

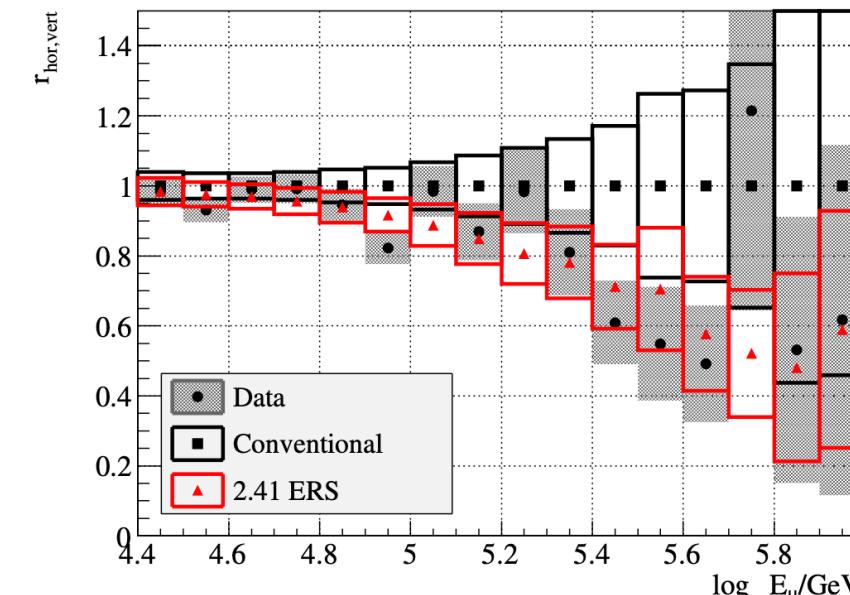
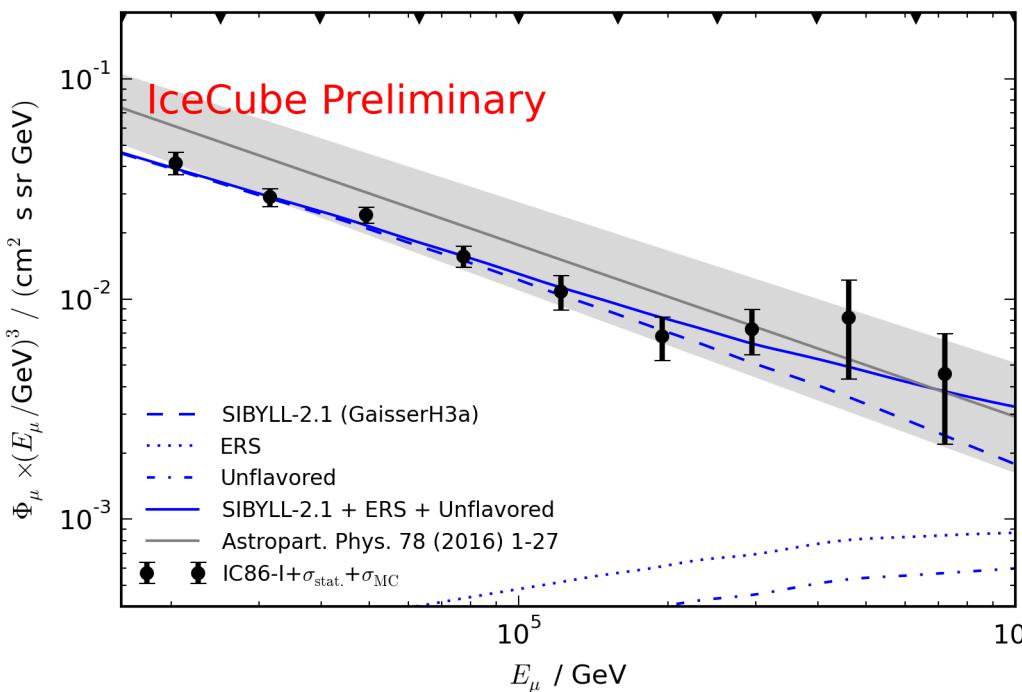
Update on prompt muon analysis – reconstructions and selection

Pascal Gutjahr and Mirco Hünnefeld

CR-WG March 1, 2024

Motivation

- Detect and measure normalization of prompt component of atmospheric muon flux
- Constrain uncertainties on hadronic interaction models at very high energies
- Former analyses:
 - Leading muon analysis: limited MC statistics (by Tomasz Fuchs, https://wiki.icecube.wisc.edu/index.php/Analysis_of_Leading_Muons)
 - Characterization of the muon flux: zenith problem (by Patrick Berghaus, <https://arxiv.org/abs/1506.07981>)



Sample	Best Fit (ERS)	1σ Interval (90% CL)	$\sigma(\Phi_{\text{prompt}} > 0)$
Uncorrected	4.93	4.05-5.87 (3.55-6.56)	9.43
Marginalized Ang. Corr.	3.19	1.64-5.48 (0.98-7.26)	3.46

- Good analyses with some challenges
- Prompt MC truth not available -> new CORSIKA simulations

Overview

Final goals

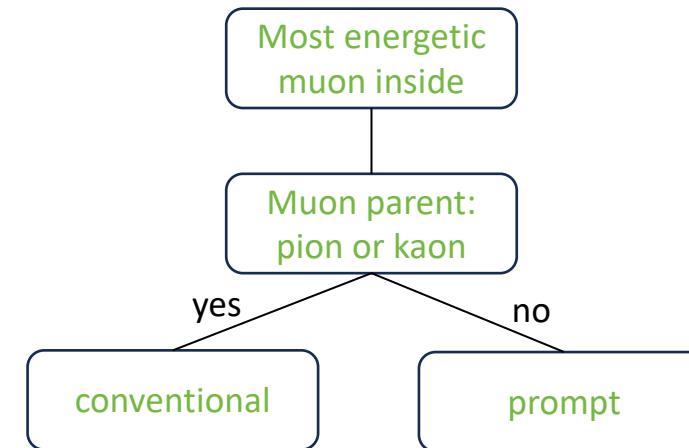
- Measure normalization of the atmospheric prompt muon flux
- Unfold muon energy spectrum

Steps for normalization measurement

- Verify CORSIKA extended history simulations
- Tag prompt muons
- Comparisons to MCEq
- Set up preliminary analysis chain
- Reconstruct muon energy and direction
- Data/MC comparisons
- Include systematics
- Run full statistics simulation

Additional steps for unfolding

- Effective area



Terminology

- Muon bundle: all muons in a bundle
- Leading muon: most energetic muon in a muon bundle
- Single muon: no single muons at high energies
- Prompt muon: parent is not pion or kaon

New (preliminary) CORSIKA Ehist simulation

- CORSIKA 77420
- SIBYLL 2.3d
- 600 GeV – 50 EeV
- `/data/sim/IceCube/2023/generated/CORSIKA_EHISTORY/`

Intention

For today

1. General update

For the upcoming collaboration meeting

1. Ask for WG reviewer
2. Storage request for large-scale CORSIKA extended history simulation

What we have done

- ★ Reconstruction
 - Trained networks to reconstruct several properties
- ★ Selection
 - Level 3 (L2MuonFilter + 200 TeV bundle energy cut at surface)
 - Level 4 (add reconstructions)
- Data-MC
 - Check several properties
 - Largest mismatch in z-vertex
- Forward fit
 - Test NNMFit for analysis
- Unfolding
 - Unfold event rate
 - Calculate effective area
- New simulations
 - Preparation for large scale IceProd simulation (latest software, switch some options)
- ★ Wiki
 - Created and uploaded

Today: ★

Münster: ►

DNN reconstructions

Reconstructed properties

Energy

- `entry_energy`: Leading muon energy at the detector entry
- `bundle_energy_at_entry`: Muon bundle energy at the detector entry
- `muon_energy_first_mctree`: Leading muon energy at surface
- `bundle_energy_in_mctree`: Muon bundle energy at surface

Track geometry

- `Length`: Propagation length of muon in the ice
- `LengthInDetector`: Propagation length of muon in the detector
- `center_pos_x`: Closest x position of muon to center of the detector
- `center_pos_y`: Closest y position of muon to center of the detector
- `center_pos_z`: Closest z position of muon to center of the detector
- `center_pos_t`: Time of closest approach to the center of the detector
- `entry_pos_x`: x position of muon at the detector entry
- `entry_pos_y`: y position of muon at the detector entry
- `entry_pos_z`: z position of muon at the detector entry
- `entry_pos_t`: Time of muon at the detector entry

Direction

- `zenith`: Zenith angle of muon
- `azimuth`: Azimuth angle of muon



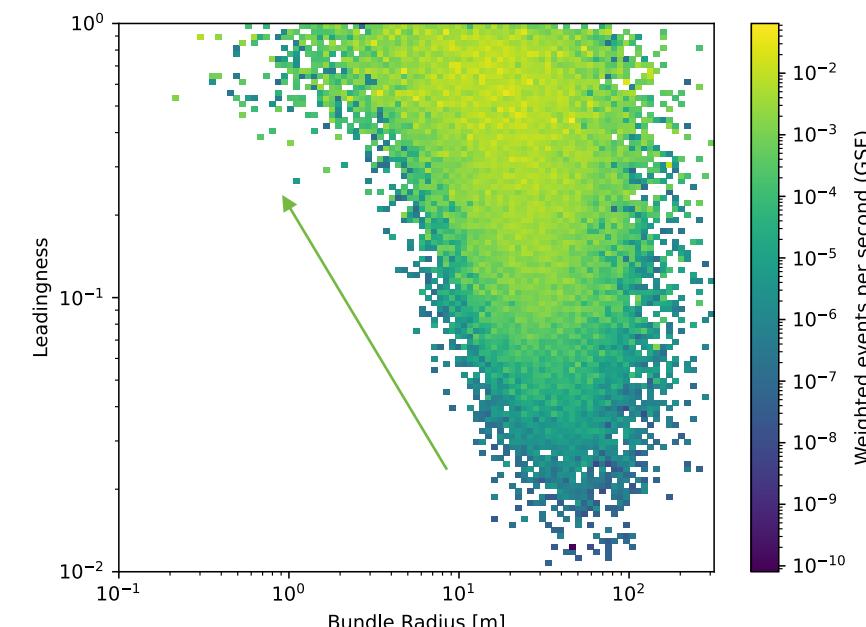
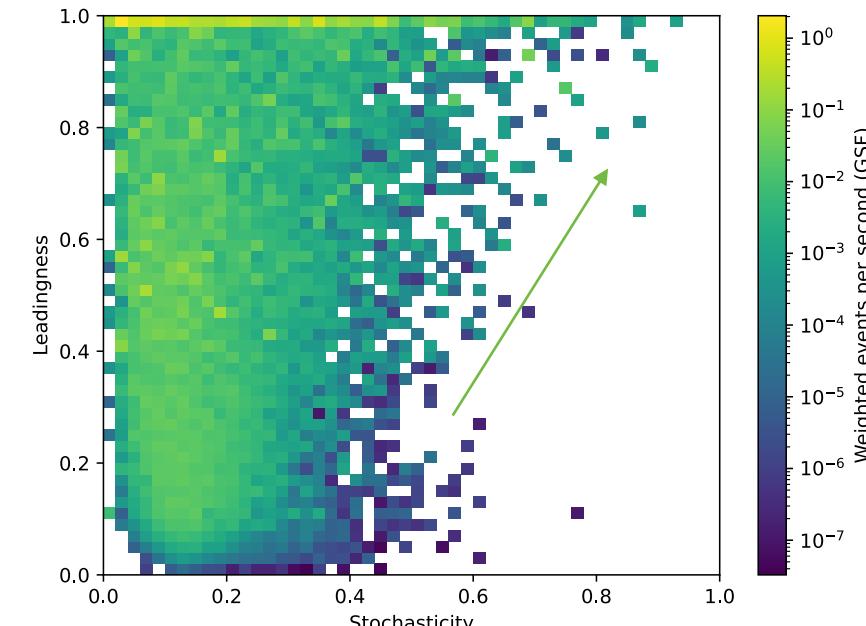
DNN Reconstructions

