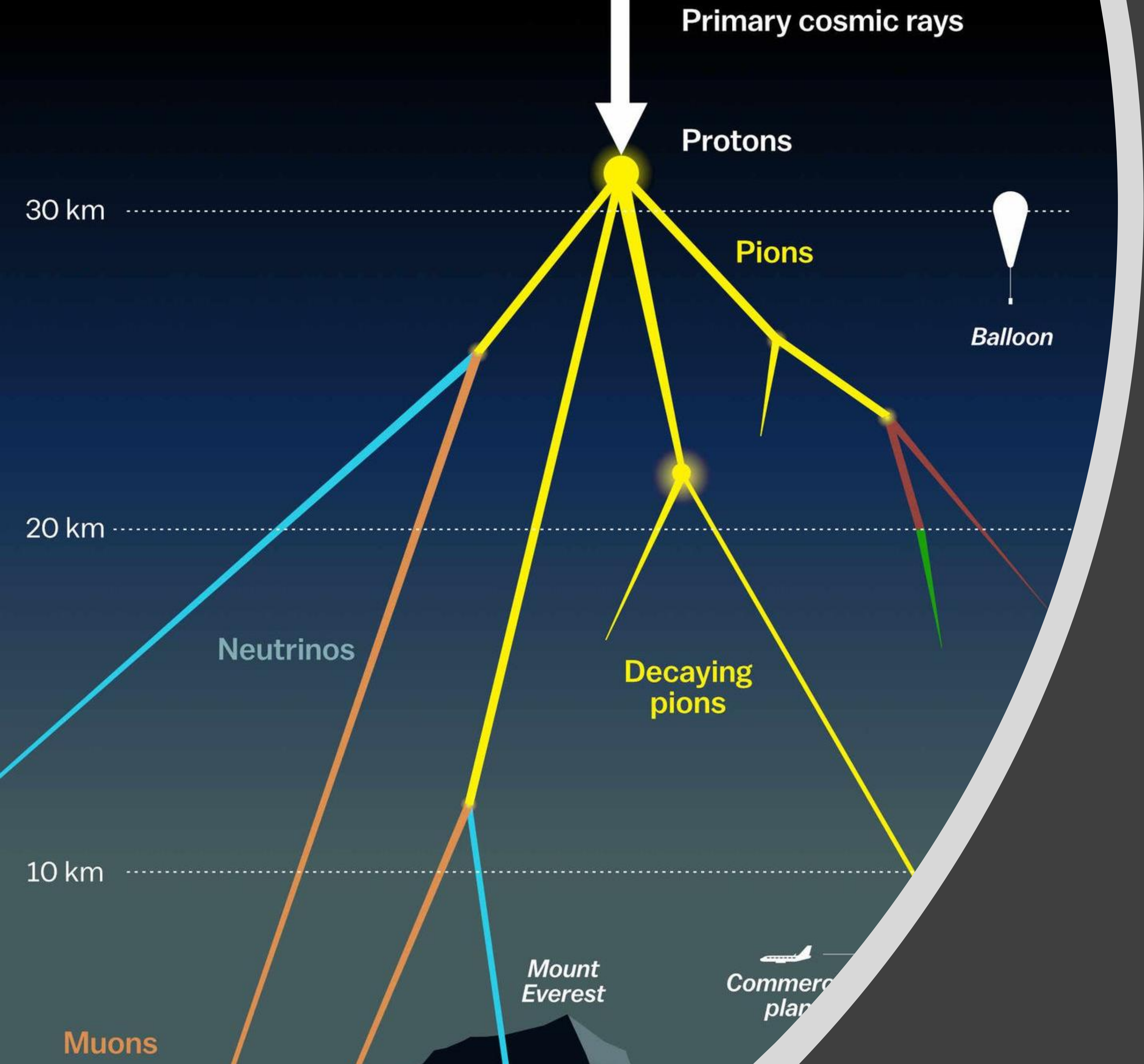


Source: NASA

BERKELEY LAB
Bringing Science Solutions to the World
SFB1491
tu dortmund university
ICECUBE NEUTRINO OBSERVATORY

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

Pascal Gutjahr

March 18, 2025

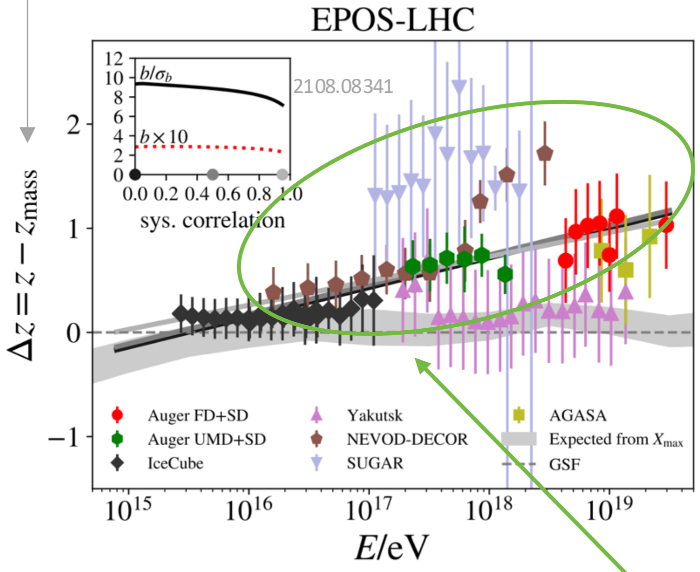
APS JOINT MARCH MEETING AND APRIL MEETING
Global Physics Summit

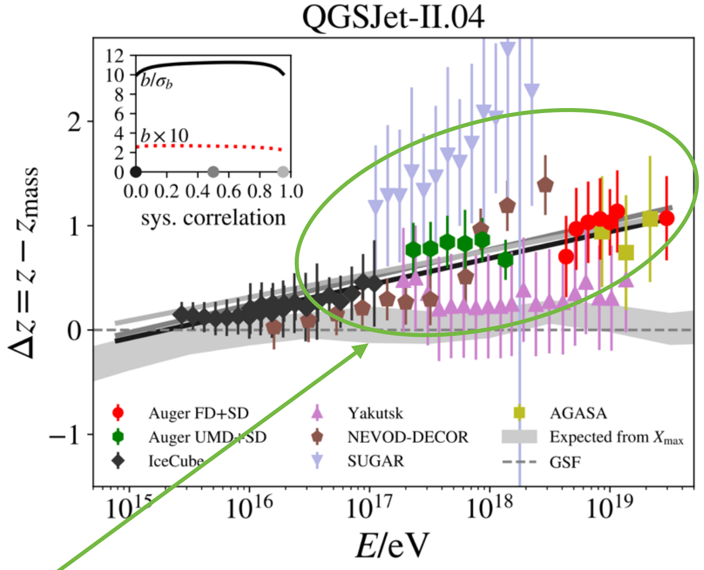
Muon Puzzle & Hadronic Uncertainties

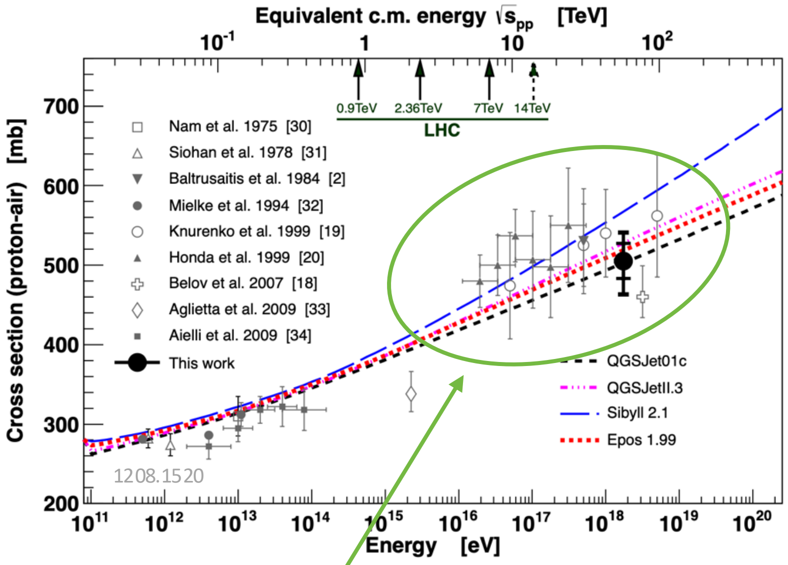
"muon number"

