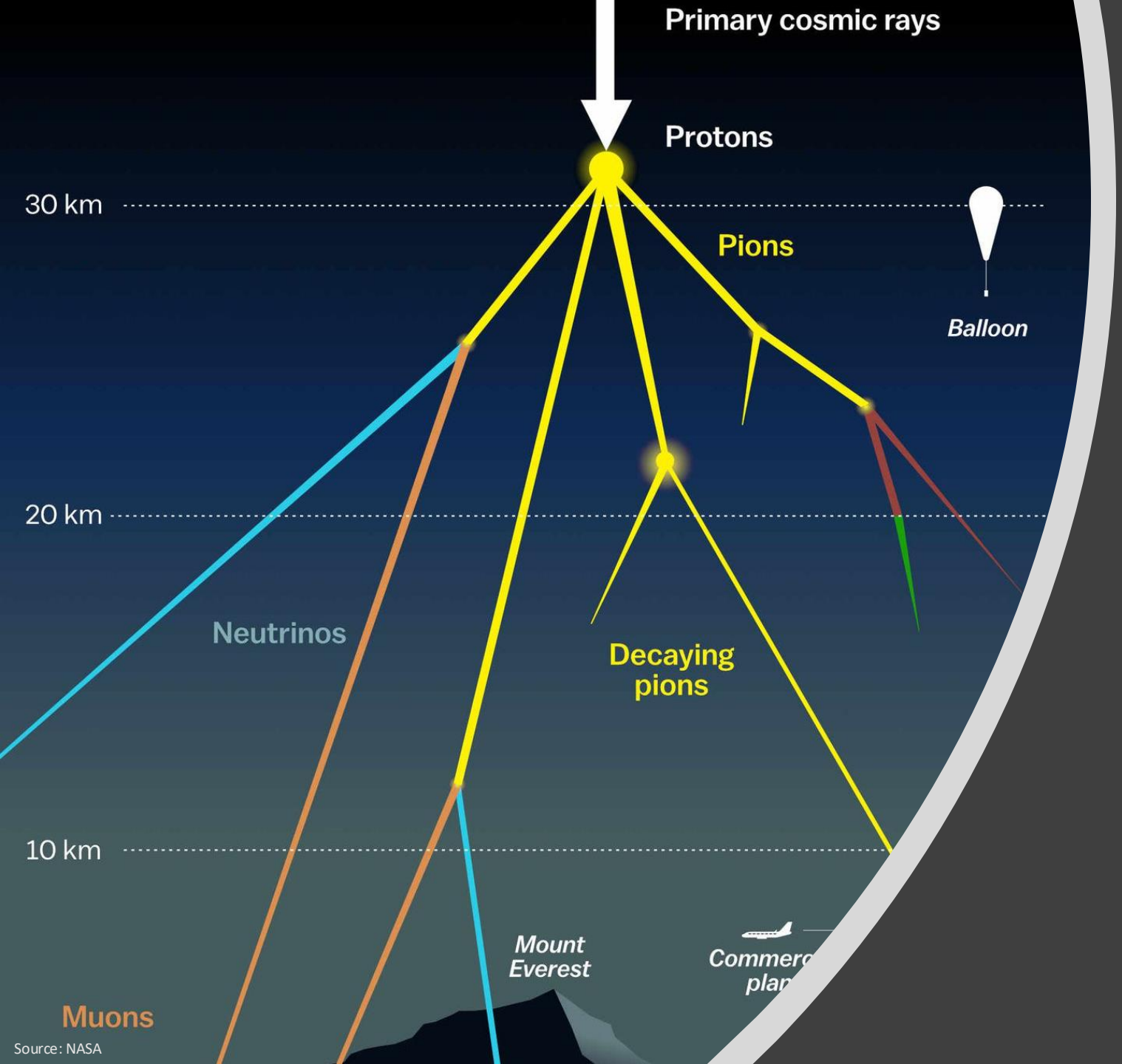


Exploring High-Energy Atmospheric Muons with IceCube: Investigating Prompt Muon Normalization and Unfolding the Muon Flux

Pascal Gutjahr

March 18, 2025

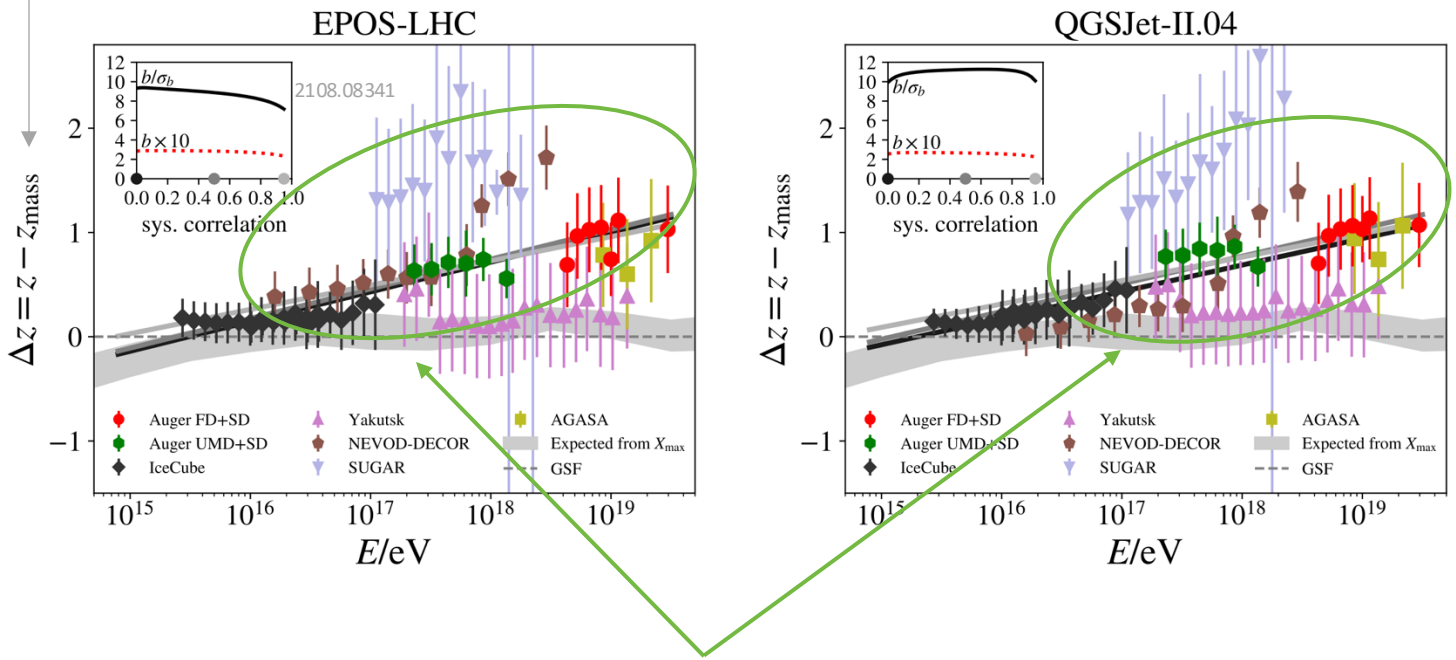
APS JOINT MARCH MEETING AND APRIL MEETING Global Physics Summit

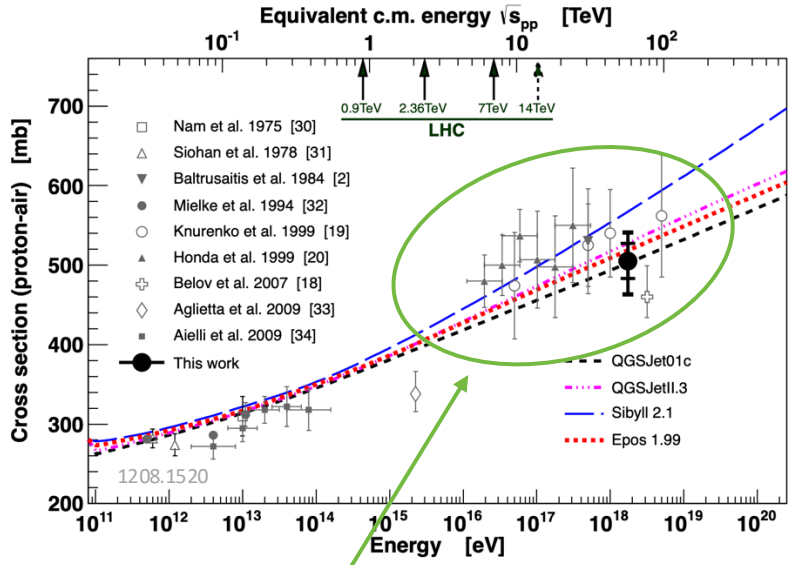
Muon Puzzle & Hadronic Uncertainties

”muon number”

Expected z
(“muon number”)

