

Monte Carlo generator tuning for cosmic-ray induced air shower simulations



CORSIKA 8 Workshop 2023

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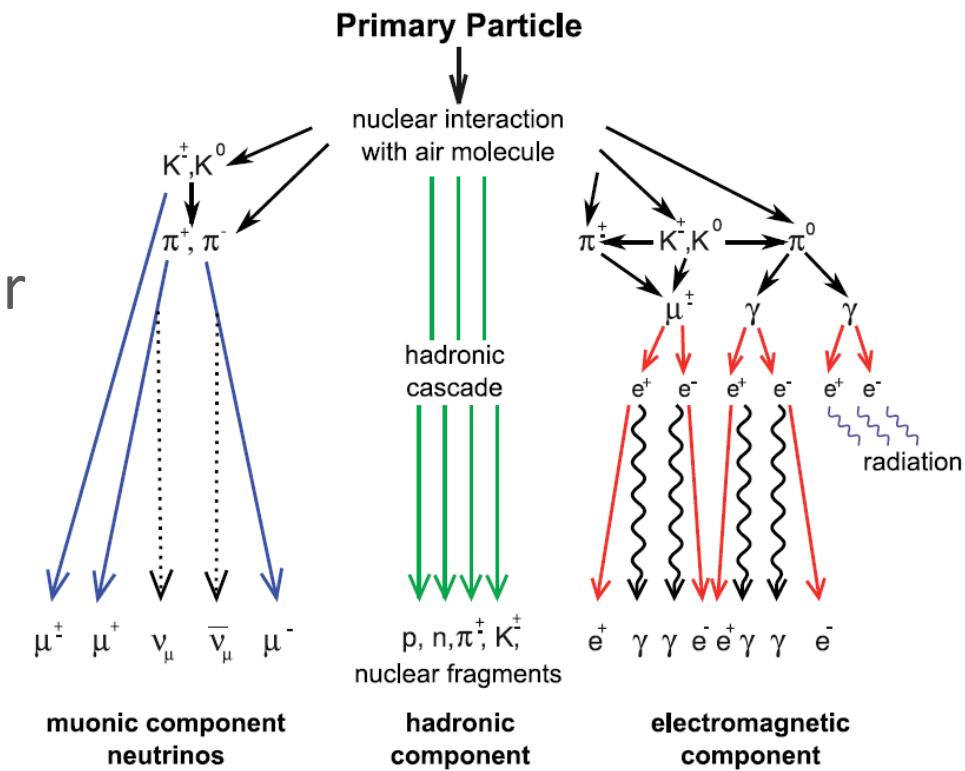
The need for MC generator tuning

Hadronization of process cannot be calculated from first principle
→ Need for hadronic models (MC generators)

