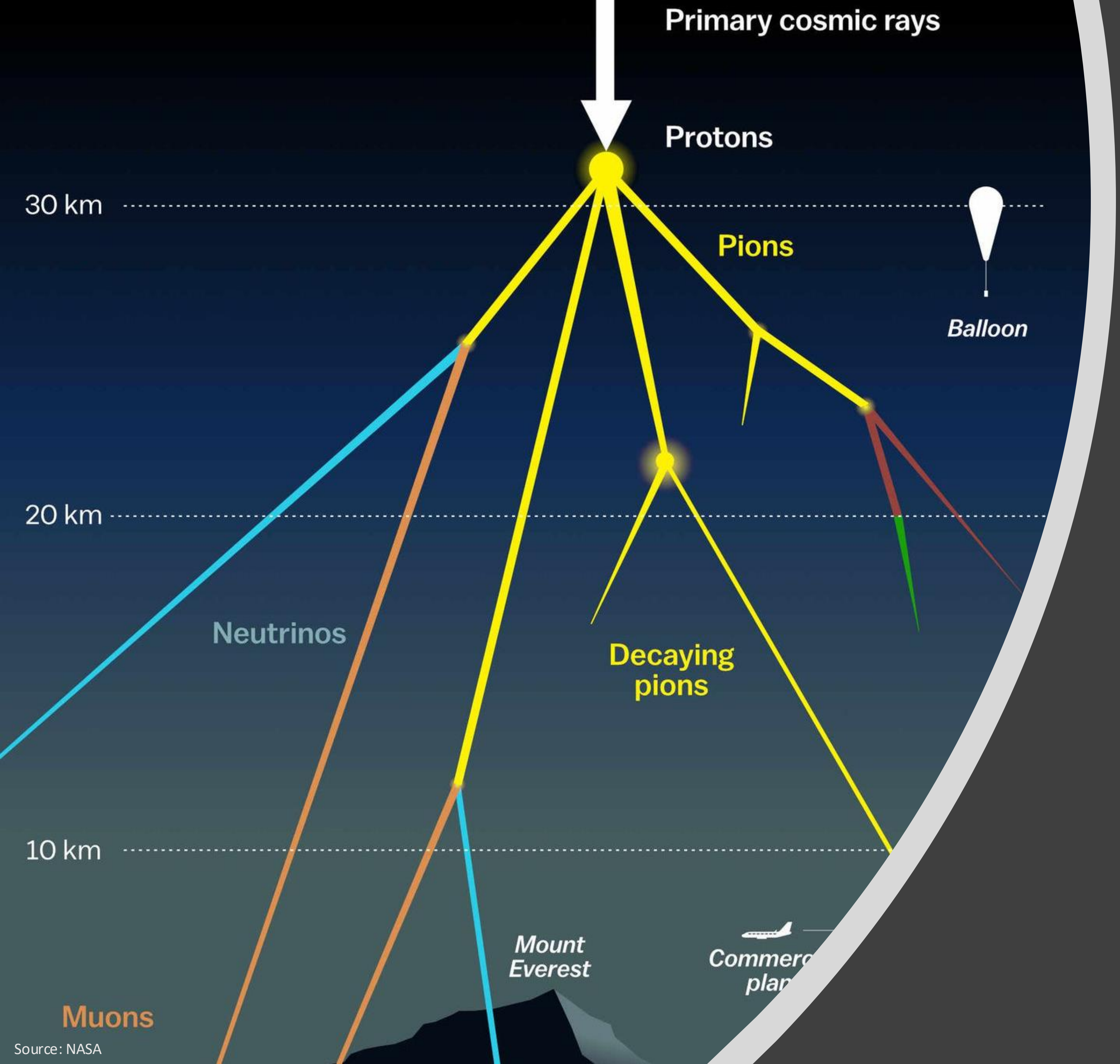


Source: NASA

Exploring High-Energy Atmospheric Muons with IceCube: Investigating Prompt Muon Normalization and Unfolding the Muon Flux

Pascal Gutjahr

March 18, 2025

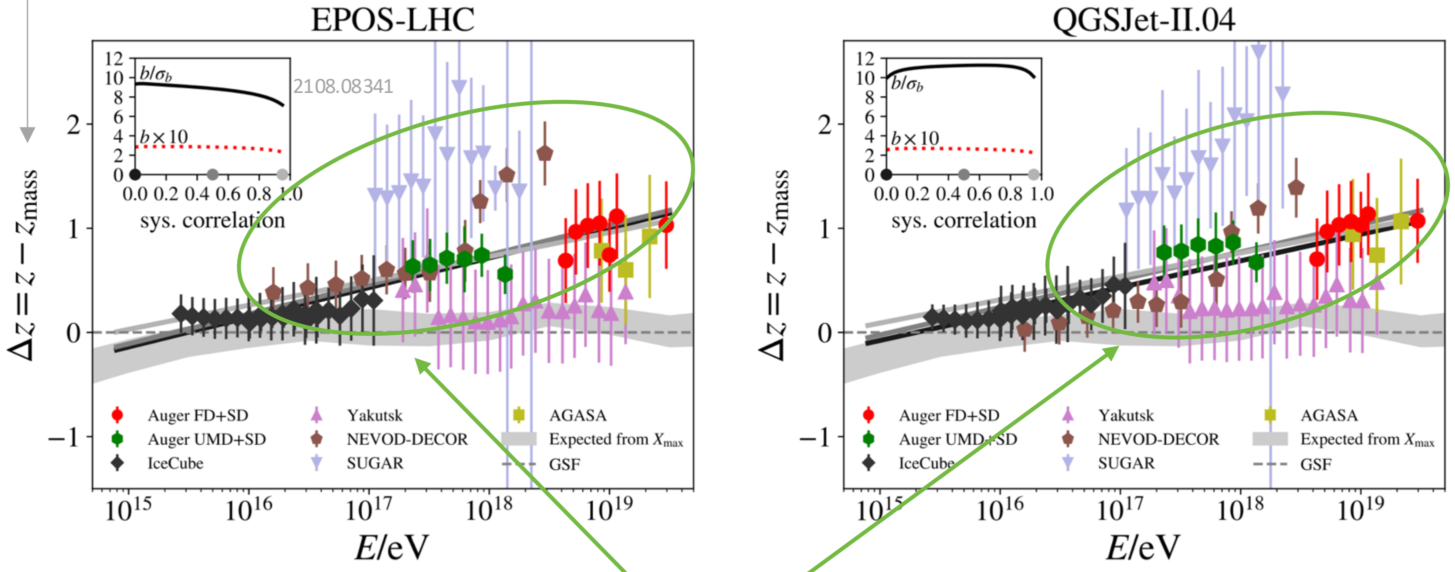
JOINT MARCH MEETING AND APRIL MEETING
Global Physics Summit

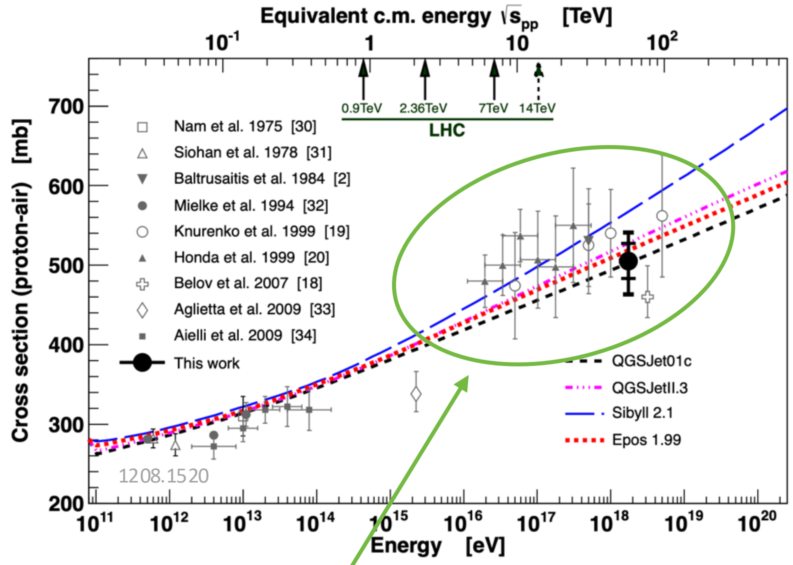
Muon Puzzle & Hadronic Uncertainties

"muon number"

Expected z ("muon number")