Reconstruct

- Energy
- Track geometry
- Direction

Physics motivation

- Muons lose energy stochastically
 - High leadingness: energy depositions are dominated by large stochastic losses
 - Low leadingness: stochastic losses sum up and appear continuously
- High energies: forward production
 - High leadingness: small bundle radius
 - Low leadingness: larger bundle radius



Input data per DOM

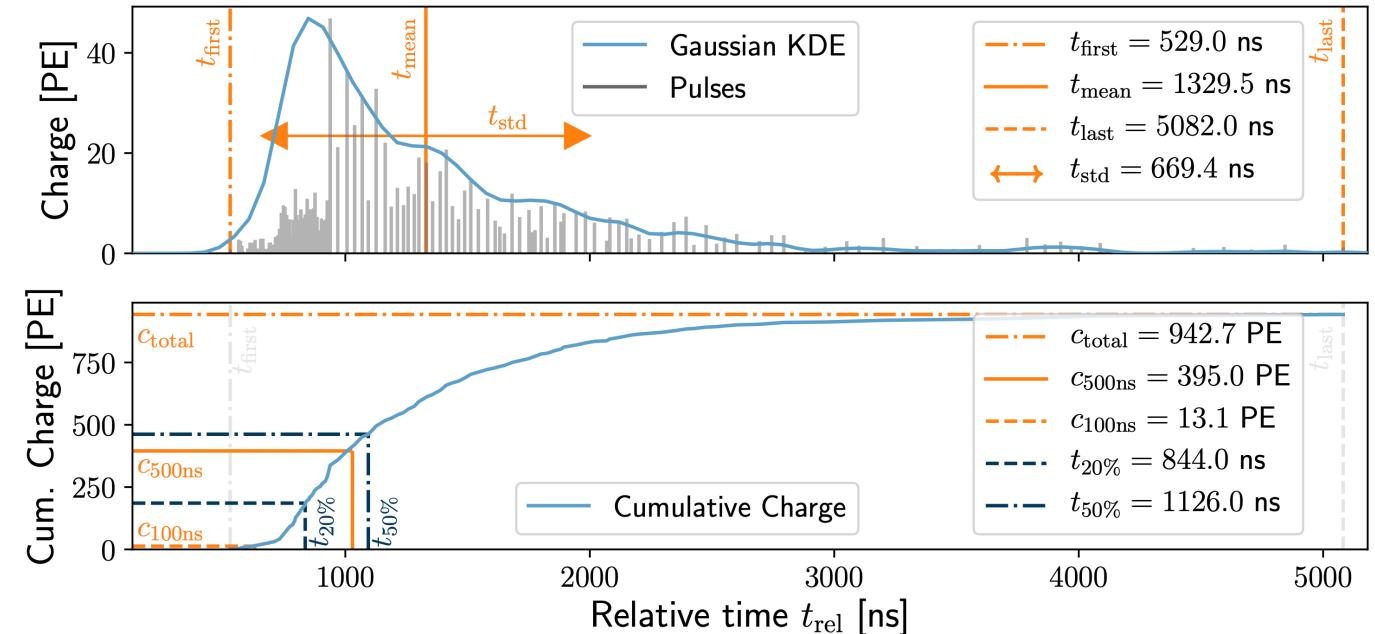
10.1088/1748-0221/16/07/P07041

3 inputs

- c_{total} : Total charge
 - Sum of charge
- t_{first} : Relative time of first pulse
 - Relative to total time offset, calculated as the charge weighted mean time of all pulses
- t_{std} : Standard deviation of first pulse
 - Charge weighted standard deviation of pulse times relative to total time offset

9 inputs

- t_{last} : Relative time of last pulse
 - Relative to total time offset, calculated as the charge weighted mean time of all pulses
- $t_{20\%}$: Relative time of 20% charge
 - Relative to total time offset, calculated as the charge weighted mean time of all pulses
- $t_{50\%}$: Relative time of 50% charge
 - Relative to total time offset, calculated as the charge weighted mean time of all pulses
- t_{mean} : Mean time
 - Charge weighted mean time of all pulses relative to total time offset
- $c_{500\text{ns}}$: Charge at 500ns
 - Sum of charge after 500ns
- $c_{100\text{ns}}$: Charge at 100ns
 - Sum of charge after 100ns



Input pulses

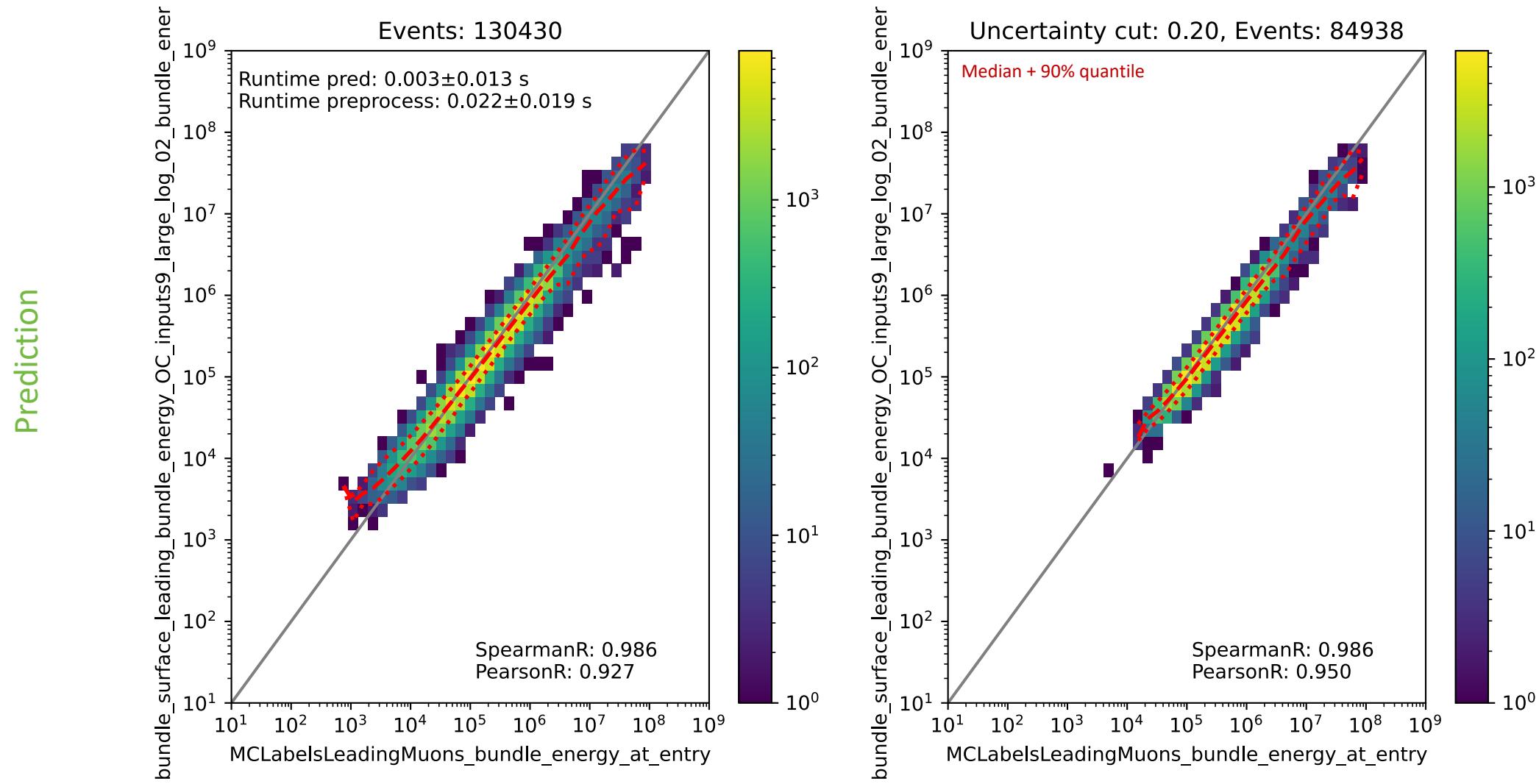
- SplitInIceDSTPulses
- SplitInIceDSTPulsesTWCleaning6000ns
- (DNN framework performs an internal cleaning)

