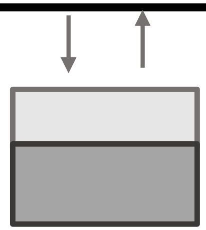
Bayesian Inference

Output

Best estimate of forced and internal temperature variations

Linear stochastic two-box Energy Balance Model

$$\boldsymbol{C}\,\frac{d\boldsymbol{T}}{dt}(t) = \boldsymbol{K}\,\boldsymbol{T}(t) + \boldsymbol{F}(t) + \boldsymbol{\xi}(t)$$



$$T(t) = \int R(t-s)(F(s)ds + dW(s))$$

forced internal

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Separating forced from internal variability

1

Linear stochastic EBM

$$T(t) = \mathit{forced} + \mathit{internal}$$

Data

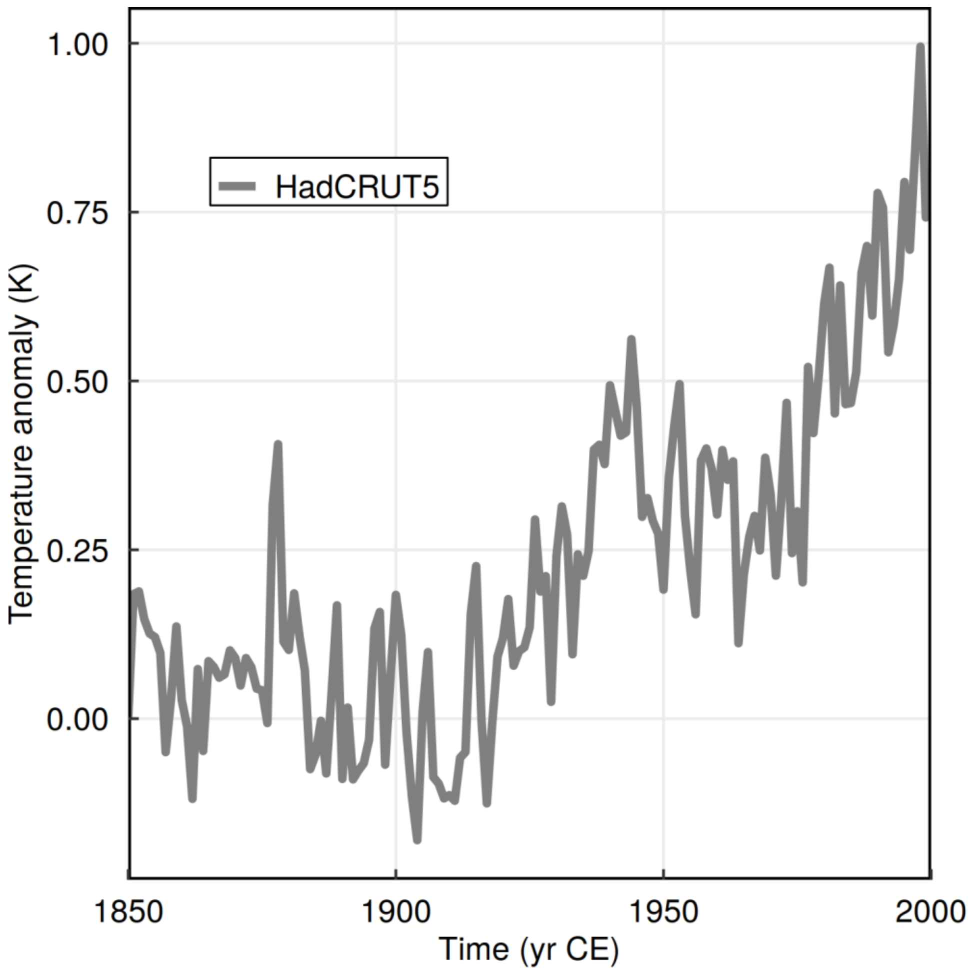
temperature

Bayesian Inference

Emulated variability

Best estimate of forced and internal temperature variations

Example: historical data



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Separating forced from internal variability

1

Linear stochastic EBM

$T(t) = forced + internal$

Data

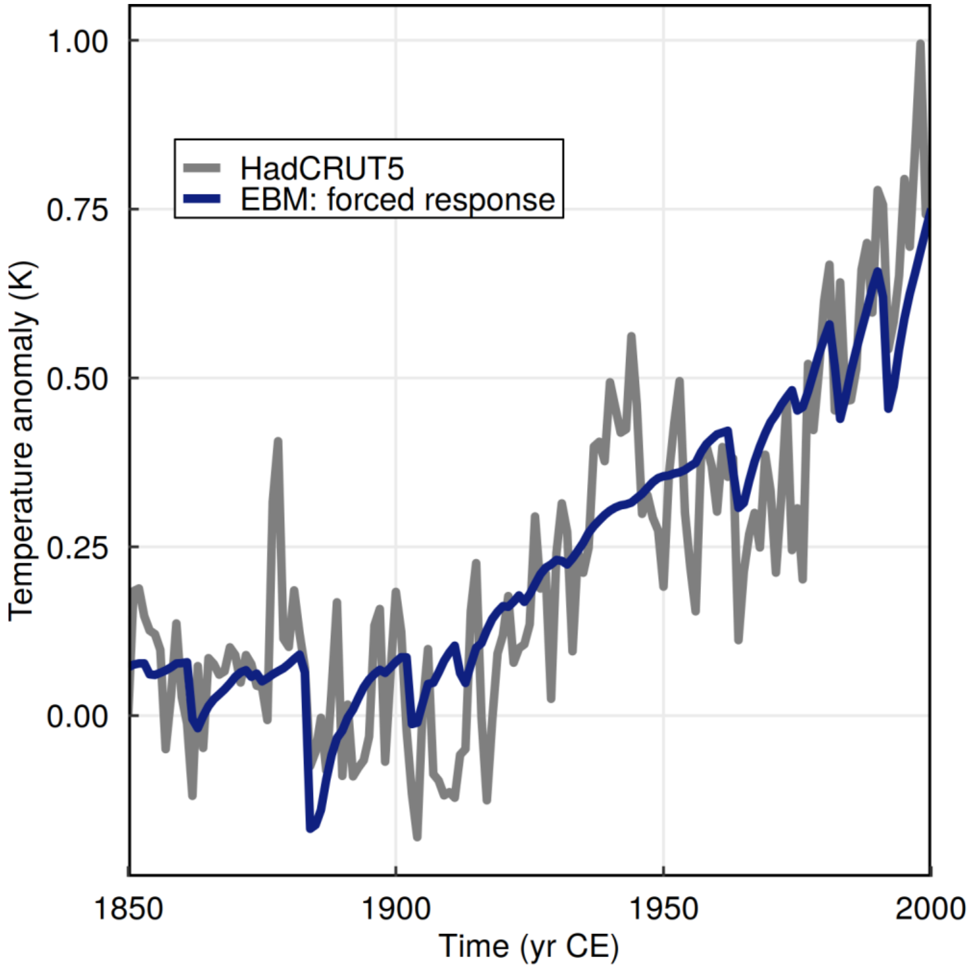
temperature

Bayesian Inference

Emulated variability

Best estimate of
forced and
forced+internal
temperature variations

Example: historical data



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Separating forced from internal variability

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Linear stochastic EBM

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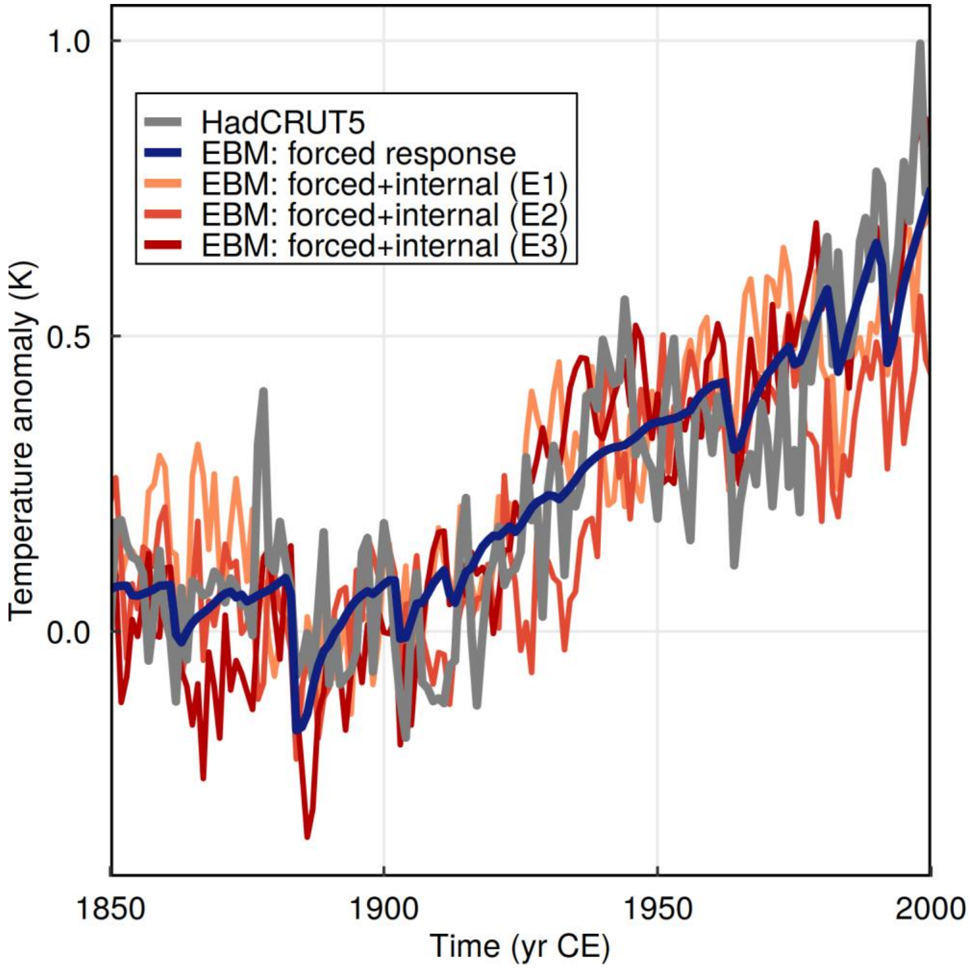
Emulated variability