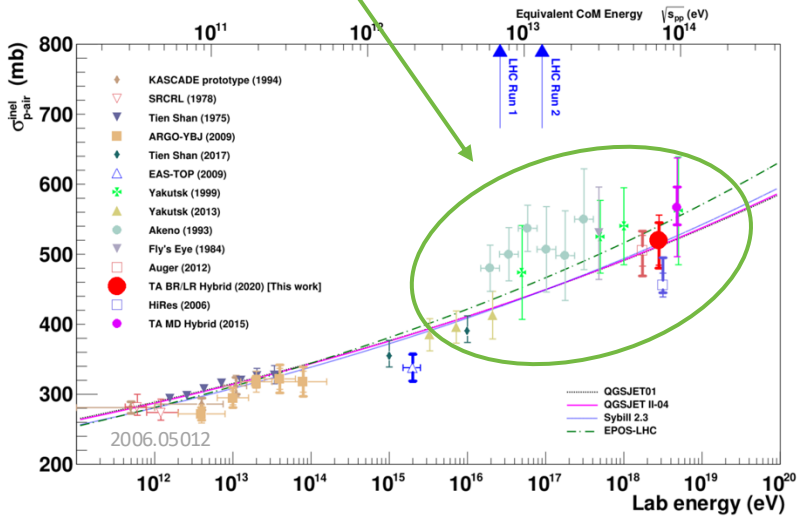
$$z = \frac{\ln\langle N_\mu\rangle - \ln\langle N_\mu\rangle_p}{\ln\langle N_\mu\rangle_{\mathrm{Fe}} - \ln\langle N_\mu\rangle_p}$$





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

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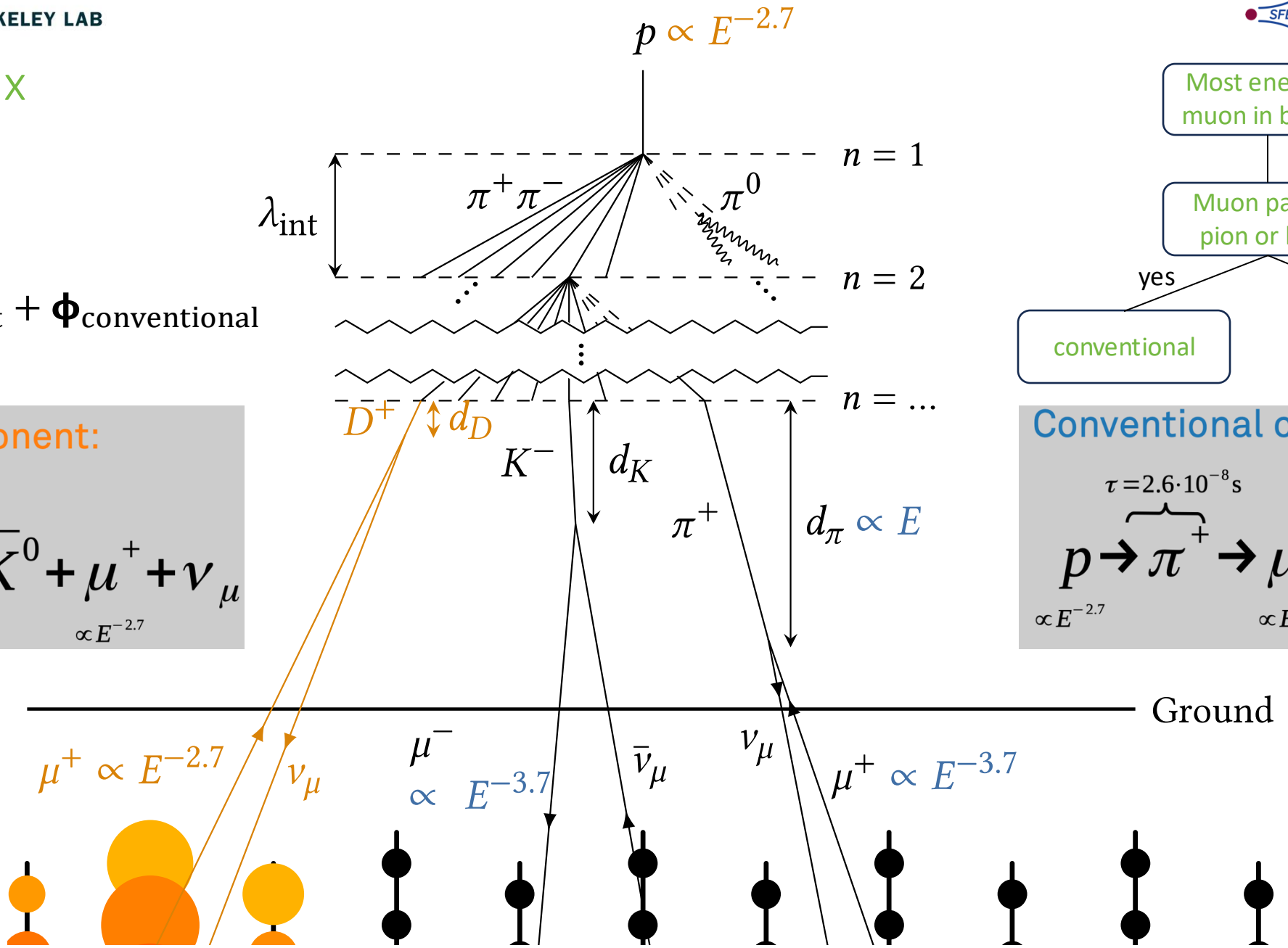
Muon Flux

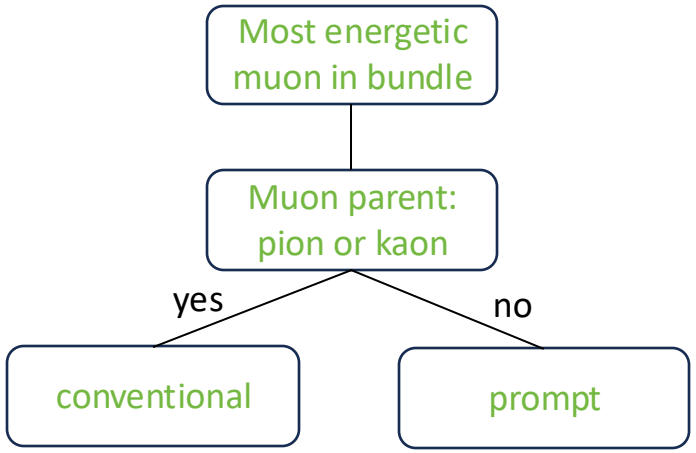
$$\Phi_{tot} = \Phi_{prompt} + \Phi_{conventional}$$



prompt component:

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

$\propto E^{-2.7}$ $\propto E^{-2.7}$



Conventional component:

$$p \rightarrow \overbrace{\pi^+}^{\tau = 2.6 \cdot 10^{-8}\,s} \rightarrow \mu^+ + \nu_\mu$$

$\propto E^{-2.7}$ $\propto E^{-3.7}$

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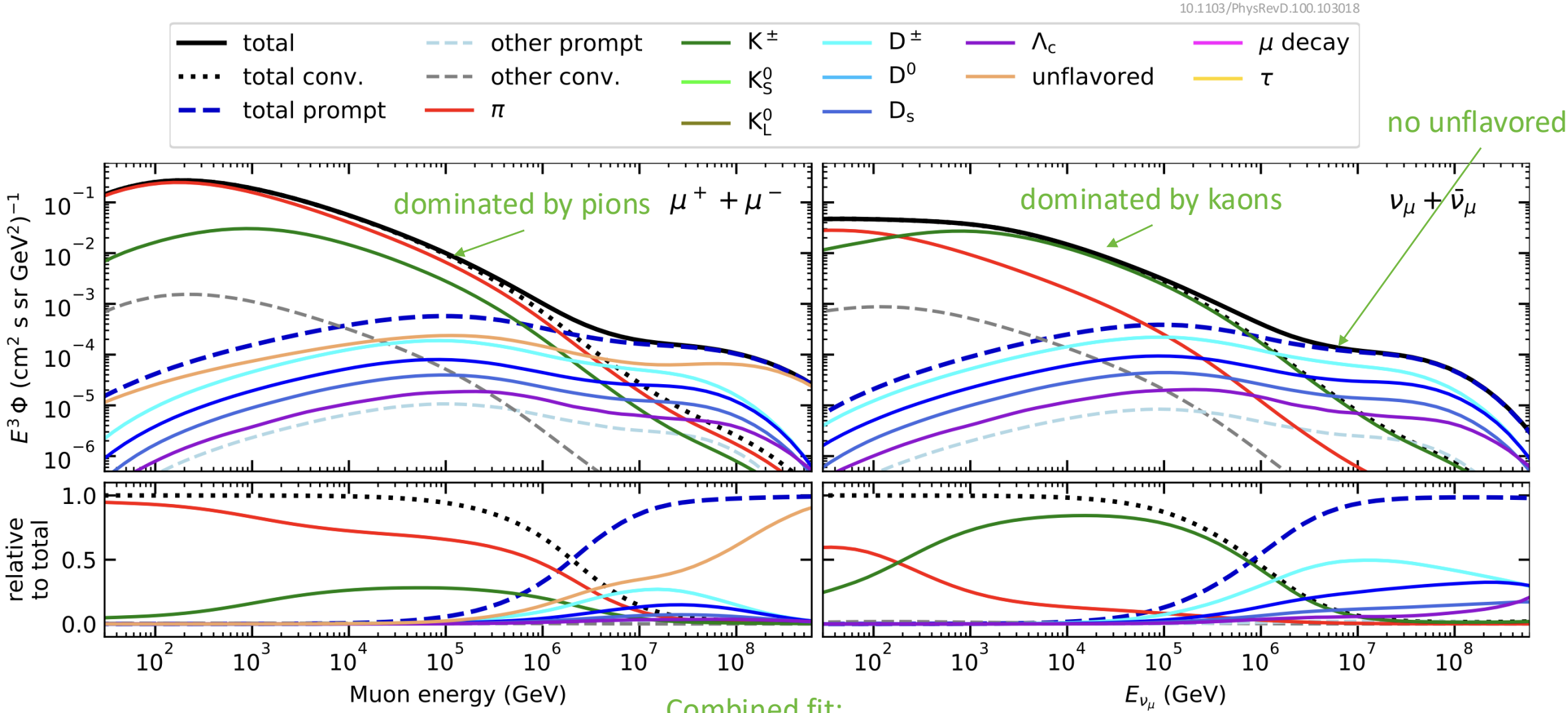
Credit: Ludwig Neste