Hadronization process has large impact on air shower features

Tuning essential to achieve high-quality simulations

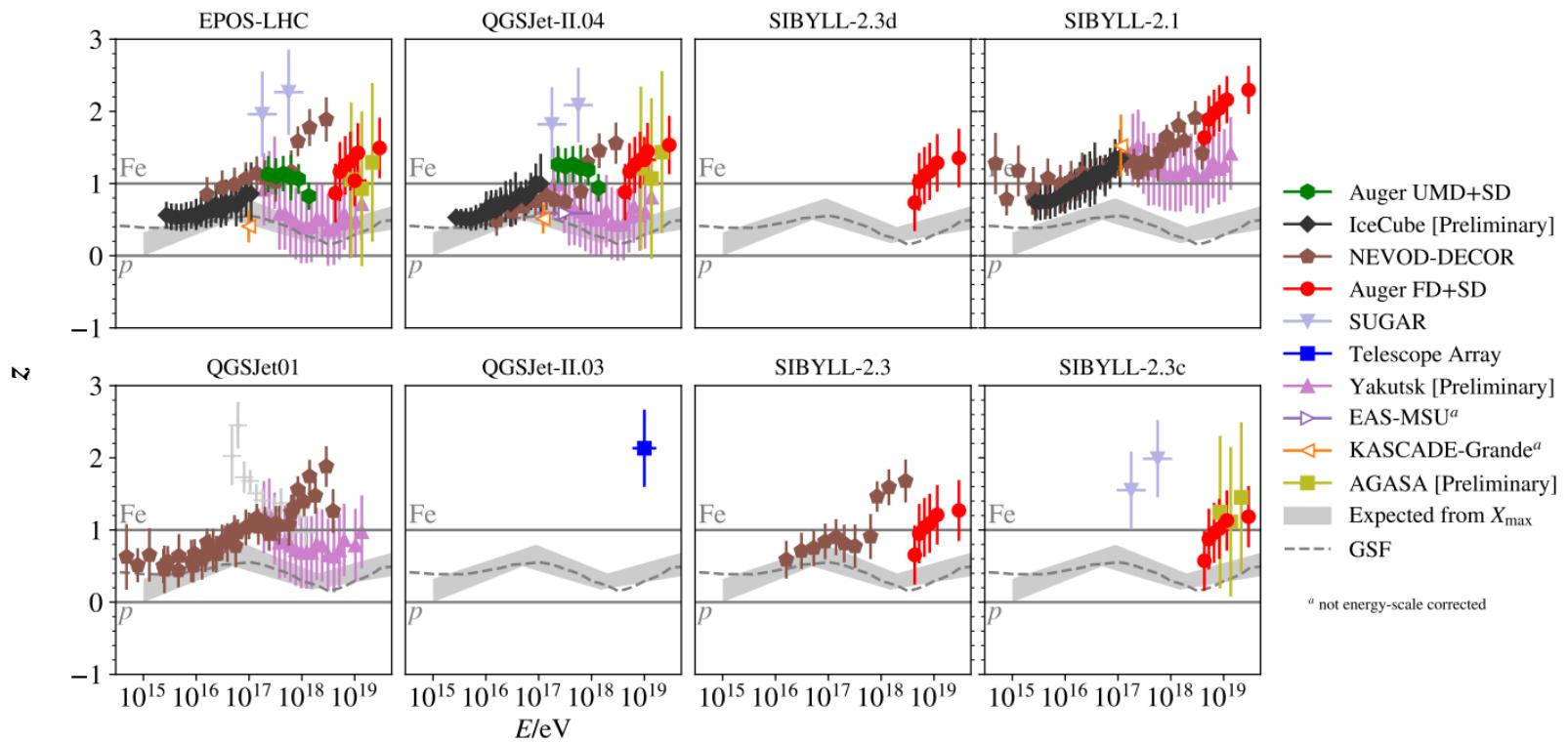
→ Muon Puzzle



Muon Puzzle

High energies: Muon excess in observations compared to simulations

$$z = \frac{\ln(N_{\mu}^{\text{det}}) - \ln(N_{\mu,p-\text{sim}}^{\text{det}})}{\ln(N_{\mu,\text{Fe-sim}}^{\text{det}}) - \ln(N_{\mu,p-\text{sim}}^{\text{det}})}$$



J. Albrecht et al., *The Muon Puzzle in cosmic-ray induced air showers and its connection to the Large Hadron Collider*, *Astrophys. Space Sci.* 367 (2022) 3, 27

Tuning of Free Parameters

Adjust free parameters in order to achieve a good description of the data

Manual or brute-force tuning difficult due to high computing cost

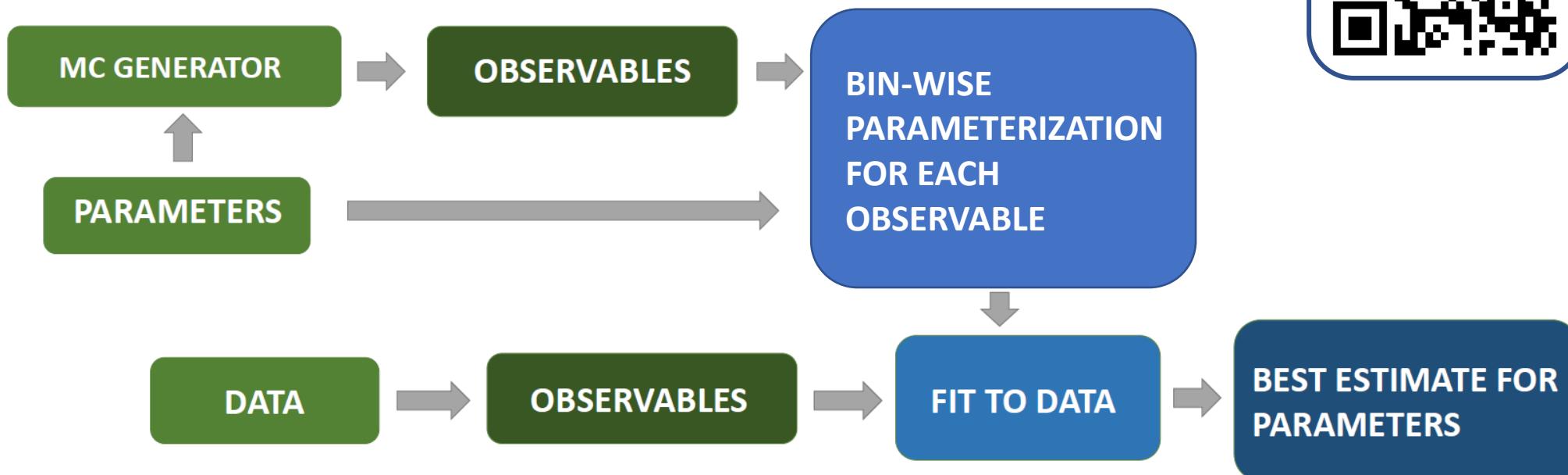
Systematic event generator tuning workflow: Professor tuning system

[arXiv:0907.2973](https://arxiv.org/abs/0907.2973)

Parameter based generator tuning

Optimize free parameters of MC generator using experimental data and Bayesian Methods