Training datasets

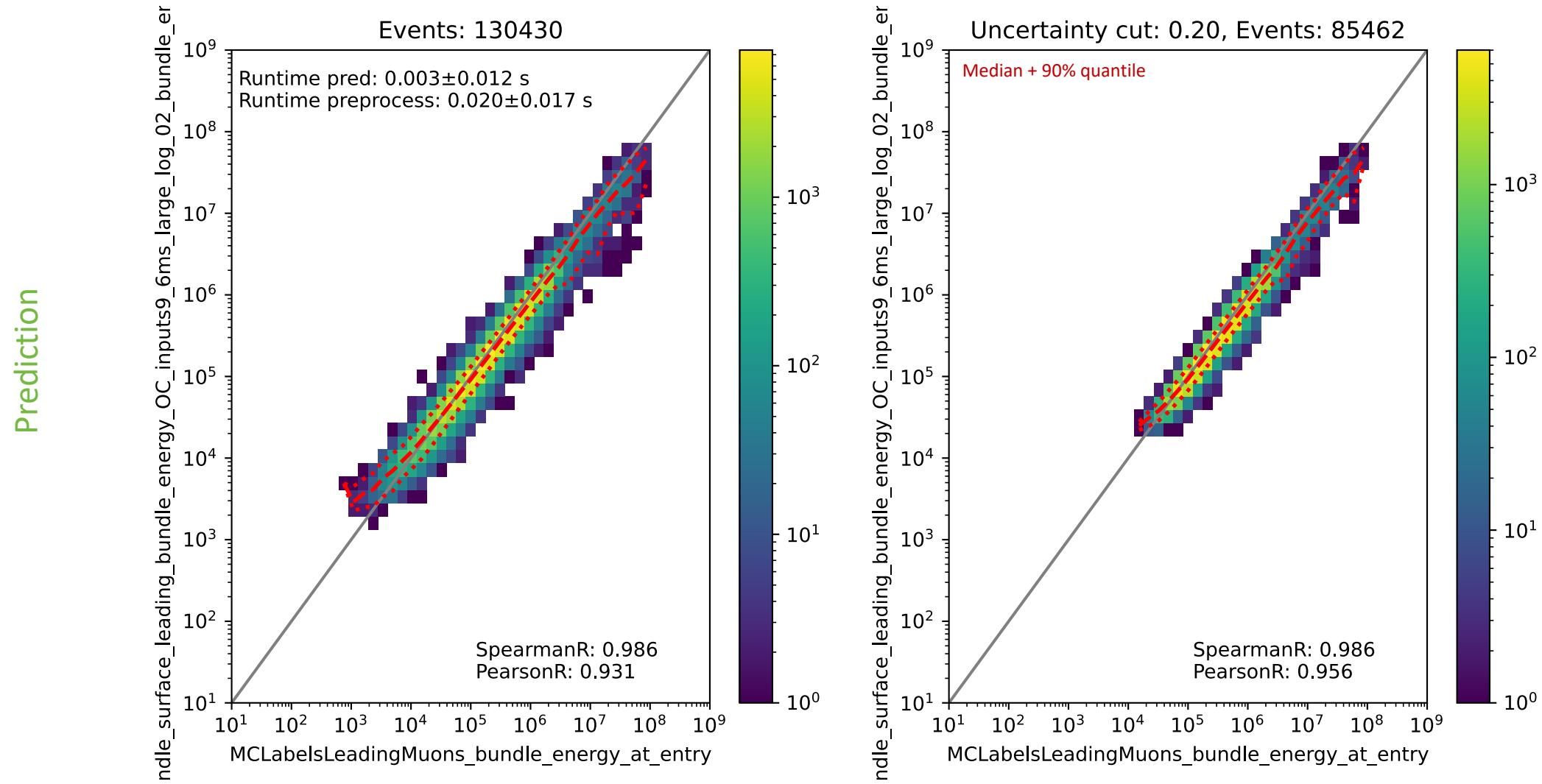
- 20904
- 21962
- 22020
- 22187

Network evaluation - Energy

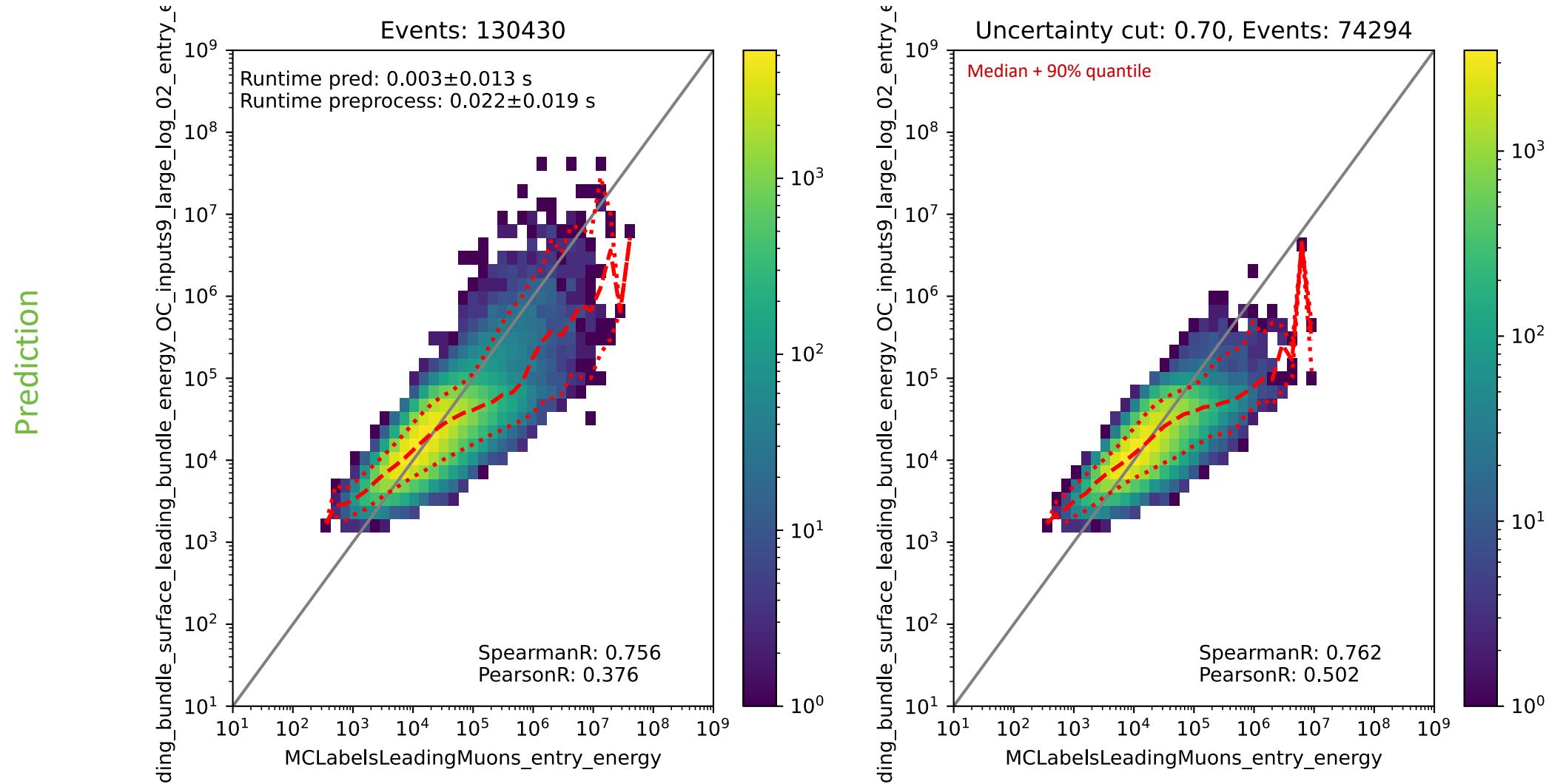
Bundle energy at entry – internal cleaned pulses



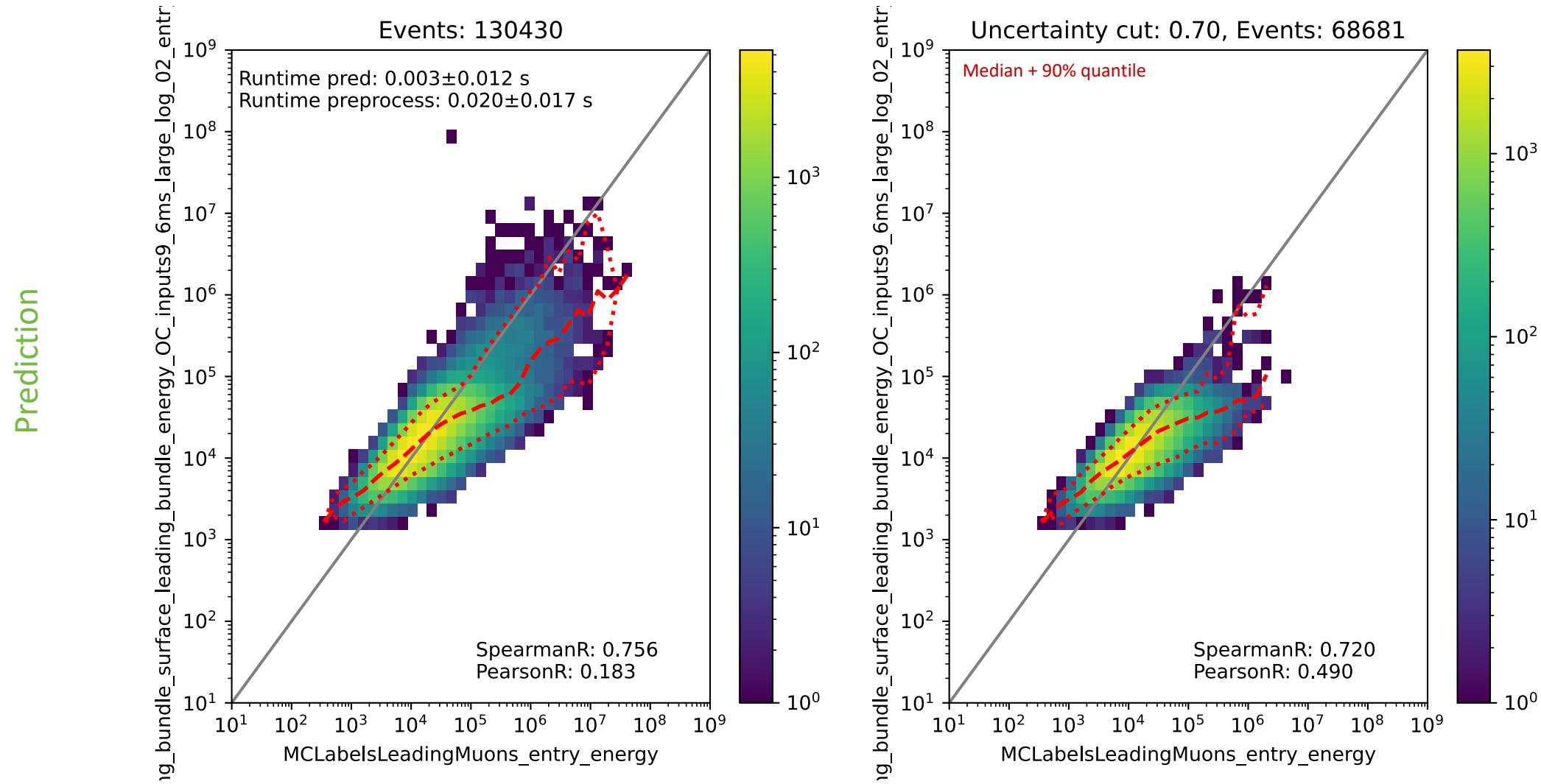
Bundle energy at entry – 6 ms cleaned pulses



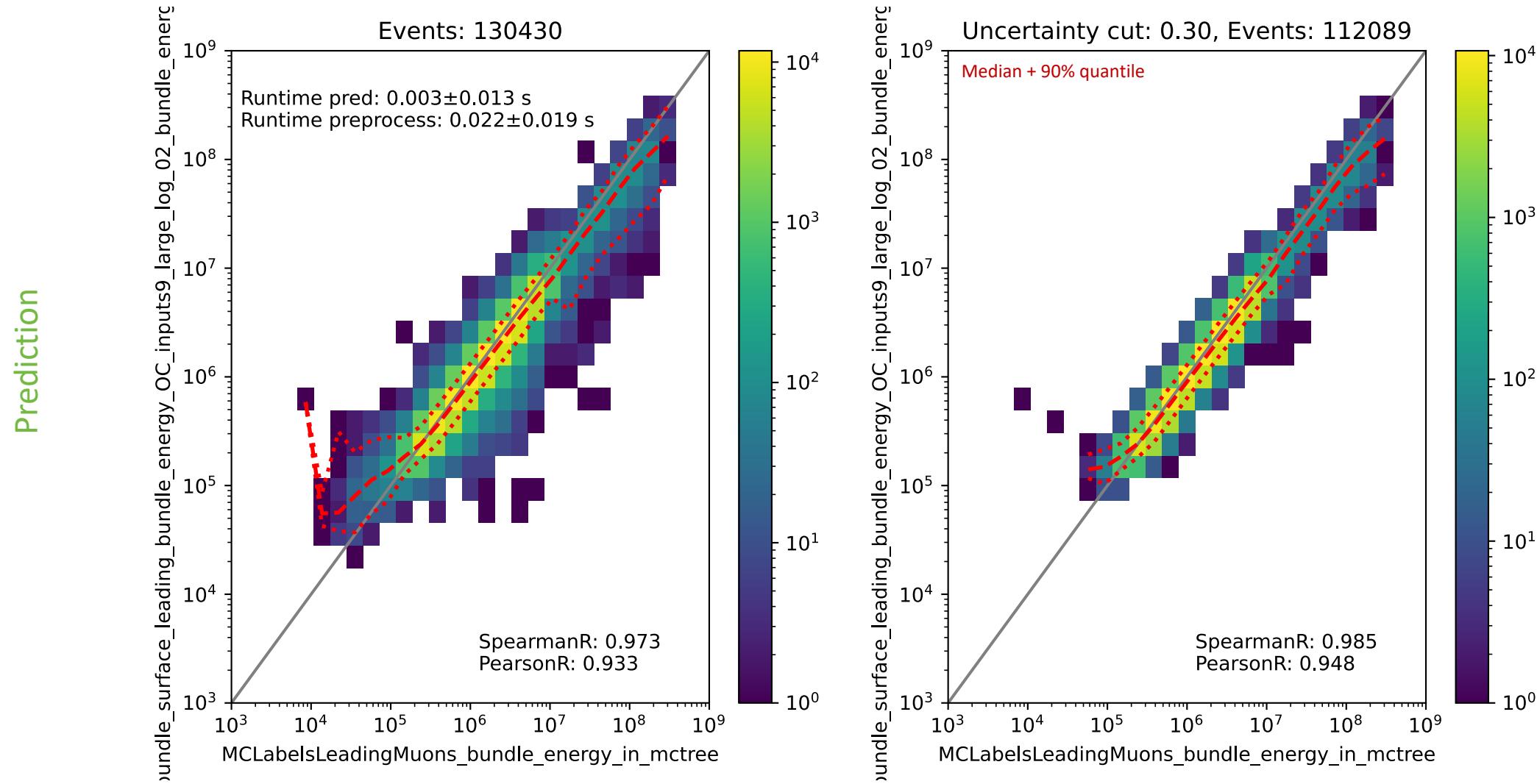
Leading muon energy at entry – internal cleaned pulses