Best estimate of forced and forced+internal temperature variations

Example: historical data



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Separating forced from internal variability

1

Linear stochastic EBM

$T(t) = \mathit{forced} + \mathit{internal}$

Data

temperature

Bayesian Inference

Emulated variability

Best estimate of forced and forced+internal temperature variations

2

Spectral analysis

Forced and forced+internal variability in temperature data on different timescales

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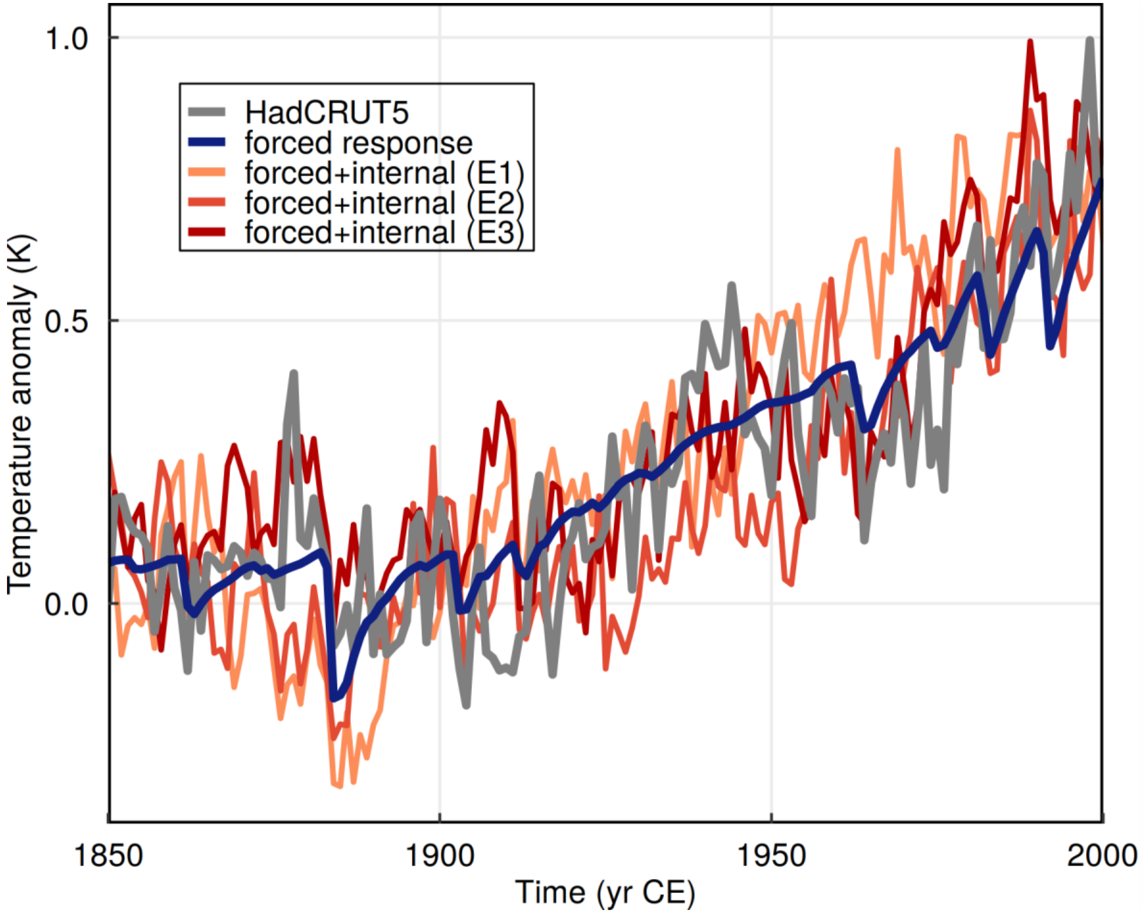
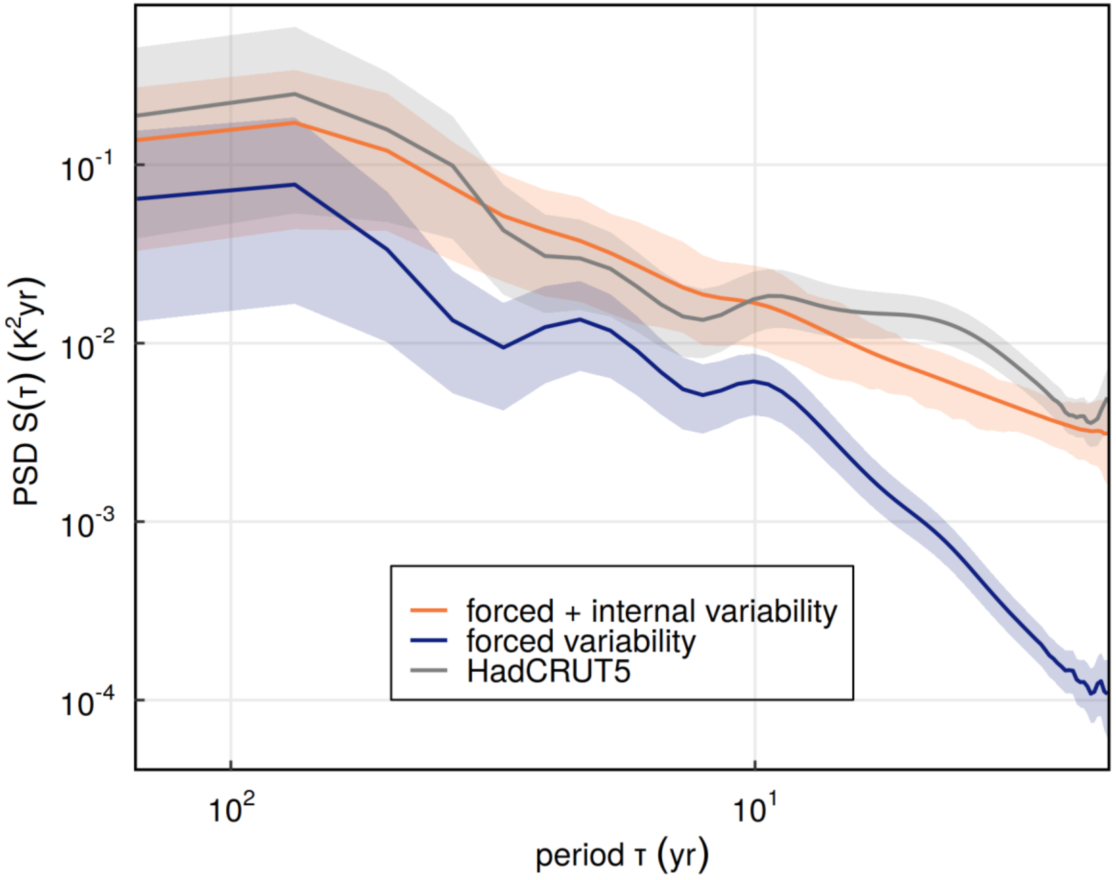
Step 2: Spectral analysis





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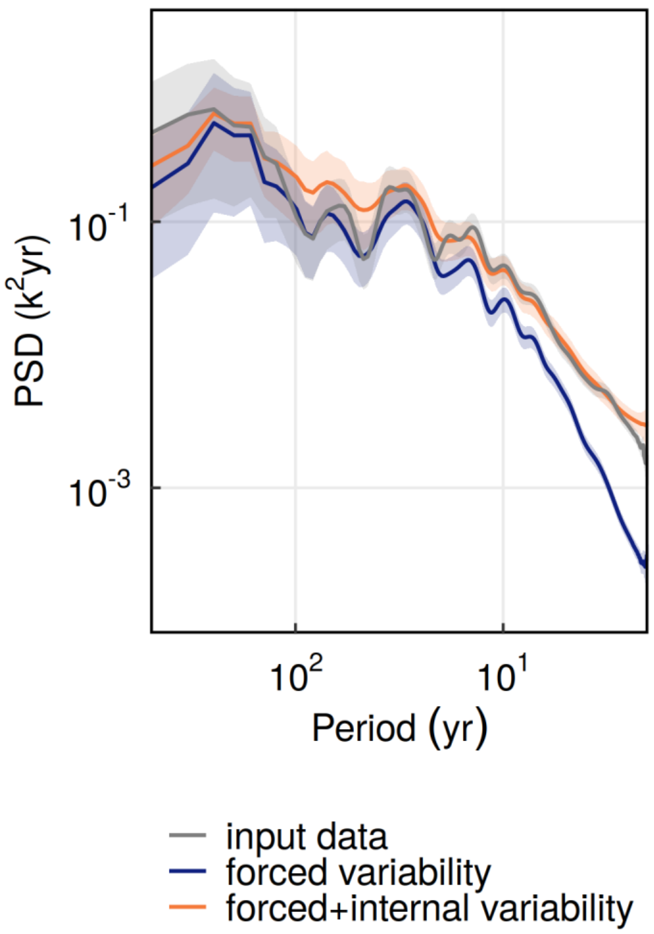
From the power spectrum to spectral ratios