Prompt Atmospheric Muons & Neutrinos

10.1103/PhysRevD.100.103018



Combined fit:

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

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Analysis Goals

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

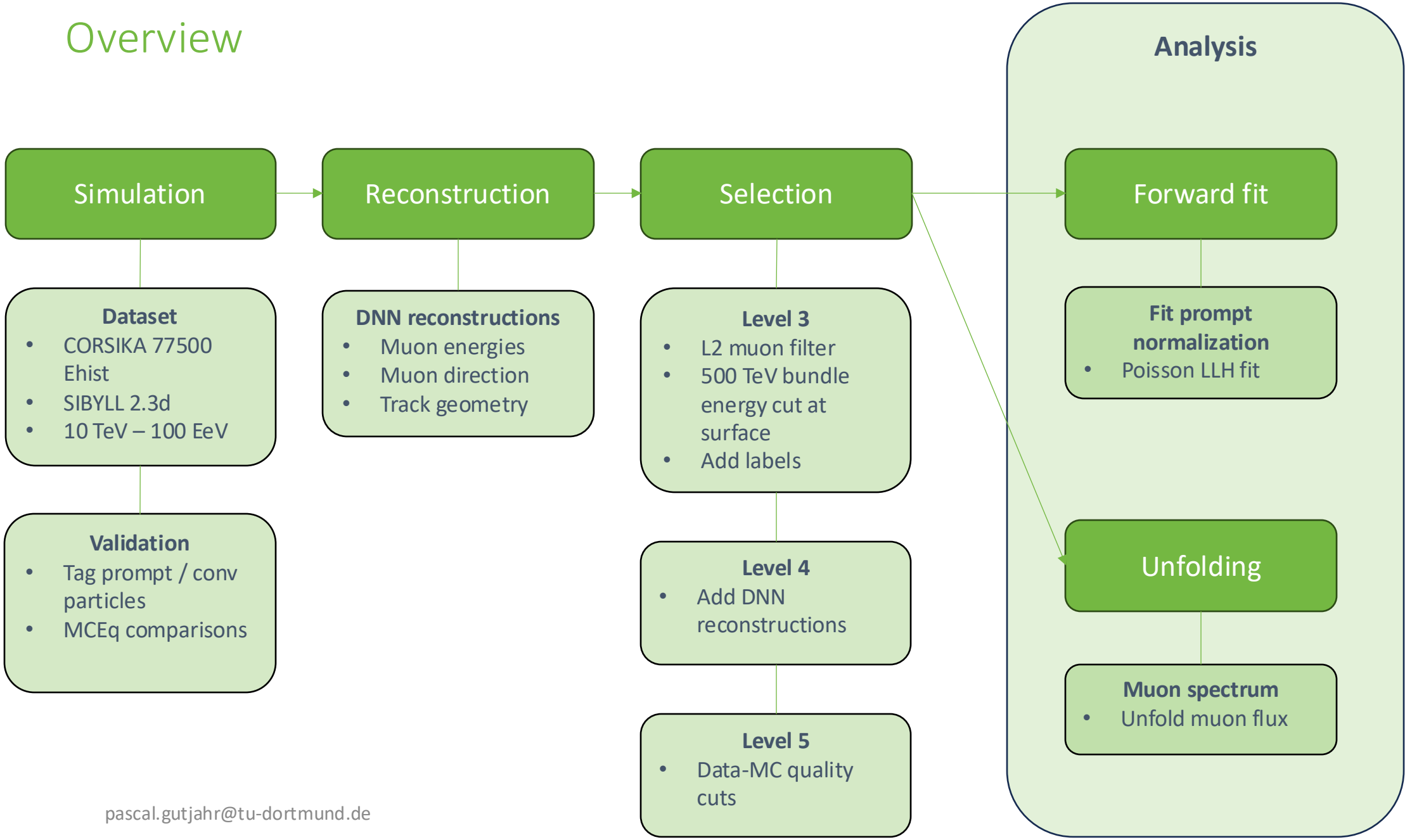
Idea:

- 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

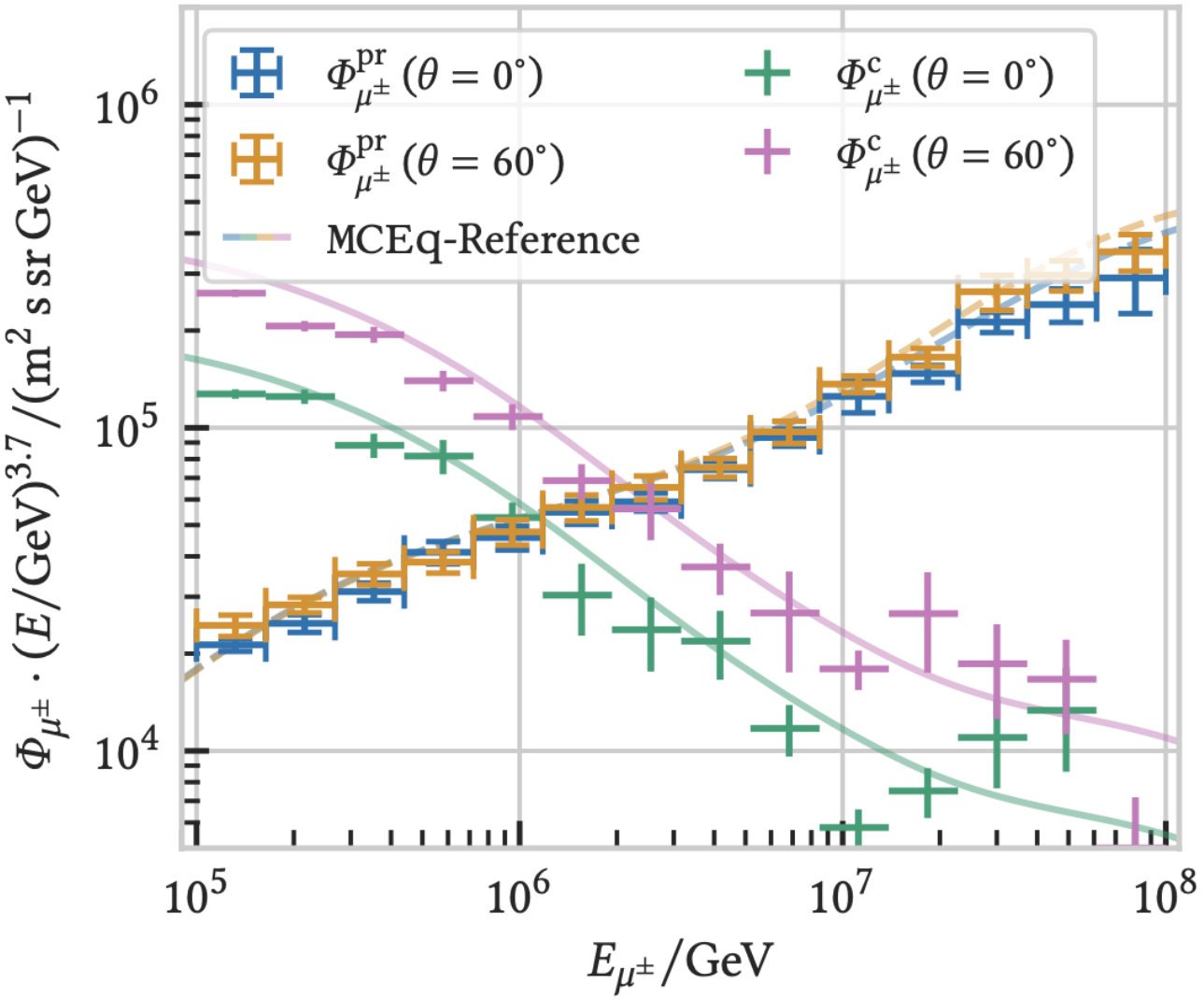
Overview


Simulation
Reconstruction
Selection
Analysis
Forward fit
Dataset
• CORSIKA 77500 Ehist
• SIBYLL 2.3d
• 10 TeV – 100 EeV
DNN reconstructions
• Muon energies
• Muon direction
• Track geometry
Level 3
• L2 muon filter
• 500 TeV bundle energy cut at surface
• Add labels
Fit prompt normalization
• Poisson LLH fit
Validation
• Tag prompt / conv particles
• MCEq comparisons
Level 4
• Add DNN reconstructions
Unfolding
Level 5
• Data-MC quality cuts
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