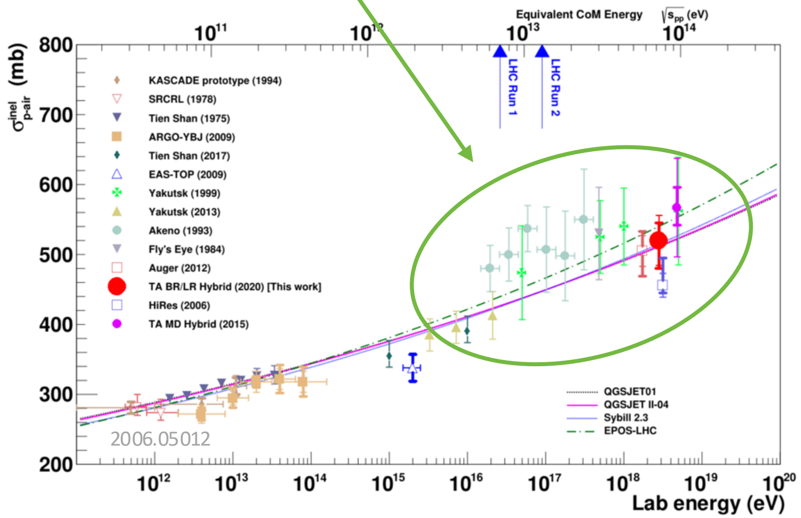
$$z = \frac{\ln\langle N_\mu\rangle - \ln\langle N_\mu\rangle_p}{\ln\langle N_\mu\rangle_{\mathrm{Fe}} - \ln\langle N_\mu\rangle_p}$$





2012

- Uncertainties at E > 10 PeV

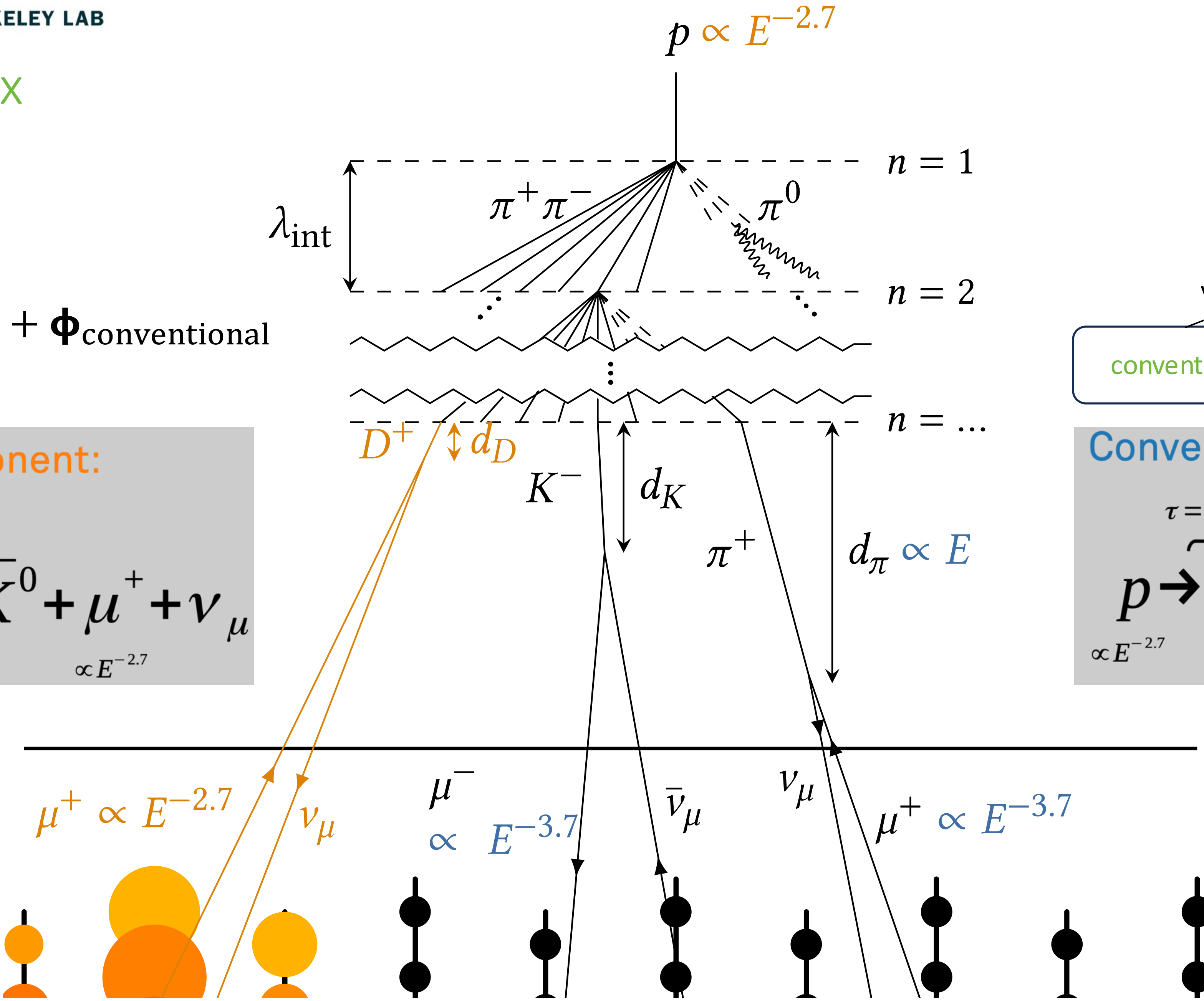


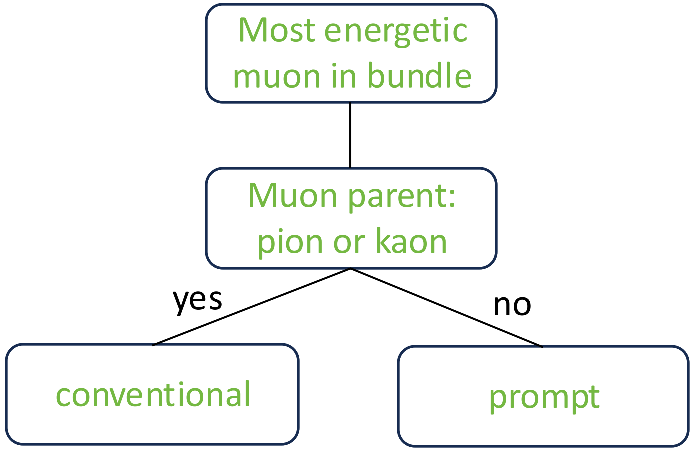
2020

- More muons measured than simulated for E > 40 PeV ~ cms 8 TeV
- Precise pion/kaon ratio measurement needed

Muon Flux

$$\Phi_{\mathrm{tot}} = \Phi_{\mathrm{prompt}} + \Phi_{\mathrm{conventional}}$$





prompt component:

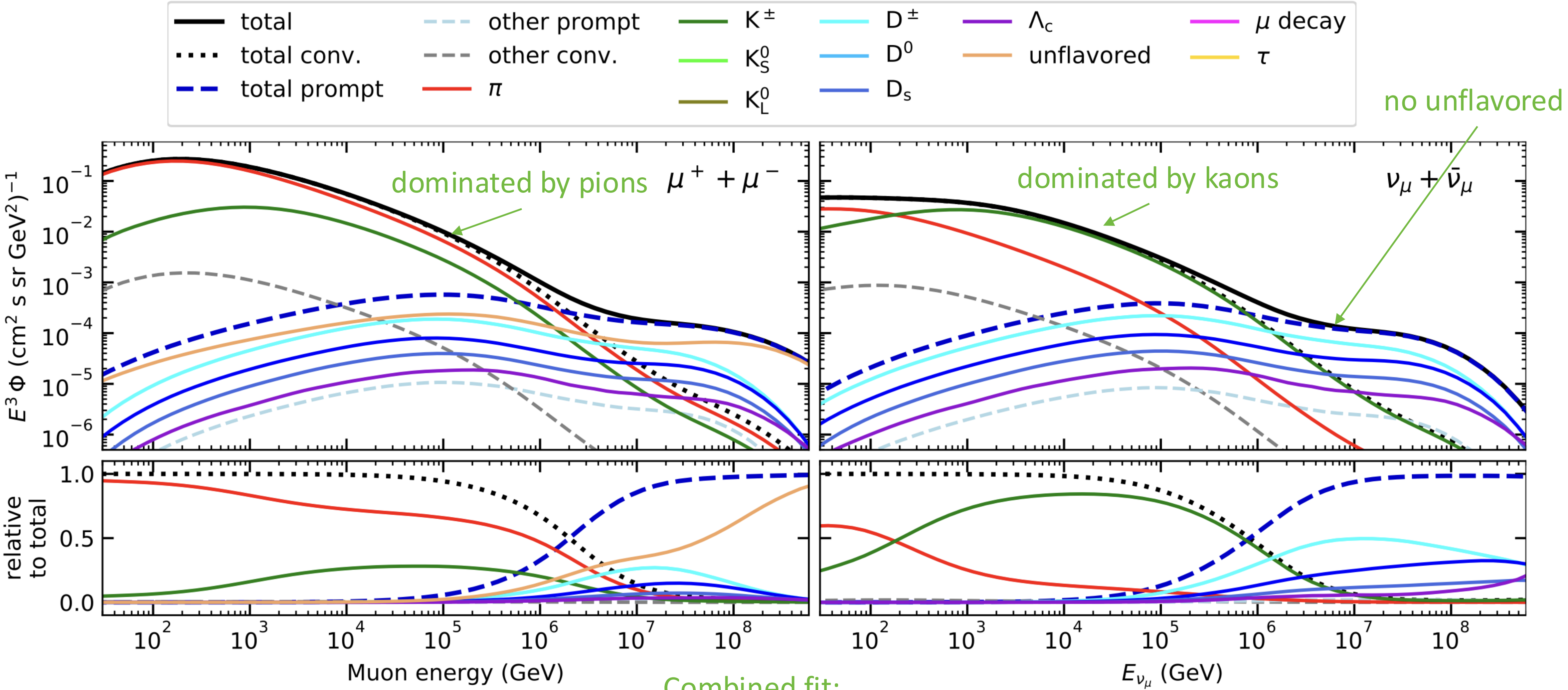
$$\underset{\propto E^{-2.7}}{p} \rightarrow \overbrace{D^+}^{\tau = 1.04\cdot 10^{-12}\,\mathrm{s}} \rightarrow \bar{K}^0 + \underset{\propto E^{-2.7}}{\mu^+} + \nu_\mu$$