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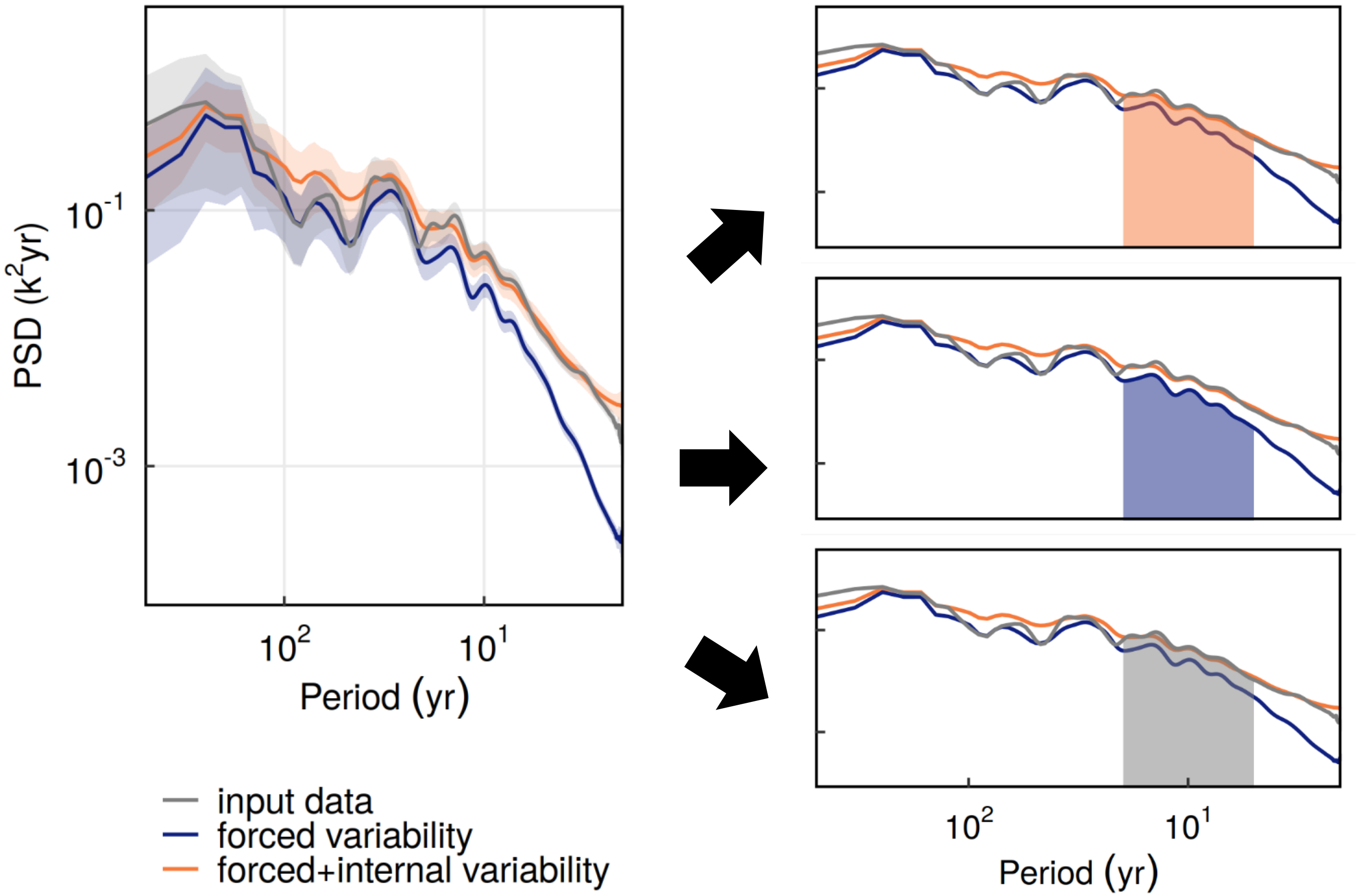
From the power spectrum to spectral ratios



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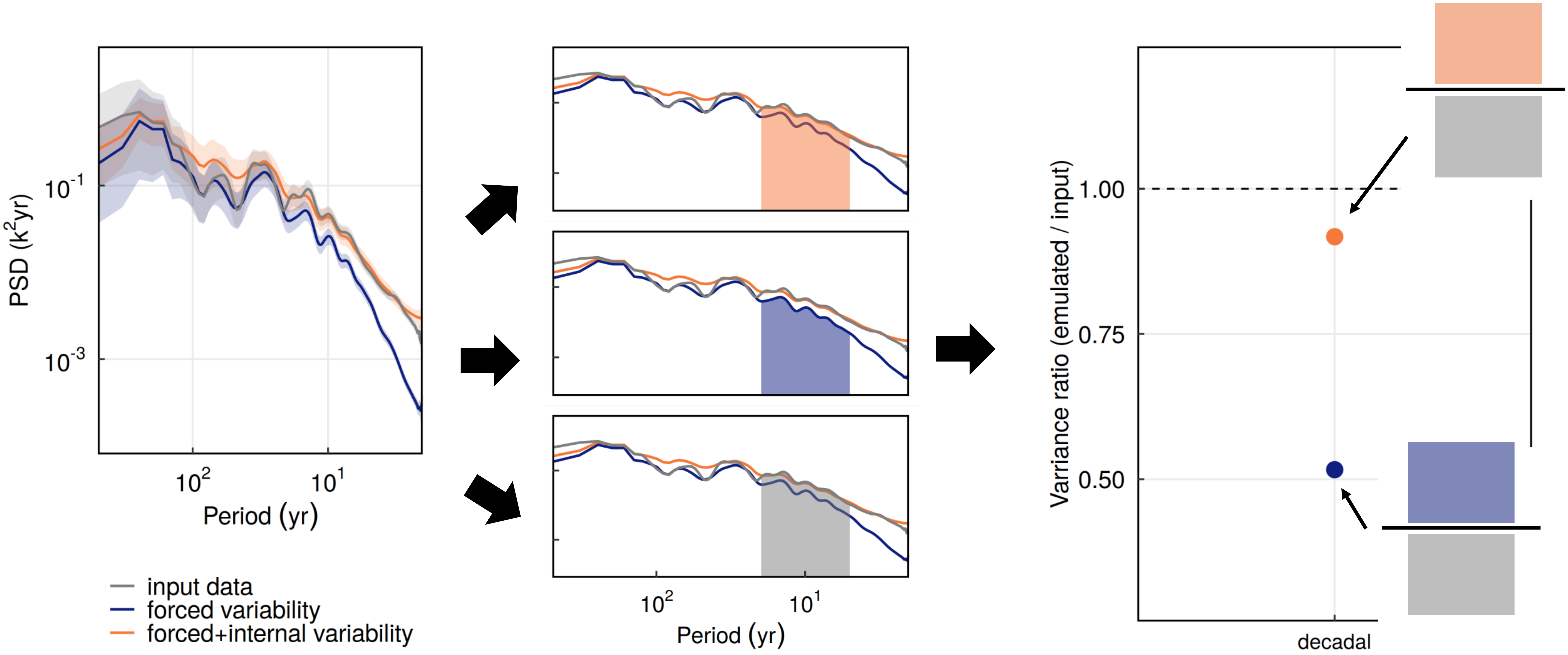
From the power spectrum to spectral ratios