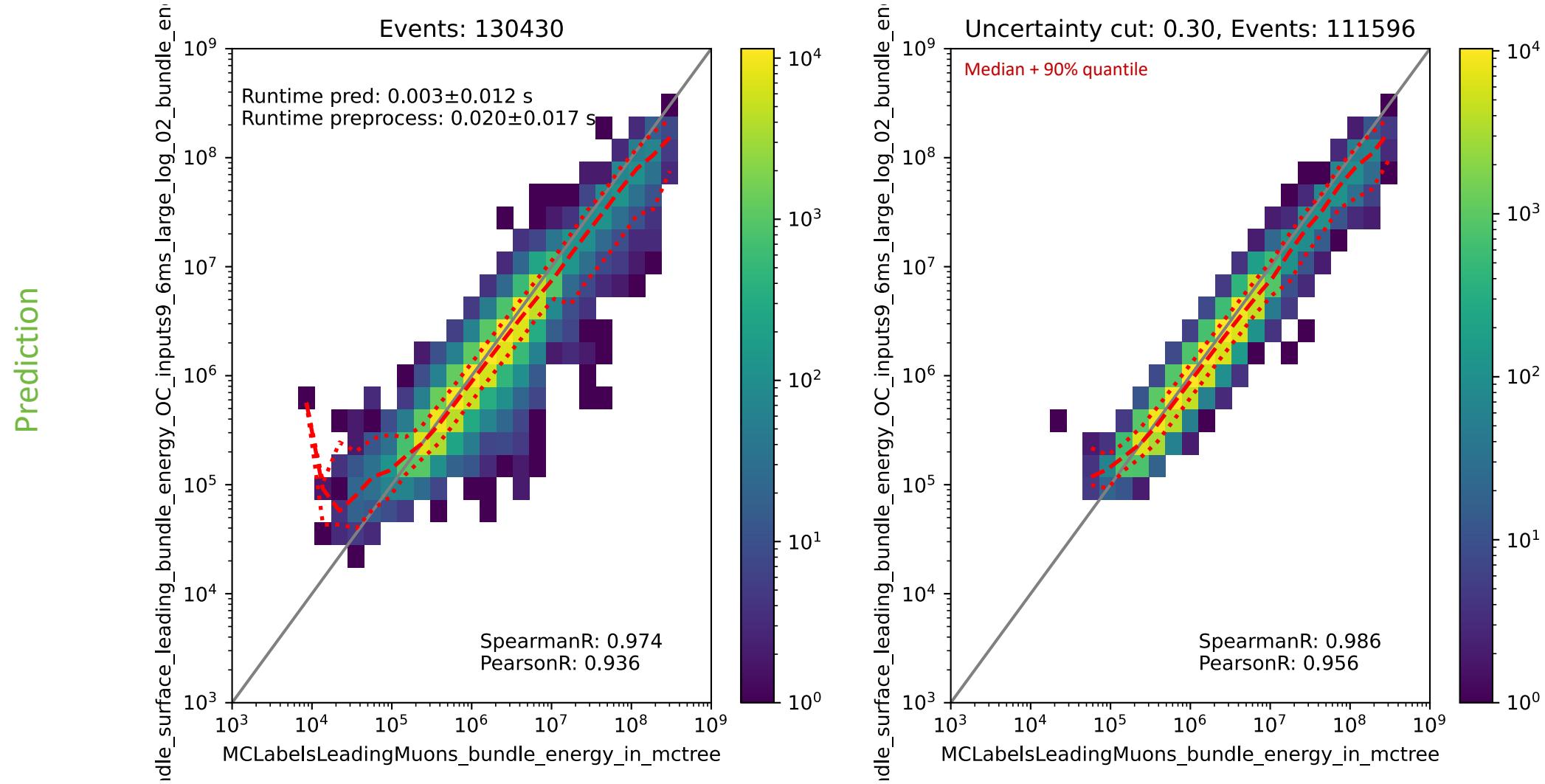
Leading muon energy at entry – 6 ms cleaned pulses



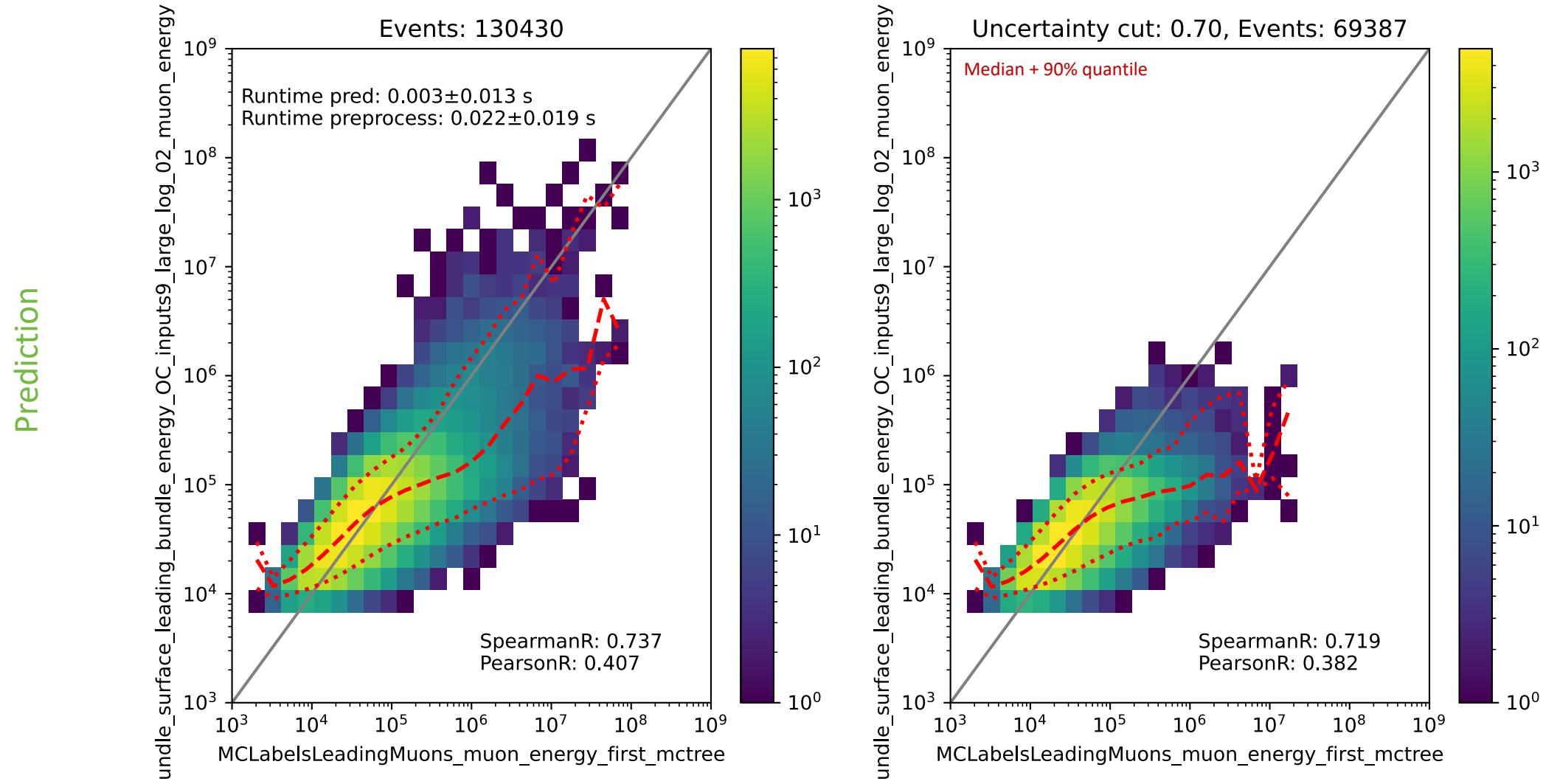
Bundle energy at surface – internal cleaned pulses



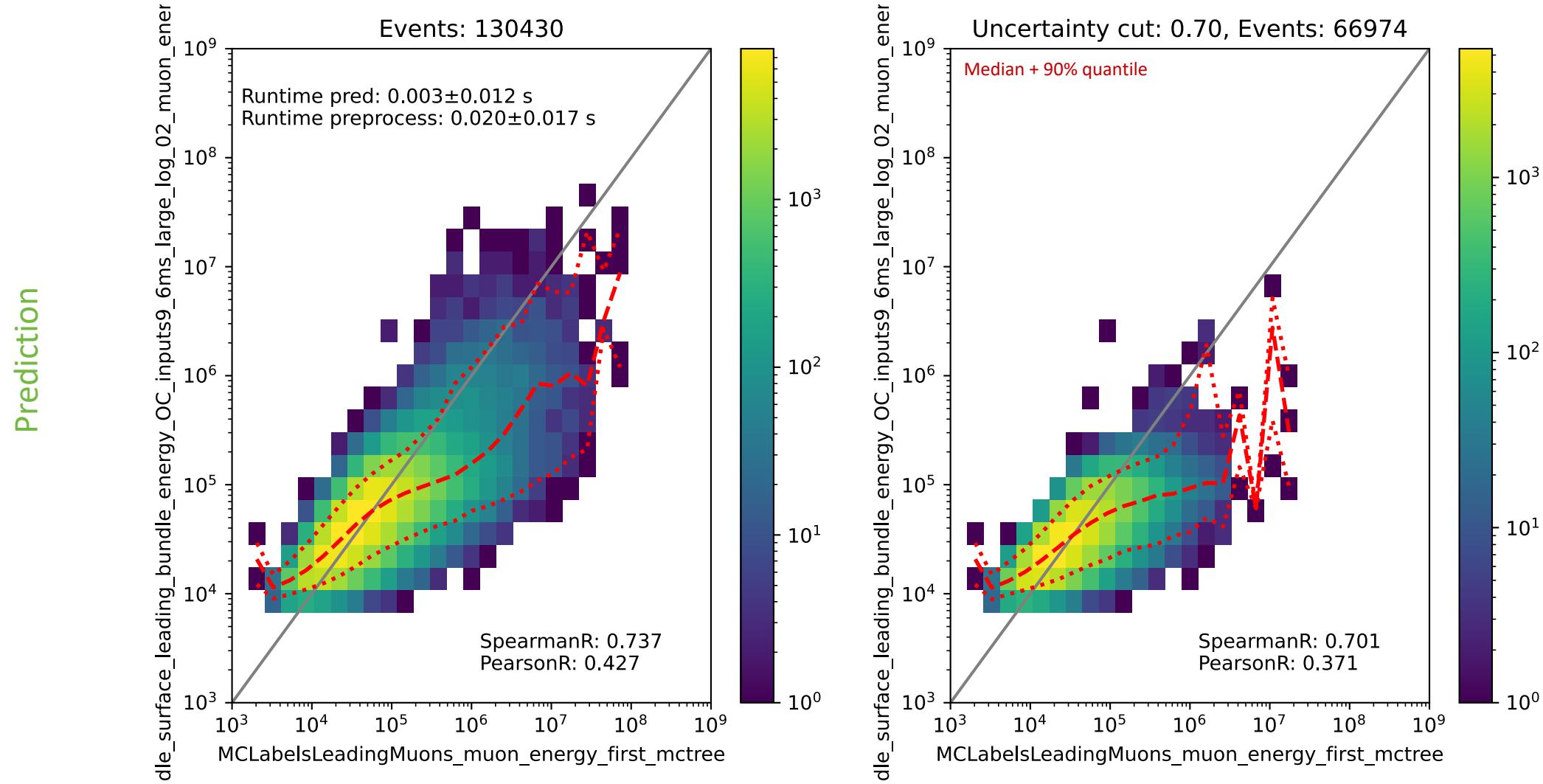
Bundle energy at surface – 6 ms cleaned pulses



