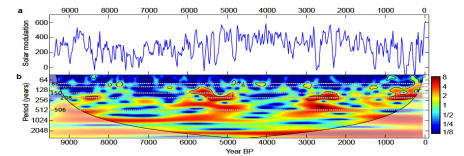
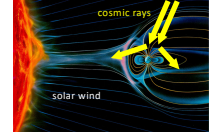


Bayesian parameter inference with stochastic solar dynamo models

Simone Ulzega (ZHAW) and Carlo Albert (Eawag)

Solar magnetic activity: cosmogenic radionuclides open up new frontiers

- **Sunspots** provide the longest DIRECT record of solar magnetic activity (covering **only 400 years!**)
- Time-series of **cosmogenic radionuclides** (^{10}Be , ^{14}C) stored in natural archives such as ice cores and tree rings are a **proxy** for solar magnetic activity on **multi-millennial time-scales**
- **New data** have uncovered **exciting features** (e.g., intermittent long-period stable cycles, Grand Minima)
- Solar physicists have put great efforts into the development of sound physically based **stochastic solar dynamo models** that can qualitatively reproduce the observed features
- **OUR GOAL:** carry out the first quantitative calibration of the models to the data (**Bayesian inference**) and run model performance comparisons to shed light on the underlying mechanisms leading to the observed features.



Solar activity based on ^{10}Be and ^{14}C records
[1] J. A. Abreu et al., A&A 548 (2012).



Bayesian inference with nonlinear stochastic models can become computationally extremely expensive



ABC (Approximate Bayesian Computation)

Basic concept:

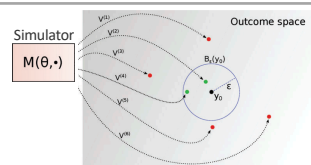
- Instead of evaluating the **expensive likelihood function** of a stochastic model, many datasets are generated from the corresponding probabilistic model, for different parameter sets, and compared with the measured data. If the match is within a certain **tolerance**, parameter sets are accepted as posterior samples.
- For computational feasibility, data needs to be compressed into few **summary statistics**.

Pros & Cons:

- ✗ Provides only **approximate results**, due to summary stats.
- ✓ Plug-n-run: only (black box) forward simulator needed.
- ✗ Computation-intensive, many simulations required that need to be discarded.
- ✓ Population method, **well suited for parallel computing**.

From [3]:

- Stochastic simulator M is run multiple times with fixed parameters θ
- The proportion of outcomes less than ε away from observed data (y_0) provides an approximation to the likelihood of θ



[2] C. Albert et al., Stat. Comput. 25 (2015). [3] Lintusaari et al., Syst. Biol. 66 (2017).

HMC (Hamiltonian Monte Carlo)

Basic concept:

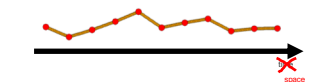
- The Bayesian posterior is re-interpreted as the **partition function** of an **interacting particle system**, and the **state of a stochastic model**, defined by its parameters and dynamic stochastic variables, is thus interpreted as the **configuration of a statistical mechanics system**.
- **Molecular Dynamics** algorithms are used to explore the space of **configurations compatible with measured data, model and prior**.

Pros & Cons:

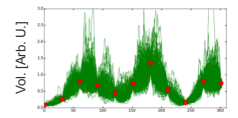
- ✓ Provides **exact results**, no summary statistics needed.
- ✗ Requires encoding the **probability density of model realizations**, not just a forward simulator.
- ✓ Very efficient (it exploits the local shape of the posterior landscape to suppress the random-walk nature of standard MCMC algorithms).
- ✓ Local interactions, **well suited for parallel computing**.

Simple hydrological application from [4]:

Observations / stat. mechanics system



System realizations



[4] C. Albert, S. Ulzega and R. Stoop, Phys. Rev. E, 93 (2016).

Solar dynamo models: a "simple" stochastic iterative map

- Magnetic field dynamics exhibit a well-known 11y cycle that can be captured by a **stochastic iterative map**:

$$p_{n+1} = \alpha \cdot f(p_n) + \varepsilon_n \quad \varepsilon_n \in [0, \varepsilon_2]$$

- **External periodic forcing** representing **planetary gravitational effects** can be included in the iterative map:

$$\tau = \sum_i A_i \sin(2\pi \frac{t}{T_i})$$

- Power spectral density at the frequencies of interest is used as **summary statistics**



Can planets be responsible for low-frequency modulations through **stochastic resonances**?

ABC posterior distribution for α, ε_2, A (with $T = 208y$)