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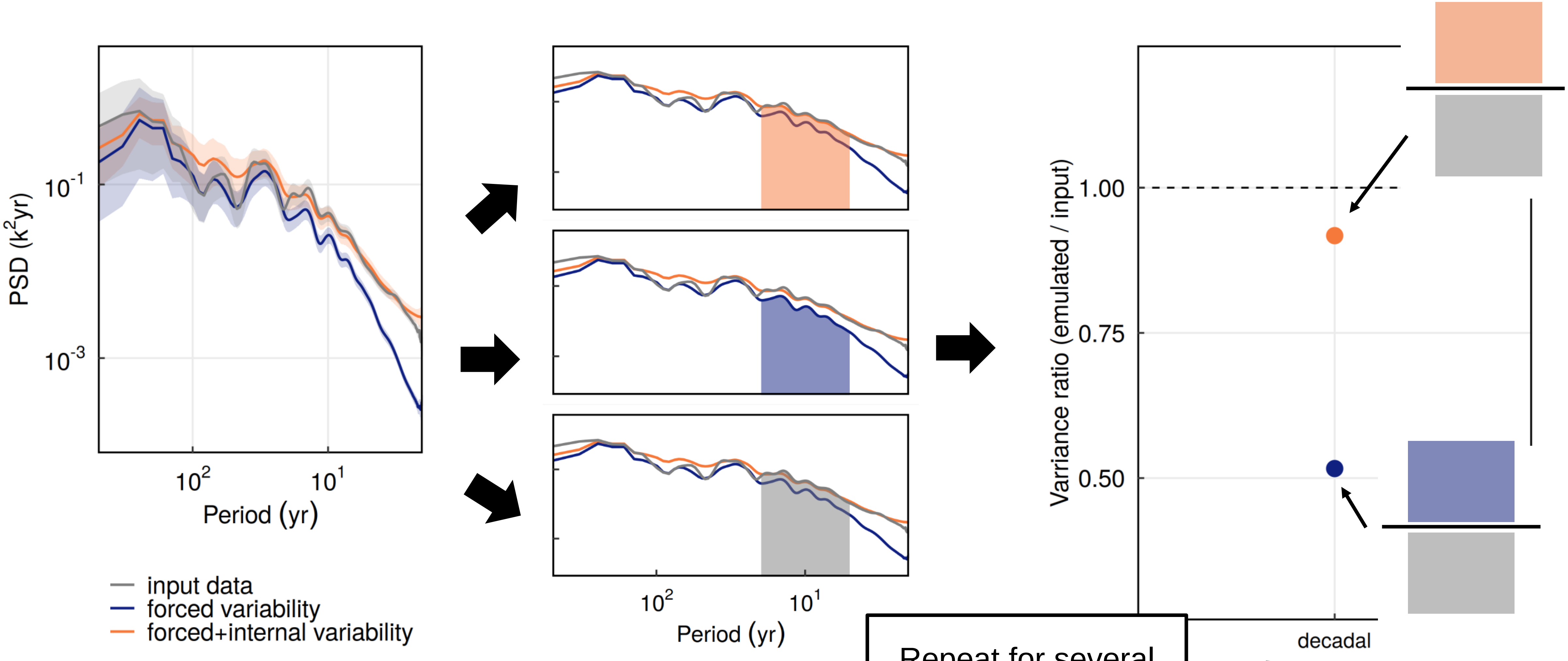
From the power spectrum to spectral ratios



Repeat for several timescales

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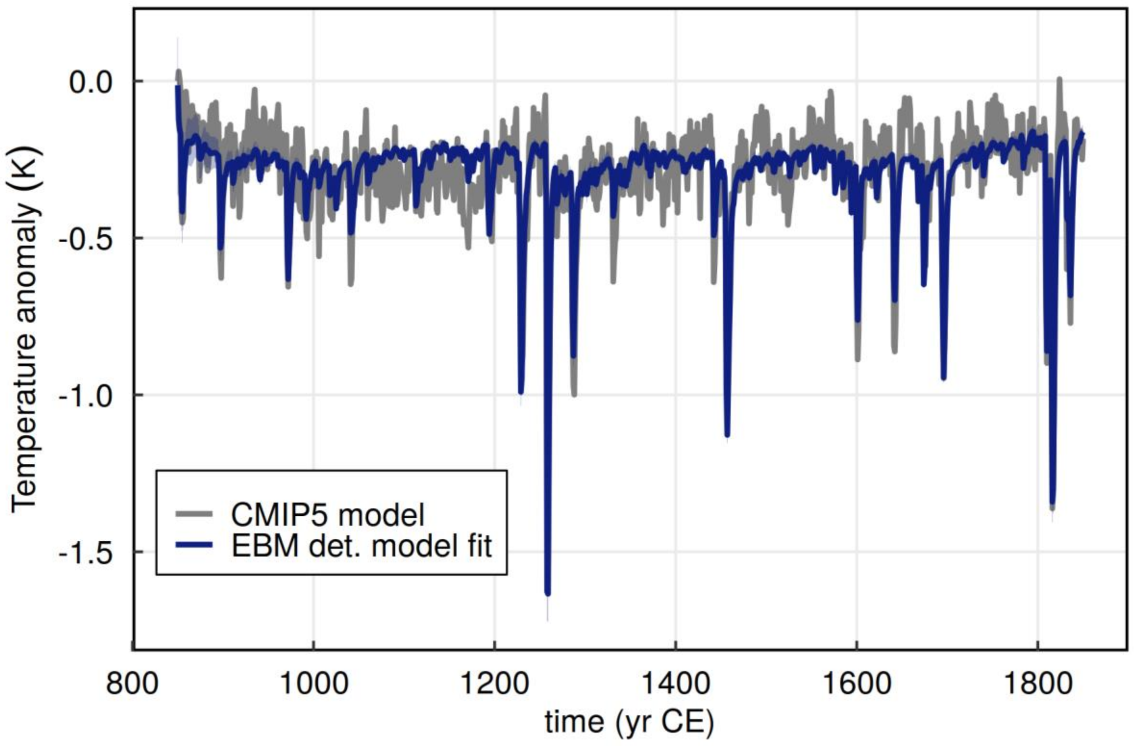
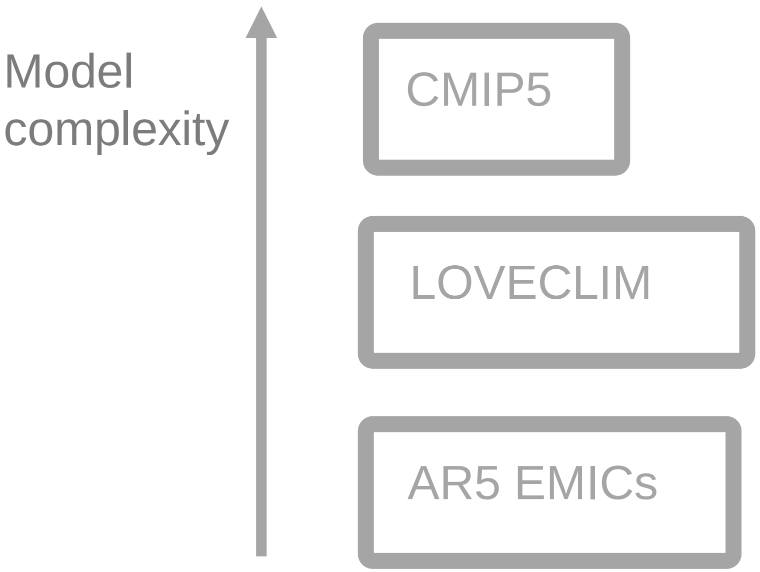
Input data for main analysis

Data from Last Millennium (850-1850)



Models of varying complexity


Model complexity

CMIP5

LOVECLIM

AR5 EMICs

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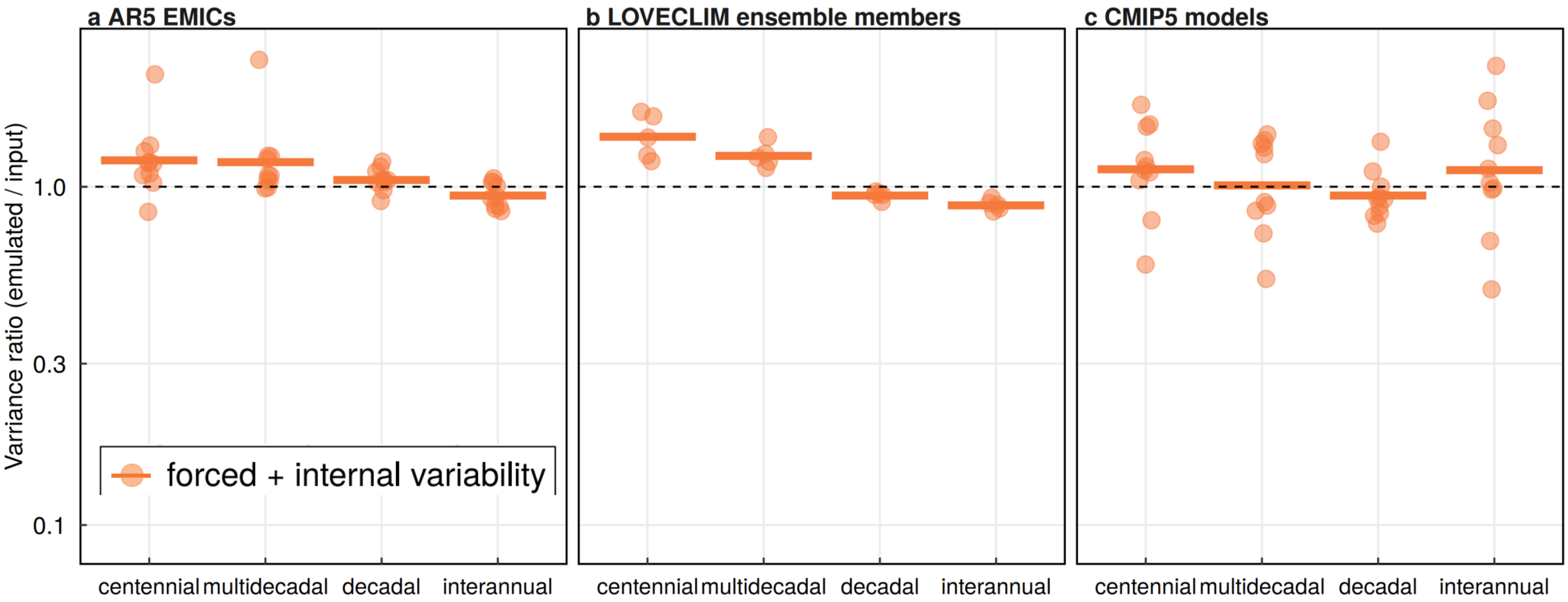
Internal & externally-forced contribution to global temperature variability