Leading muon energy at surface – internal cleaned pulses

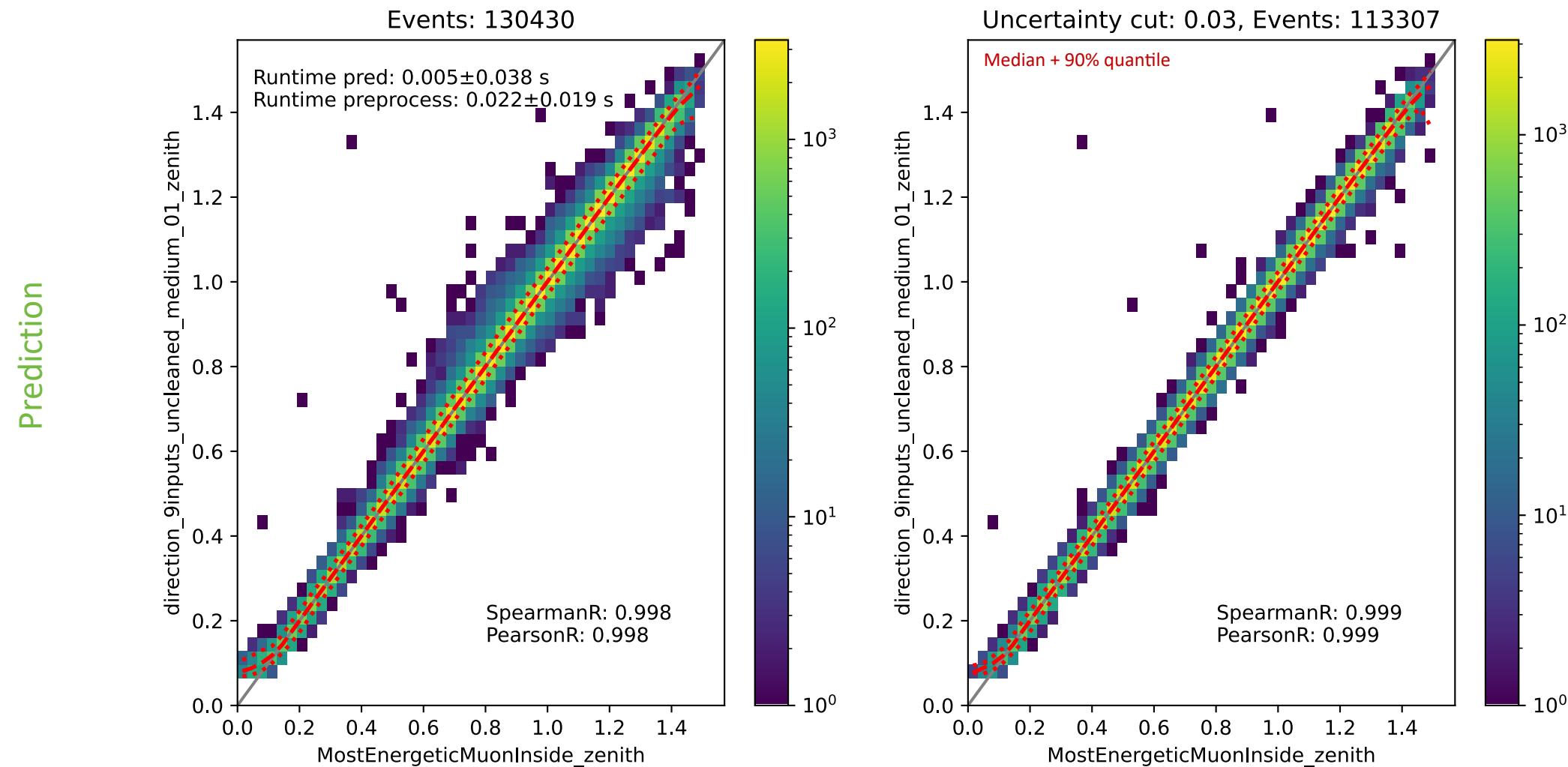


Leading muon energy at surface – 6 ms cleaned pulses

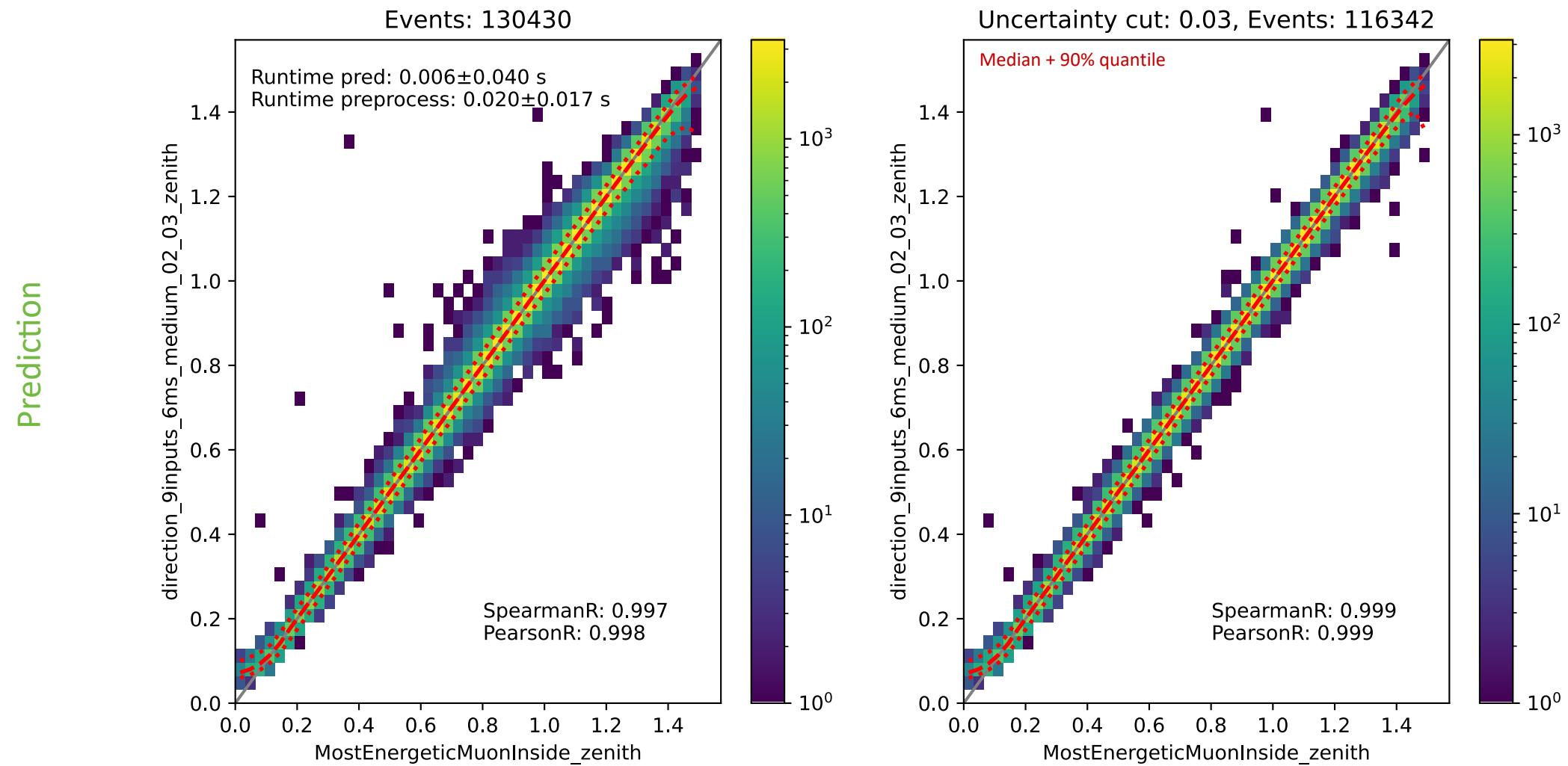


Network evaluation - Direction

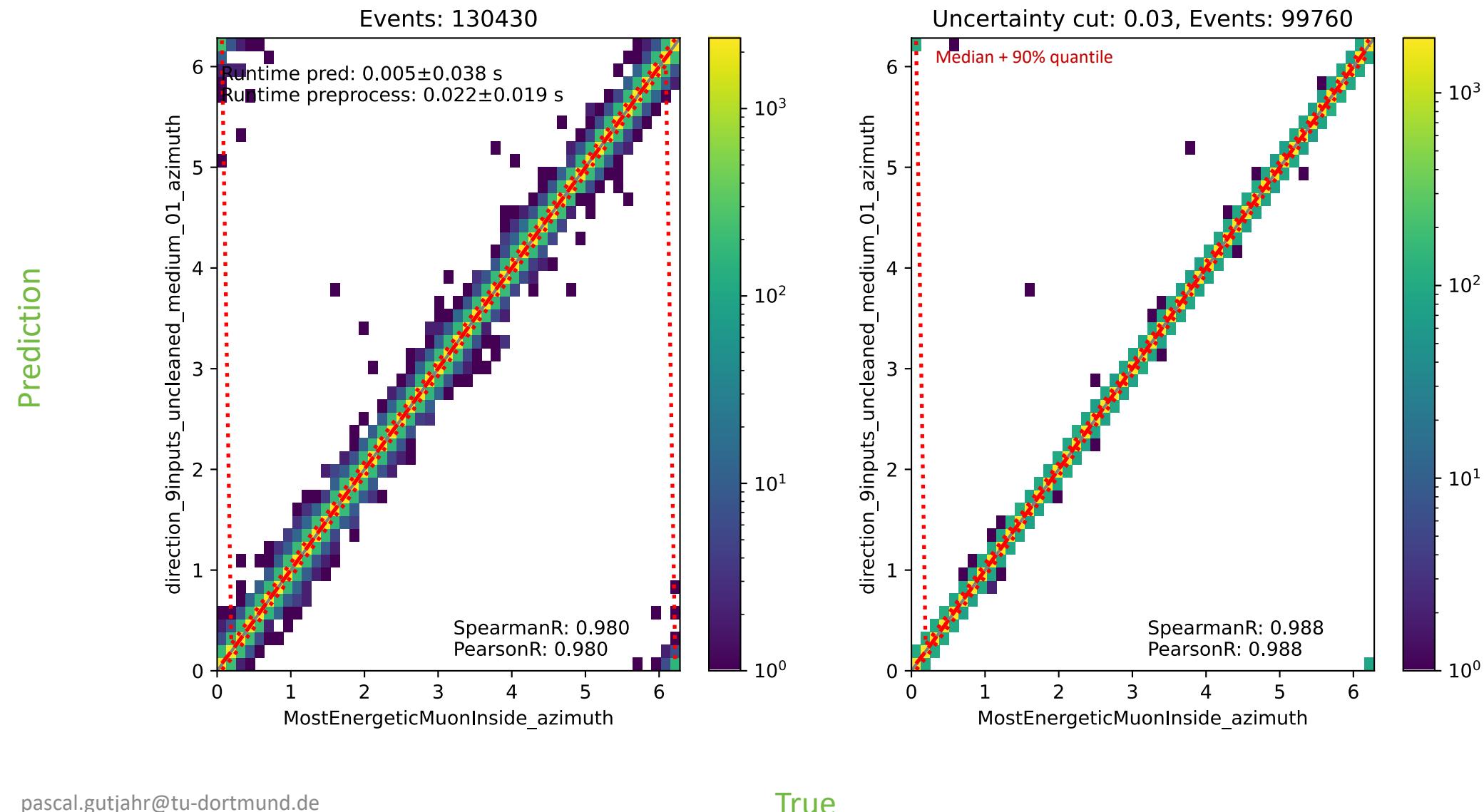