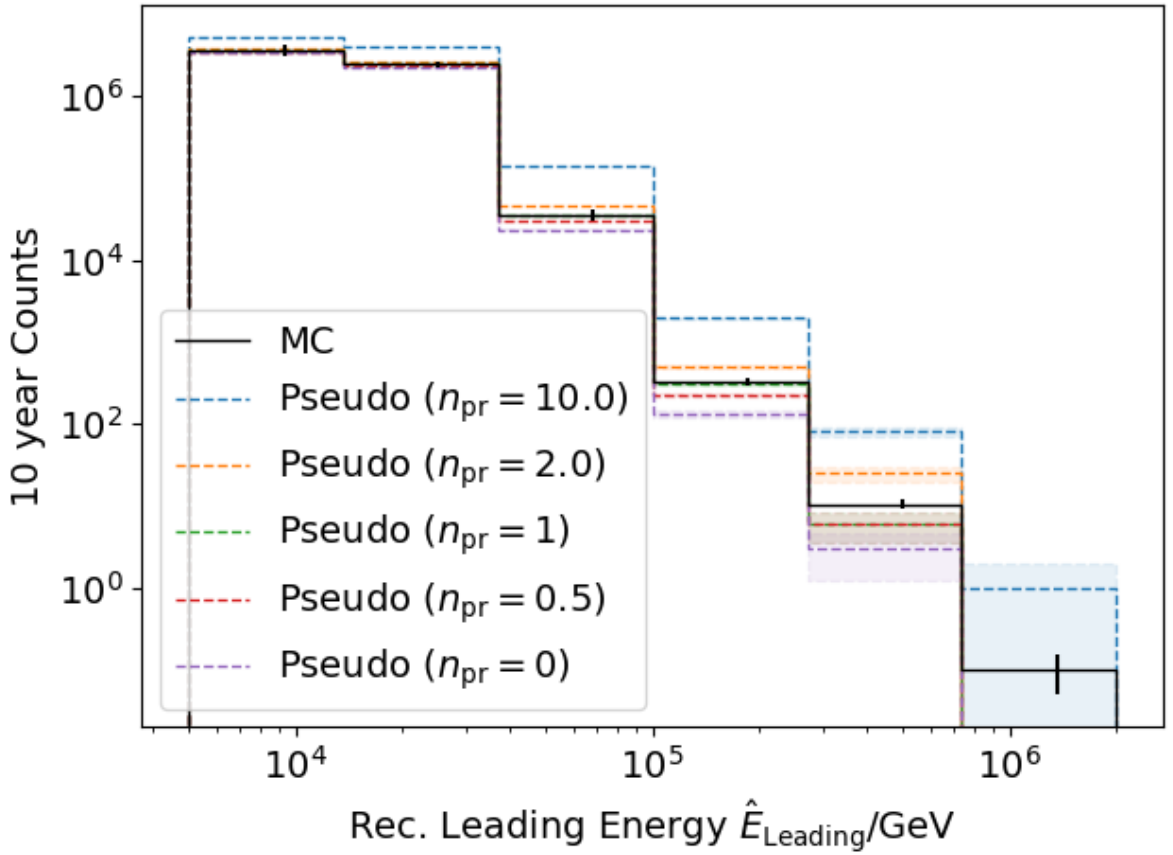
- Execute CORSIKA 7 (multi core)
- Read DAT files → pandas DataFrames
- Parse EHIST option
- Calculate primary weightings

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

Forward Fit

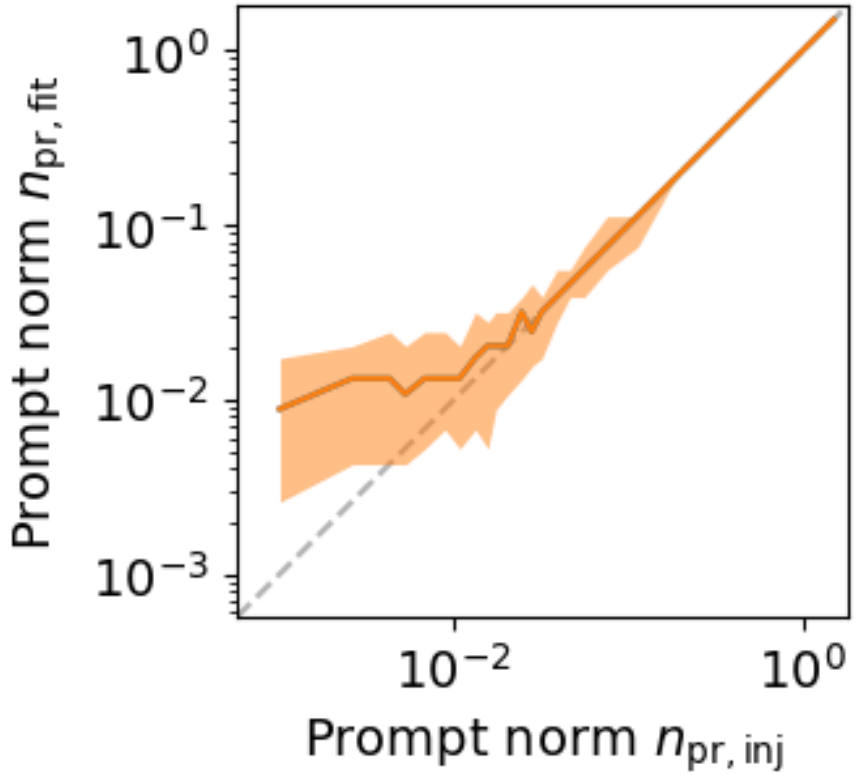
Cuts:
L2 MuonFilter
Bundle energy at entry > 100 TeV

Poisson Likelihood Fit



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

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



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

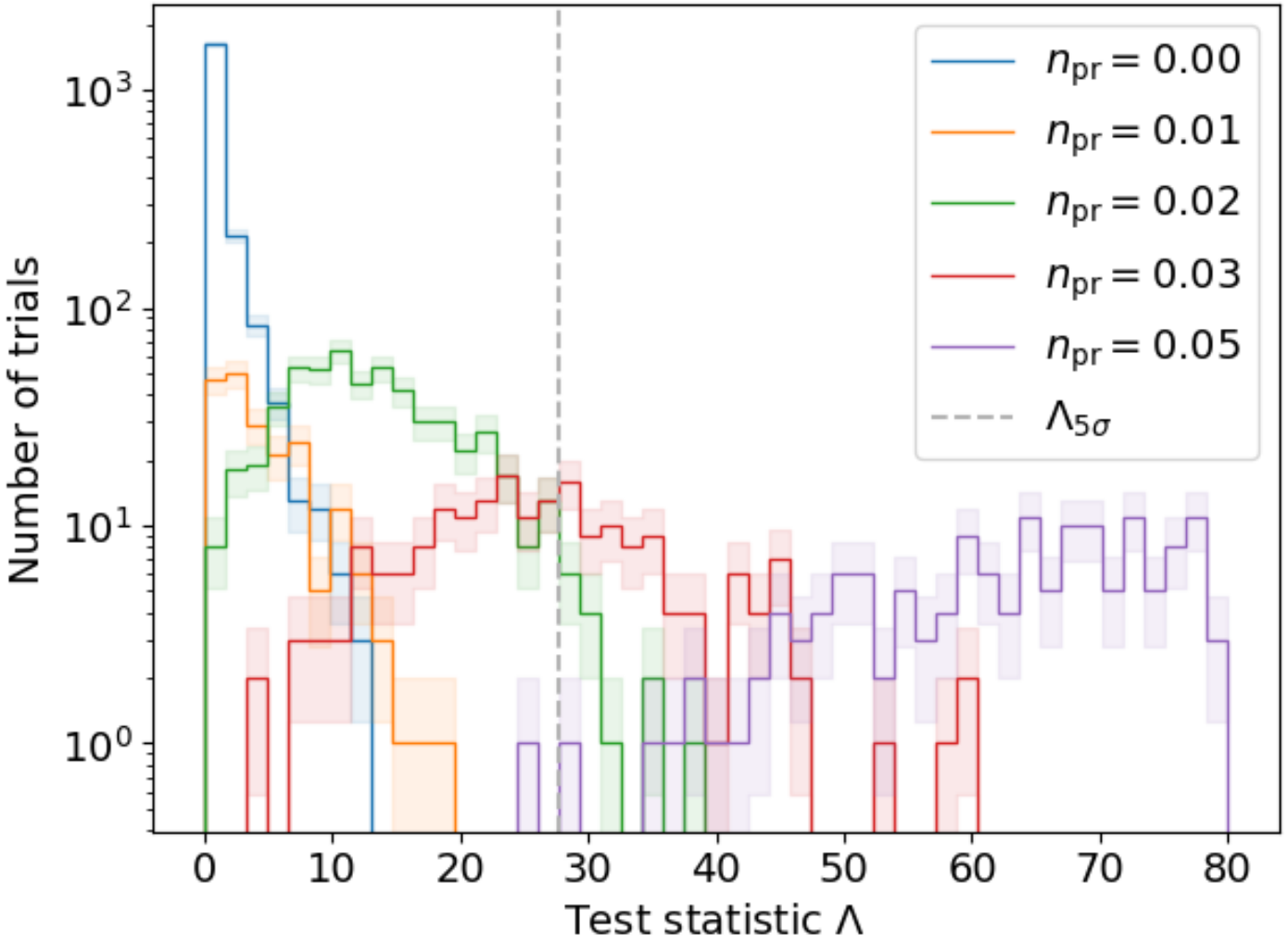
Cuts:
L2 MuonFilter
Bundle energy at entry > 100 TeV