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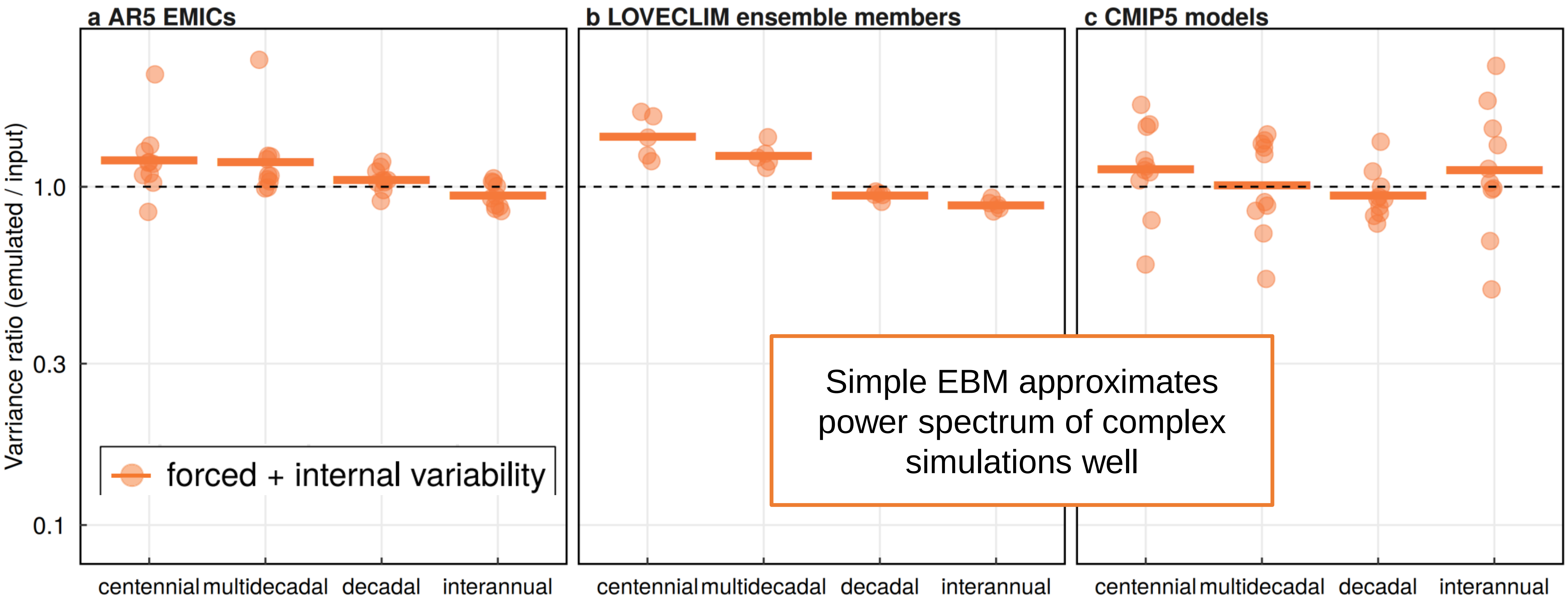
Internal & externally-forced contribution to global temperature variability



Simple EBM approximates power spectrum of complex simulations well

Model complexity

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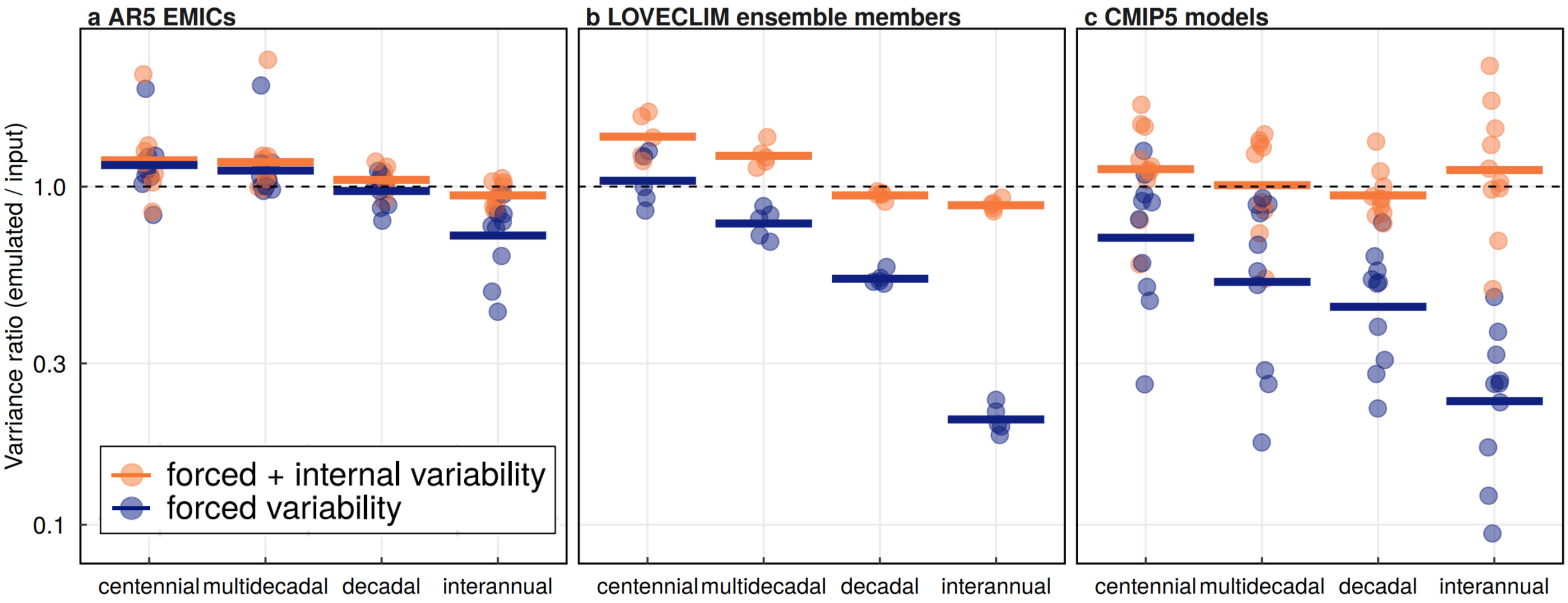
Internal & externally-forced contribution to global temperature variability



Model complexity

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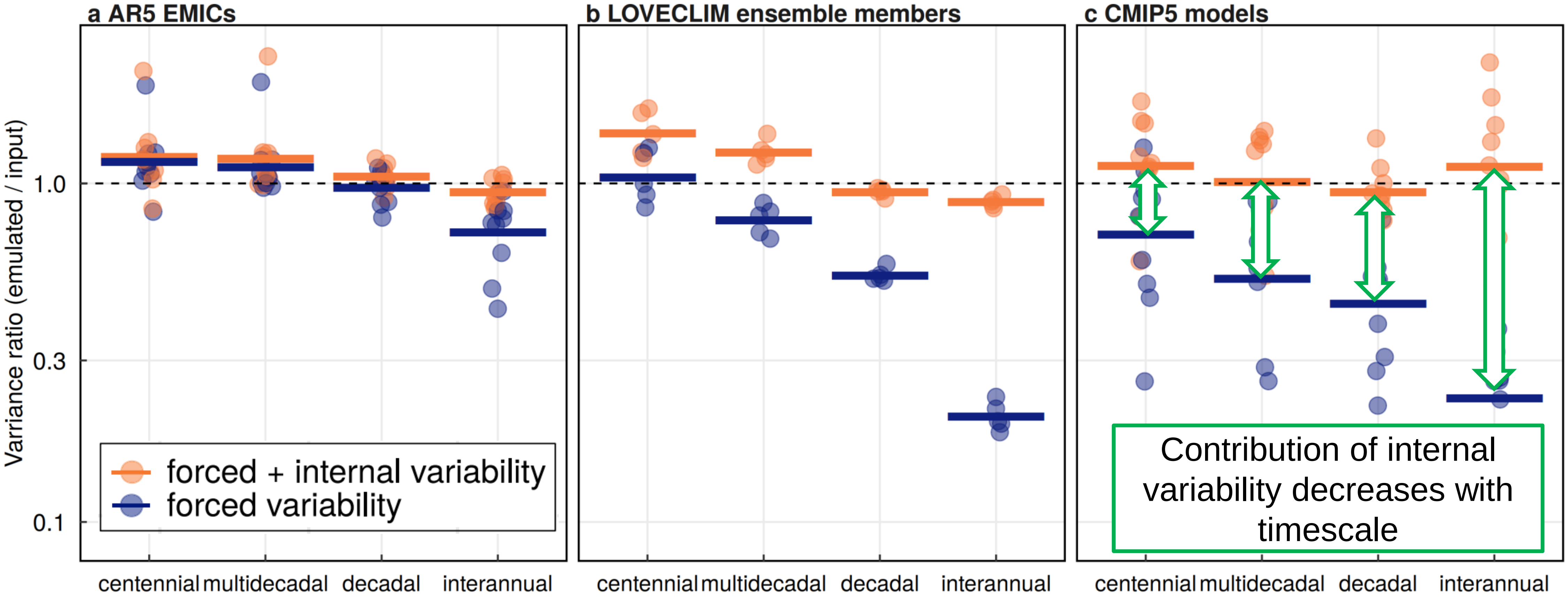
Internal & externally-forced contribution to global temperature variability