Conventional component:

$$\underset{\propto E^{-2.7}}{p} \rightarrow \overbrace{\pi^+}^{\tau = 2.6\cdot 10^{-8}\,\mathrm{s}} \rightarrow \underset{\propto E^{-3.7}}{\mu^+} + \nu_\mu$$

Prompt Atmospheric Muons & Neutrinos

10.1103/PhysRevD.100.103018



Combined fit:
- handle on pion/kaon ratio
- handle on charmed mesons

Analysis Goals

1) Measure prompt component of the atmospheric muon flux
2) Unfold a muon energy spectrum

Idea:

- New CORSIKA simulations with extended history
- Tag muons by parent → prompt or conventional
- Scale amount of prompt particles
  - Scaling saves time and resources instead of doing multiple simulations with different interaction models
  - Perform forward fit of the prompt normalization

Future:

- Measure prompt neutrinos
- Combined muon and neutrino fit → pion/kaon ratio

Overview

Simulation

Dataset
- CORSIKA 77500 Ehist
- SIBYLL 2.3d
- 10 TeV – 100 EeV

Validation
- Tag prompt / conv particles
- MCEq comparisons

Reconstruction

DNN reconstructions
- Muon energies
- Muon direction
- Track geometry

Selection

Level 3
- L2 muon filter
- 500 TeV bundle energy cut at surface
- Add labels

Level 4
- Add DNN reconstructions

Level 5
- Data-MC quality cuts

Analysis

Forward fit

Fit prompt normalization
- Poisson LLH fit

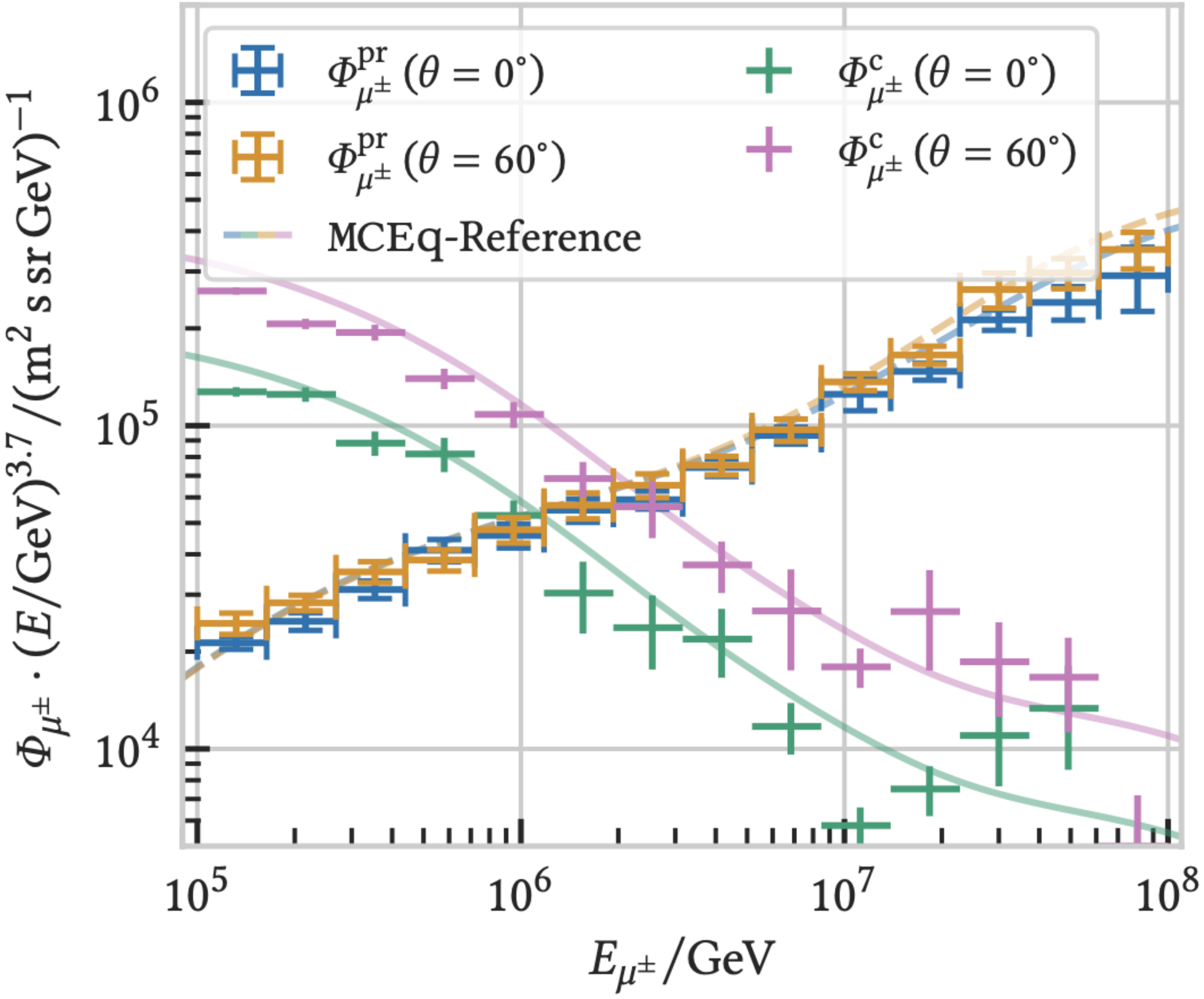
Unfolding

Muon spectrum
- Unfold muon flux

Simulation

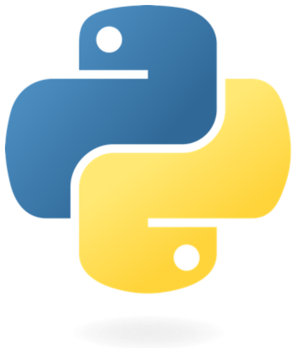
CORSIKA 7 vs. MCEq

MCEq: tool to numerically solve the cascade equations that describes the evolution of particle densities as they propagate through a gaseous, dense medium
https://github.com/mceq-project/MCEq



- Good agreement for inclusive flux

Python package developed – PANAMA



- Execute CORSIKA 7 (multi core)
- Read DAT files → pandas DataFrames
- Parse EHIST option
- Calculate primary weightings