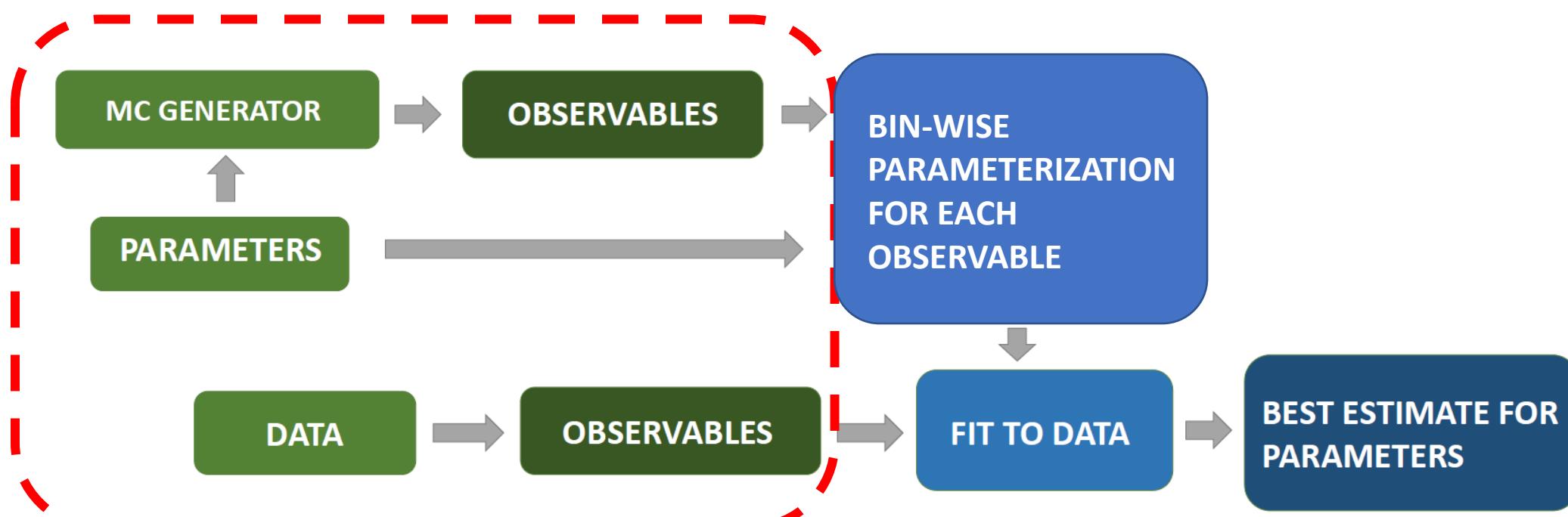
La Cagnina et al.; arXiv:2302.01139



Parameter based generator tuning

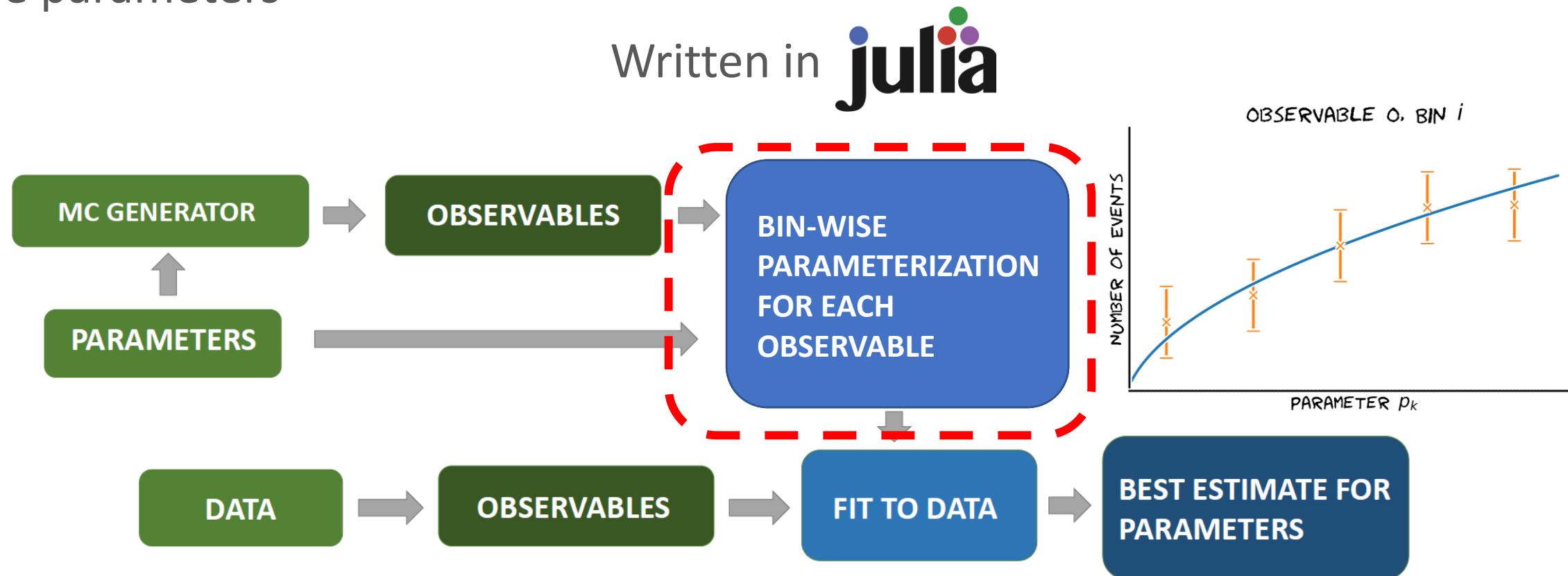
Generate MC samples for different sets of parameter configurations