Expected z
("muon number")

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

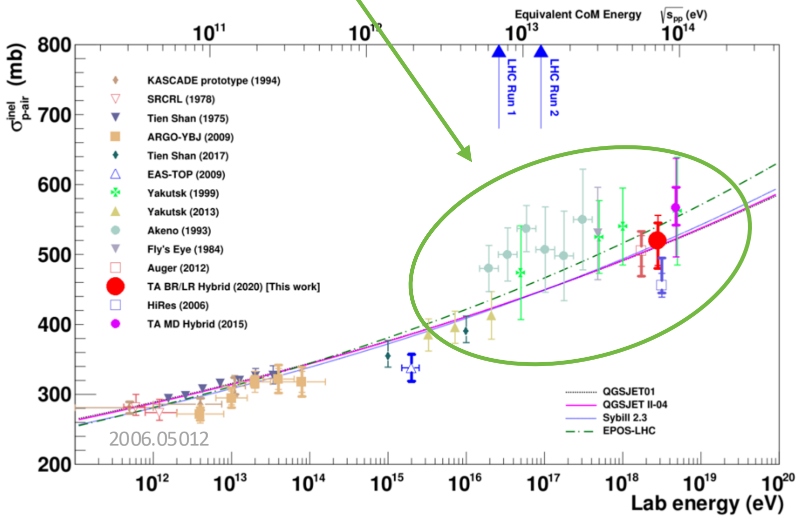






2012

➢ Uncertainties at E > 10 PeV



2020

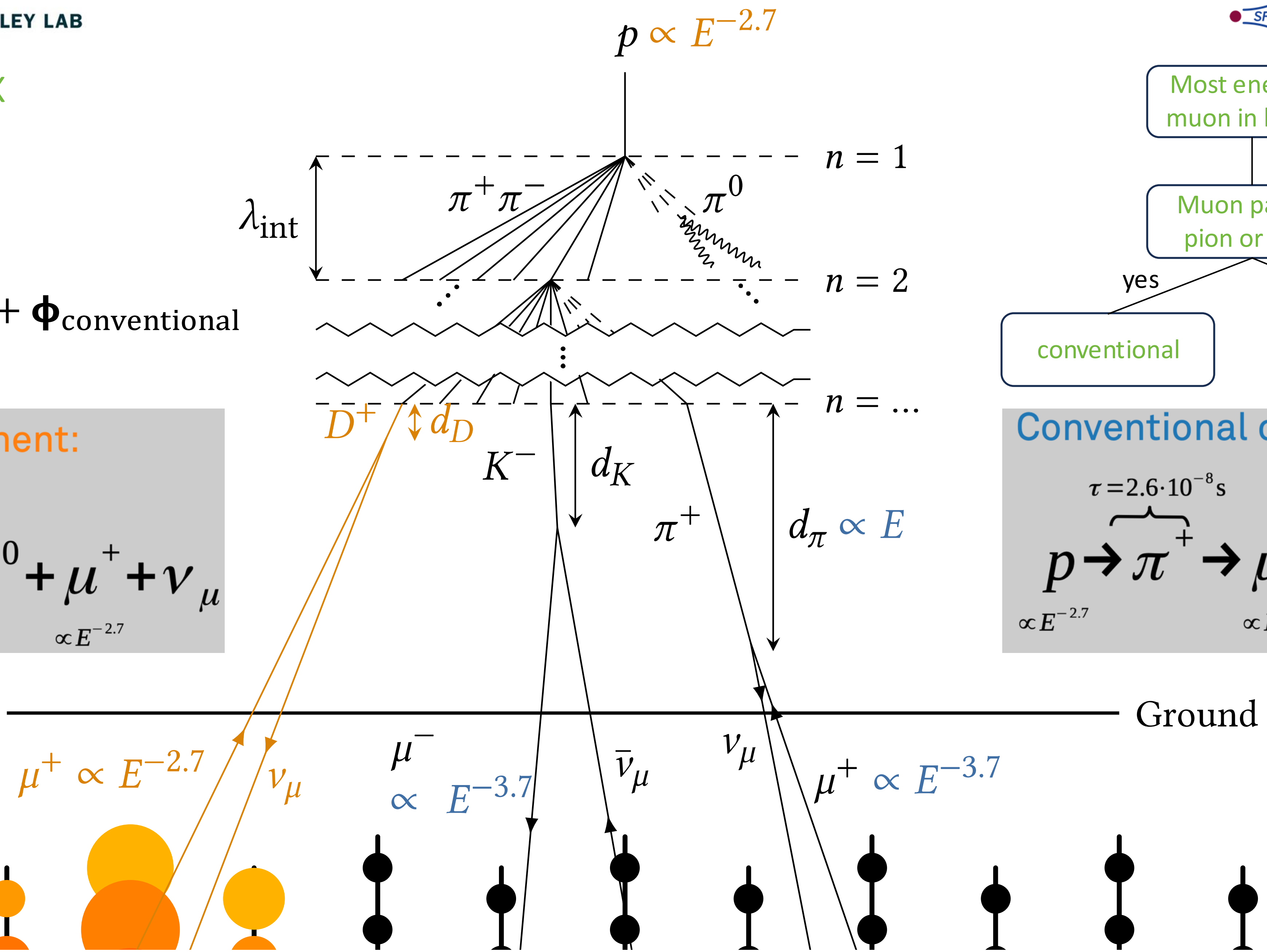
➢ More muons measured than simulated for E > 40 PeV ~ cms 8 TeV
➢ Precise pion/kaon ratio measurement needed

Muon Flux

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

prompt component:

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



Most energetic muon in bundle

Muon parent: pion or kaon

yes → conventional

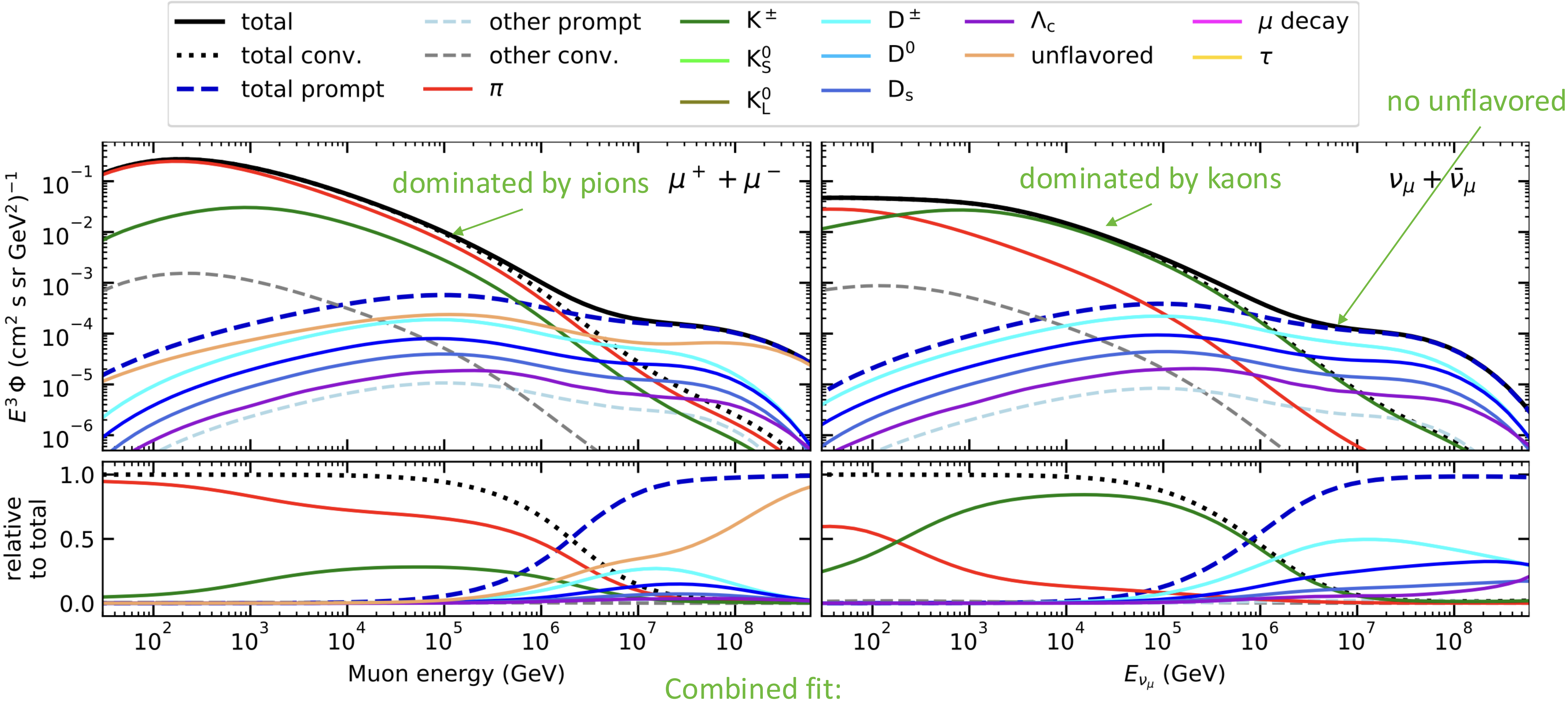
no → prompt

Conventional component:

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

Prompt Atmospheric Muons & Neutrinos

10.1103/PhysRevD.100.103018



Combined fit:

- ➢ handle on pion/kaon ratio
- ➢ handle on charmed mesons

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

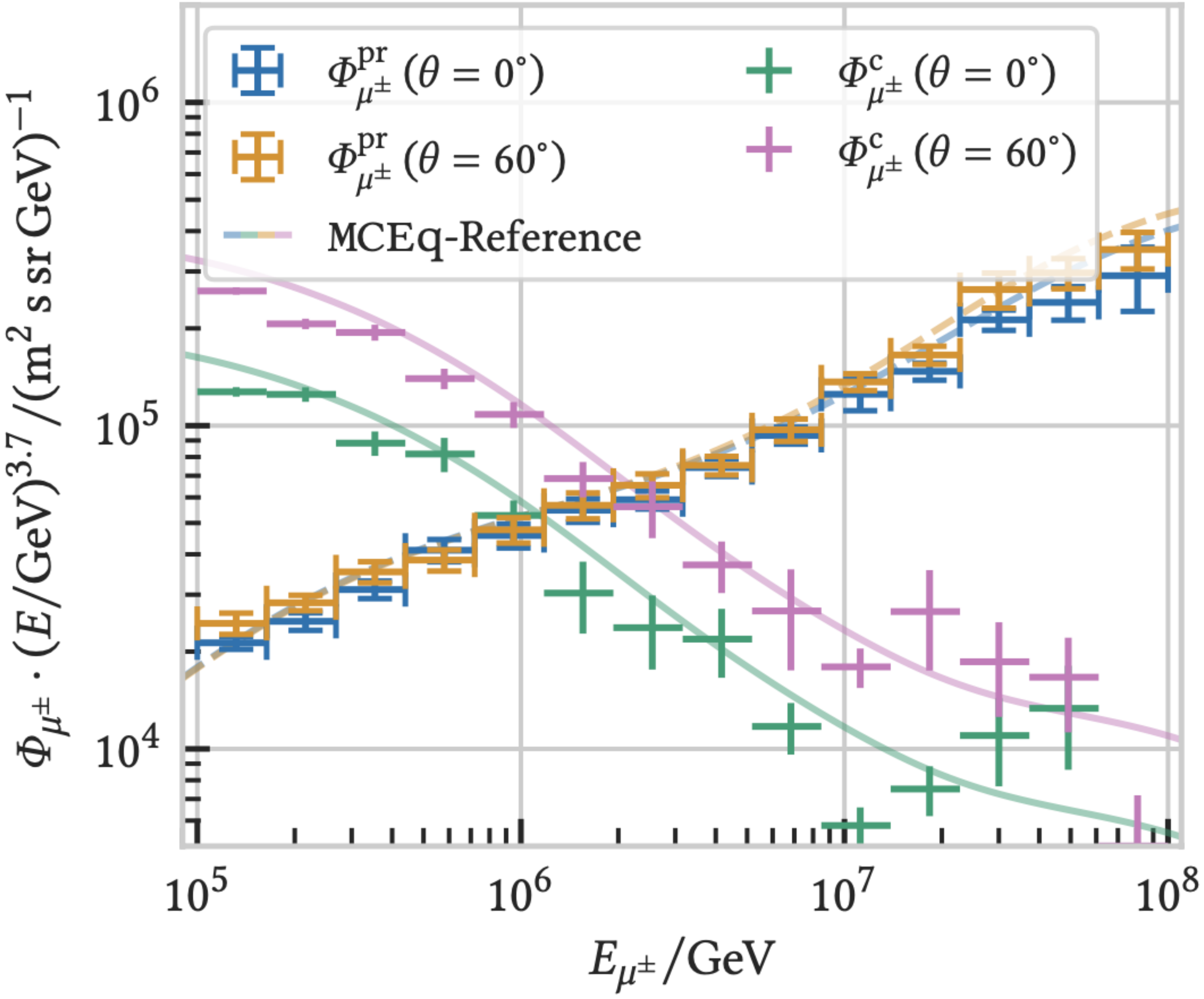
Fit prompt normalization
- Poisson LLH fit