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



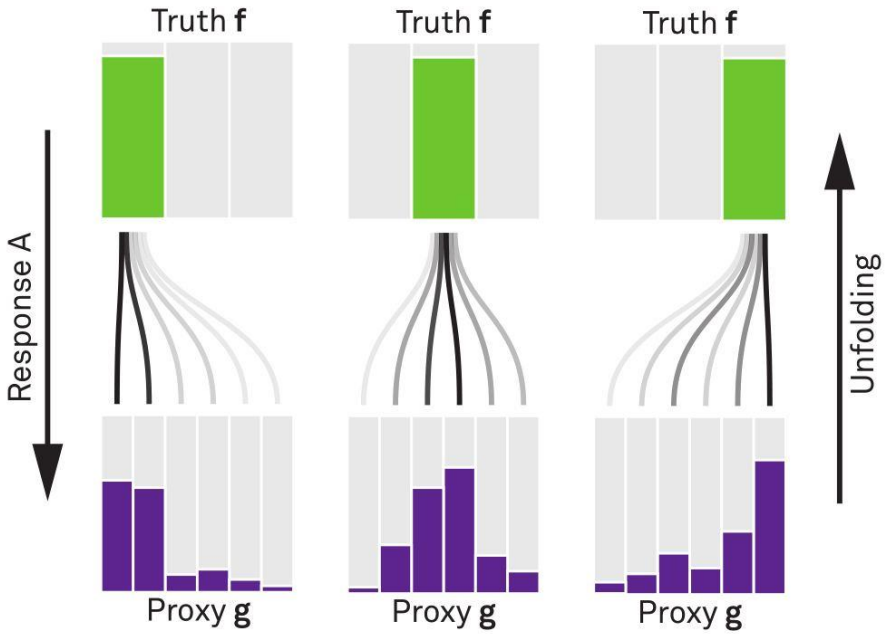
Unfolding

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



Credit: T. Hoinka

folding — unfolding

1. discretized form: $\vec{g} = A\vec{f} \leftrightarrow \vec{f} = A^{-1}\vec{g}$

2. maximum likelihod method:

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

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

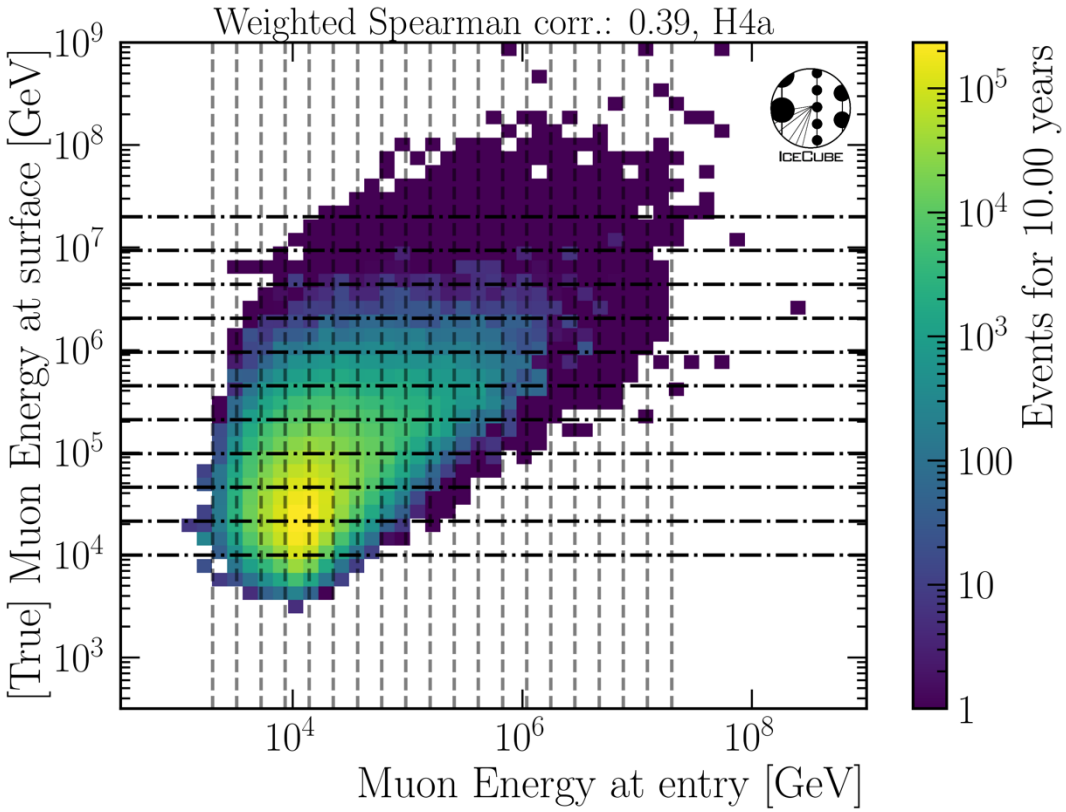
3. Thikonov regularization:

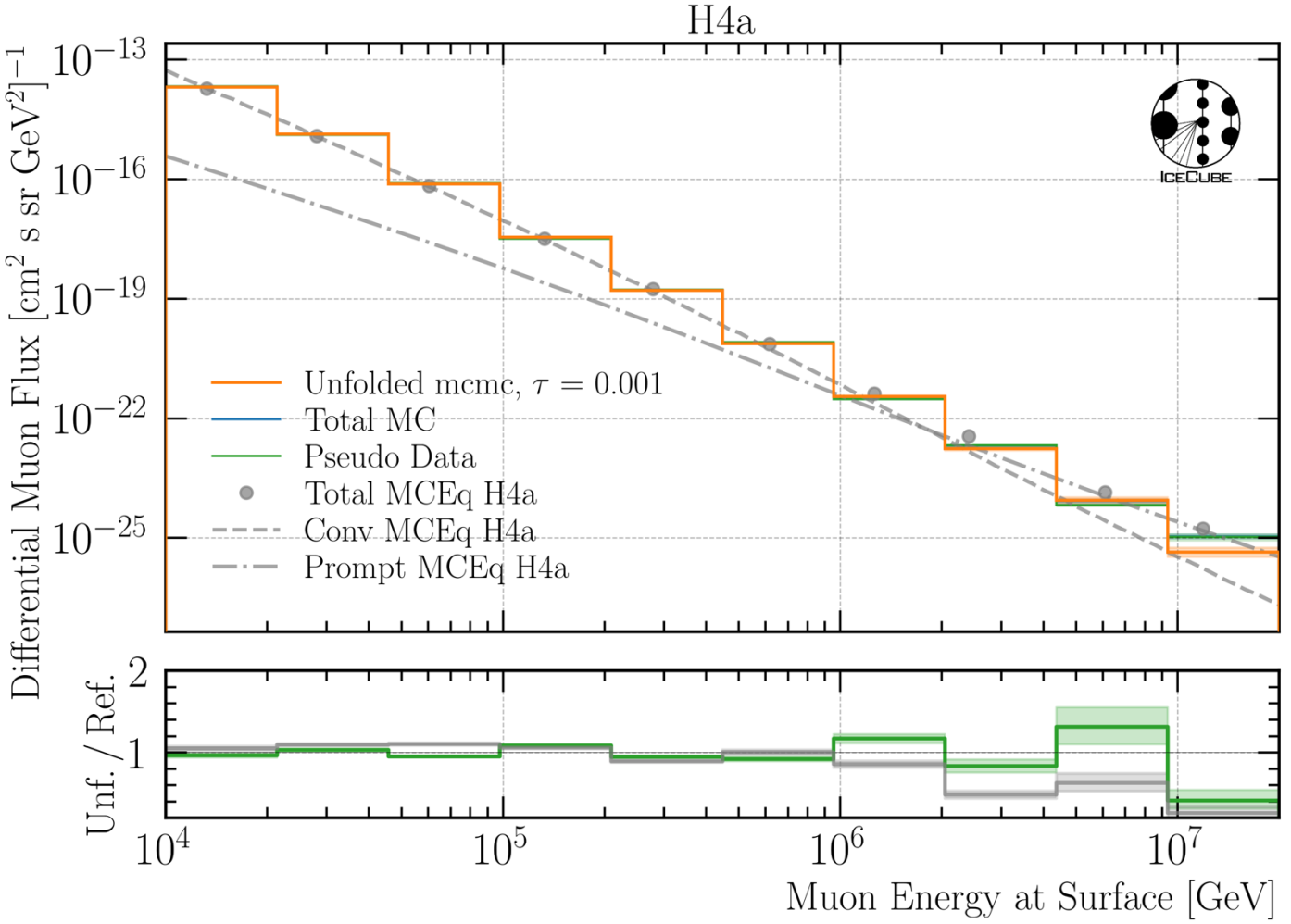
$$t(\vec{f}) = -\frac{1}{2}(C\vec{f})^T(\tau 1)^{-1}(C\vec{f})$$

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.

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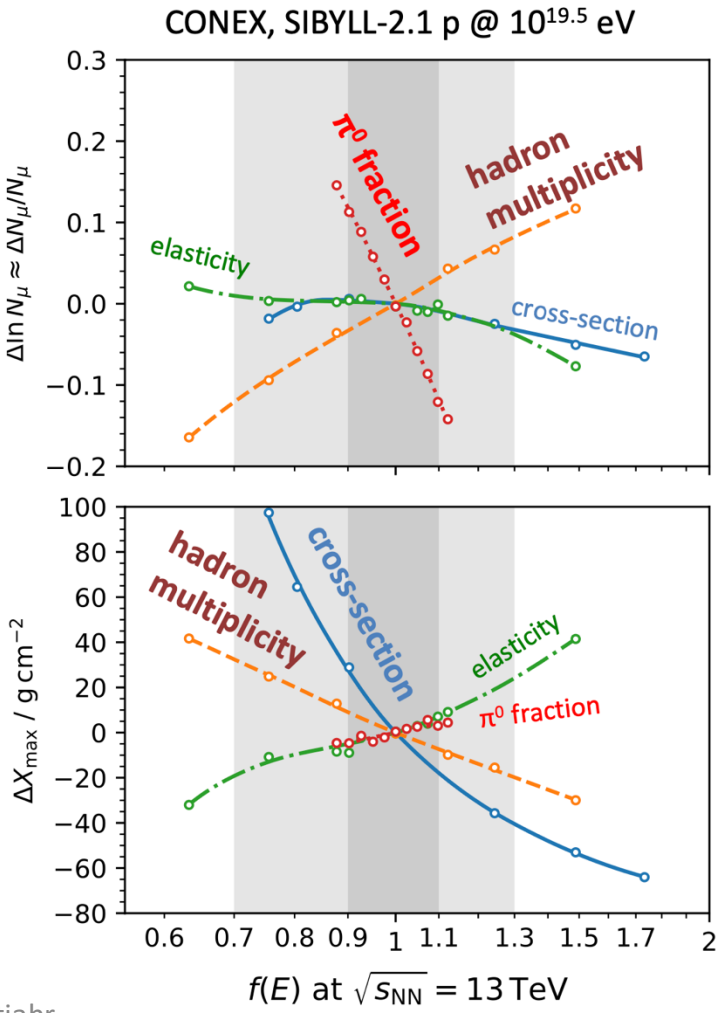
Thank you for your attention!