Reconstruct observables



Parameter based generator tuning

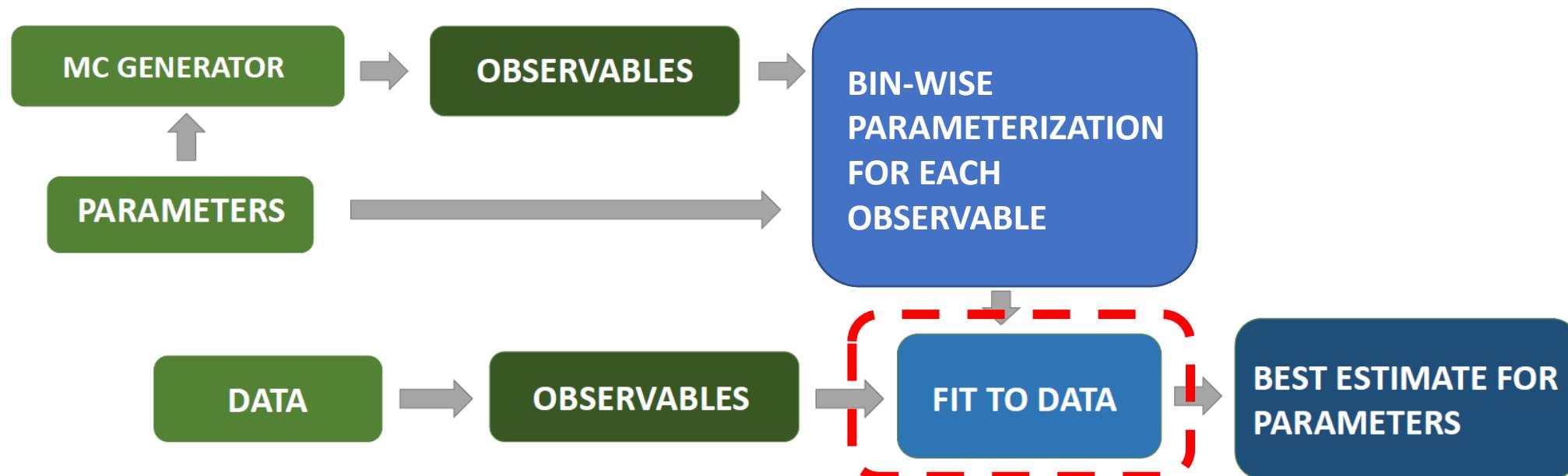
Create bin-wise parameterization of the observables as a function of the free parameters



Parameter based generator tuning

Using the EFTfitter.jl tool a likelihood model is built from the parameterization and experimental data

N. Castro et al., *EFTfitter-A tool for interpreting measurements in the context of effective field theories*, Eur. Phys. J. C 76 (2016) 8, 432



Parameter-based modeling

Using EFTfitter.jl:

inter

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EFTfitter.jl:

$$\ln L(\vec{D}|\vec{\lambda}) = -\frac{1}{2}[\vec{D} - \vec{f}(\vec{\lambda})]^T \cdot M^{-1} \cdot [\vec{D} - \vec{f}(\vec{\lambda})]$$

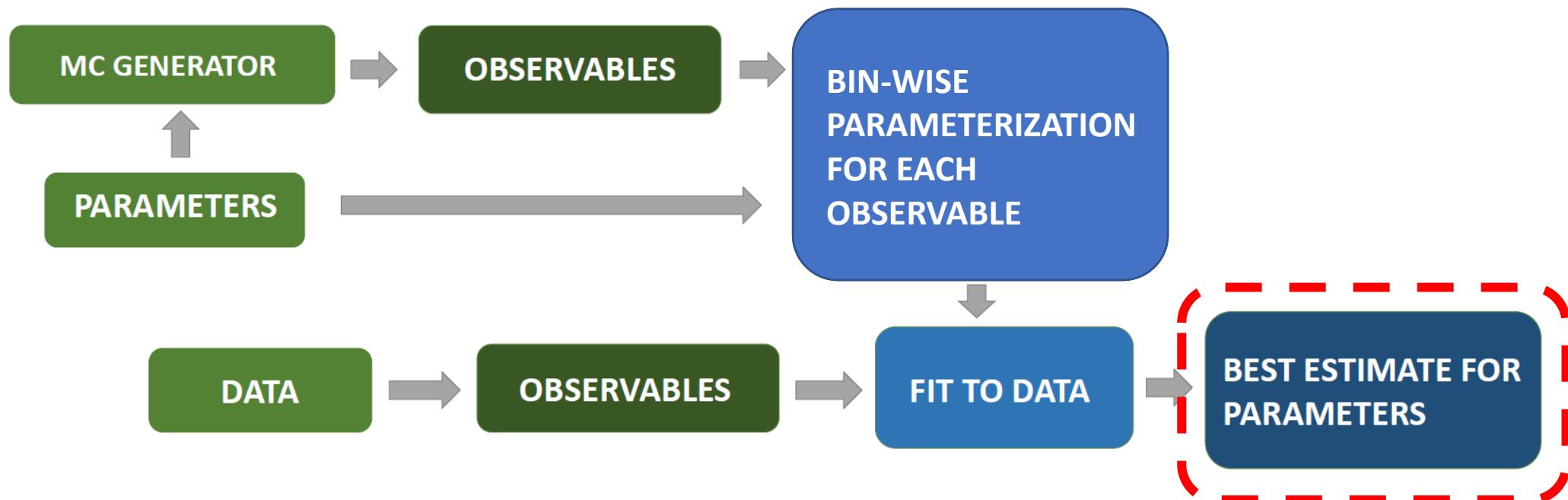
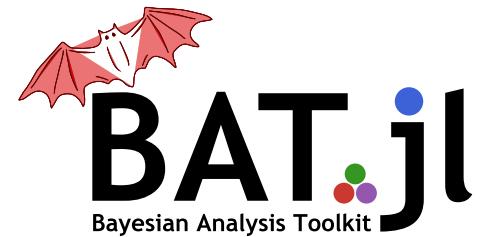
Diagram illustrating the components of the likelihood function:

- Parameters**: $\vec{\lambda}$ (represented by a blue arrow pointing to the term $\vec{\lambda}$ in the equation)
- Data**: \vec{D} (represented by a blue arrow pointing to the term \vec{D} in the equation)
- Likelihood**: $\ln L$ (represented by a blue arrow pointing to the overall expression)
- Parameterization**: $\vec{f}(\vec{\lambda})$ (represented by a blue arrow pointing to the term $\vec{f}(\vec{\lambda})$ in the equation)
- Covariance Matrix**: M (represented by a blue arrow pointing to the term M in the equation)