Zenith – internal cleaned pulses



Zenith – 6 ms cleaned pulses

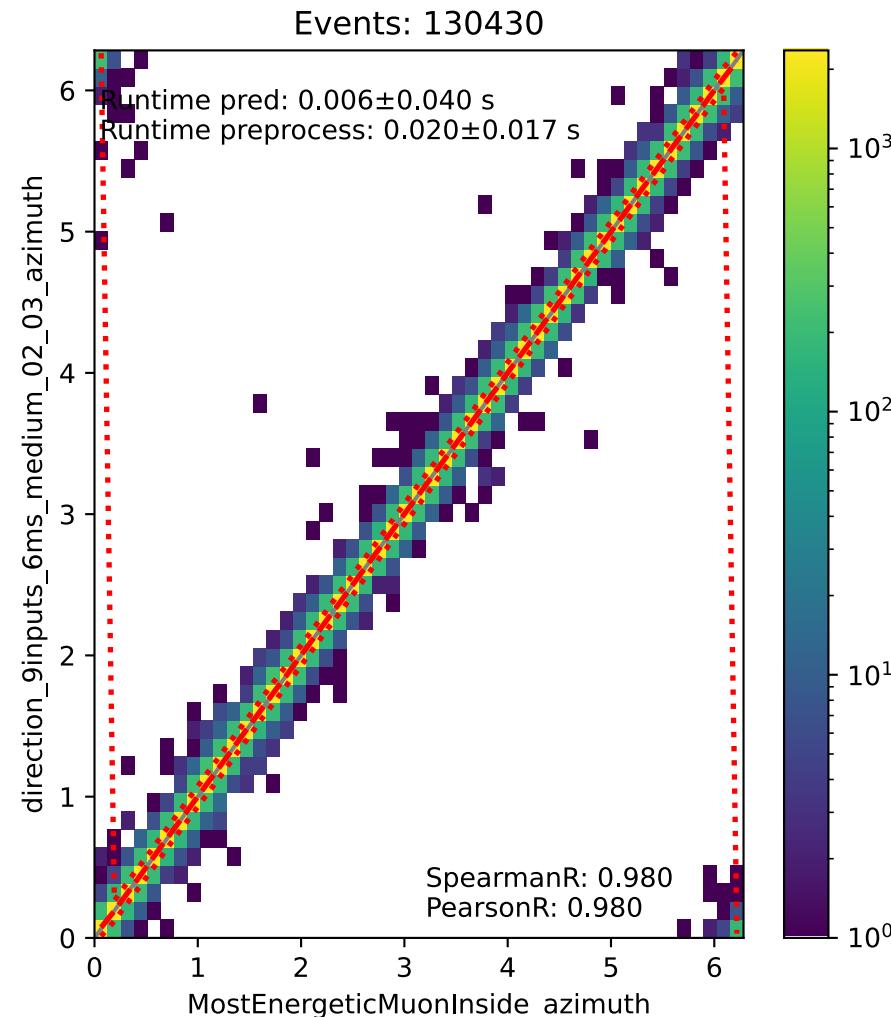


Azimuth – internal cleaned pulses

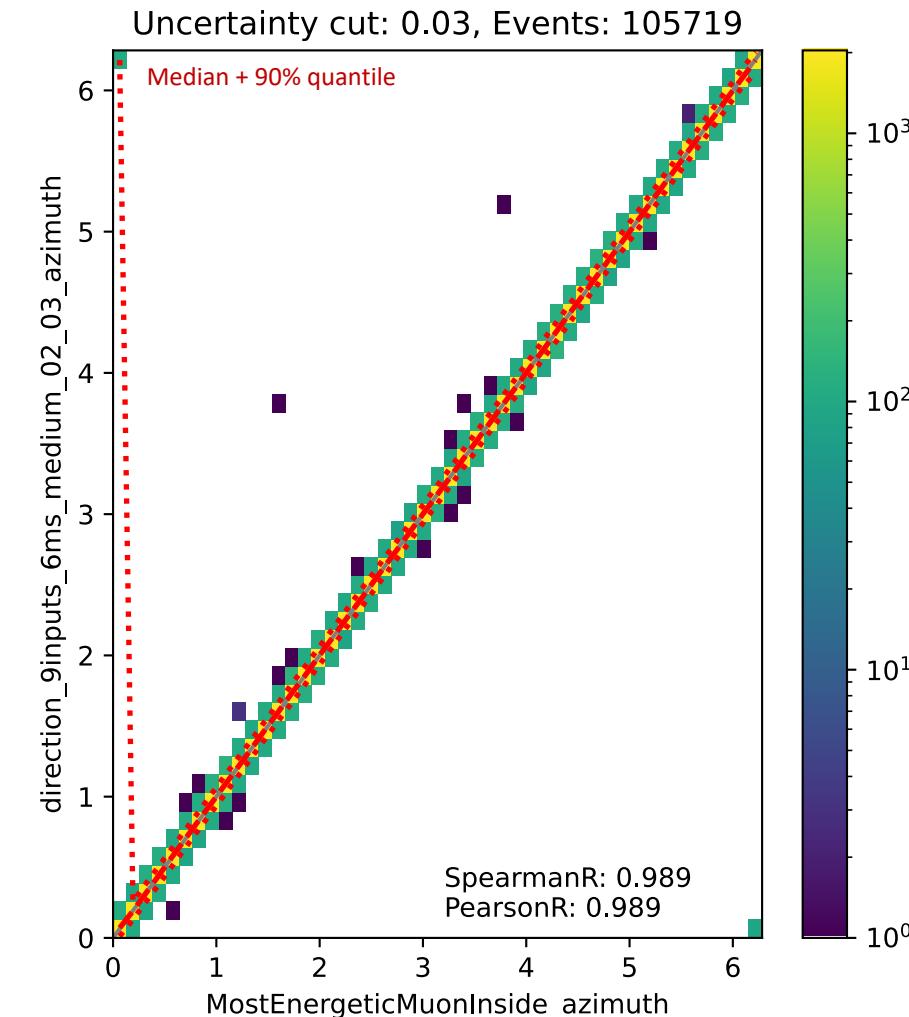


Azimuth – 6 ms cleaned pulses

Prediction

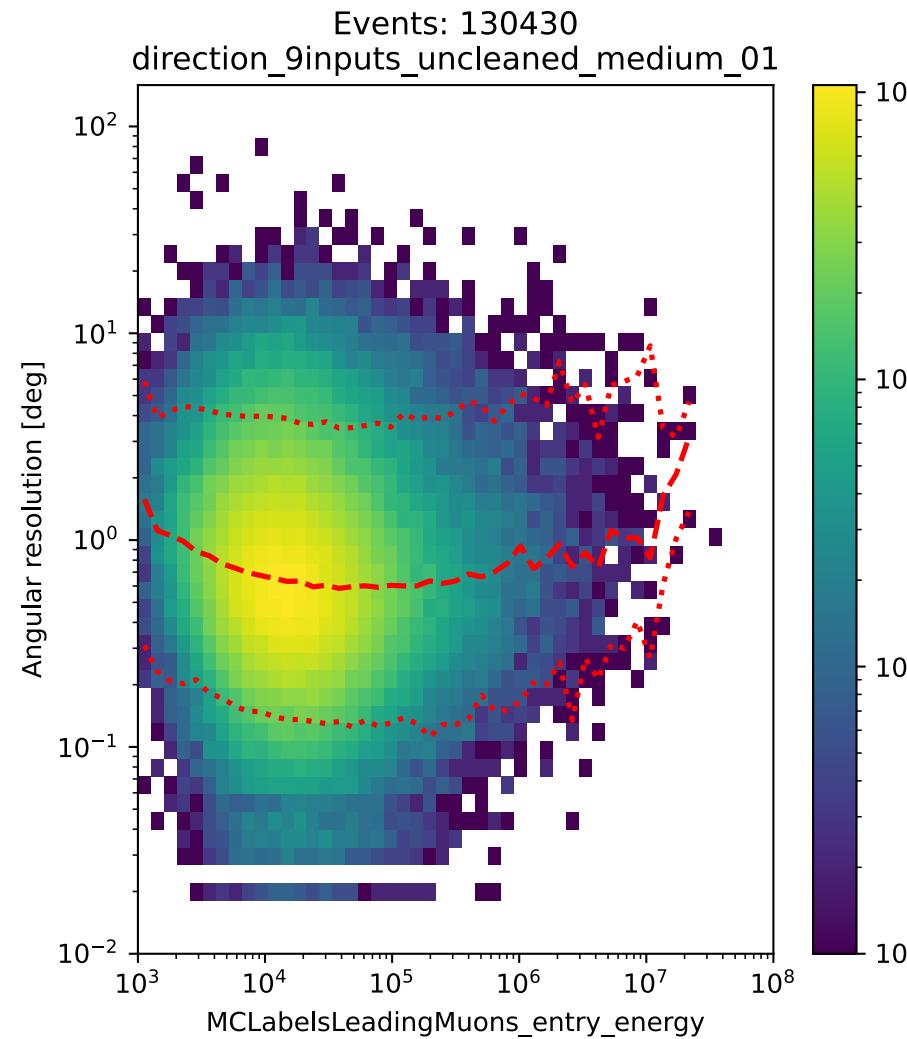


True

