

Bayesian Inference of Climate Parameters Using Multibox EBM

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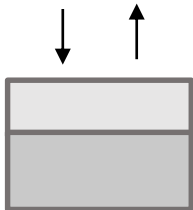
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Workflow of the ClimBayes package

Linear stochastic two-box EBM

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

↓

$$T(t) = \int_{-\infty}^t R(t-s) \left(\underbrace{\frac{1}{C_1} F(s) ds}_{\text{forced}} + \underbrace{dW(s)}_{\text{internal}} \right)$$
$$R(t) = w_1 e^{-\lambda_1 t} + w_2 e^{-\lambda_2 t}$$


Data

Temperature observations Y

Prior information on uncertain parameters

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

Deterministic forcing $F(t)$

Bayesian Inference

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



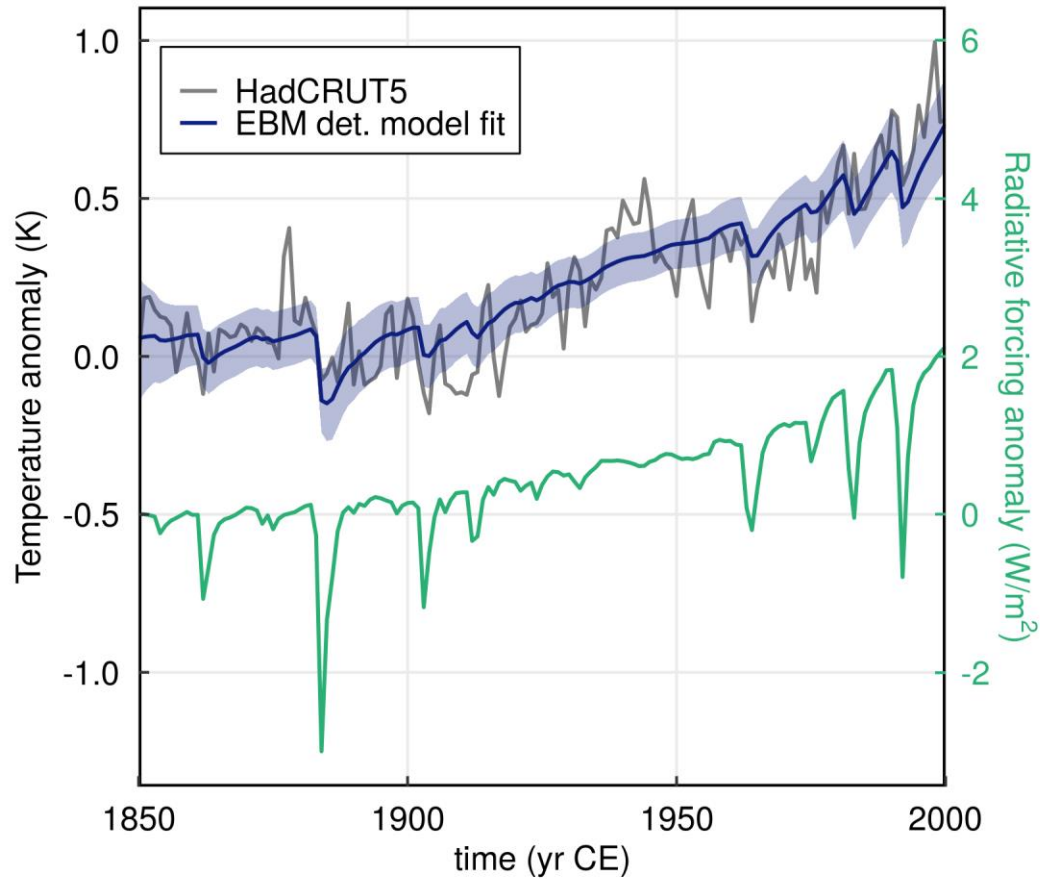
Output

Posterior distributions for X

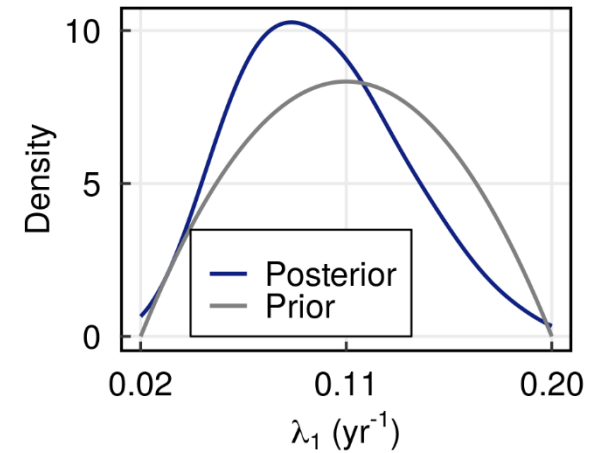
Best estimate of **forced** and **internal** temperature variations