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

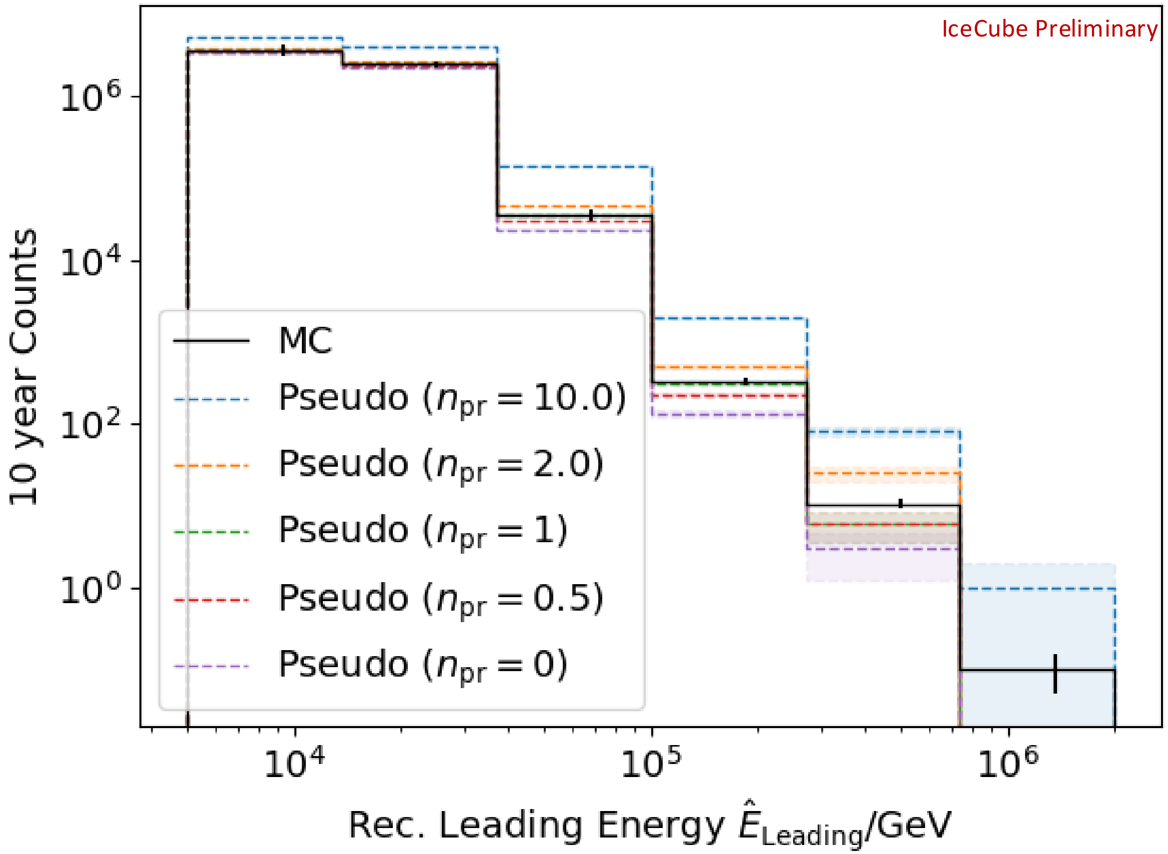
Python package developed – PANAMA

- 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

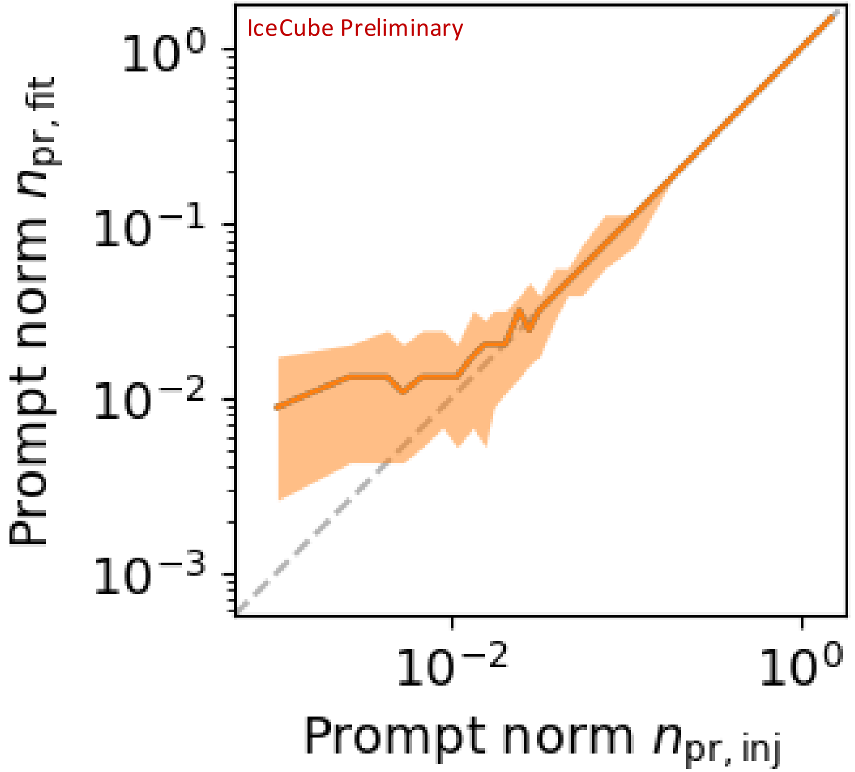
Poisson Likelihood Fit



- ➢ Tagging allows scaling of prompt by factor n_{pr}

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

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



- ➢ Bias starts at a prompt normalization of 0.1

Discovery Potential and Sensitivity

Cuts:
L2 MuonFilter
Bundle energy at entry > 100 TeV

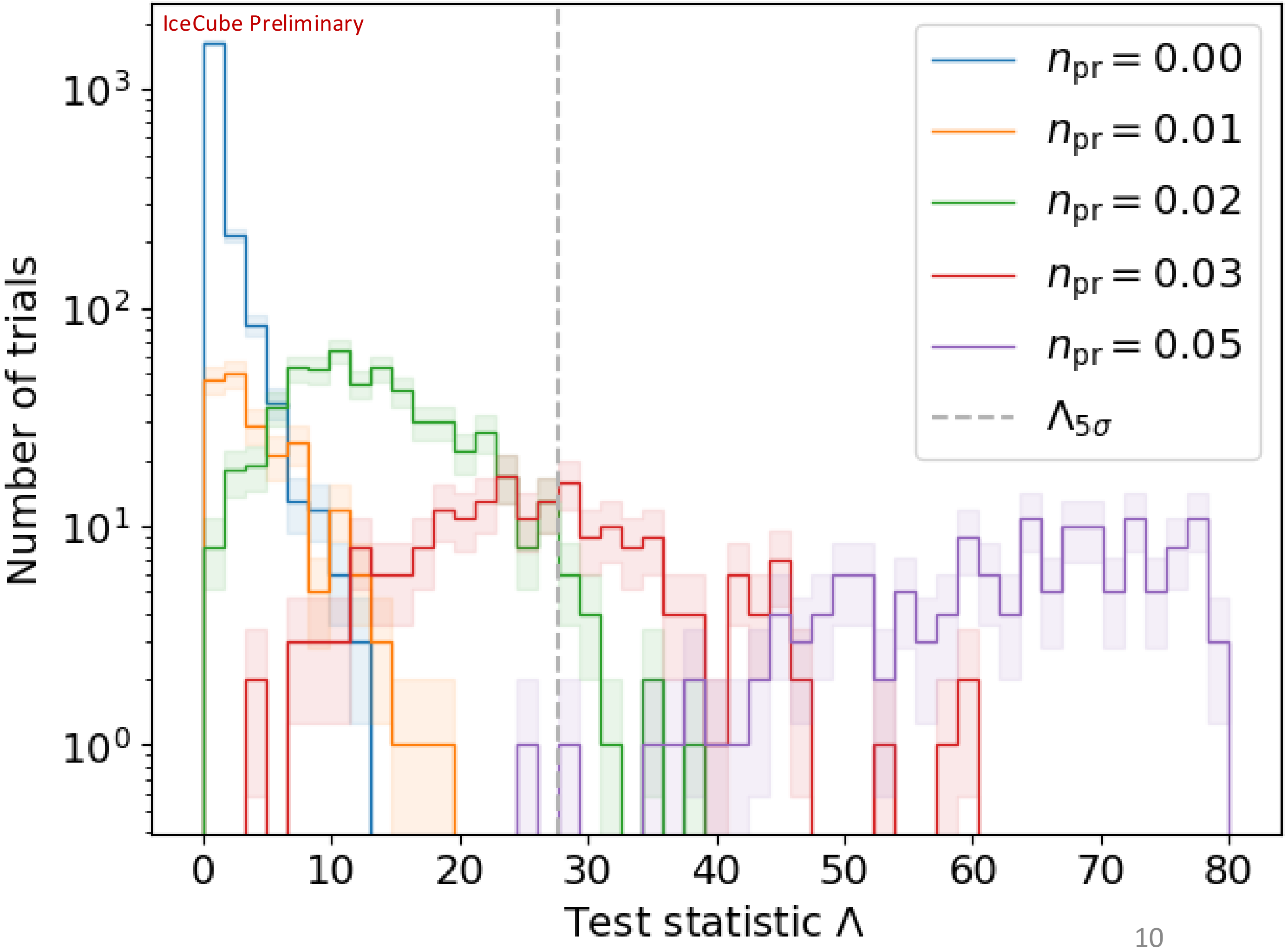
$$\Lambda = -2\ln\frac{\mathcal{L}\left(n_{\mathrm{pr}} = \hat{n}_{\mathrm{pr}}\right)}{\mathcal{L}\left(n_{\mathrm{pr}=0}\right)}$$

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

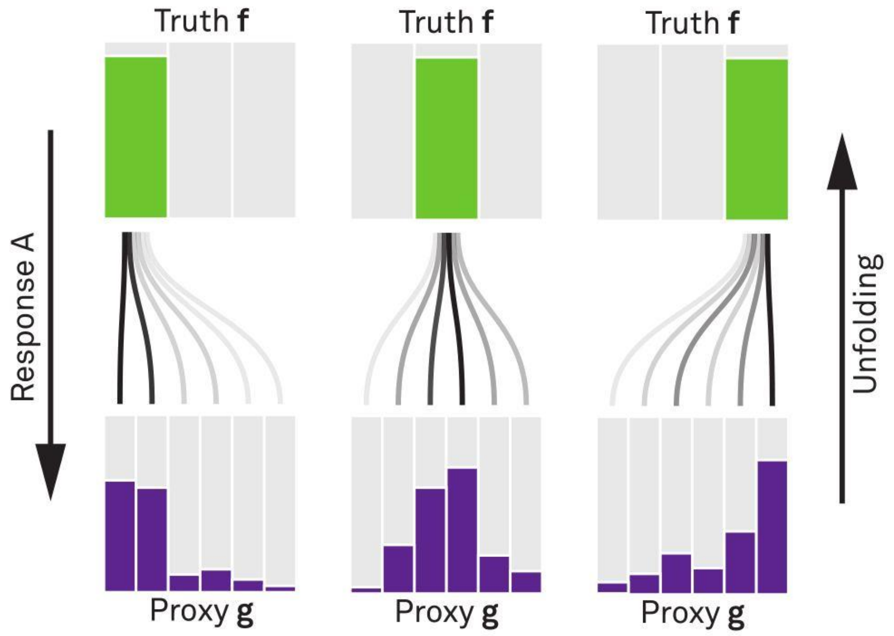
2. maximum likelihod method:

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

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

3. Thikonov regularization:

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

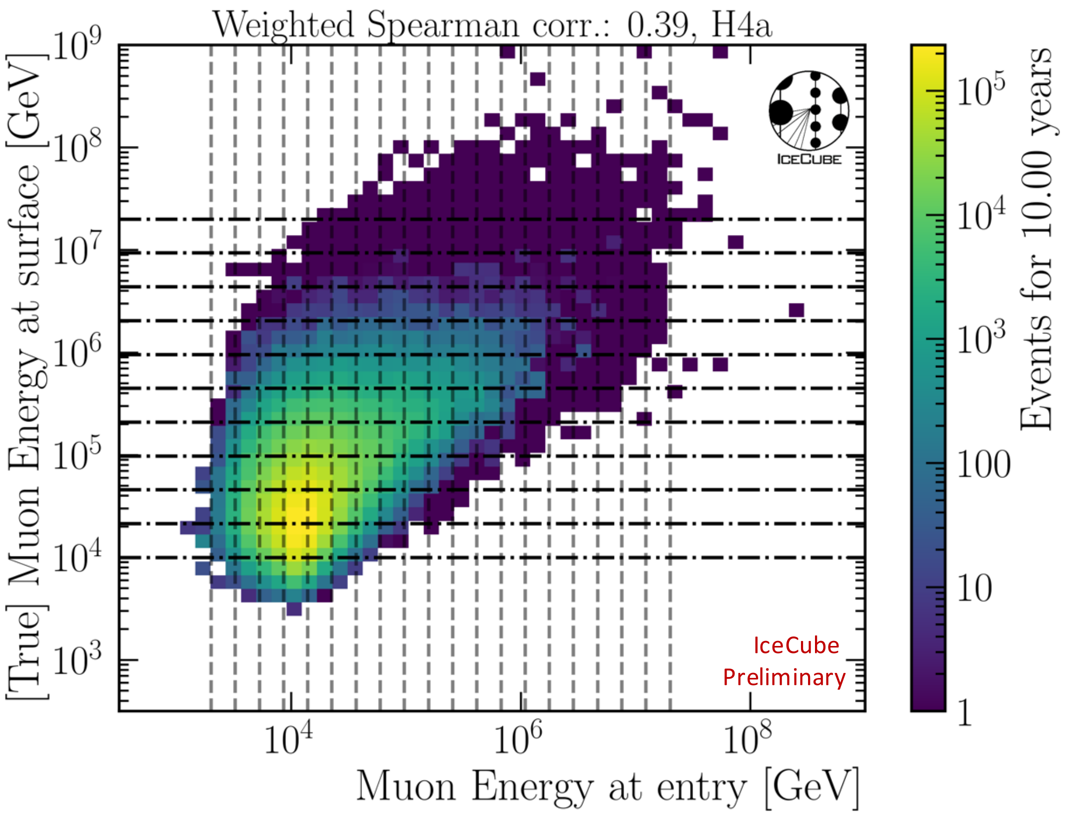


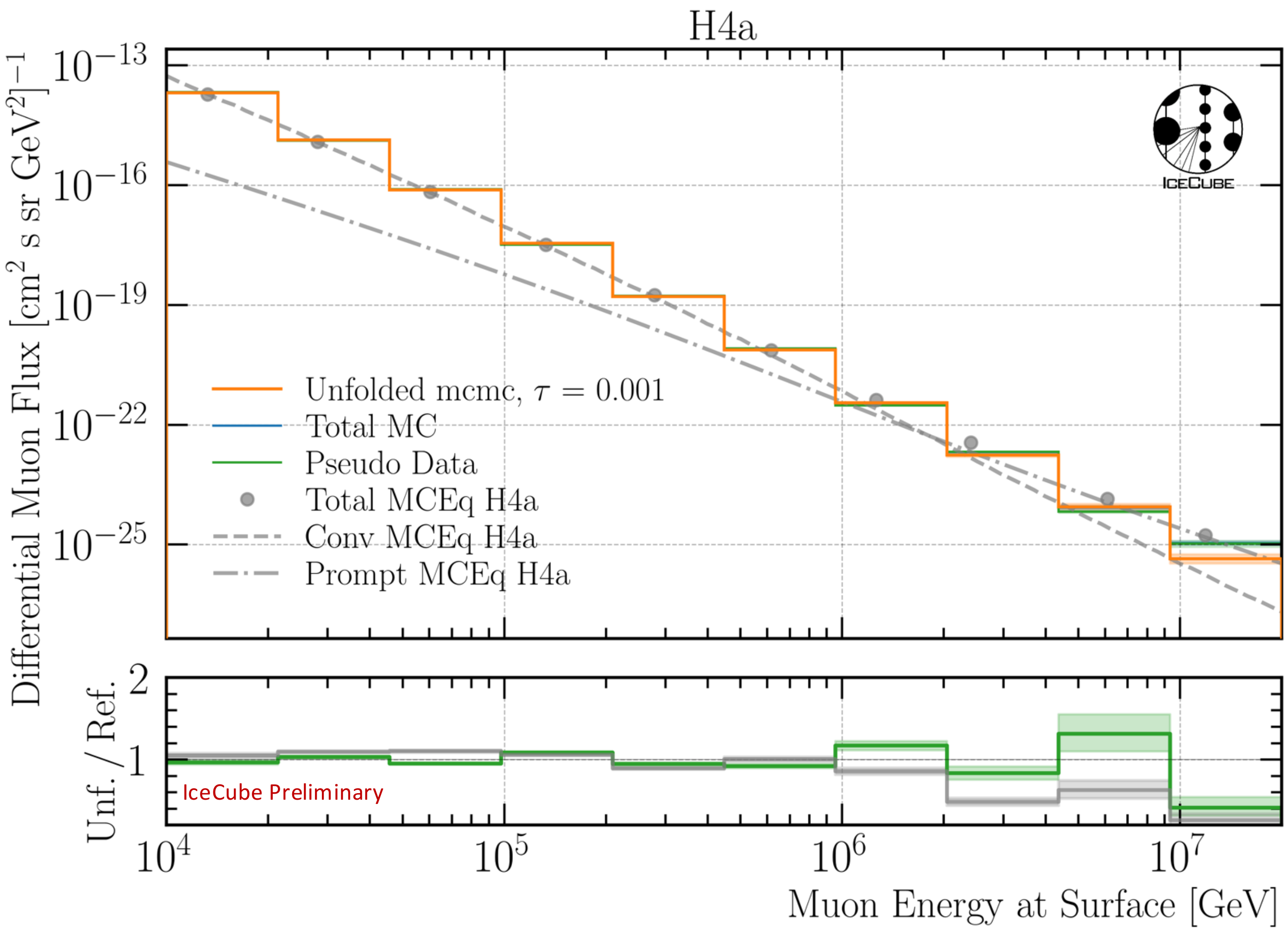
Credit: T. Hoinka

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

How ChatGPT illustrates an air shower at a California beach.

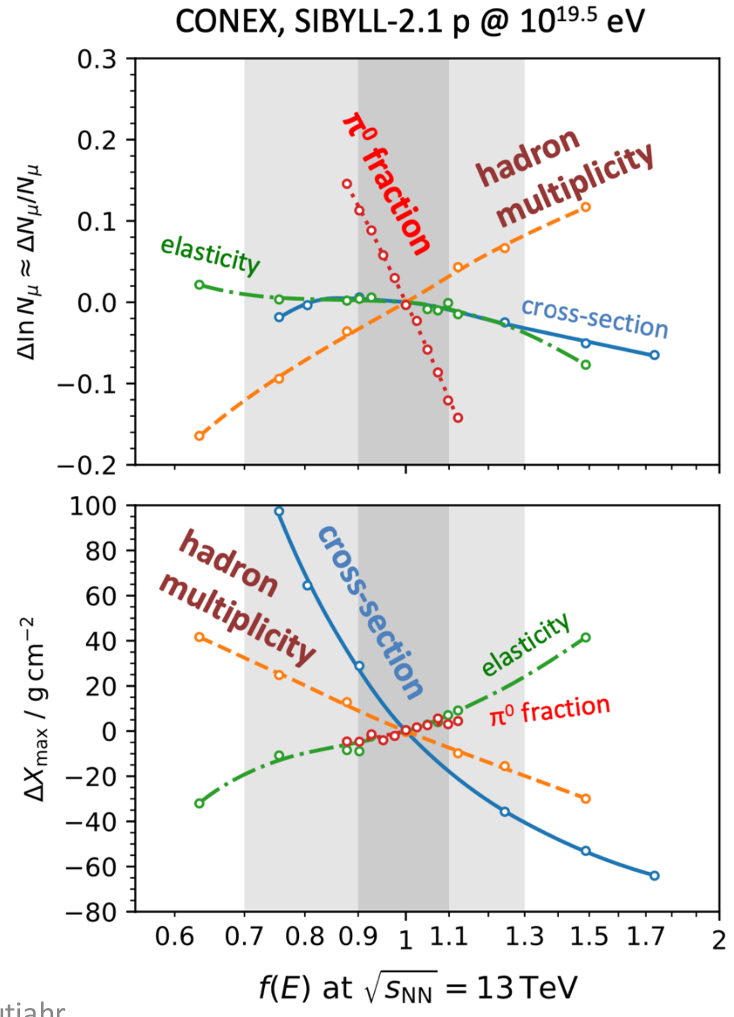
pascal.gutjahr@tu-dortmund.de

Thank you for your attention!