https://github.com/The-Ludwig/PANAMA
https://arxiv.org/pdf/2502.10951

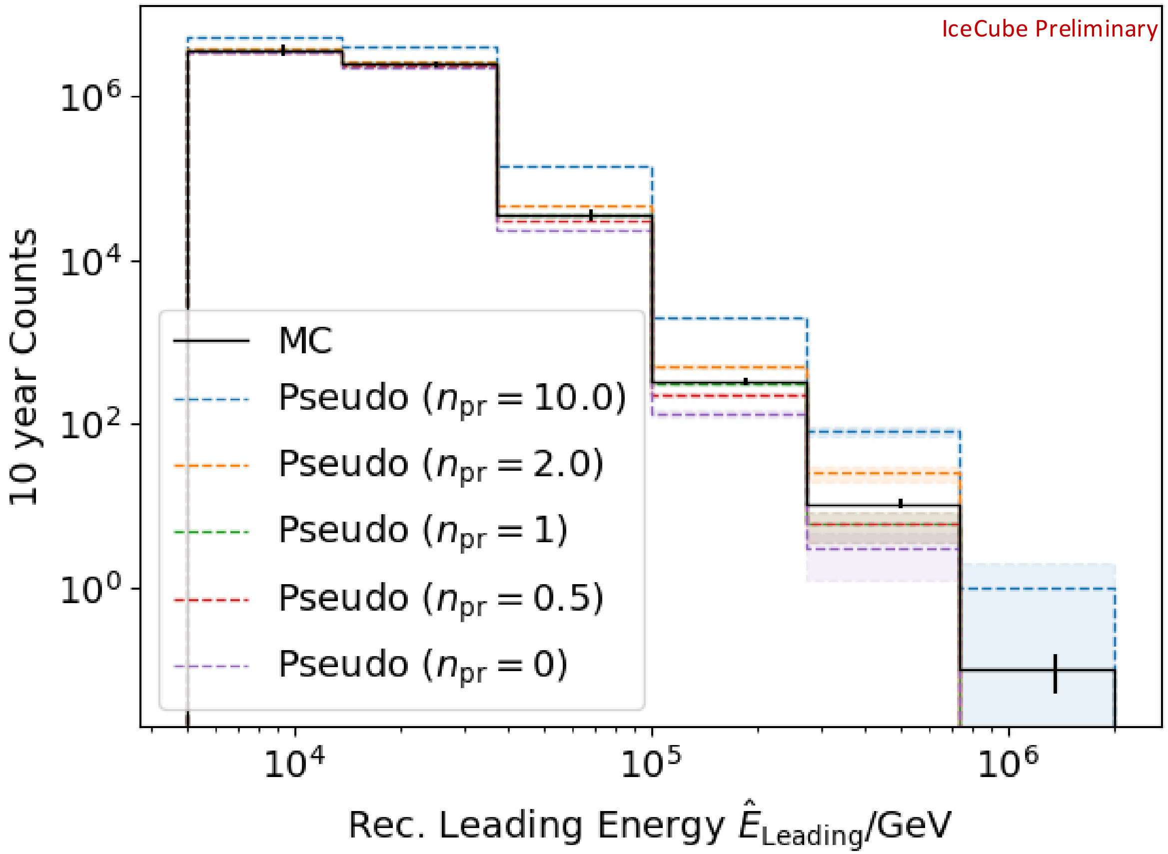
Forward Fit

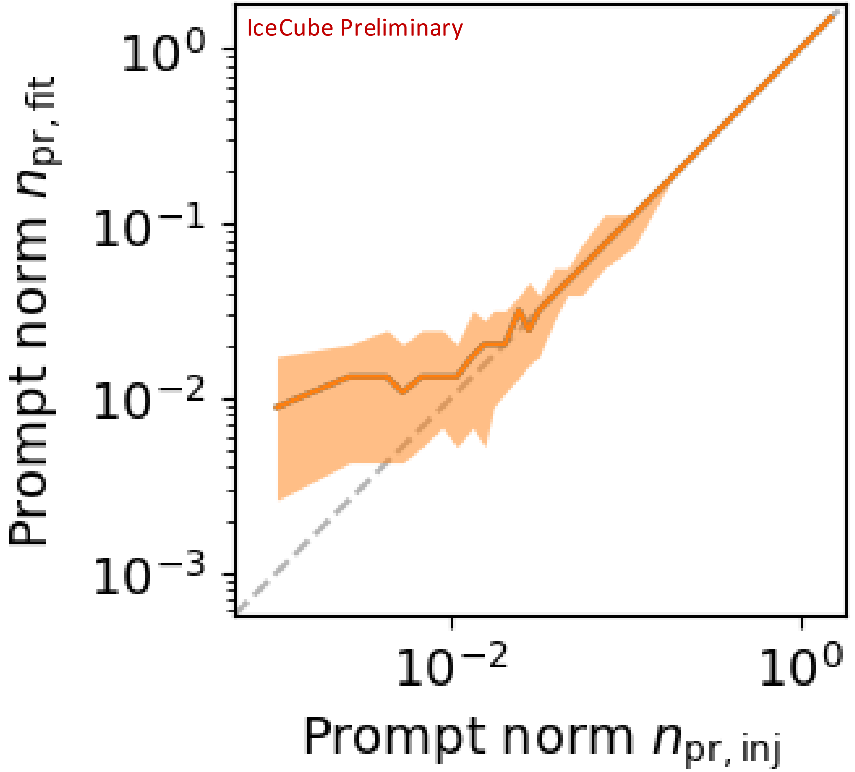
Cuts:
L2 MuonFilter
Bundle energy at entry > 100 TeV

Poisson Likelihood Fit

$$C_1^{MC} = n_{pr} C_1^{MC,pr} + n_{conv} C_1^{MC,conv}, \dots, C_M^{MC} = n_{pr} C_M^{MC,pr} + n_{conv} C_M^{MC,conv}$$

$$p(C_i) = p_{poisson}\left(C_i; \lambda(n_{pr}) = C_i^{MC}(n_{pr})\right) = \frac{\lambda(n_{pr})^{C_i} e^{-\lambda(n_{pr})}}{C_i!}$$





- Tagging allows scaling of prompt by factor n_{pr}
- Bias starts at a prompt normalization of 0.1

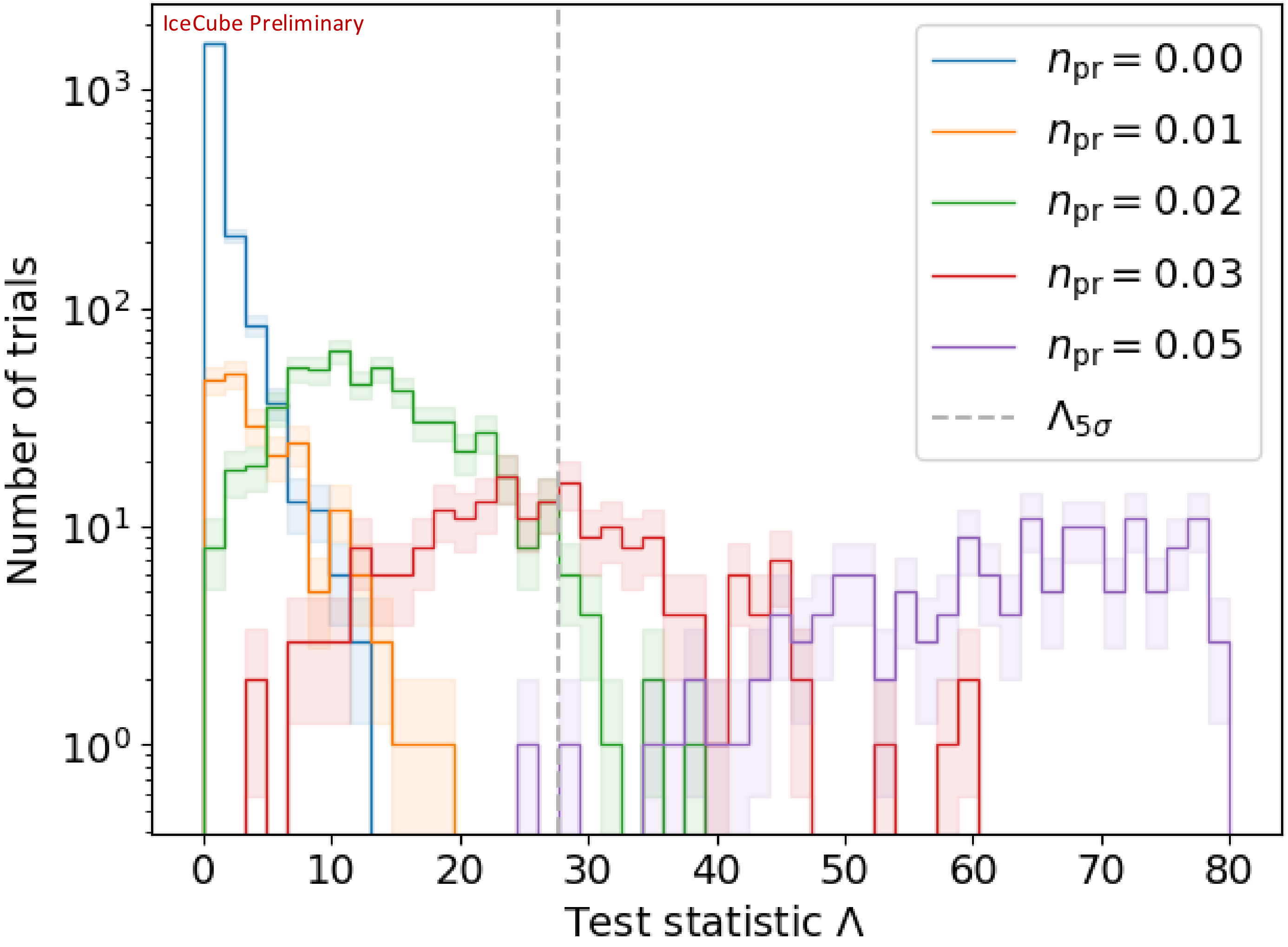
Cuts:
L2 MuonFilter
Bundle energy at entry > 100 TeV

Discovery Potential and Sensitivity

Expectation for 1 year:
- 5 sigma discovery potential: 0.102 ± 0.005
- Sensitivity: 0.024 ± 0.001

Expectation for 10 years:
- 5 sigma discovery potential: 0.032 ± 0.001
- Sensitivity: 0.007 ± 0.000

Caution:
- Limited MC statistics -> events are oversampled in pseudo dataset
- No systematics



Unfolding

Unfolding in a Nutshell

measured proxy — detector response — background

$$g(y) = \int_{E_0}^{E_1} A(E_\mu, y) f(E_\mu)\, \mathrm{d}E_\mu + b(y)$$

true energy distribution

1. discretized form: $\underbrace{\vec{g} = A\vec{f}}_{\text{folding}} \leftrightarrow \underbrace{\vec{f} = A^{-1}\vec{g}}_{\text{unfolding}}$