Parameter based generator tuning

Using the BAT.jl framework the posterior space of the free parameters is sampled to achieve a tuned parameter setting

O. Schulz et al., *BAT.jl: A Julia-Based Tool for Bayesian Inference*, SNCS (2021)



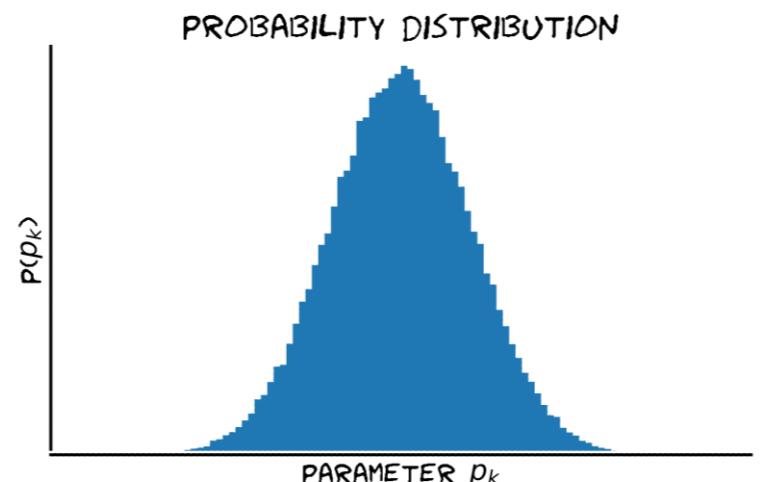
Sampling Posterior Space

Bayes' Theorem : $p(\vec{\lambda}|\vec{D}) \propto L(\vec{D}|\vec{\lambda}) \cdot p(\vec{\lambda})$

Posterior *Likelihood* *Prior*

$$p(\vec{\lambda}|\vec{D}) \propto L(\vec{D}|\vec{\lambda}) \cdot p(\vec{\lambda})$$

Markov Chain Monte Carlo
→ Metropolis-Hastings Algorithm (as default)



Verify Tuning Algorithm

Simple toy study to test and demonstrate potential usefulness
of tuning algorithm

Toy study based on PYTHIA example *main183*

→ Example includes simple study on air shower evolution in the atmosphere

T. Sjöstrand, M. Utheim, Hadron interactions for arbitrary energies and species, with applications to cosmic rays. Eur. Phys. J. C 82, 21 (2022)

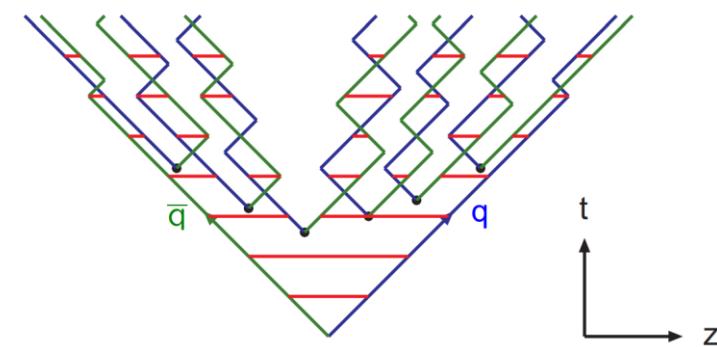
→ Provides quick and convenient generation of air shower observables for testing of tuning algorithm

Toy Study

Study and test tuning method

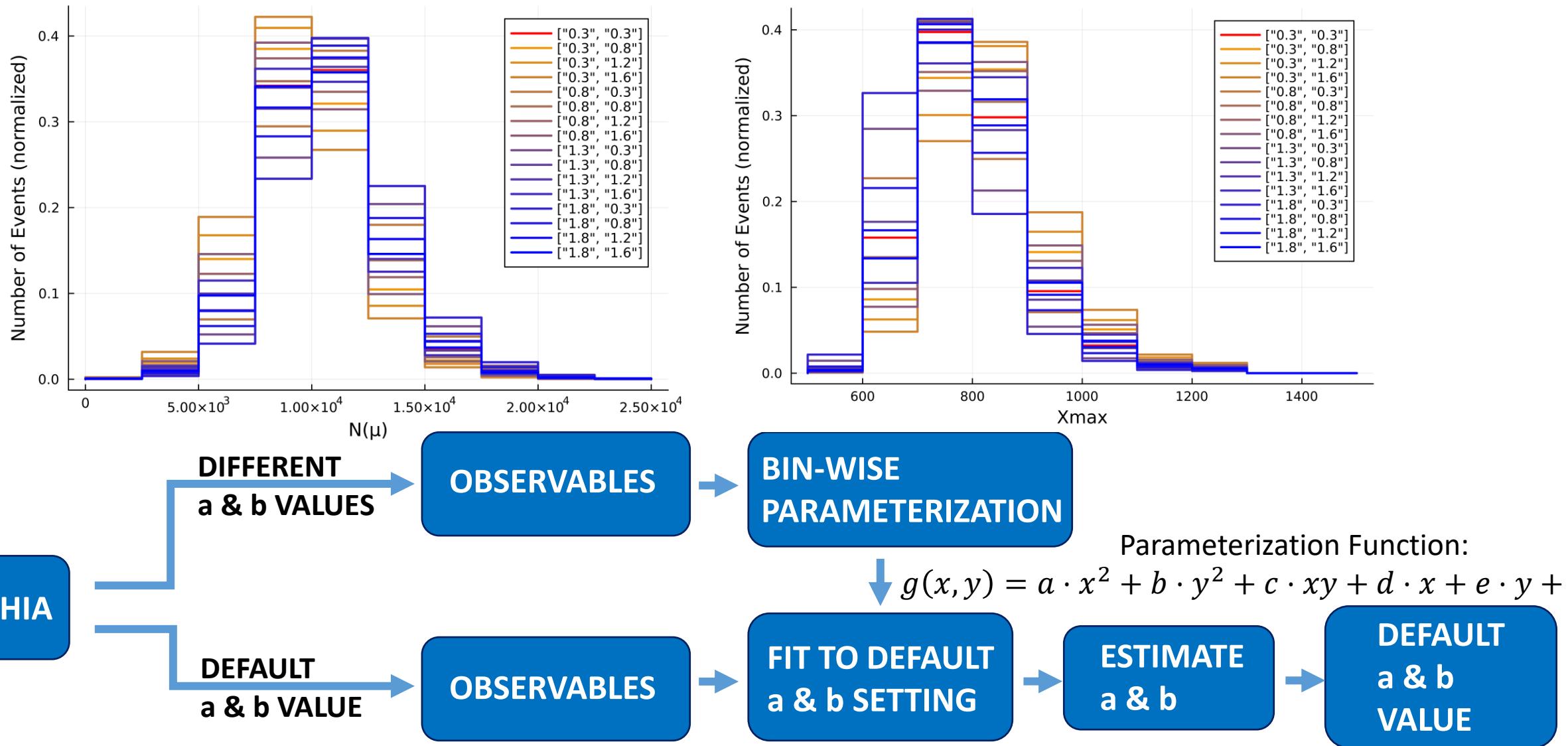
→ Generate muon number and shower maximum observable
for different aLund and bLund parameter settings