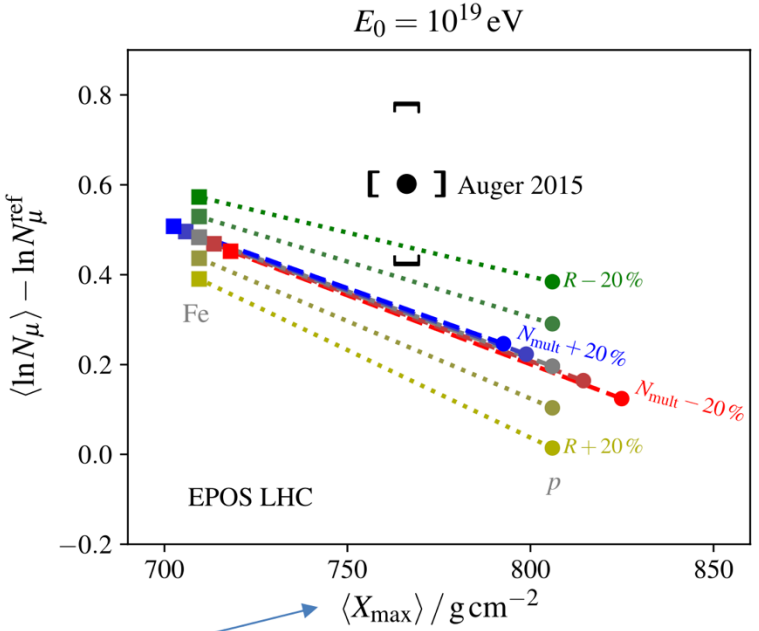
Backup

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

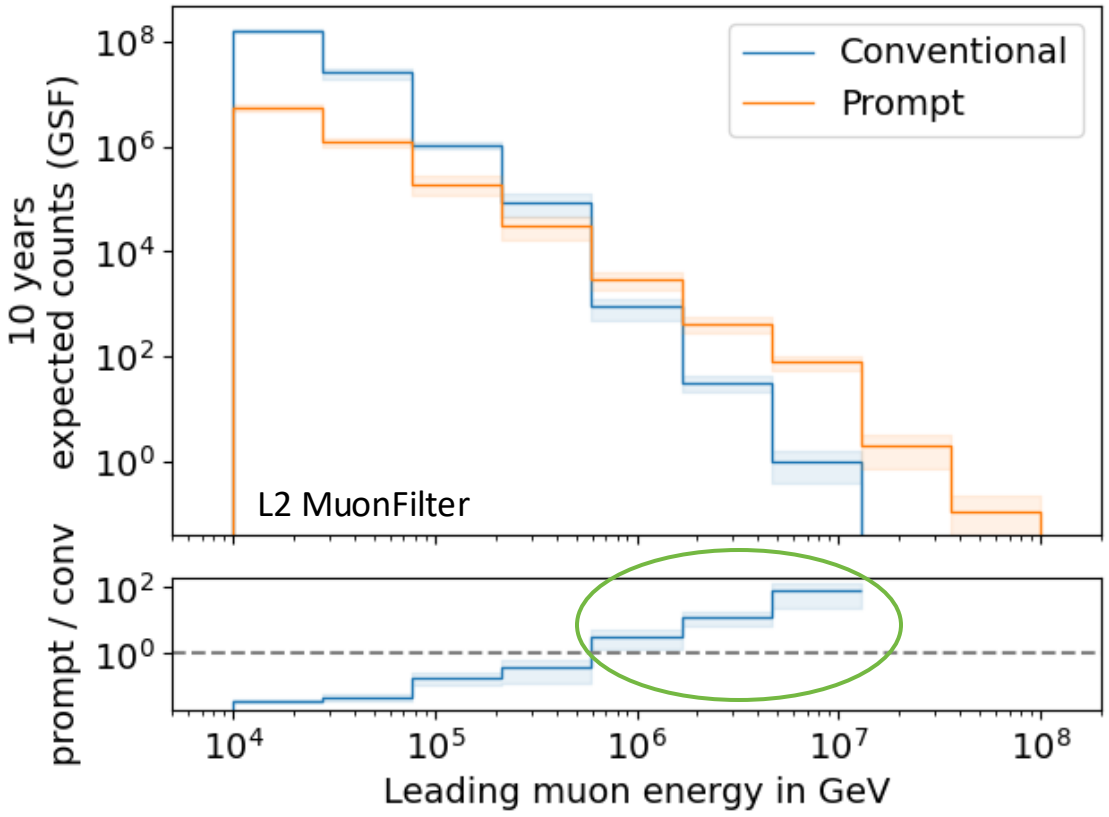


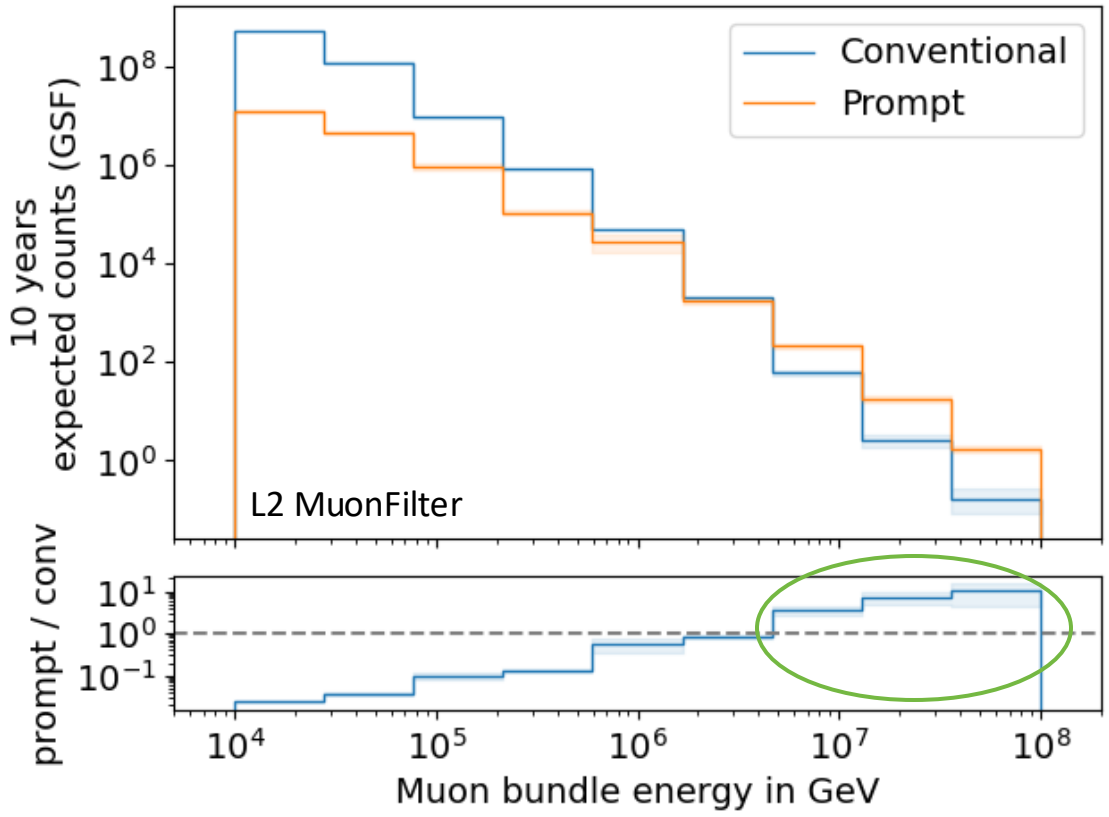
$$R = \frac{E_{\pi^0}}{E_{\text{other hadrons}}}$$