Contribution of internal variability decreases with timescale

Model complexity

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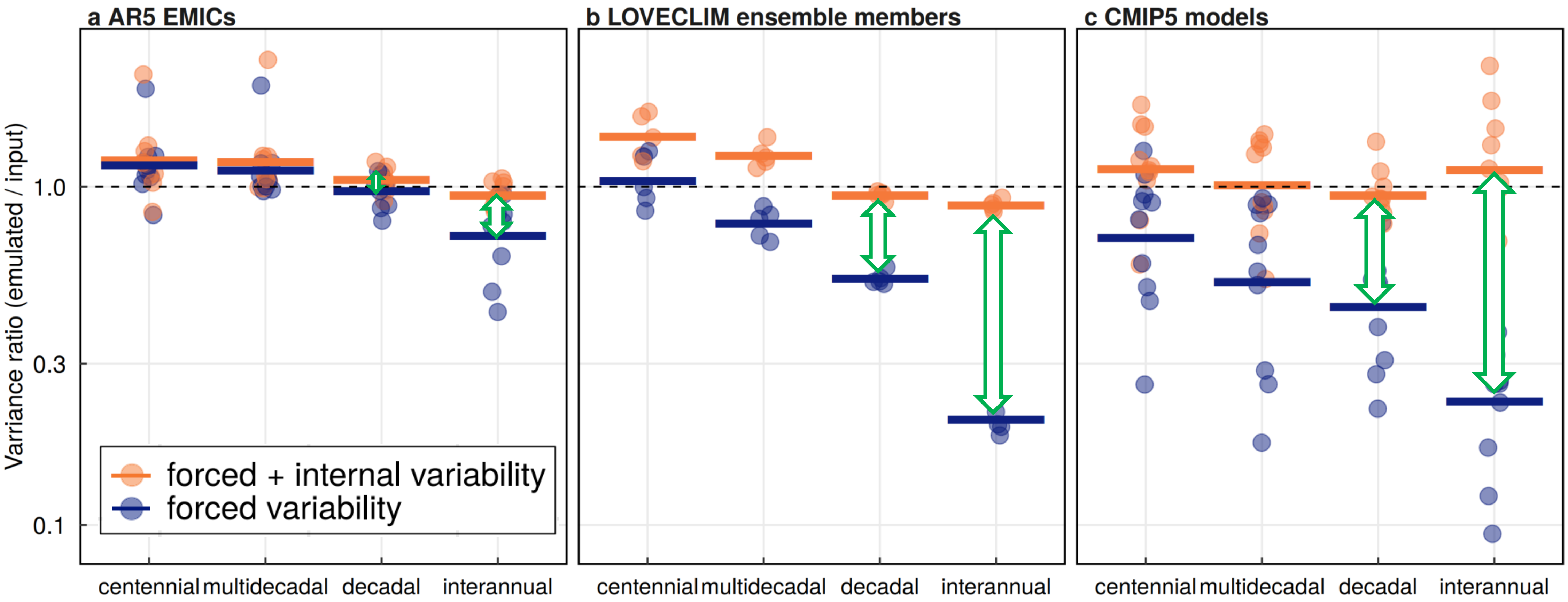
Internal & externally-forced contribution to global temperature variability



Contribution of internal variability increases with model complexity

Model complexity

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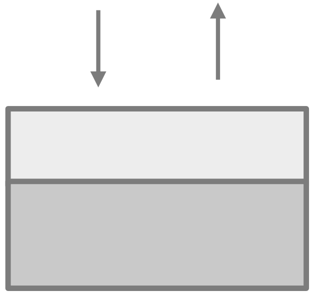
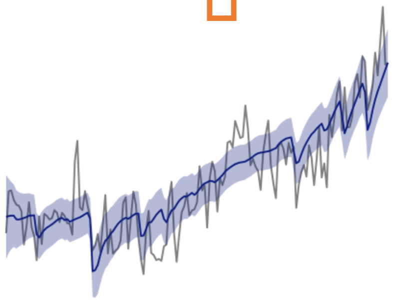
Summary

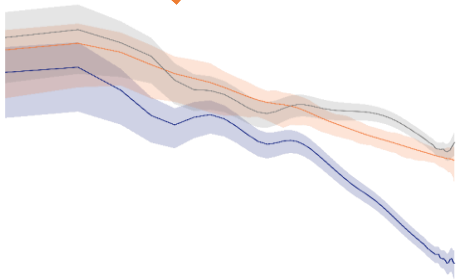
Separating forced from internal variability



Energy Balance Model



Bayesian model fit



Spectral analysis

Paper: M. Schillinger et al.: Separating internal and externally forced contributions to global temperature variability using a Bayesian stochastic energy balance framework. Chaos, https://doi.org/10.1063/5.0106123 (2022).

Package ClimBayes: https://github.com/m-schillinger/ClimBayes

Questions?

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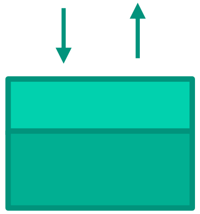
Appendix

Detailled Workflow of the ClimBayes package

Linear stochastic two-box EBM

$$\boldsymbol{C}\,\frac{d\boldsymbol{T}}{dt}(t) = \boldsymbol{K}\,\boldsymbol{T}(t) + \boldsymbol{F}(t) + \boldsymbol{\xi}(t)$$



$$\Downarrow$$

$$T(t) = \int R(t-s)(F(s)ds + dW(s))$$

forced   internal

$$R(t) = w_1 e^{-\lambda_1 t} + w_2 e^{-\lambda_2 t}$$

Data

Temperature observations Y

Prior information on uncertain parameters

$$X = (\lambda_1, \lambda_2, w_1, T_0, F_0)$$

Deterministic forcing F

Bayesian Inference

Approximate posterior $p_{X|Y=y}(x)$

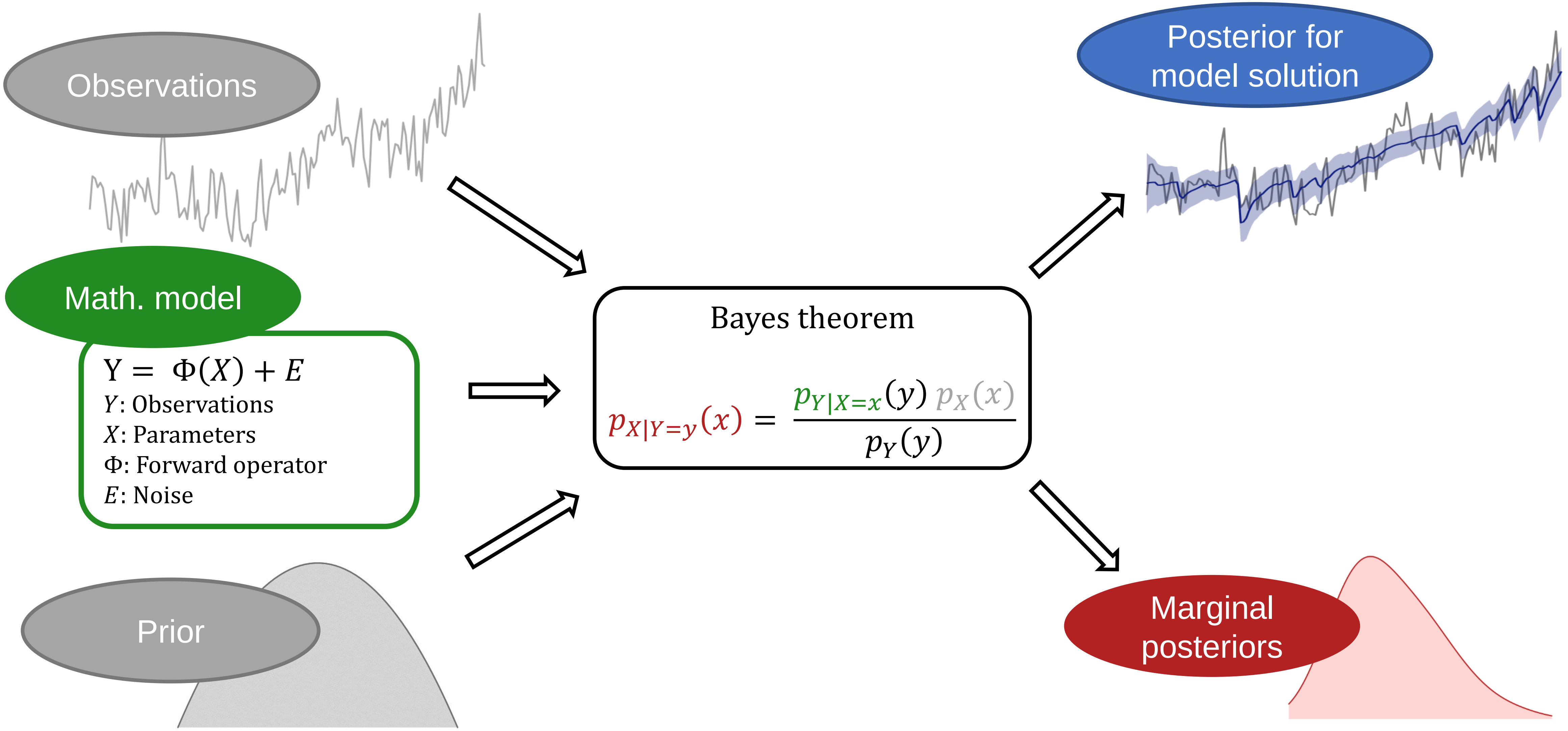
Output

Posterior distributions for X

Best estimate of forced and internal temperature variations

Figure adapted from Schillinger, M. et al. 2022; Ref.: Geoffroy et al. 2013, Fredriksen and Rypdal 2017, Myrvoll-Nilsen et al. 2020