Example: historical data

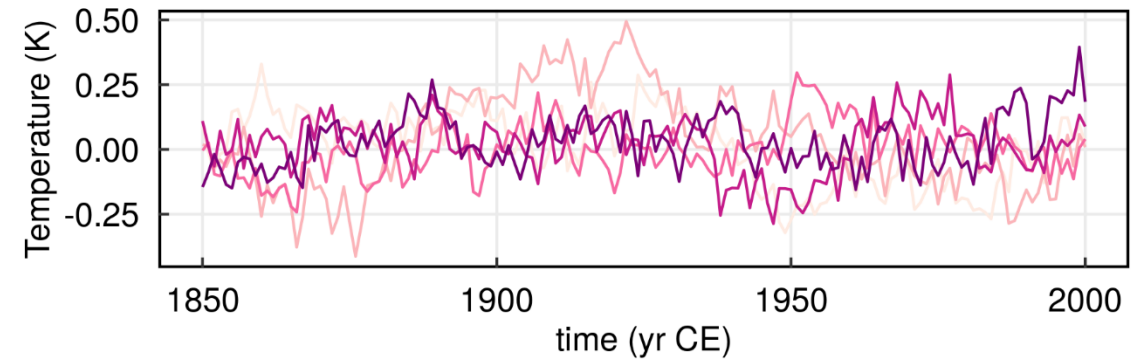
Estimate of forced response



Posteriors for X , e.g.