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

Hans Dembinski

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

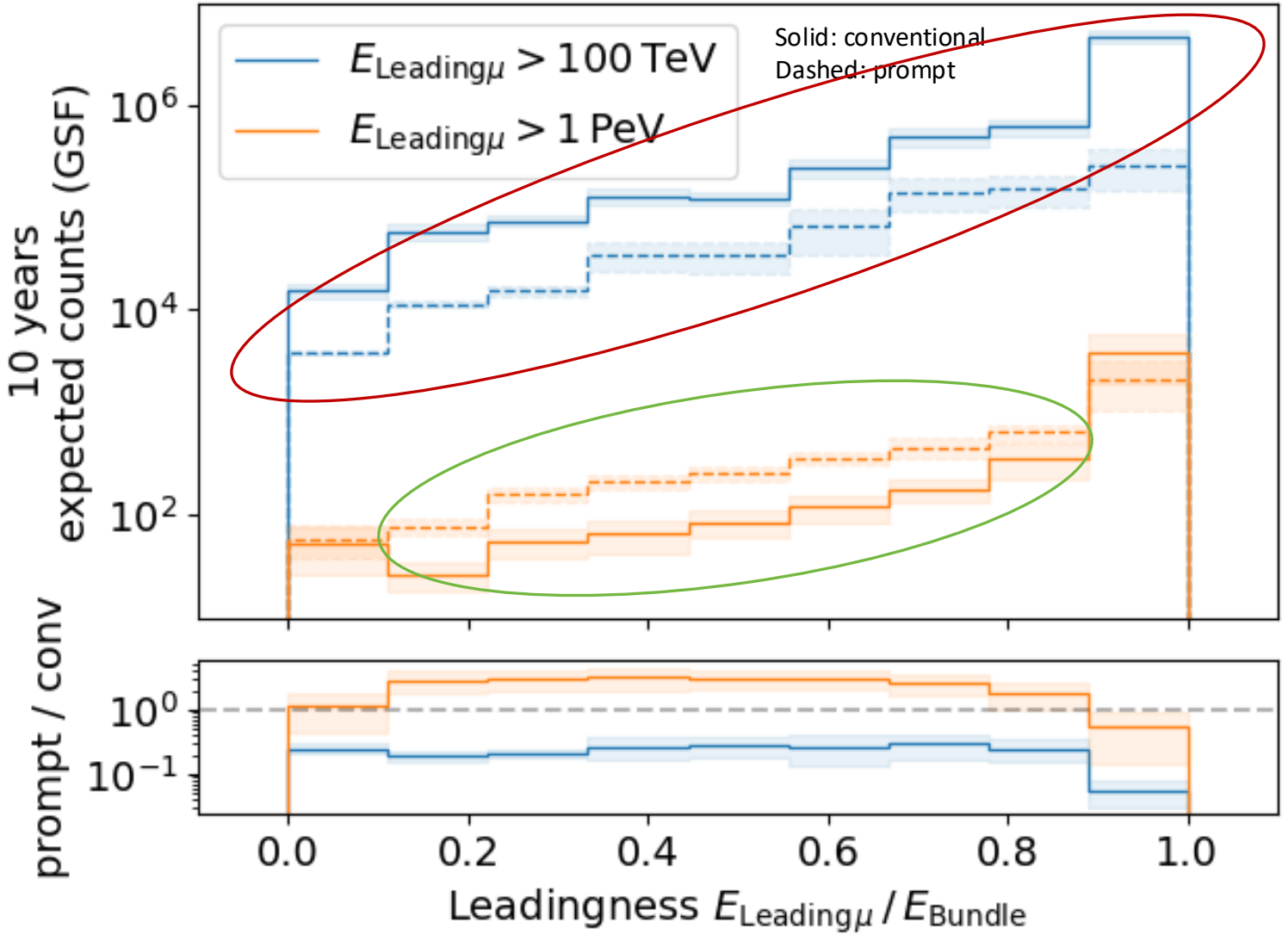




- Both leading and bundle energy are sensitive to detect prompt
- Leading muon energy is more sensitive

Leading Muon Energy Fraction

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



Leading Muon Contribution

Patrick Berghaus

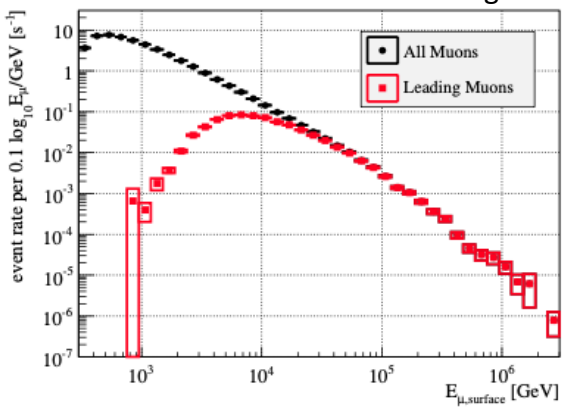
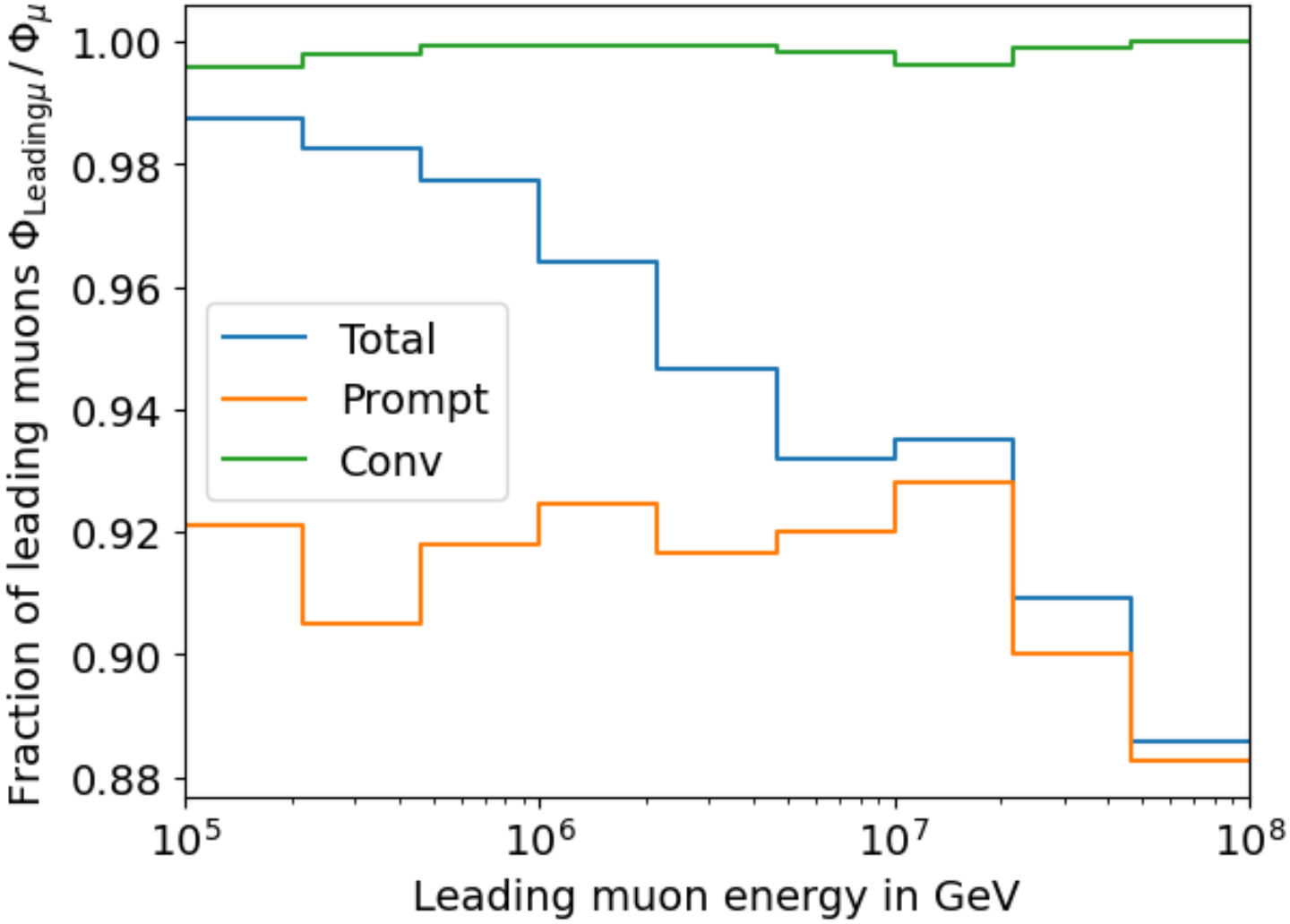


Figure 10: Surface energy distribution for all and most energetic ("leading") muons in simulated events with a total of more than 1,000 registered photo-electrons in IceCube.

- 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

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

Maximize likelihood

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

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

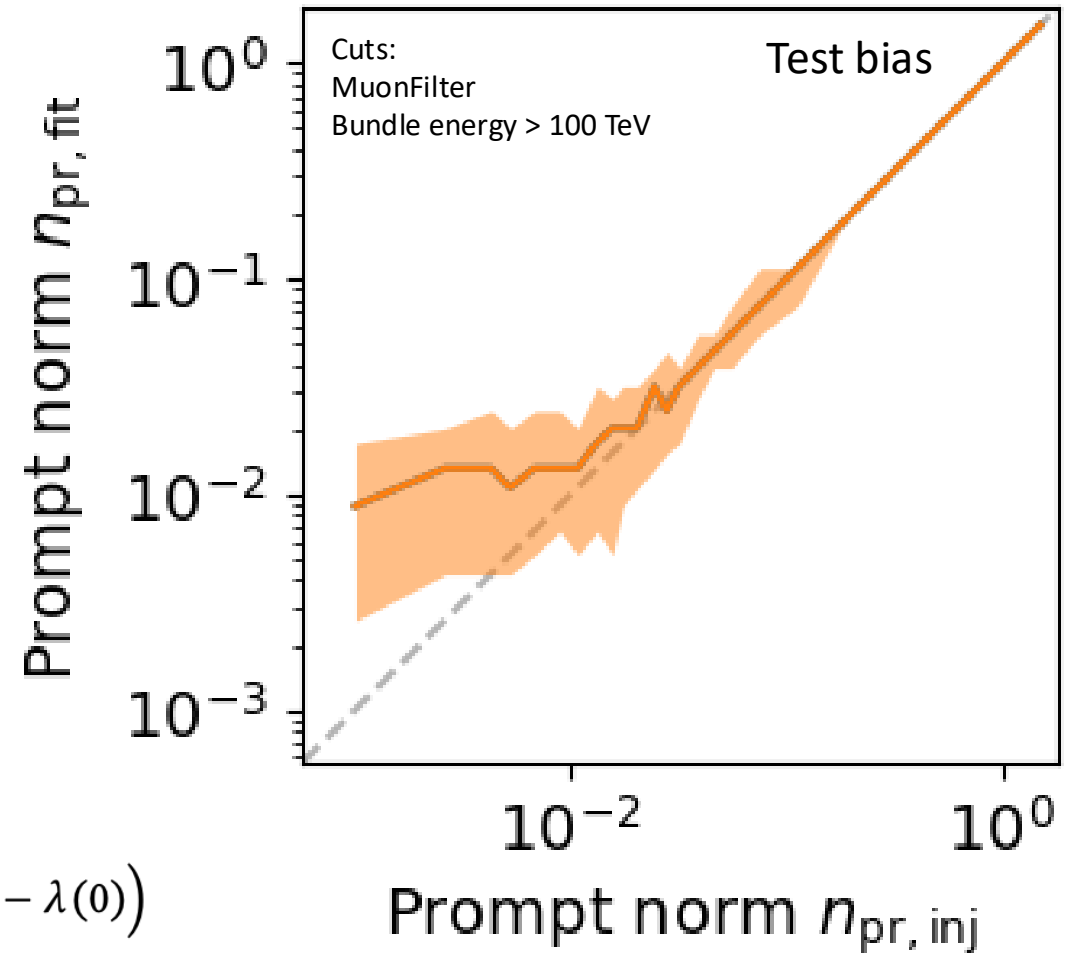
Easier:
minimize negative
log-likelihood