Bayesian parameter estimation



Observations

Math. model

$Y = \Phi(X) + E$

Y: Observations

X: Parameters

Φ: Forward operator

E: Noise

Prior

Bayes theorem

$$p_{X|Y=y}(x) = \frac{p_{Y|X=x}(y)\, p_X(x)}{p_Y(y)}$$

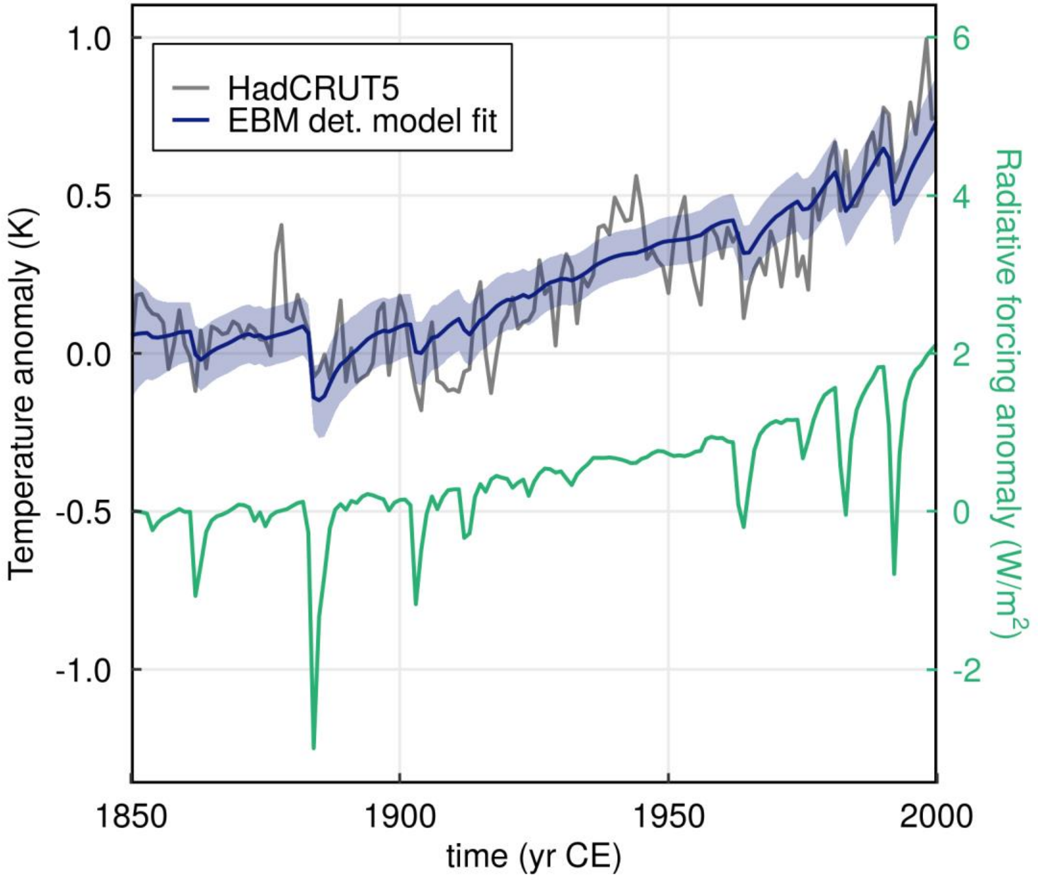
Posterior for model solution

Marginal posteriors

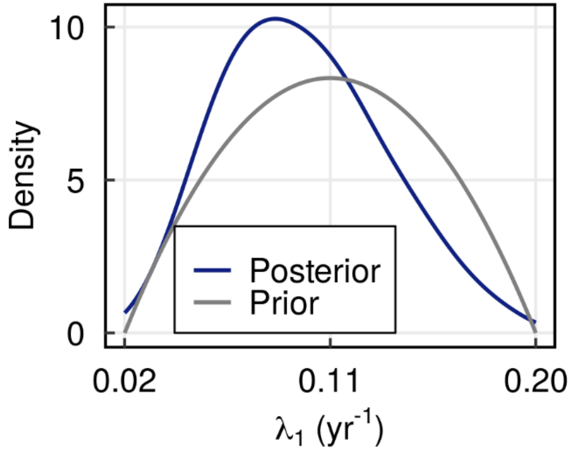
Data: Morice et al. 2021

Application to historical data

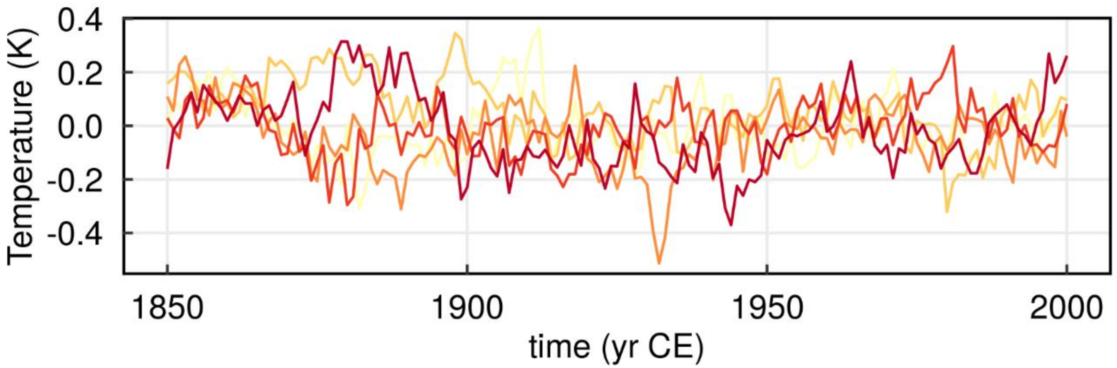
Estimate of forced response



Posteriors for X, e.g.