Estimate of internal variability

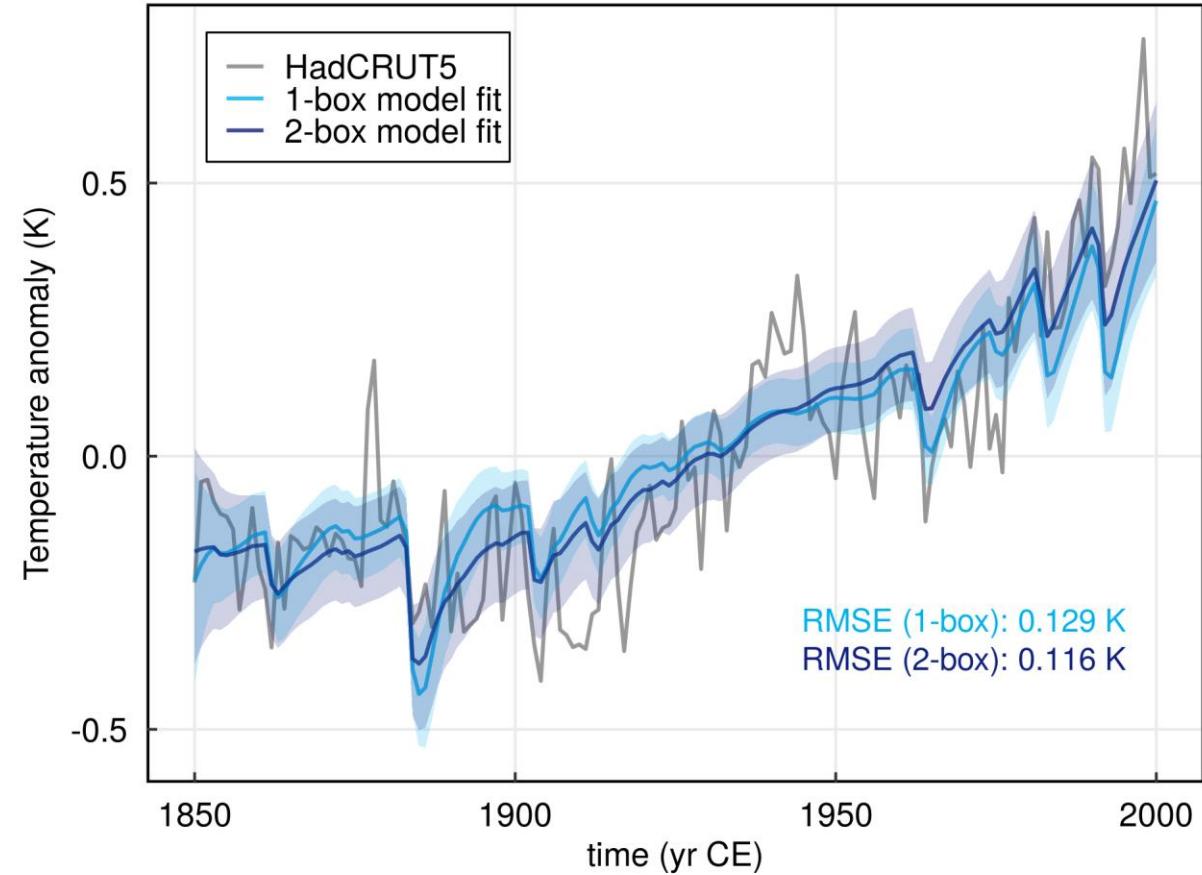


Possible applications

**Compare models
with different number
of boxes**

Fit EBM to various
data sources and
time periods

Characterise
sensitivity of
estimators to noise

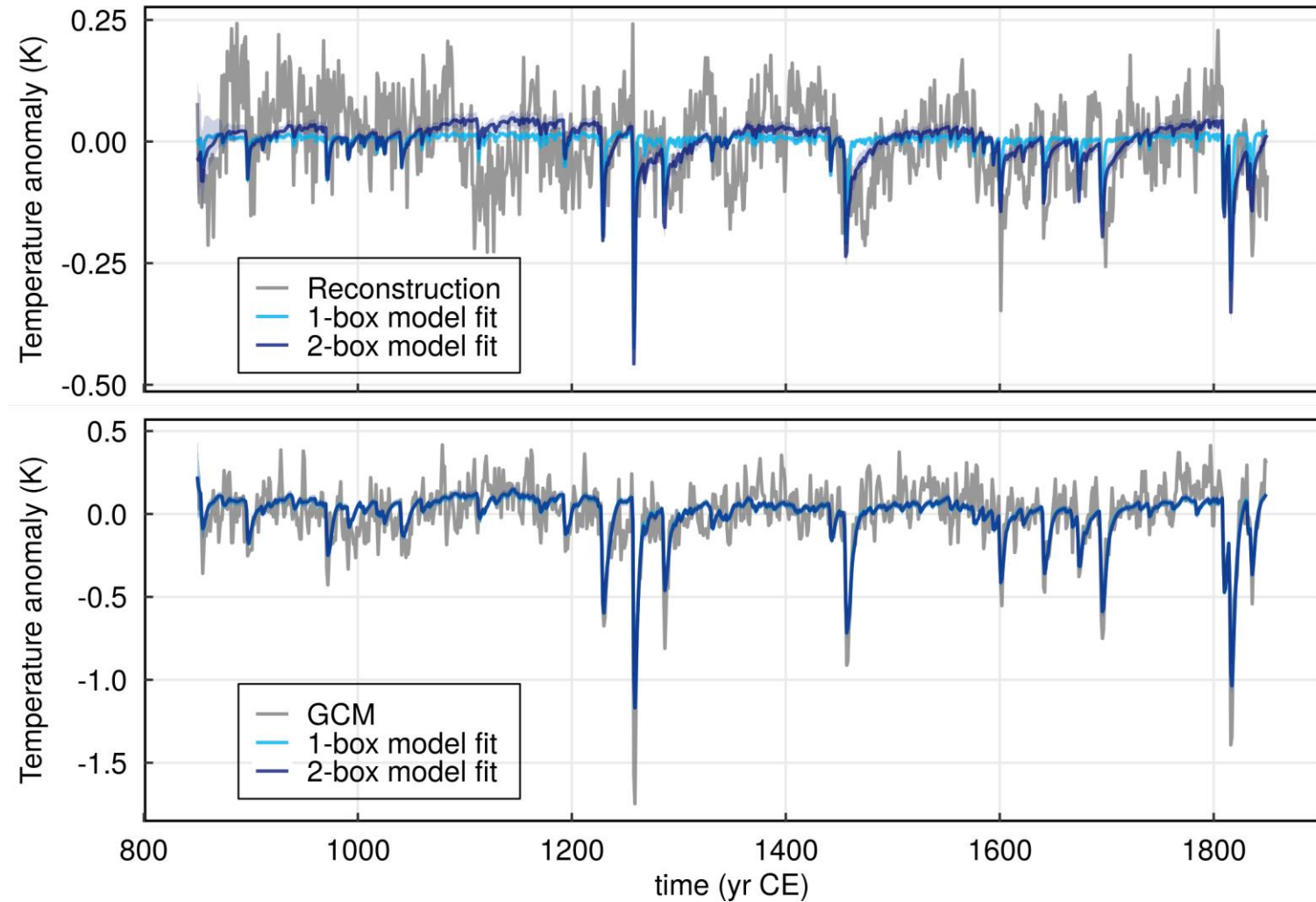


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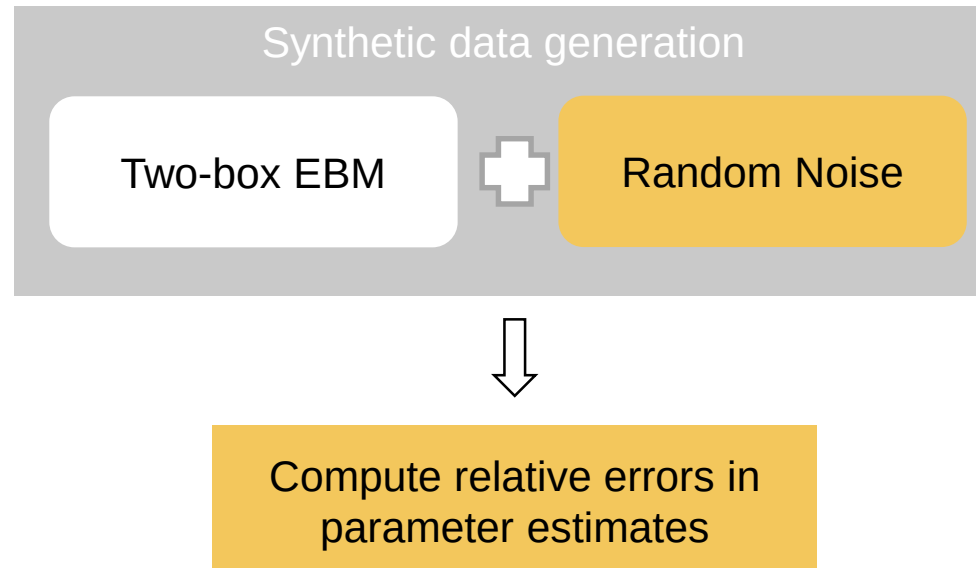
Possible applications

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**Characterise
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Question: How do the parameter estimates depend on **noise** in the data?



Separating forced from internal variability

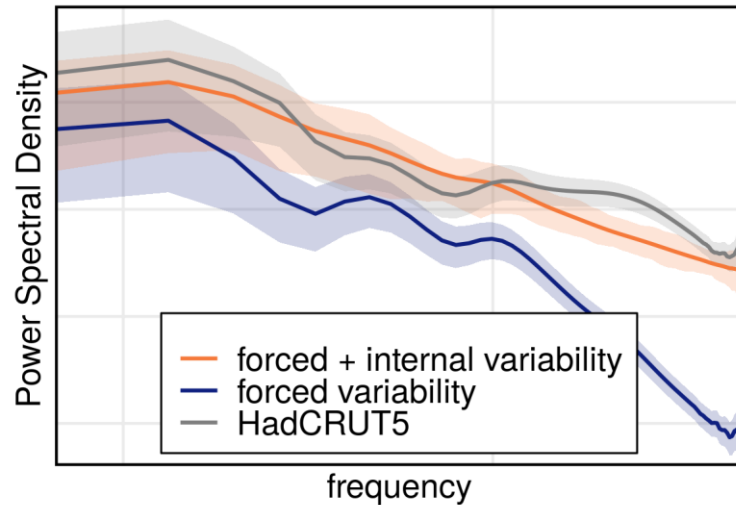
Linear stochastic EBM