$$f(z) \propto z^{-1} (1-z)^a \exp\left(\frac{-bm_{\perp}^2}{z}\right)$$



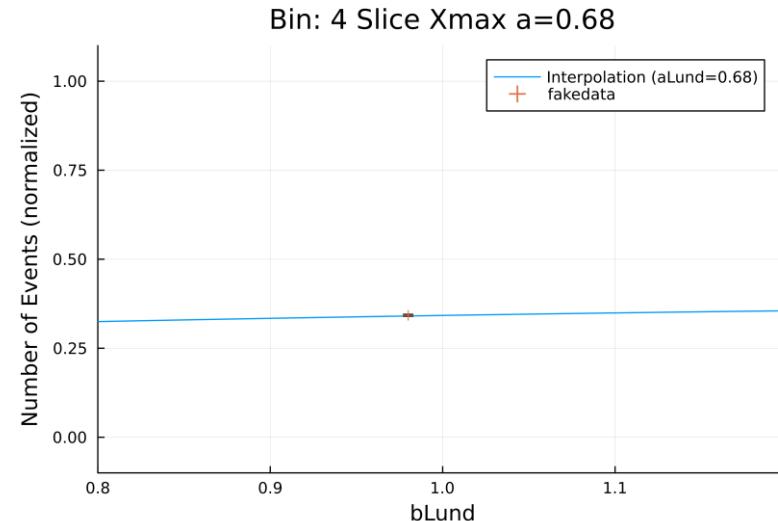
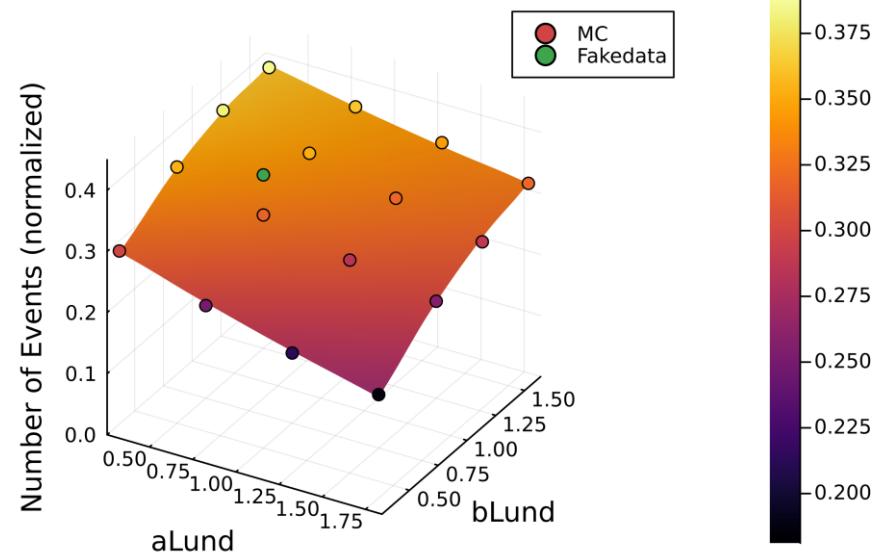
→ Use PYTHIA's default value for a- and bLund as *fake data* to tune against