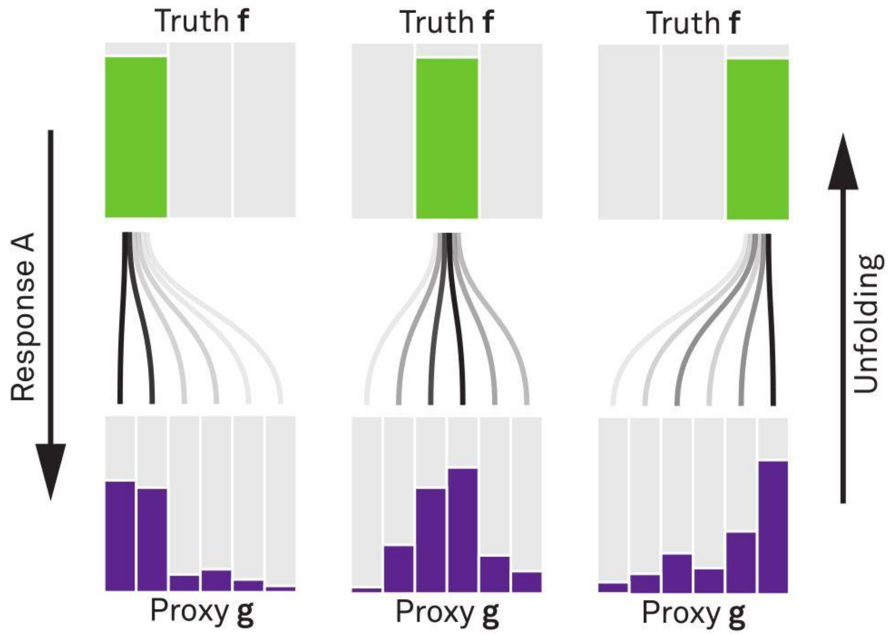
2. maximum likelihod method:

$$\mathcal{L}(\vec{g}|\vec{f}) = \prod_{j=1}^{M} \frac{\lambda_j^{g_j}}{g_j!} \exp(-\lambda_j)$$

$$= \prod_{j=1}^{M} \frac{(A\vec{f})_j^{g_j}}{g_j!} \exp(-(A\vec{f})_j)$$

3. Thikonov regularization:

$$t(\vec{f}) = -\frac{1}{2}(C\vec{f})^T(\tau 1)^{-1}(C\vec{f})$$

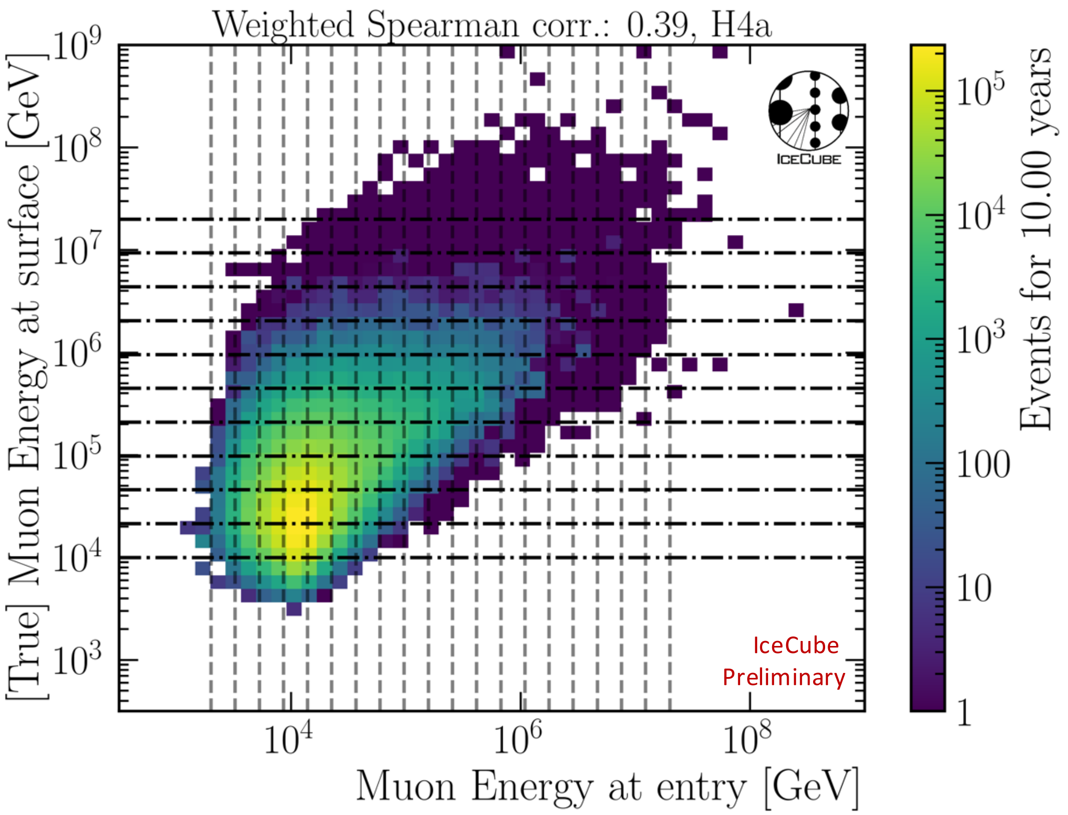


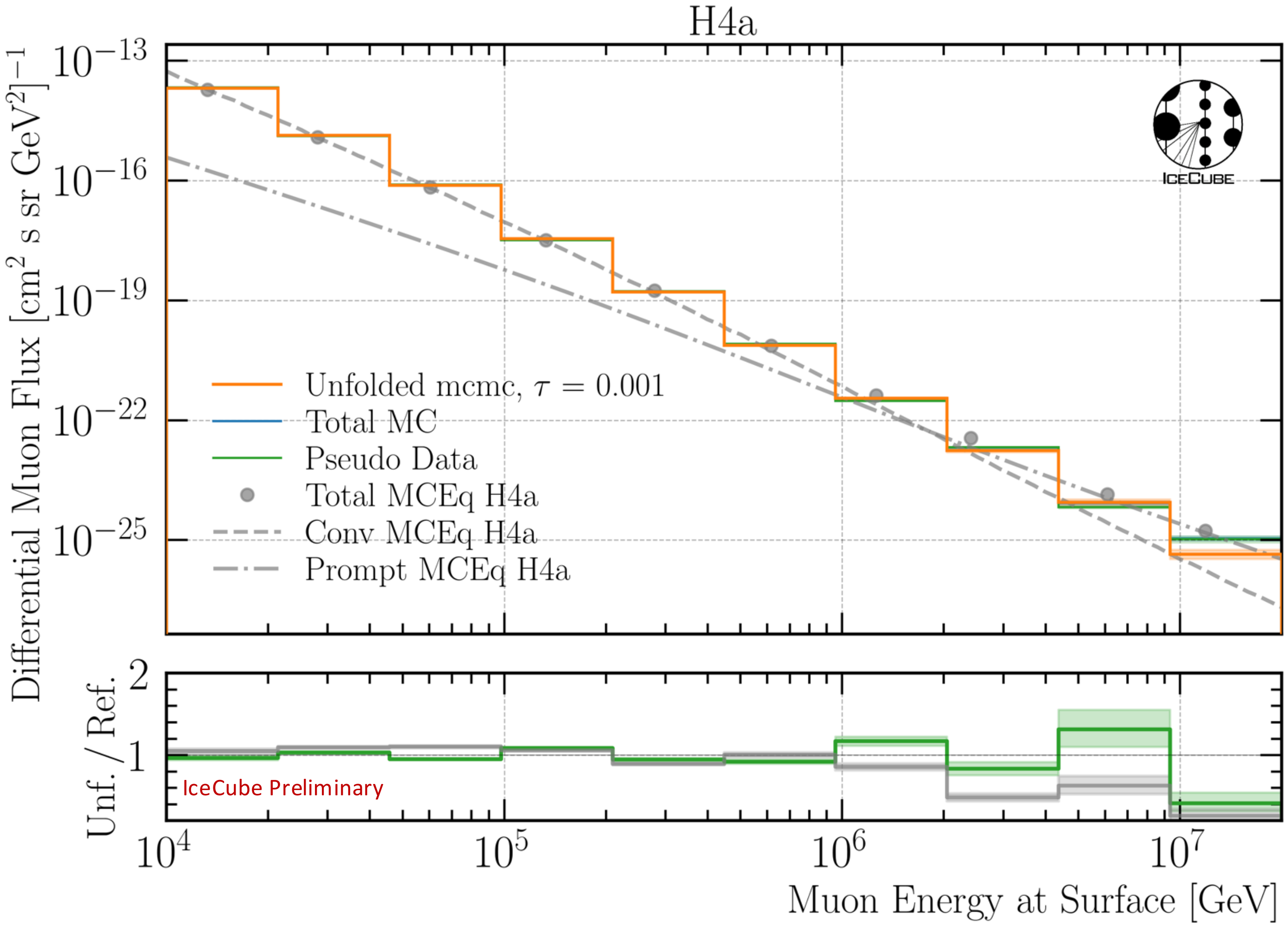
Credit: T. Hoinka

4. maximize $\log(\mathcal{L}(\vec{g}|\vec{f})) + t(\vec{f})$ with respect to $\vec{f}$ using Markov Chain Monte Carlo (MCMC) or Minuit