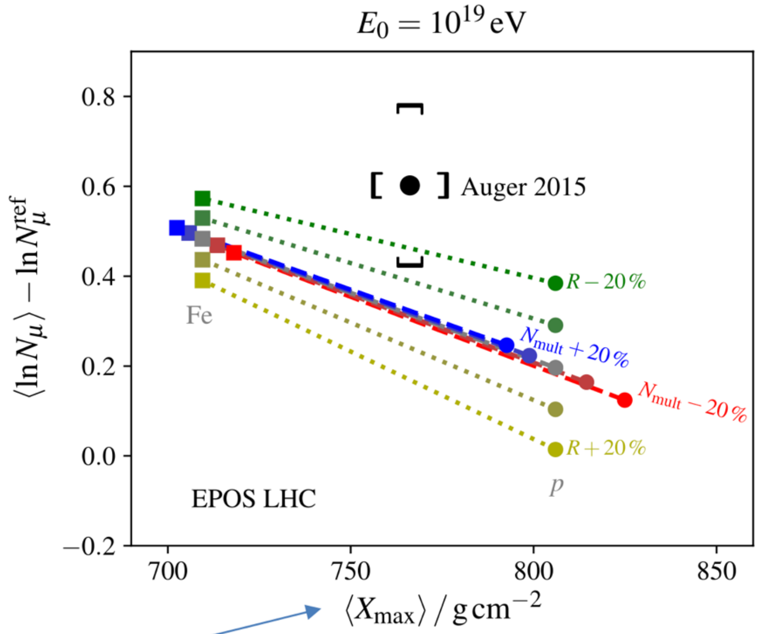
Backup

Possible Solutions

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



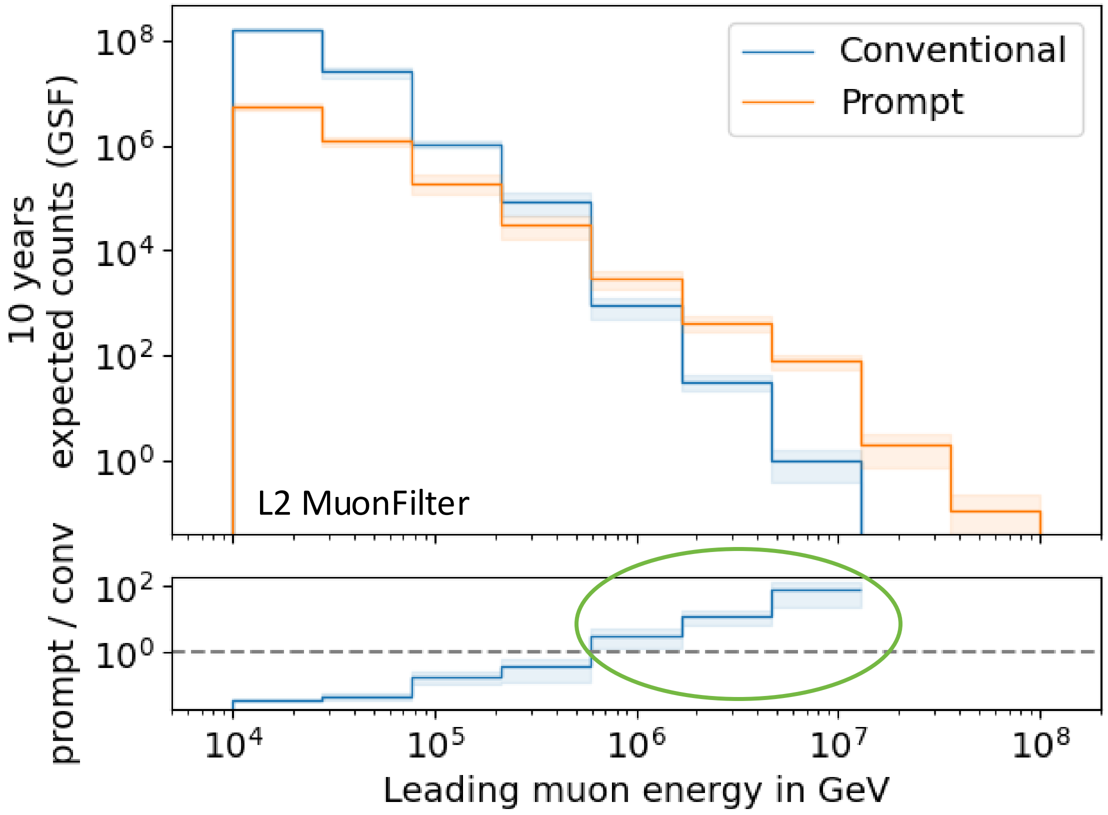
S. Baur, HD, M. Perlin, T. Pierog, R. Ulrich, K. Werner, arXiv:1902.09265