Generate air shower simulations

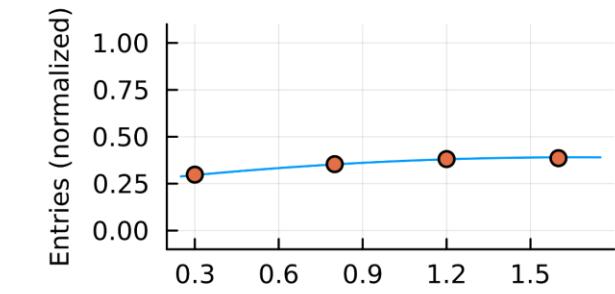


Parameterization

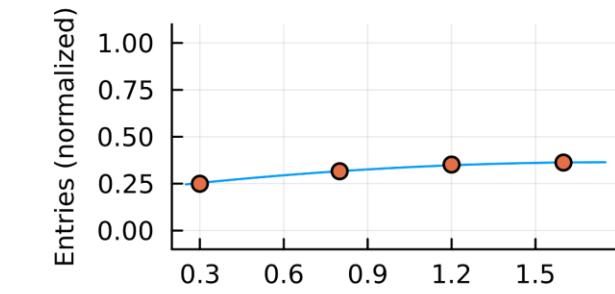
Xmax Interpolation Bin: 4



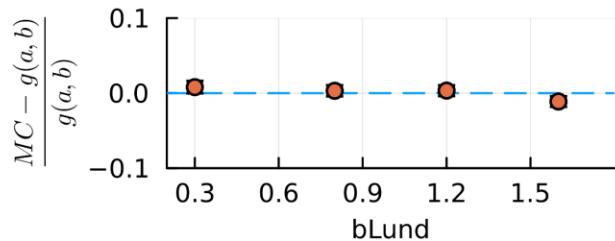
Bin: 4, Slice Xmax a=0.3



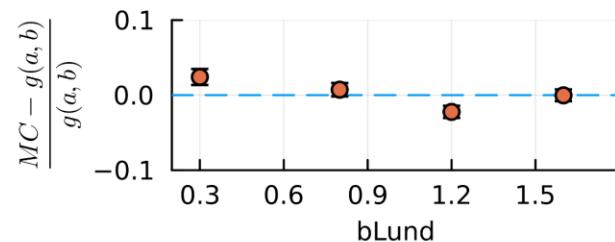
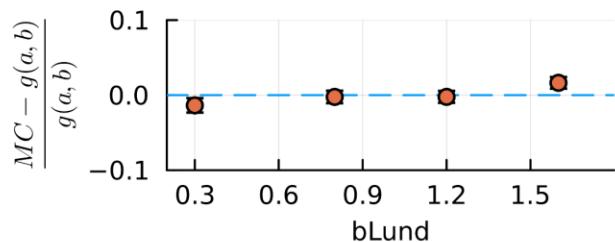
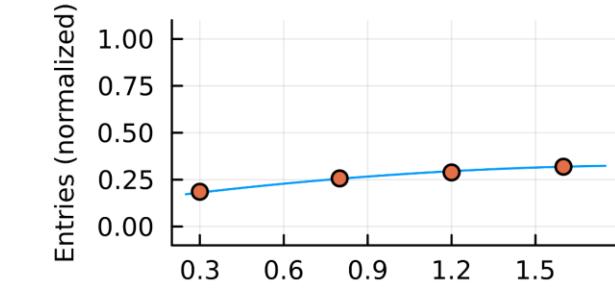
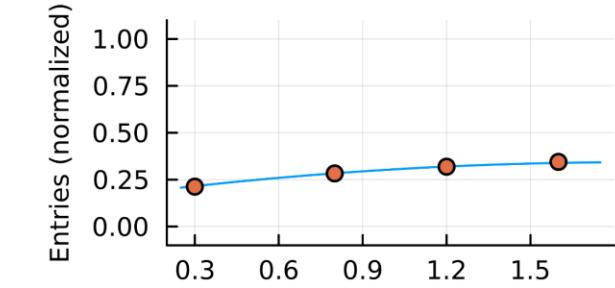
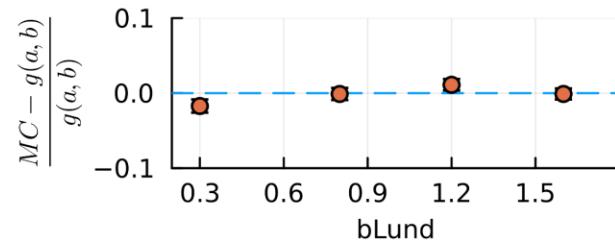
Bin: 4, Slice Xmax a=0.8