GitHub **funfolding** by M. Börner

Unfolded Muon Flux at Surface





Conclusion & Outlook

- New CORSIKA simulations with parent information
  - Tag prompt and conventional muons
  - Validation: agreement with MCEq
  - arXiv: 2502.10951
  - github.com/The-Ludwig/PANAMA
- Fit of prompt normalization is promising
  - Include systematics
- Unfolding of muon flux at surface works
  - Fine-tune regularization strength

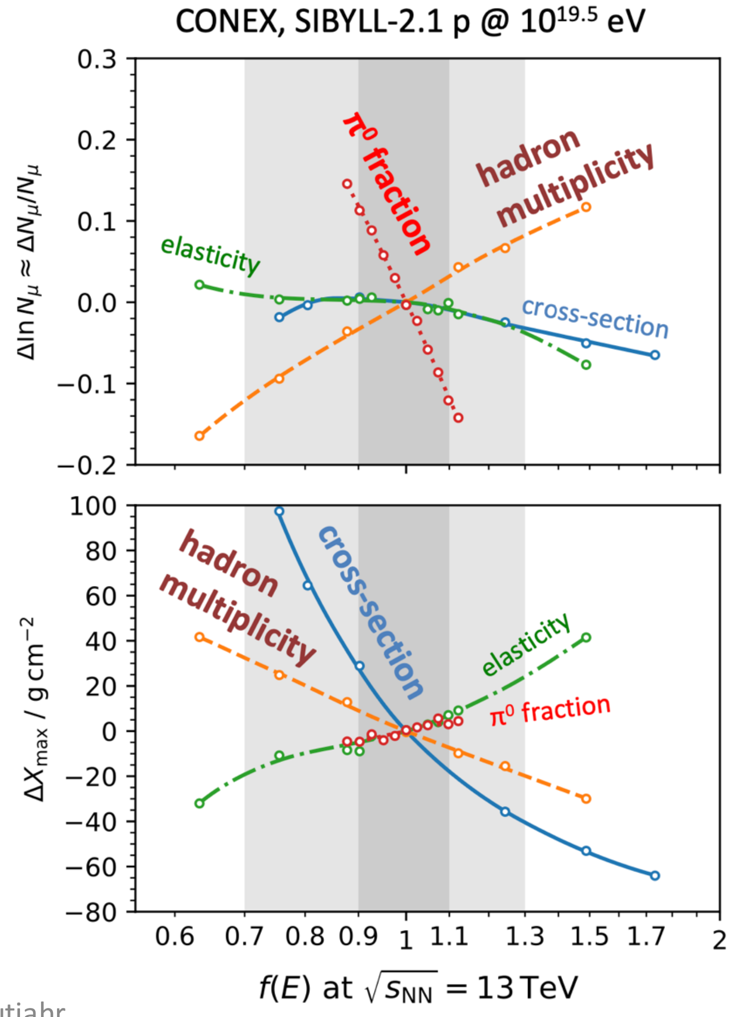
How ChatGPT illustrates an air shower at a California beach.

Thank you for your attention!

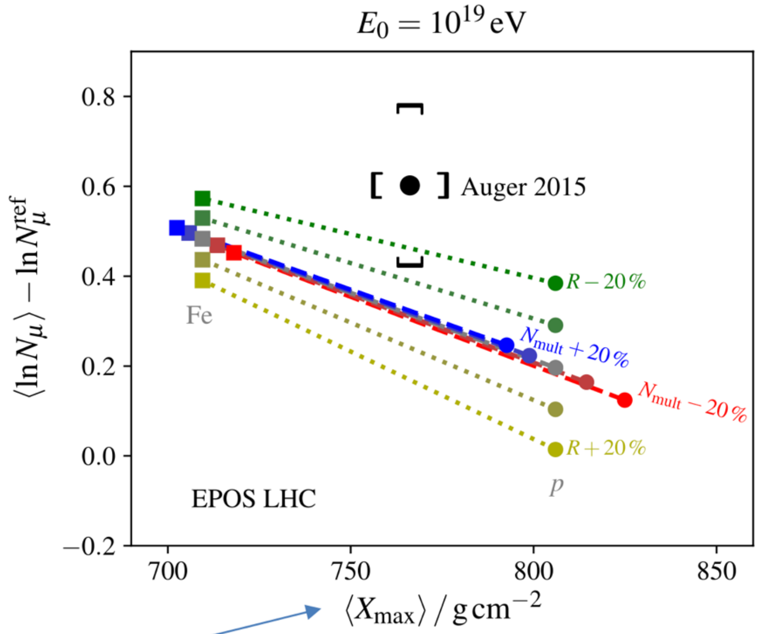
Backup

Possible Solutions

R. Ulrich, R. Engel, M. Unger, PRD 83 (2011) 054026



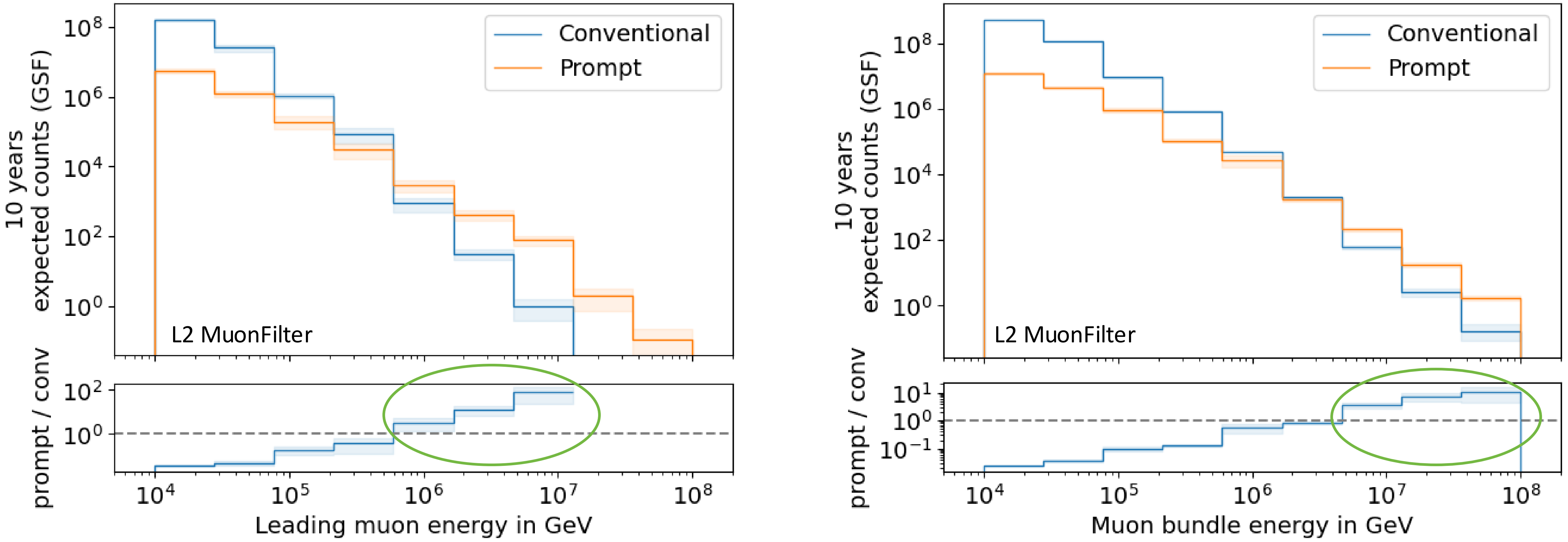
S. Baur, HD, M. Perlin, T. Pierog, R. Ulrich, K. Werner, arXiv:1902.09265