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

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

Test statistic for Wilks' theorem

Null hypothesis: no prompt



- Bias starts at a prompt normalization of 0.1

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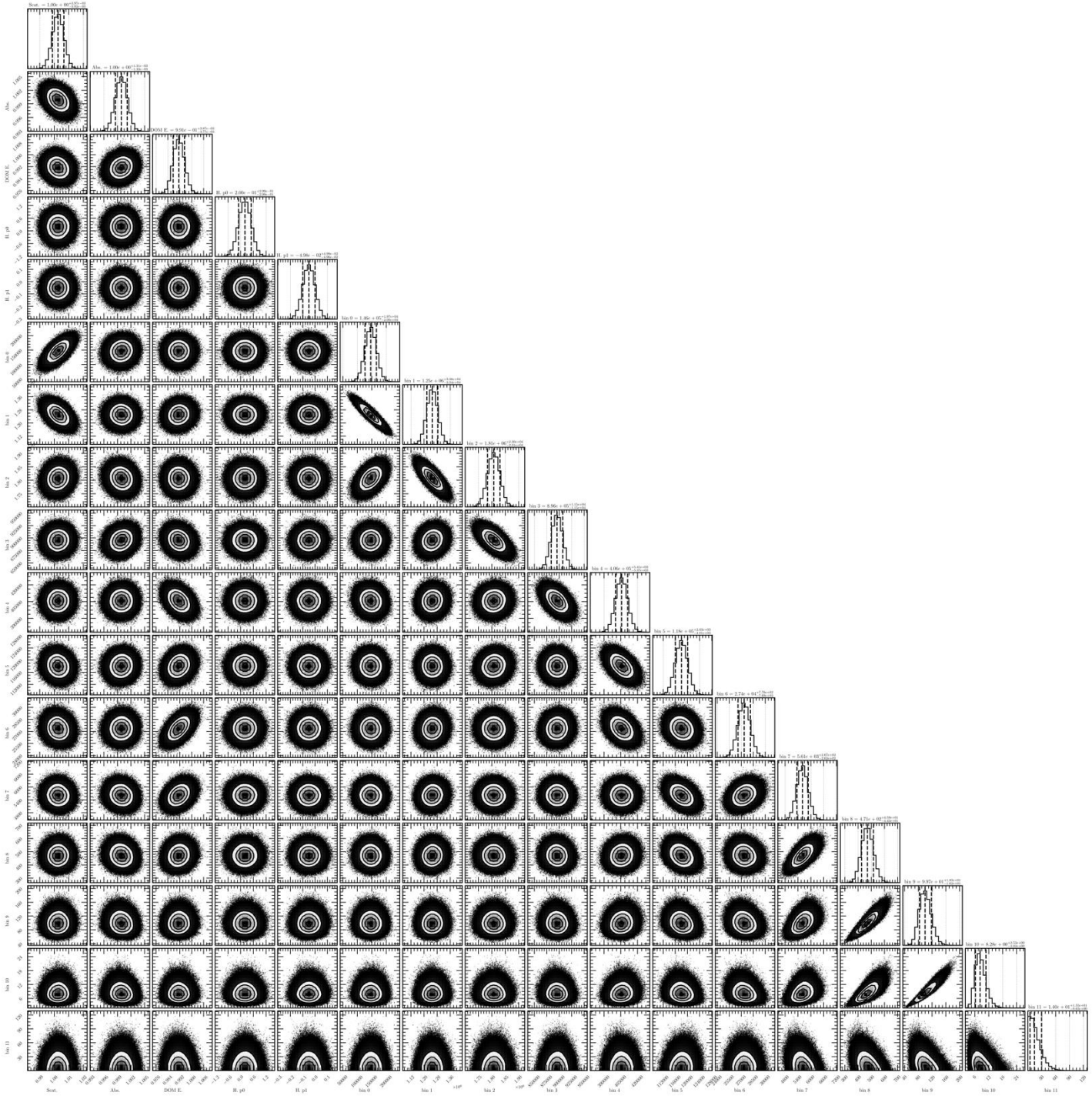
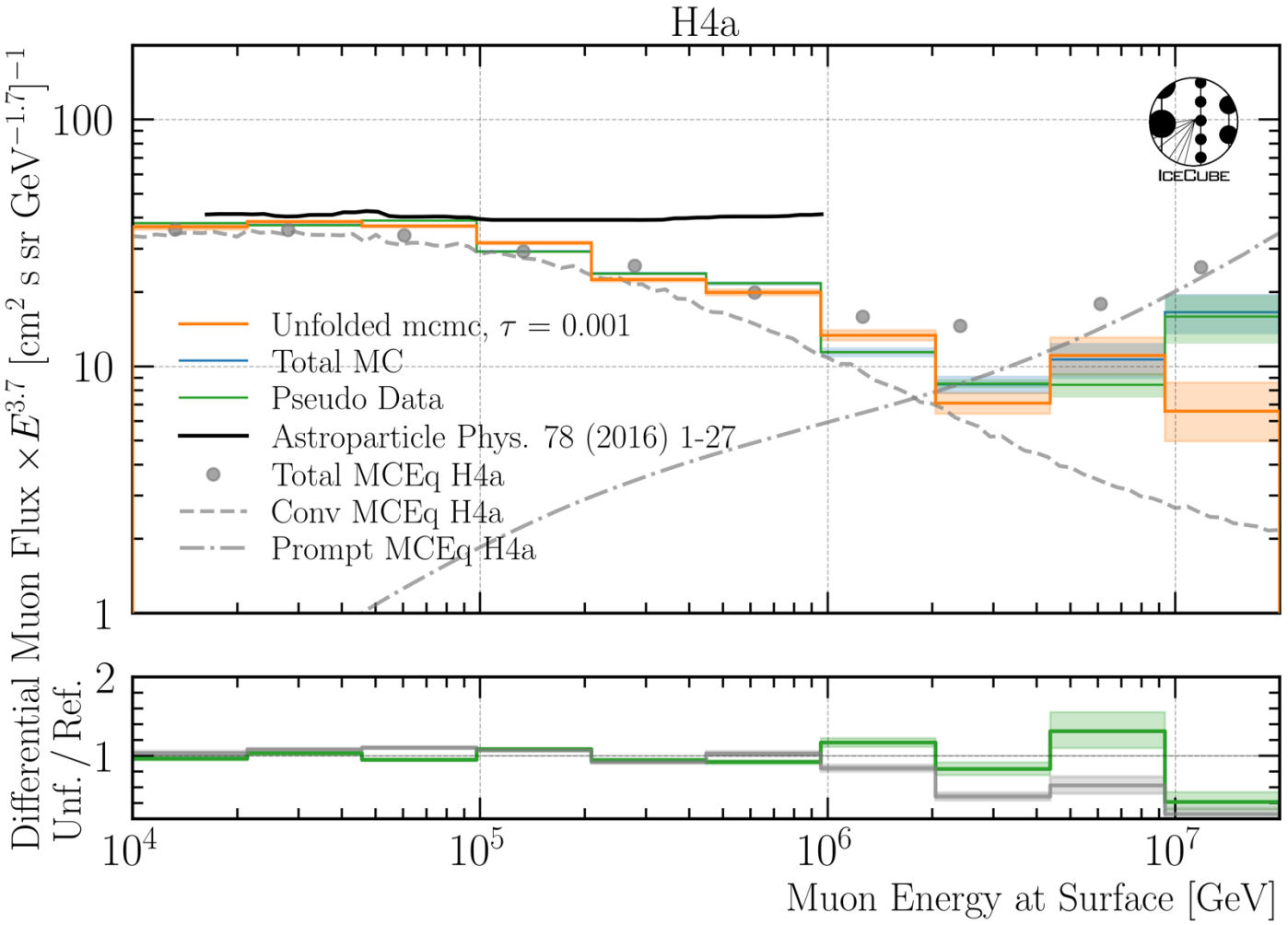
Tau = 0.001



Unfolded Muon Flux at Surface