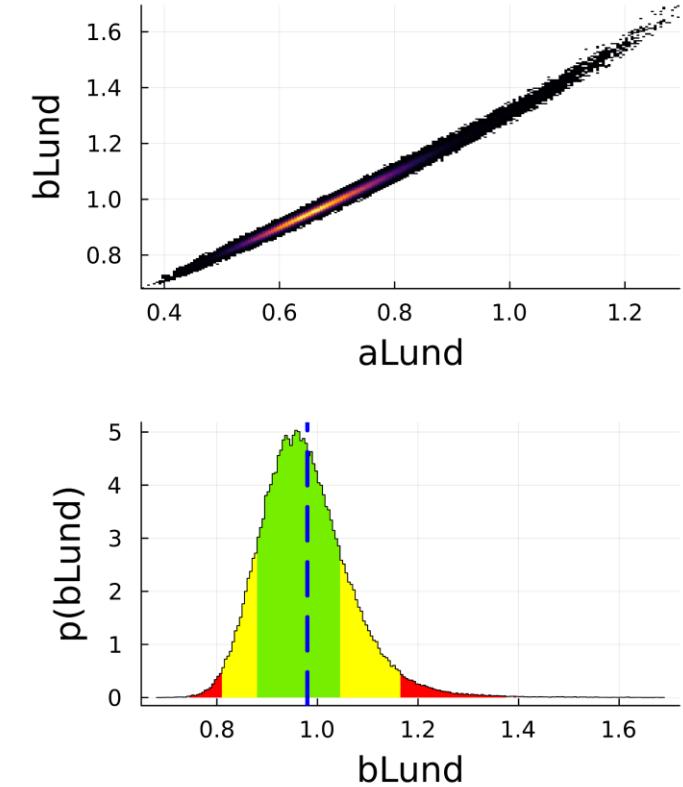
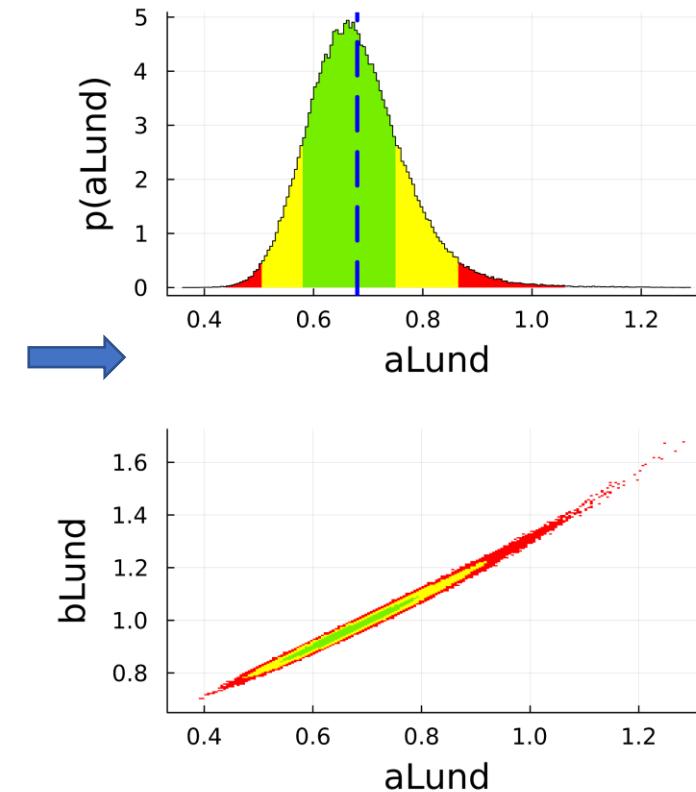
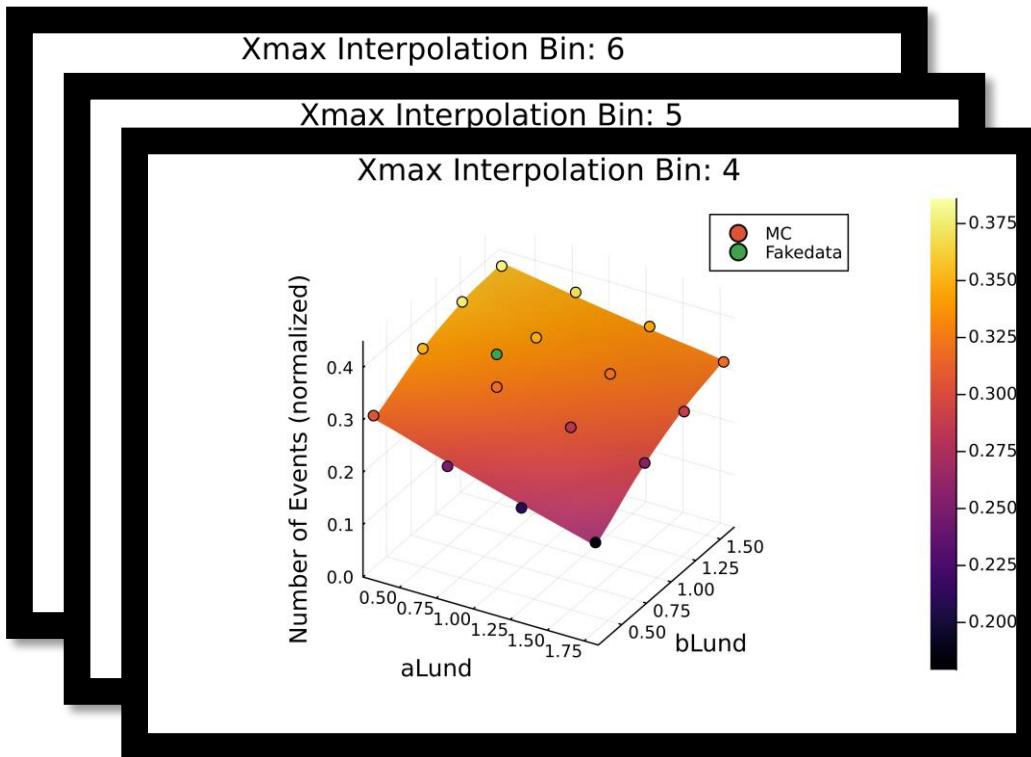
Bin: 4, Slice Xmax a=1.3



Bin: 4, Slice Xmax a=1.8



Sampling the posterior space



Air Shower Simulation and MC Generator

Choice of MC generator for tuning

→ PYTHIA: Collider background and convenient access to tuning

C. Bierlich et al., *A comprehensive guide to the physics and usage of PYTHIA 8.3.* (2022). arXiv:2203.11601

Use of air shower simulations

→ CORSIKA8

→ PYTHIA as event generator

Conclusion

Monte Carlo tuning using a Bayesian approach is possible

Tested on collider data for particle physics and in toy studies

Outlook

Investigate CORSIKA8 regarding the tuning workflow with PYTHIA

Use of air shower data and CORSIKA8 for MC generator tuning

Combine collider and air shower data for simultaneous tune