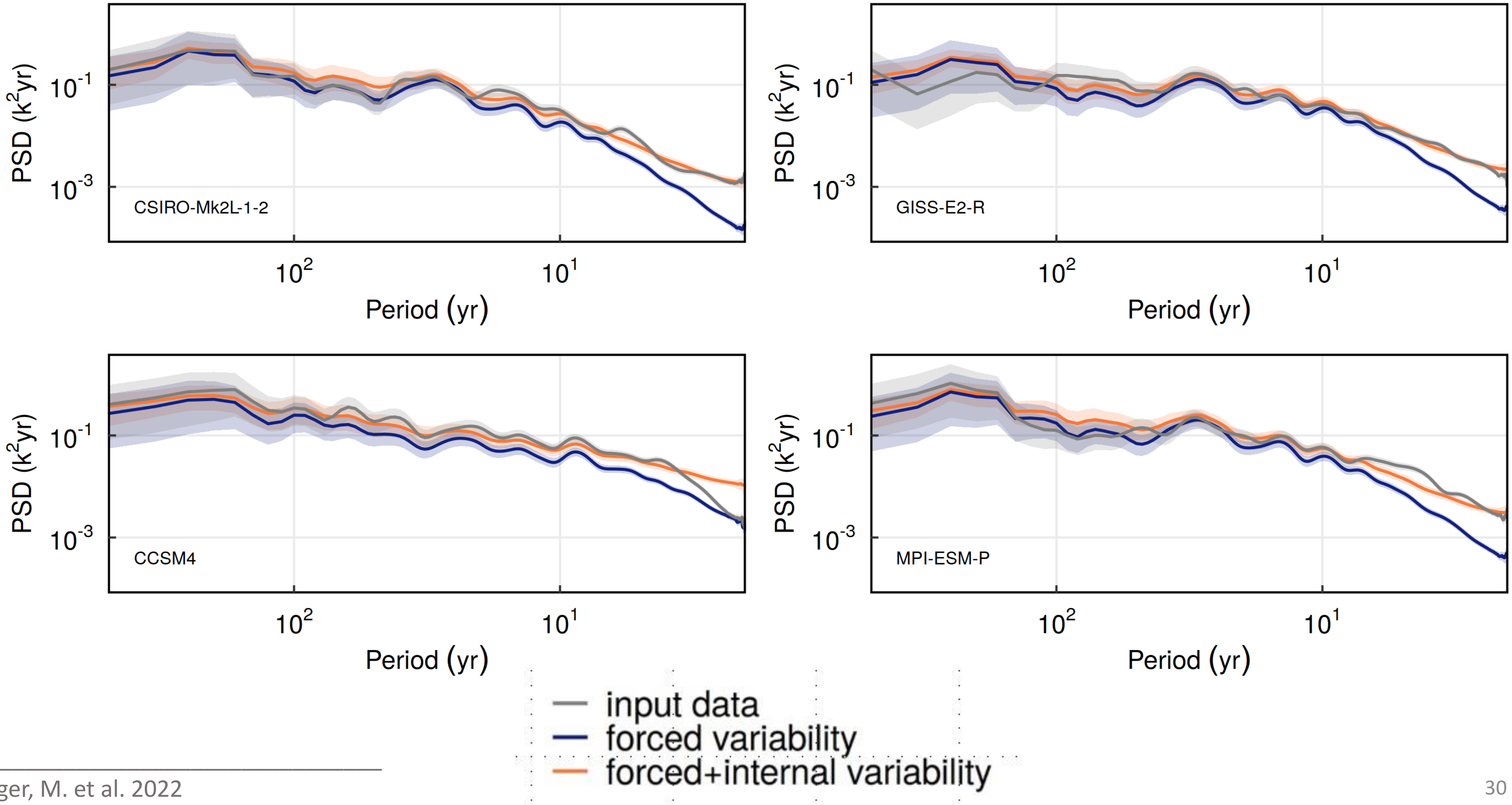


Estimate of internal variability



Data: Morice et al. 2021

Modelling the global mean temperature spectrum



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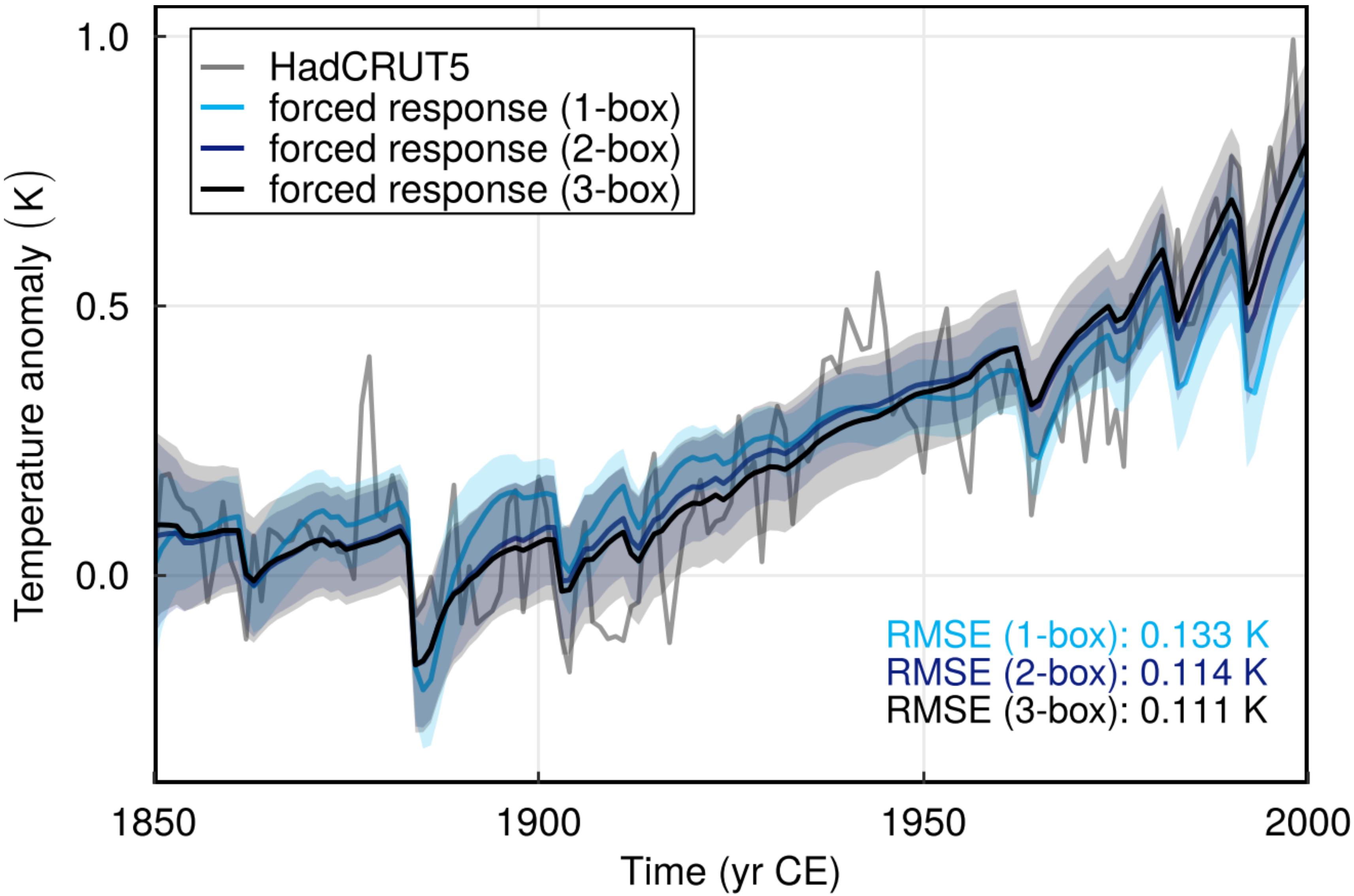
Comparison of 1-, 2- and 3-box model



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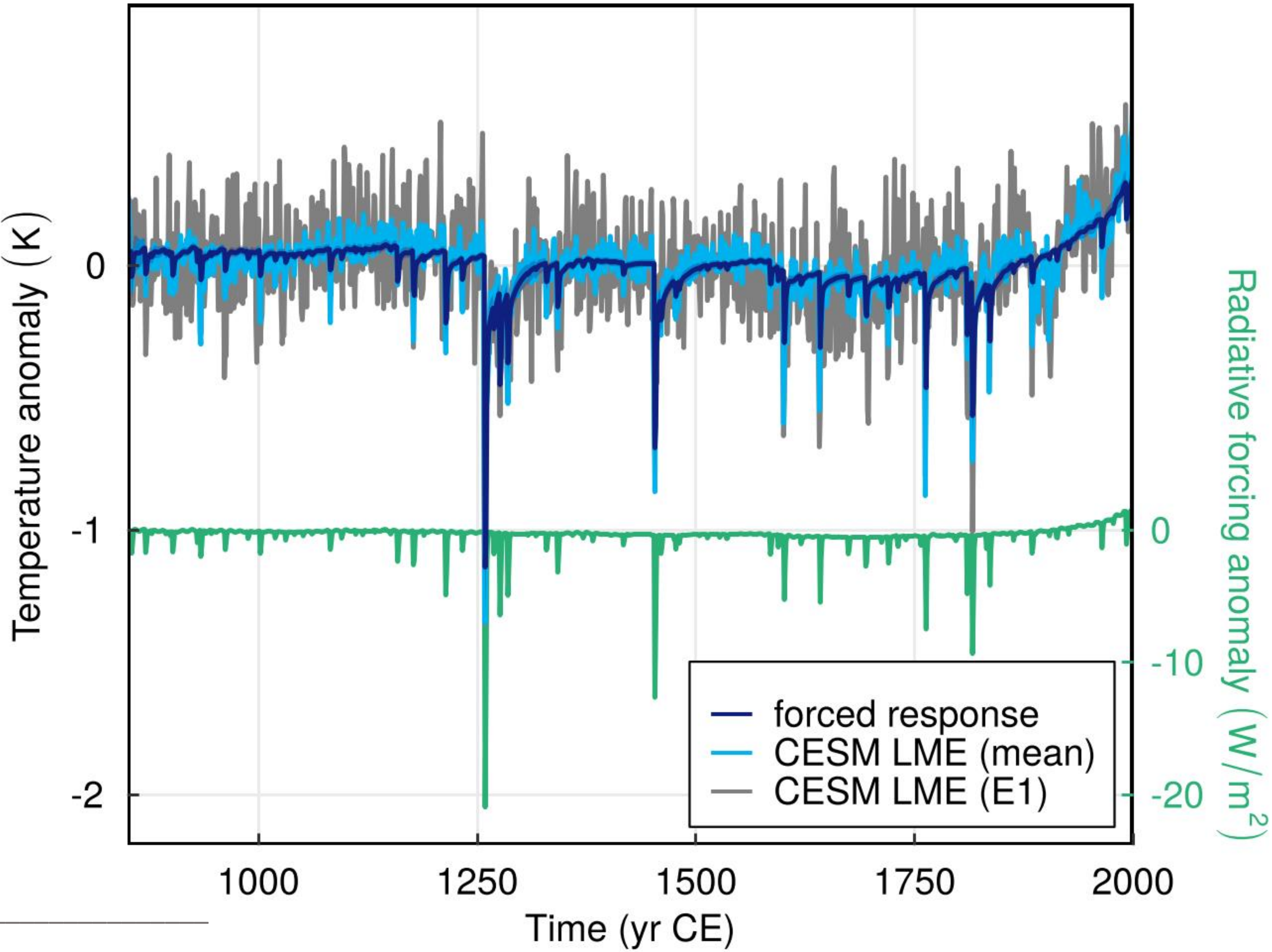
Comparison of EBM's forced response with large ensemble



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