$$R = \frac{E_{\pi^0}}{E_{\text{other hadrons}}}$$

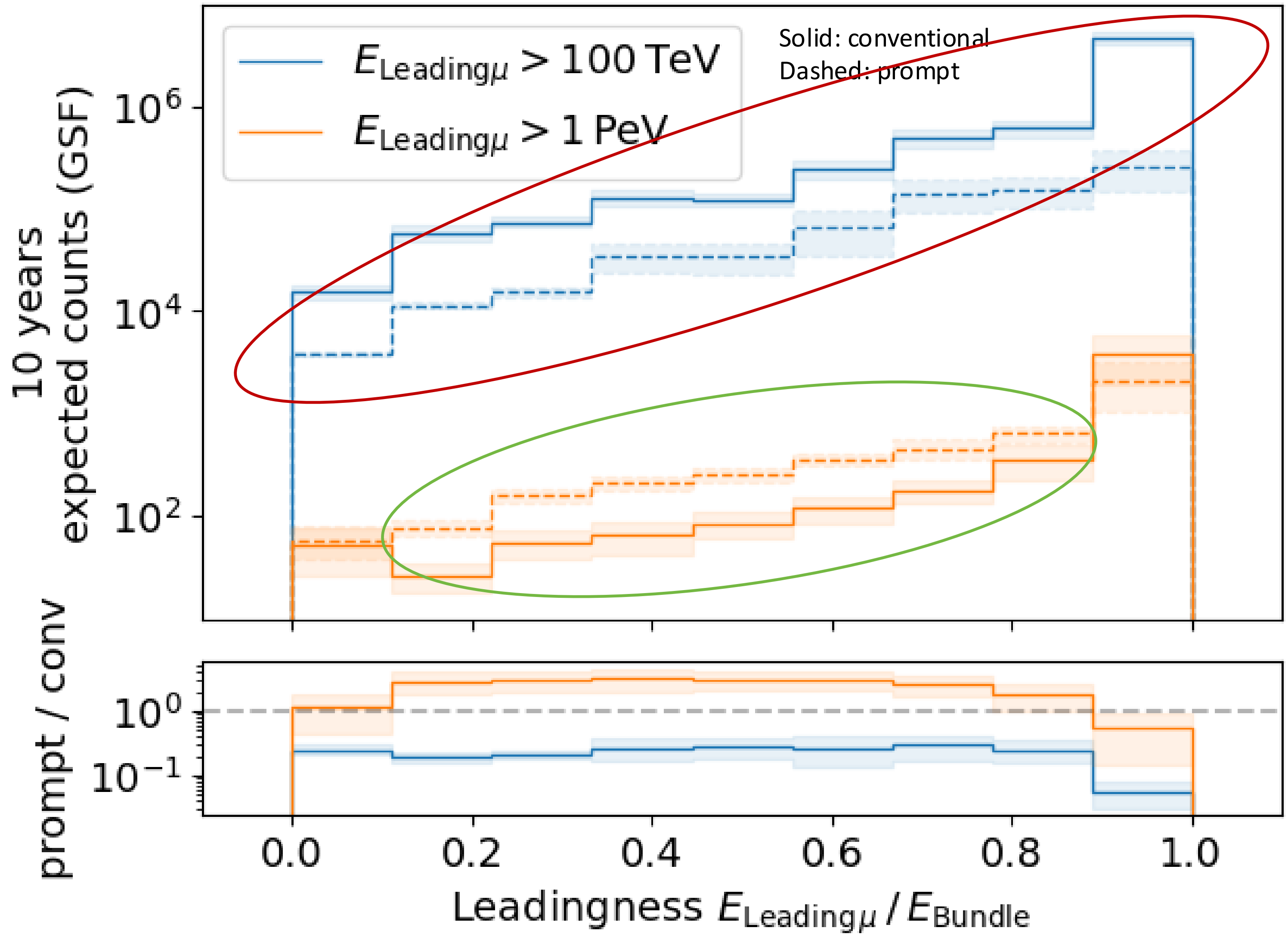
- Only changes to R can solve muon puzzle
- Small changes have large effect, R needs to be known to about 5 %

Expected Muons For 10 Years: Leading vs. Bundle Energy (GSF)



- Both leading and bundle energy are sensitive to detect prompt
- Leading muon energy is more sensitive

Leading Muon Energy Fraction



- ➢ Prompt dominates for energies > 1 PeV
- ➢ Leading energy sweet spot: 0.1 – 0.9

Leading Muon Contribution

Patrick Berghaus

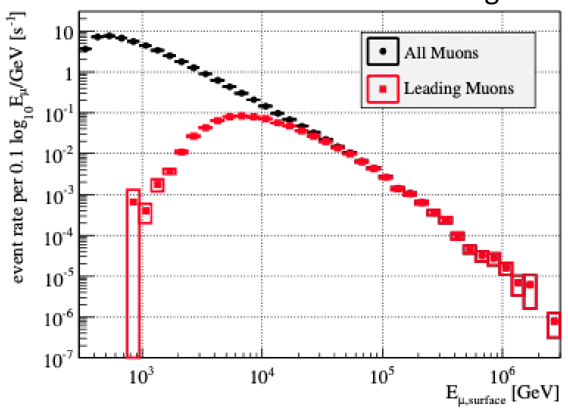
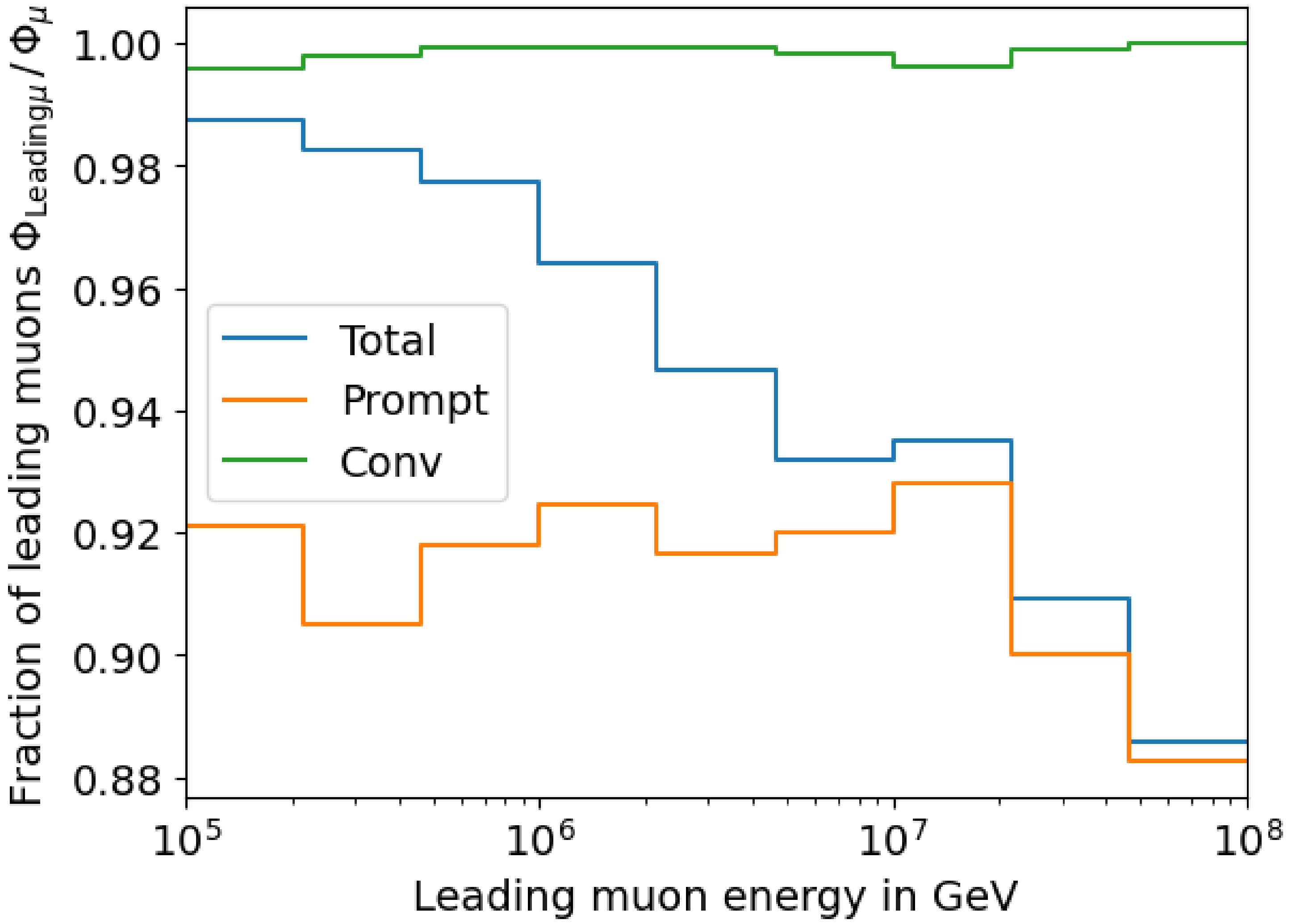


Figure 10: Surface energy distribution for all and most energetic ("leading") muons in simulated events with a total of more than 1,000 registered photo-electrons in IceCube.