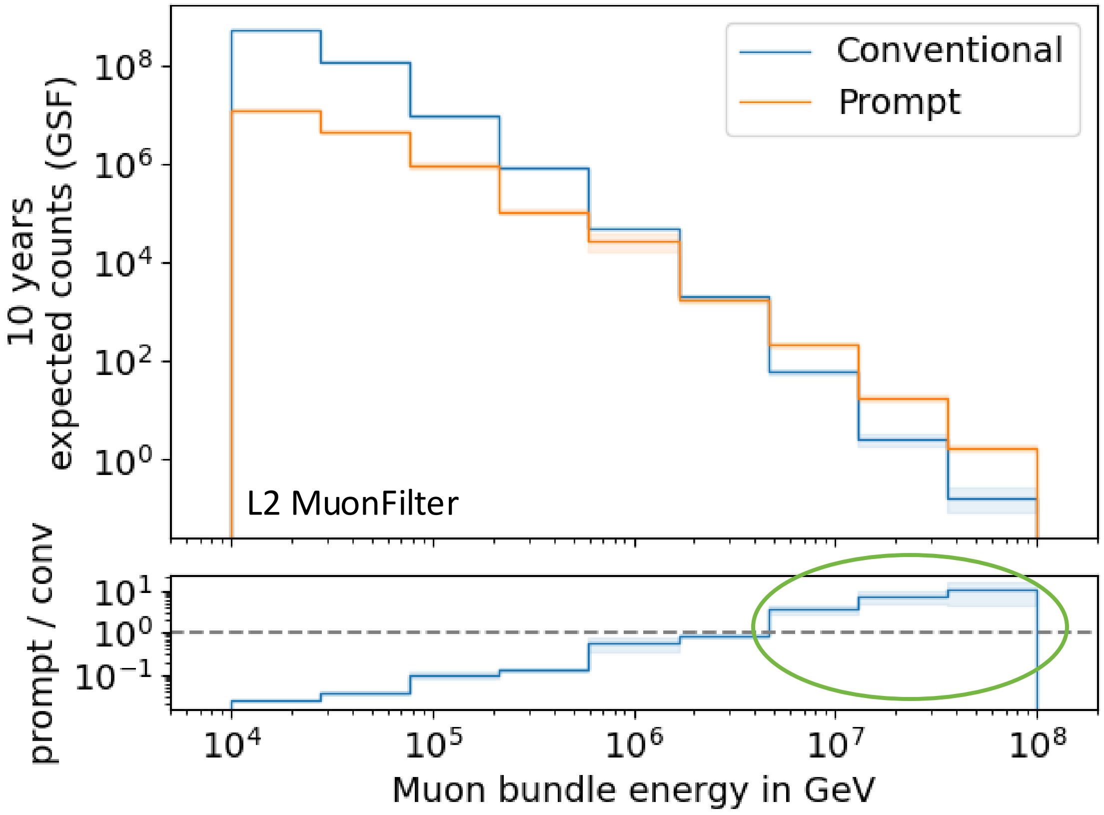


$$R = \frac{E_{\pi^0}}{E_{\text{other hadrons}}}$$

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

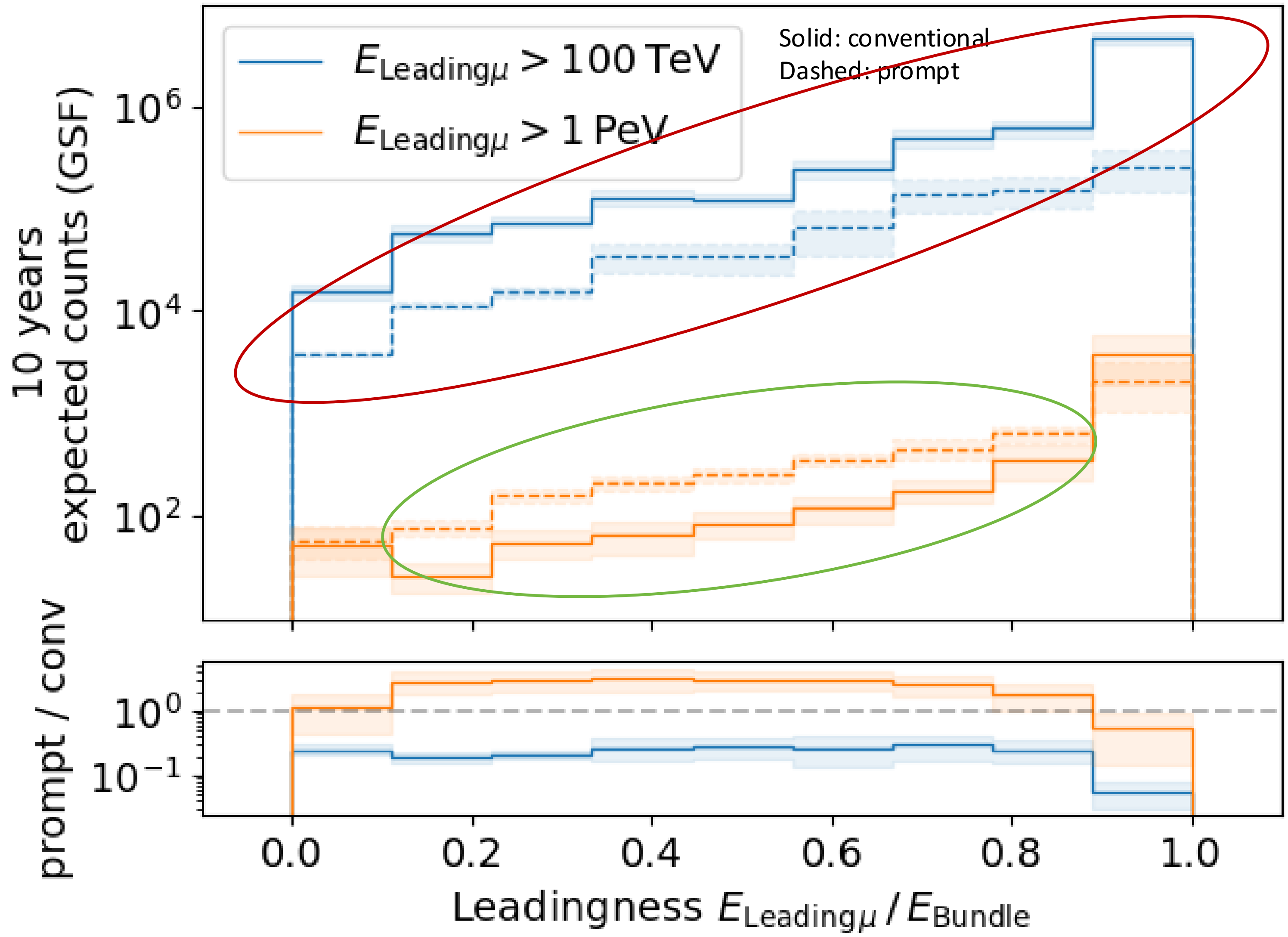
Expected Muons For 10 Years: Leading vs. Bundle Energy (GSF)





- 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

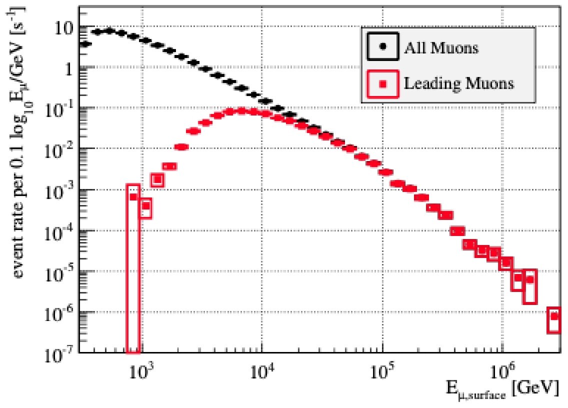
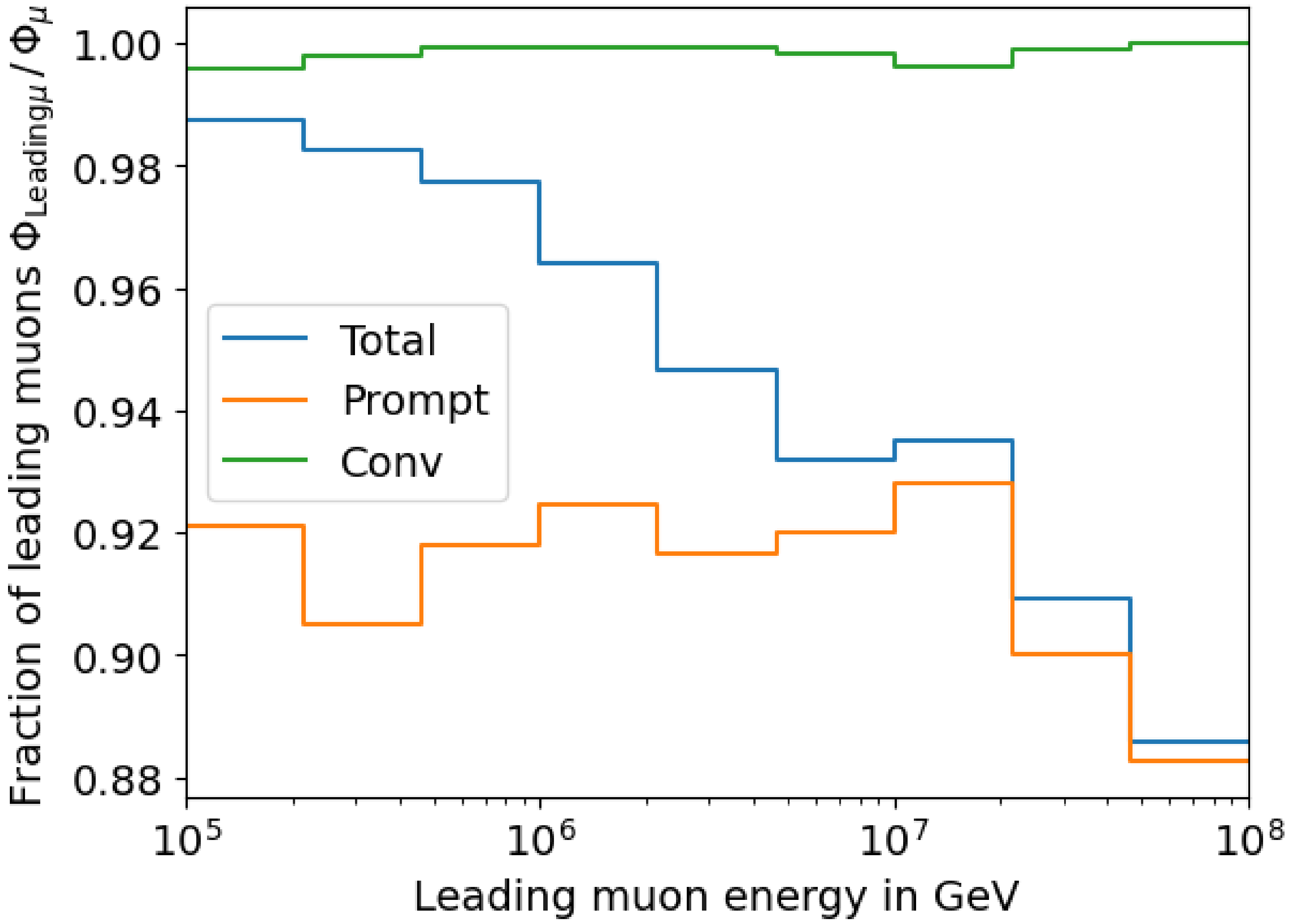


Figure 10: Surface energy distribution for all and most energetic ("leading") muons in simulated events with a total of more than 1,000 registered photo-electrons in IceCube.