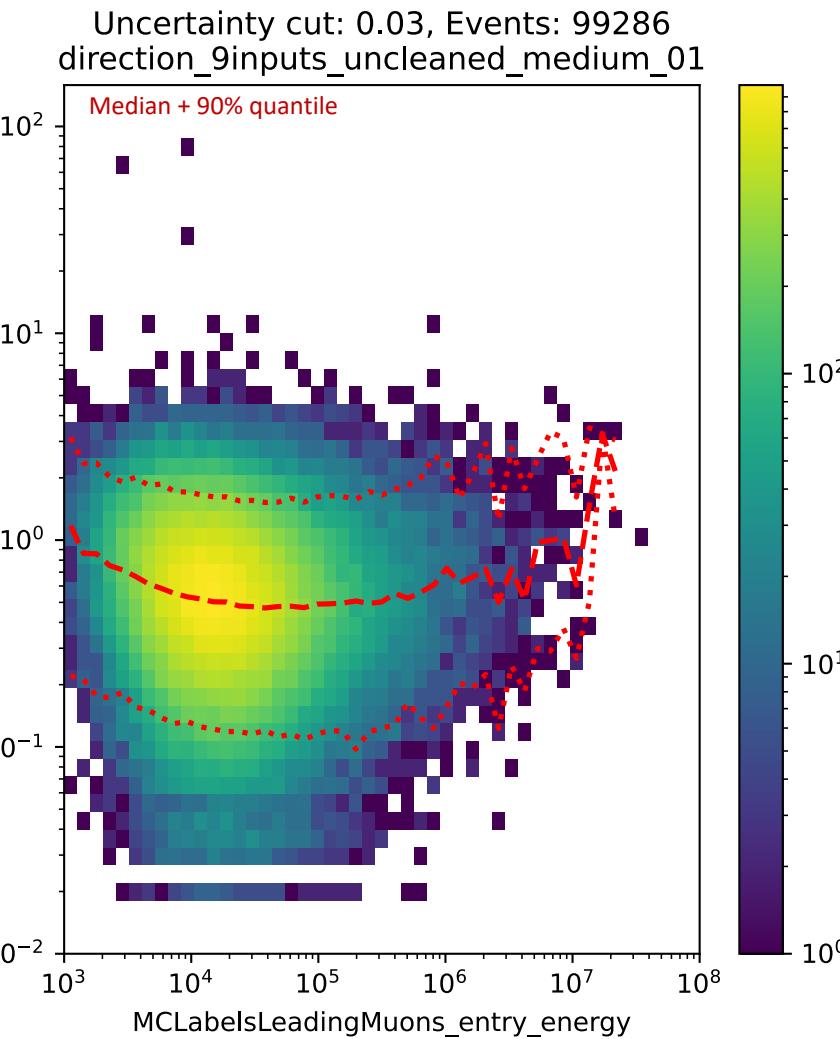


Angular resolution – internal cleaned pulses

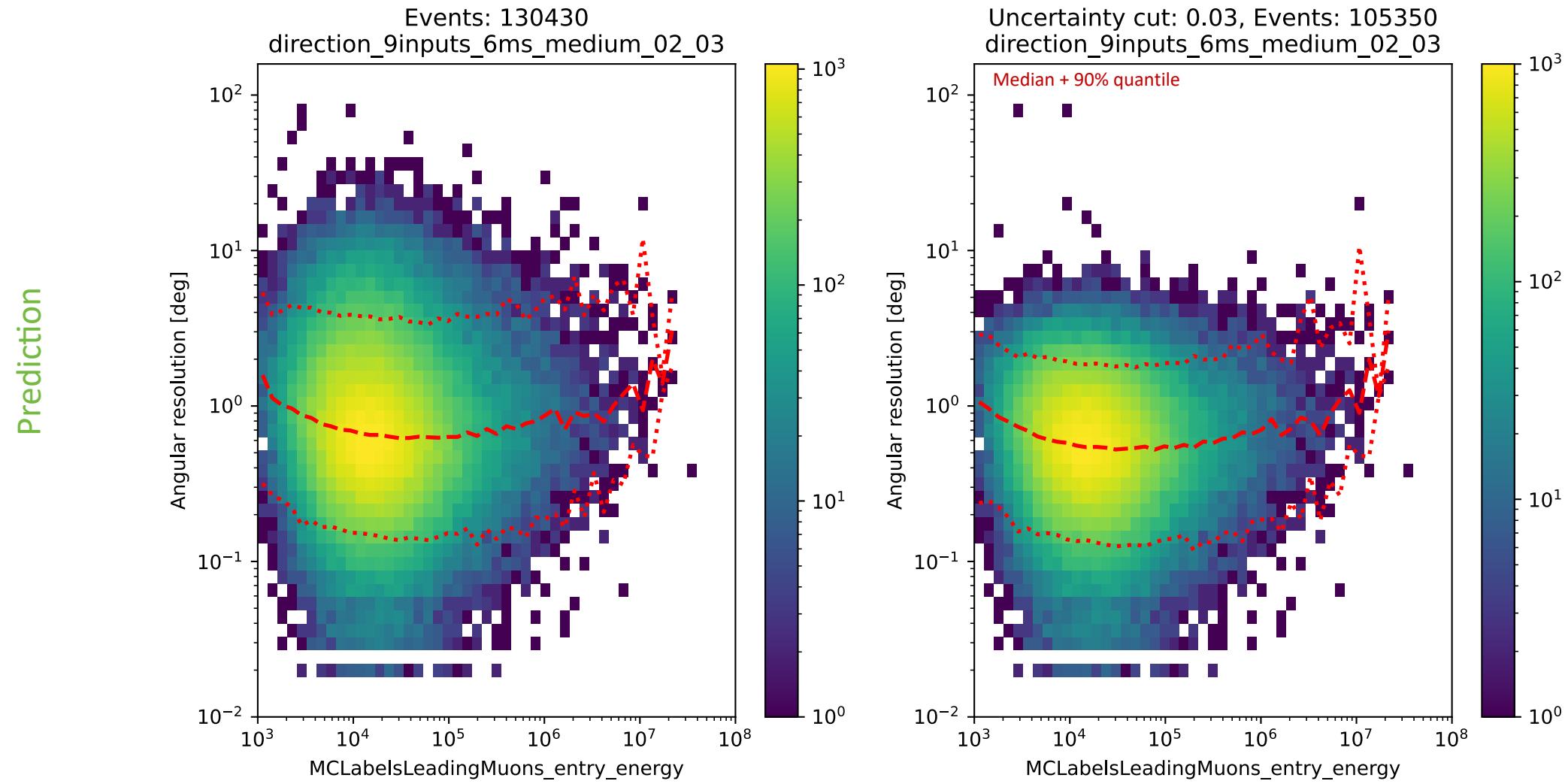
Prediction



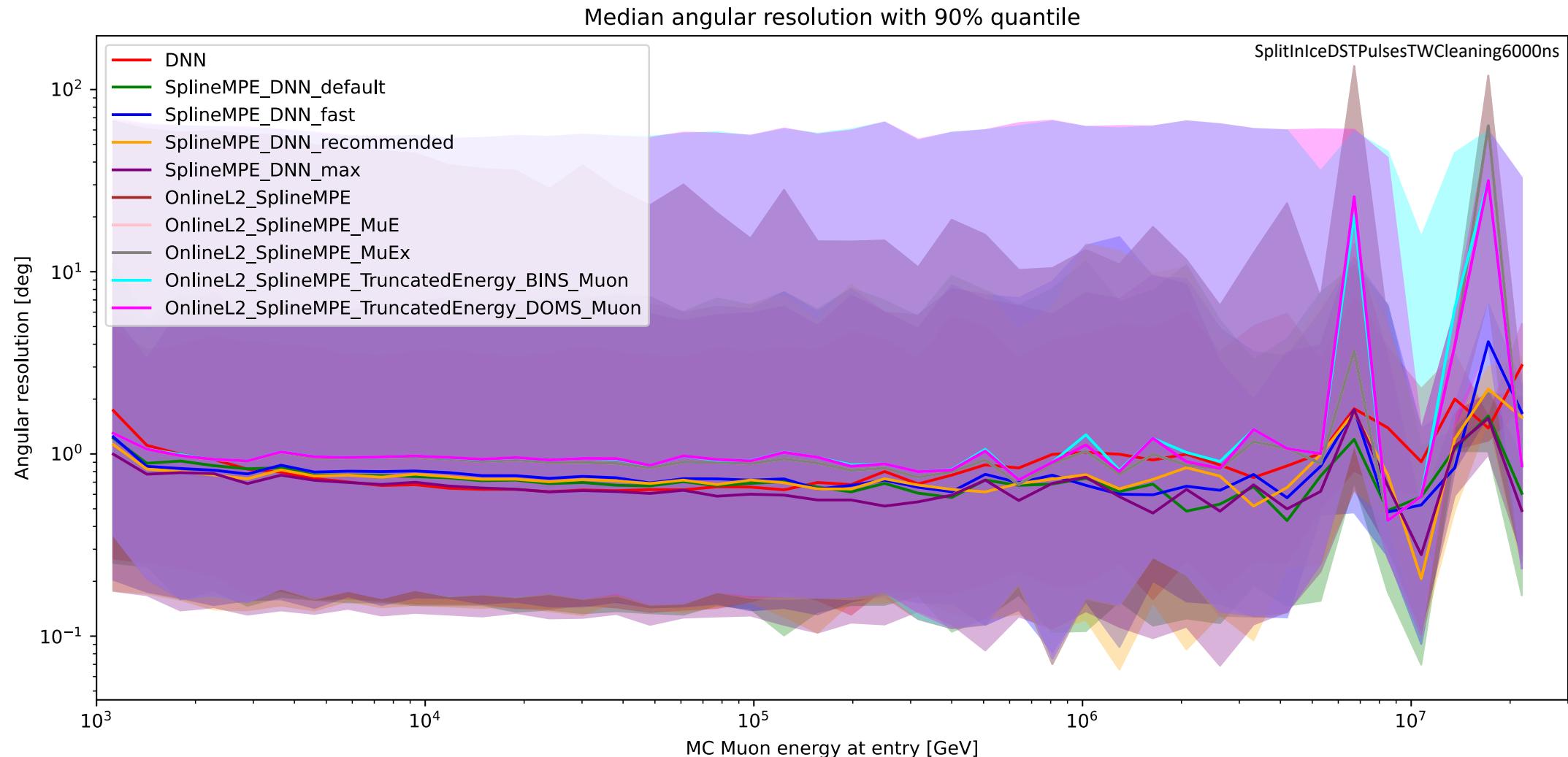
True



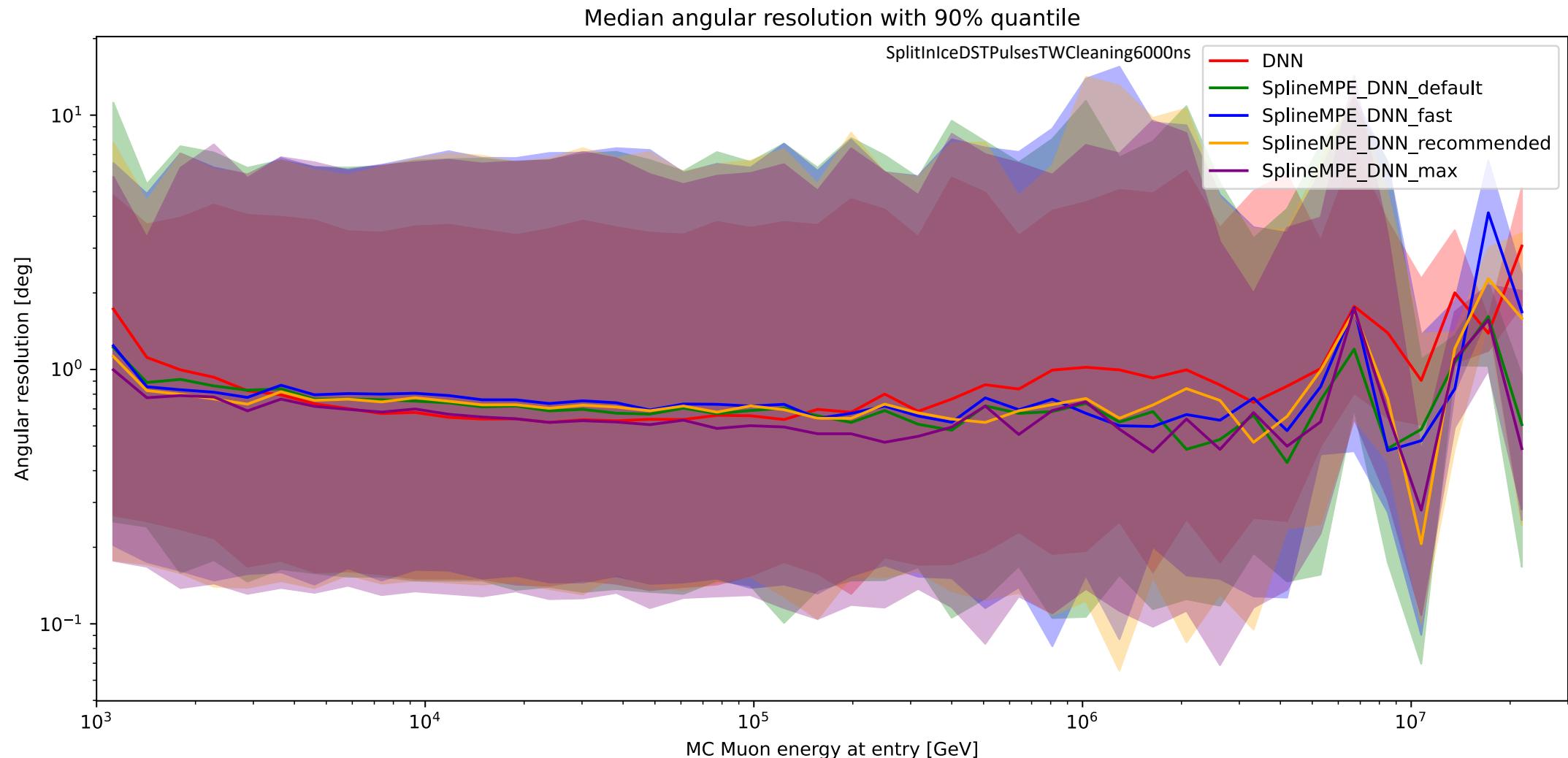
Angular resolution – 6 ms cleaned pulses