- Muons with energies between 100 TeV and 50 PeV dominate the bundle by more than 90%
- In average conventional muons are more dominant than prompt
- But: at high energies, there are more prompt than conventional events

➢ High leading energy fraction does not lead to more sensitivity to detect prompt

Poisson Likelihood Fit

Prompt scaling/normalization

Conv norm = 1

MC counts per bin i

$$C_1^{\mathrm{MC}} = n_{\mathrm{pr}} C_1^{\mathrm{MC,pr}} + n_{\mathrm{conv}} C_1^{\mathrm{MC,conv}}, \ldots, C_M^{\mathrm{MC}} = n_{\mathrm{pr}} C_M^{\mathrm{MC,pr}} + n_{\mathrm{conv}} C_M^{\mathrm{MC,conv}}$$

Experimental counts

$$p\left(C_i\right) = p_{\mathrm{poisson}}\left(C_i; \lambda\left(n_{\mathrm{pr}}\right) = C_i^{\mathrm{MC}}\left(n_{\mathrm{pr}}\right)\right) = \frac{\lambda\left(n_{\mathrm{pr}}\right)^{C_i} e^{-\lambda\left(n_{\mathrm{pr}}\right)}}{C_i!}$$

With a constant conv norm:
bin counts depend only on prompt norm
= expectation value per bin

Maximize likelihood

$$\mathscr{L}\left(n_{\mathrm{pr}}\right) = \prod_{i=1}^{M} p\left(C_i; n_{\mathrm{pr}}\right)$$

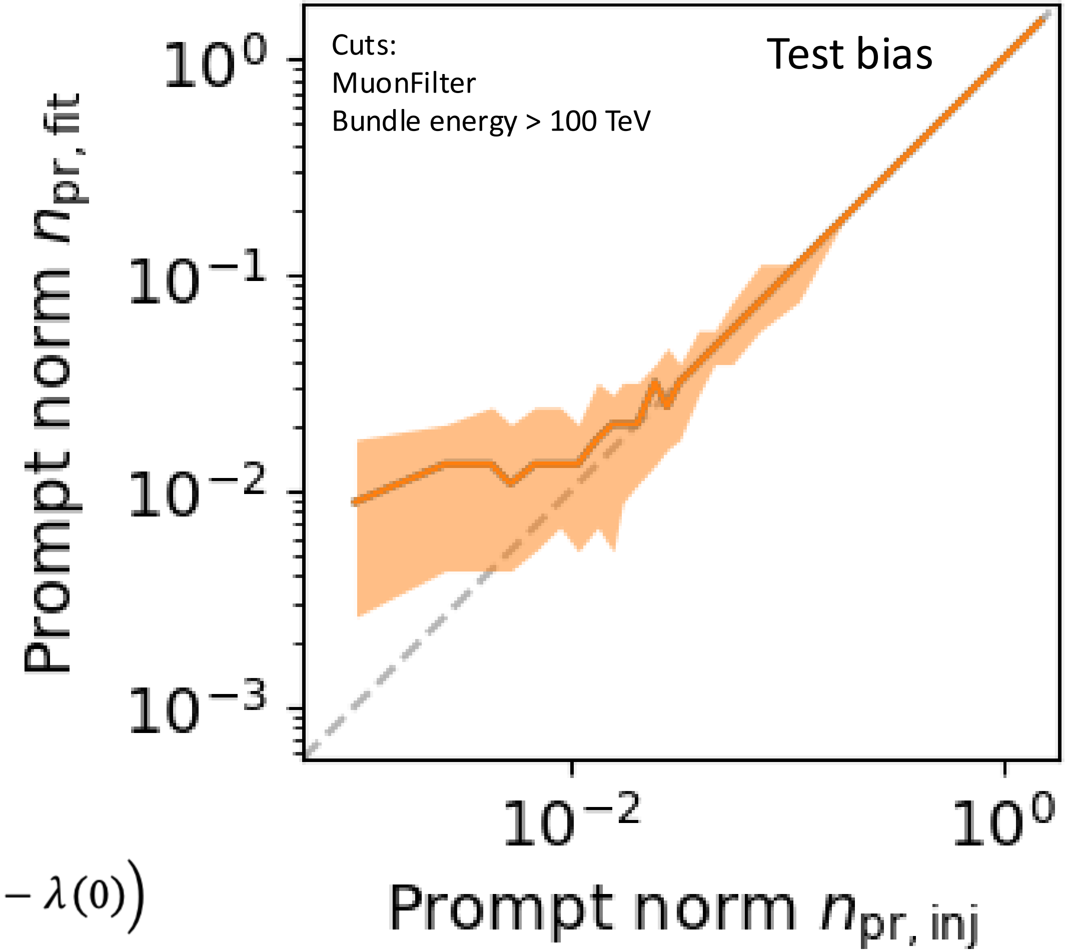
Easier:
minimize negative
log-likelihood

$$-\ln \mathscr{L} = -\sum_{i=1}^{M} C_i \ln \lambda\left(n_{\mathrm{pr}}\right) - \lambda\left(n_{\mathrm{pr}}\right) - \ln C_i!$$

$$\Lambda = -2 \ln \frac{\mathscr{L}\left(n_{\mathrm{pr}} = \hat{n}_{\mathrm{pr}}\right)}{\mathscr{L}\left(n_{\mathrm{pr}=0}\right)} = -2 \sum_{i=1}^{M} C_i \left(\ln \lambda\left(\hat{n}_{\mathrm{pr}}\right) - \ln \lambda(0)\right) - \left(\lambda\left(n_{\mathrm{pr}}\right) - \lambda(0)\right)$$

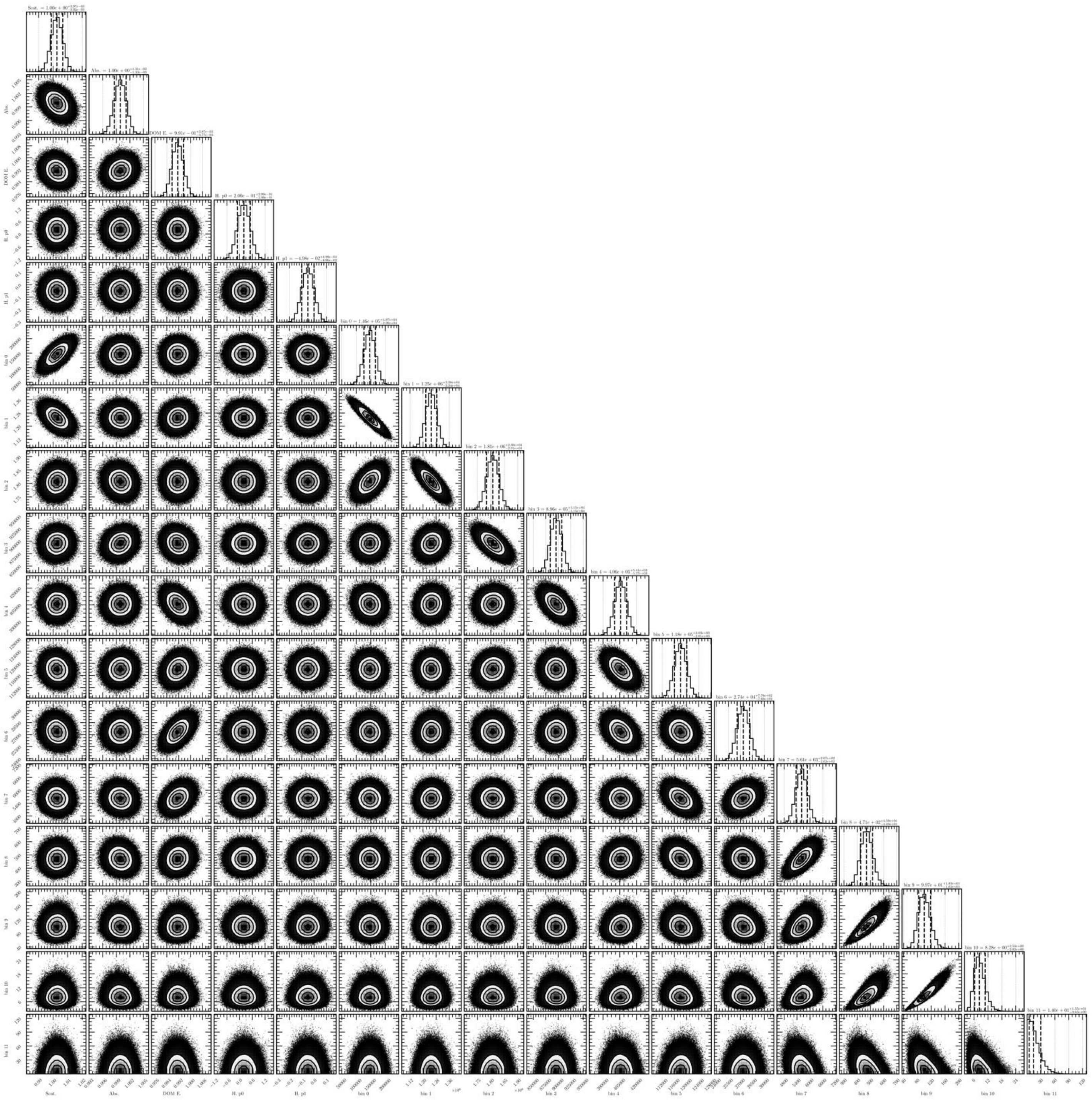
Test statistic for Wilks' theorem

Null hypothesis: no prompt



- Bias starts at a prompt normalization of 0.1

Tau = 0.001



Unfolded Muon Flux at Surface