- 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

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

Experimental counts

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

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

Maximize likelihood

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

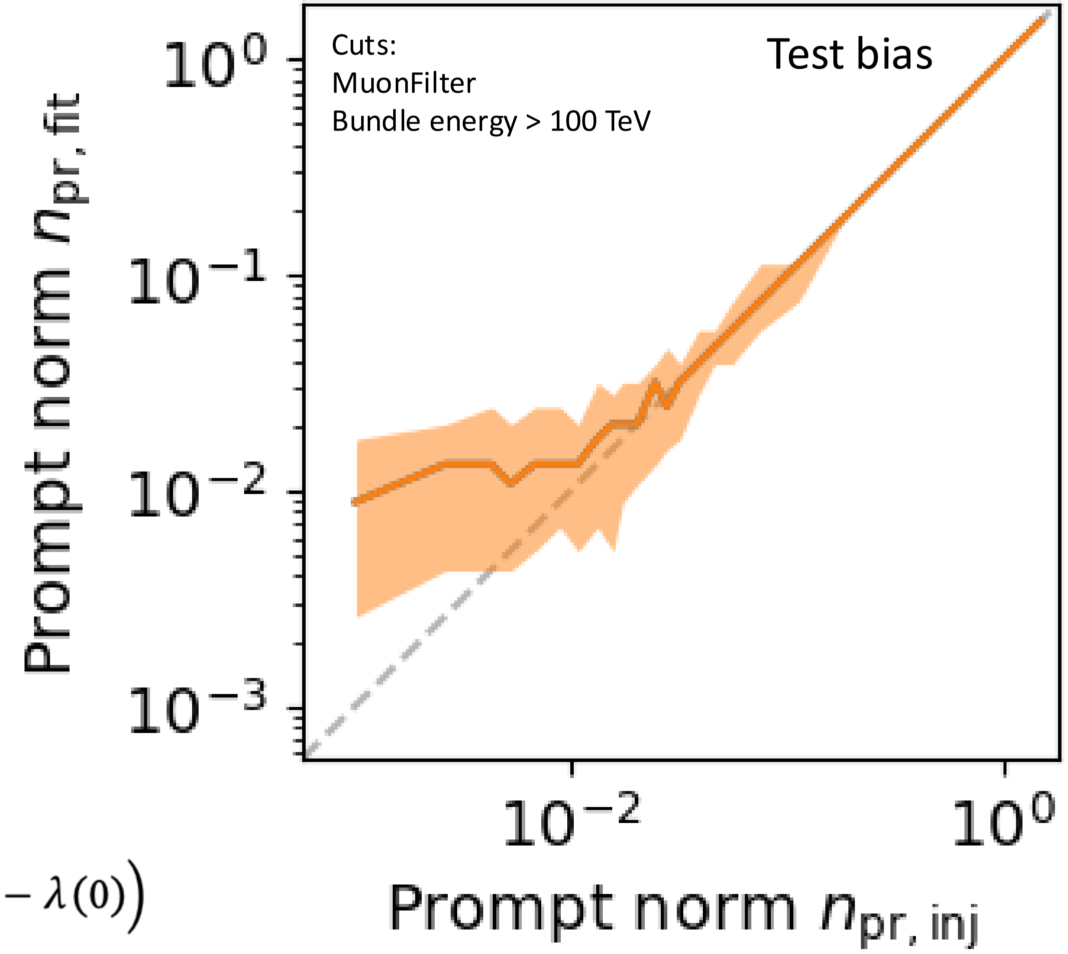
Easier:
minimize negative
log-likelihood

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

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

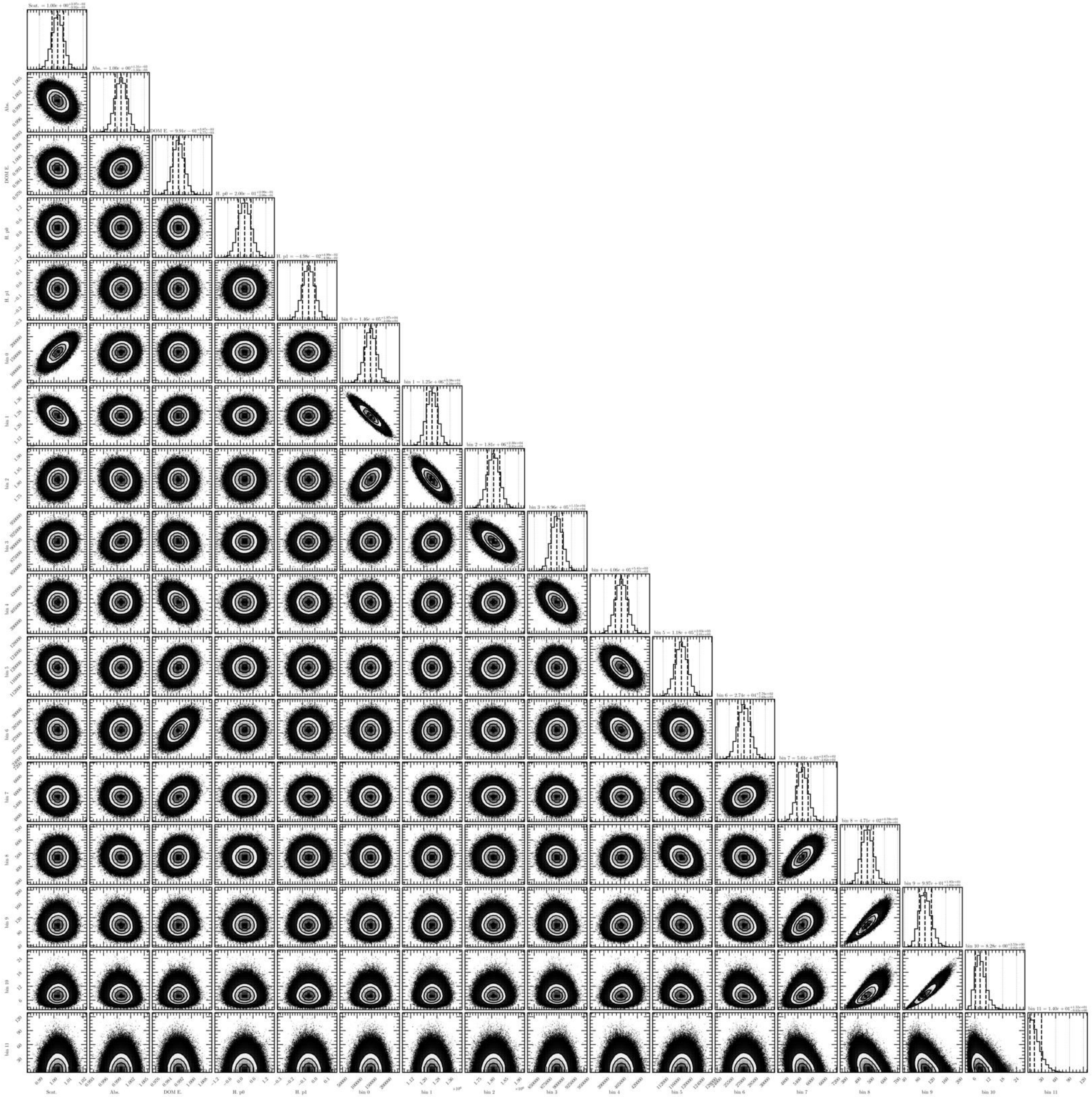
Test statistic for Wilks' theorem

Null hypothesis: no prompt



- Bias starts at a prompt normalization of 0.1

Tau = 0.001



pascal.gutjahr@tu-dortmund.de

Unfolded Muon Flux at Surface