$$T(t) = \int R(t-s) \underbrace{(F(s)ds)}_{\text{forced}} + \underbrace{dW(s)}_{\text{internal}}$$

Bayesian
Inference

Output

Best estimate of **forced** and **internal** temperature variations

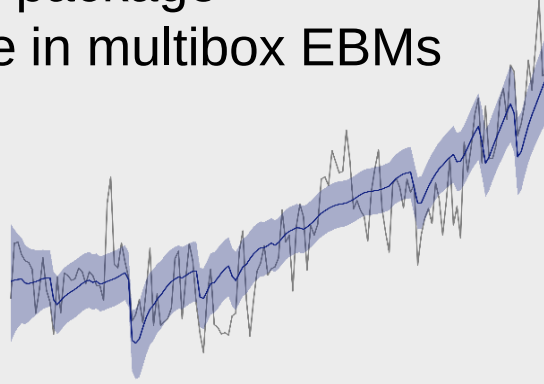


Spectral analysis

Separate **forced** from **internal** variability in temperature data on different timescales

Conclusions and Outlook

Easy-to-use & flexible package
for Bayesian inference in multibox EBMs



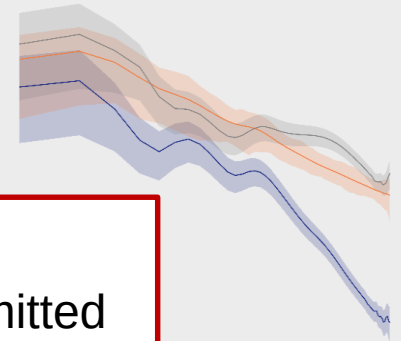
Release 01.07.2022

<https://github.com/paleovar/ClimBayes>

Separating forced from internal variability for...

... model simulations for last millennium
... along the model hierarchy

→ Variability on different time scales



Paper to be submitted



Any Questions?

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