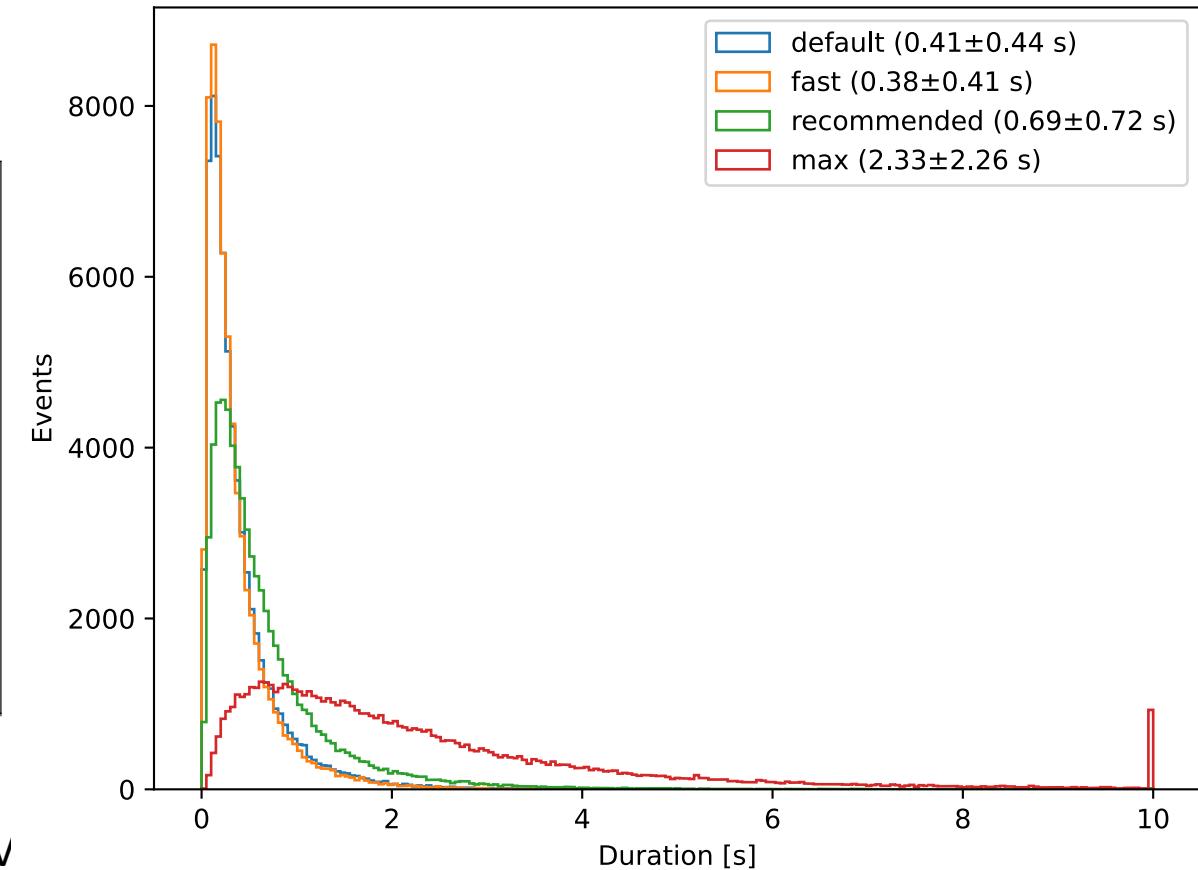
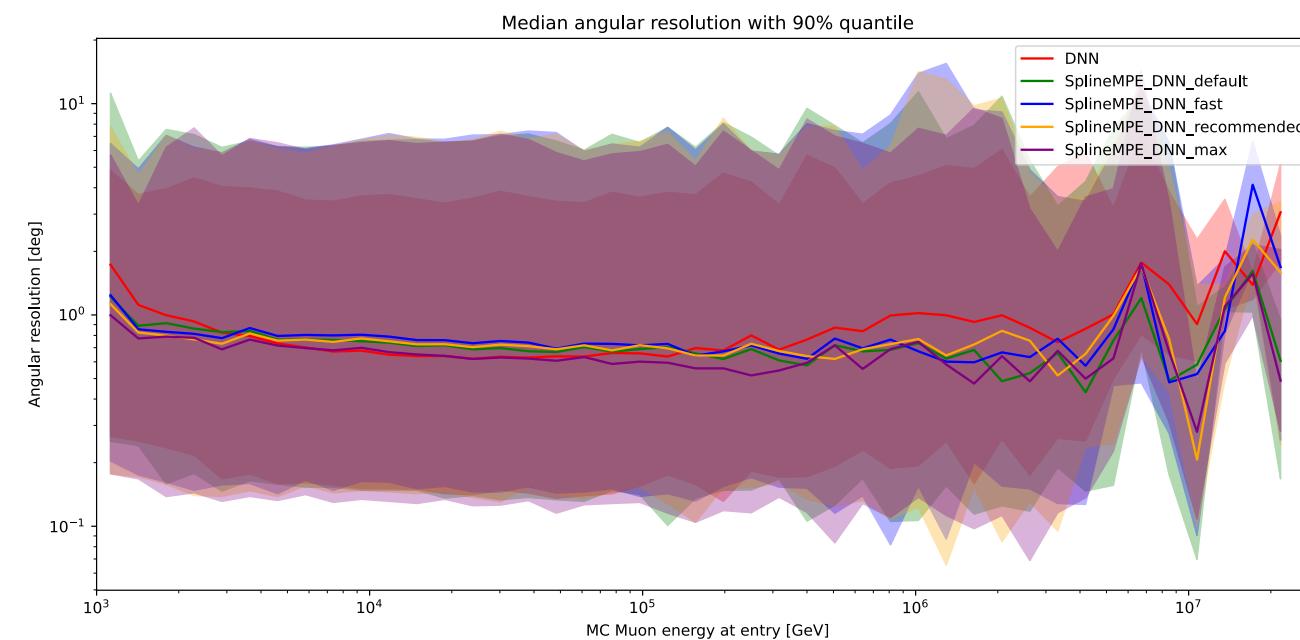
SplineMPE – DNN and conventional seeds



SplineMPE – DNN seeds



SplineMPE – duration per event



- Only small improvement at energies around 1 PeV
 - Contours are larger
 - Additional runtime
- > Use only DNN reconstruction, since we do not need the best angular resolution

Network evaluation – Track geometry

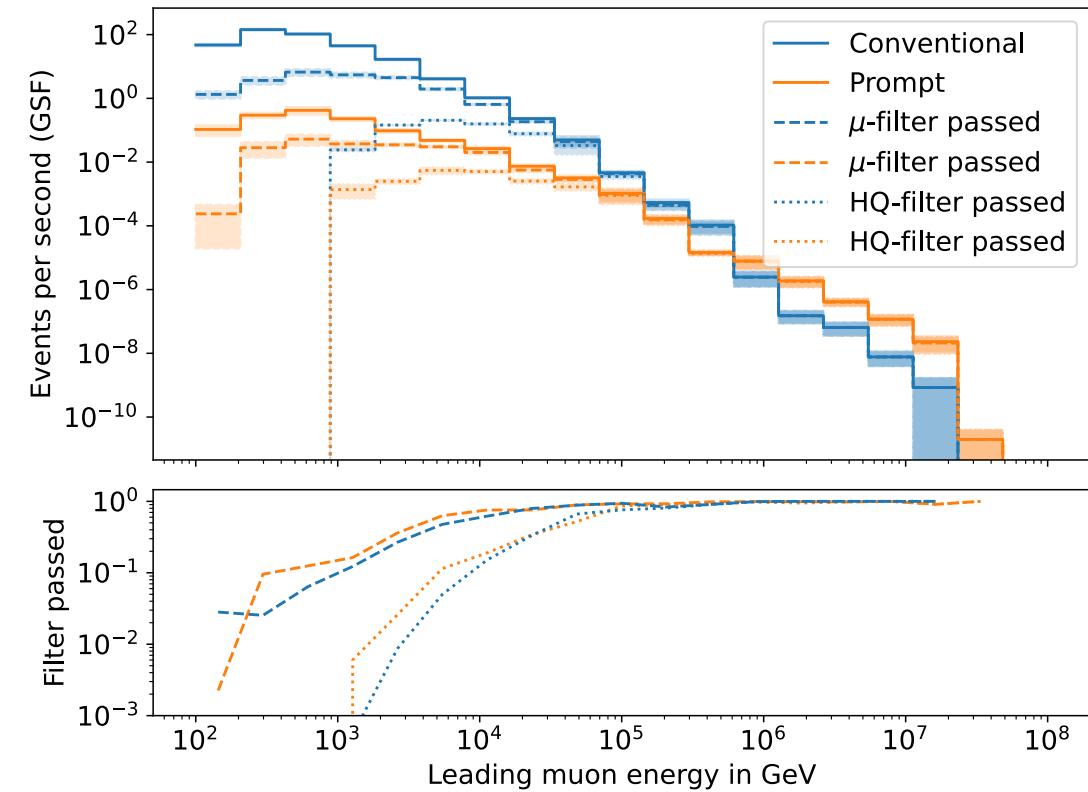
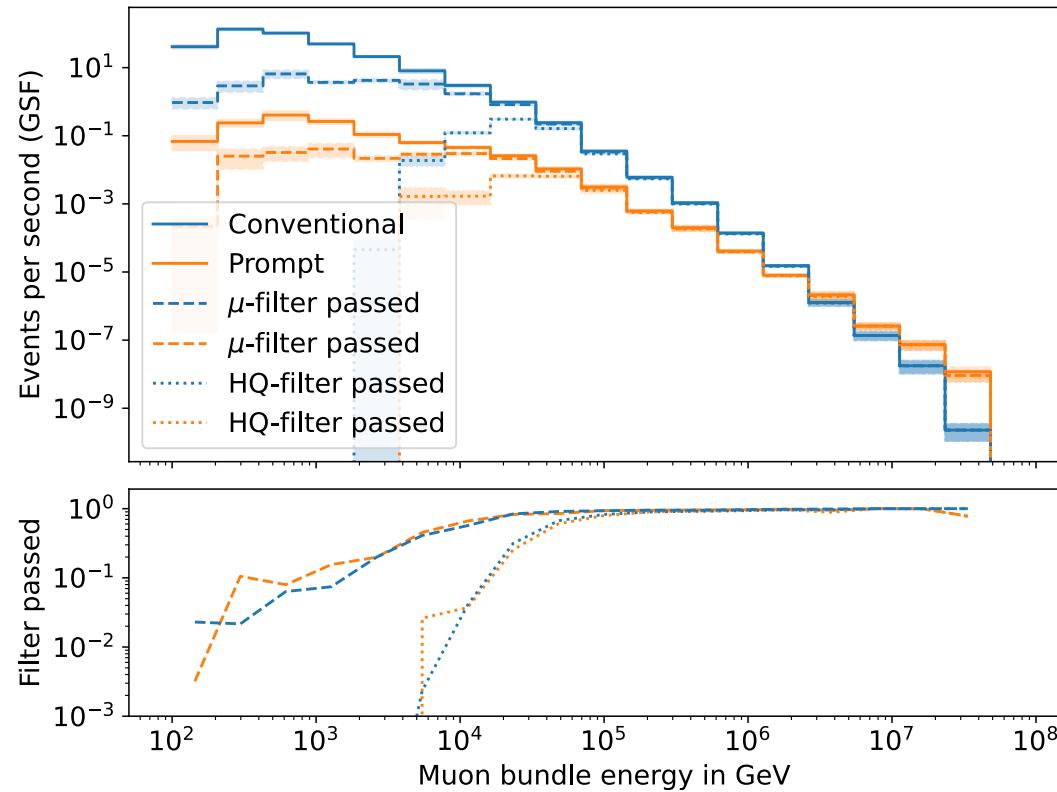
The evaluation of the track geometry works fine and can be found in the wiki

Selection – Level 3

1. L2 muon filter
2. 200 TeV bundle energy cut at surface
3. Add labels

L2 filter

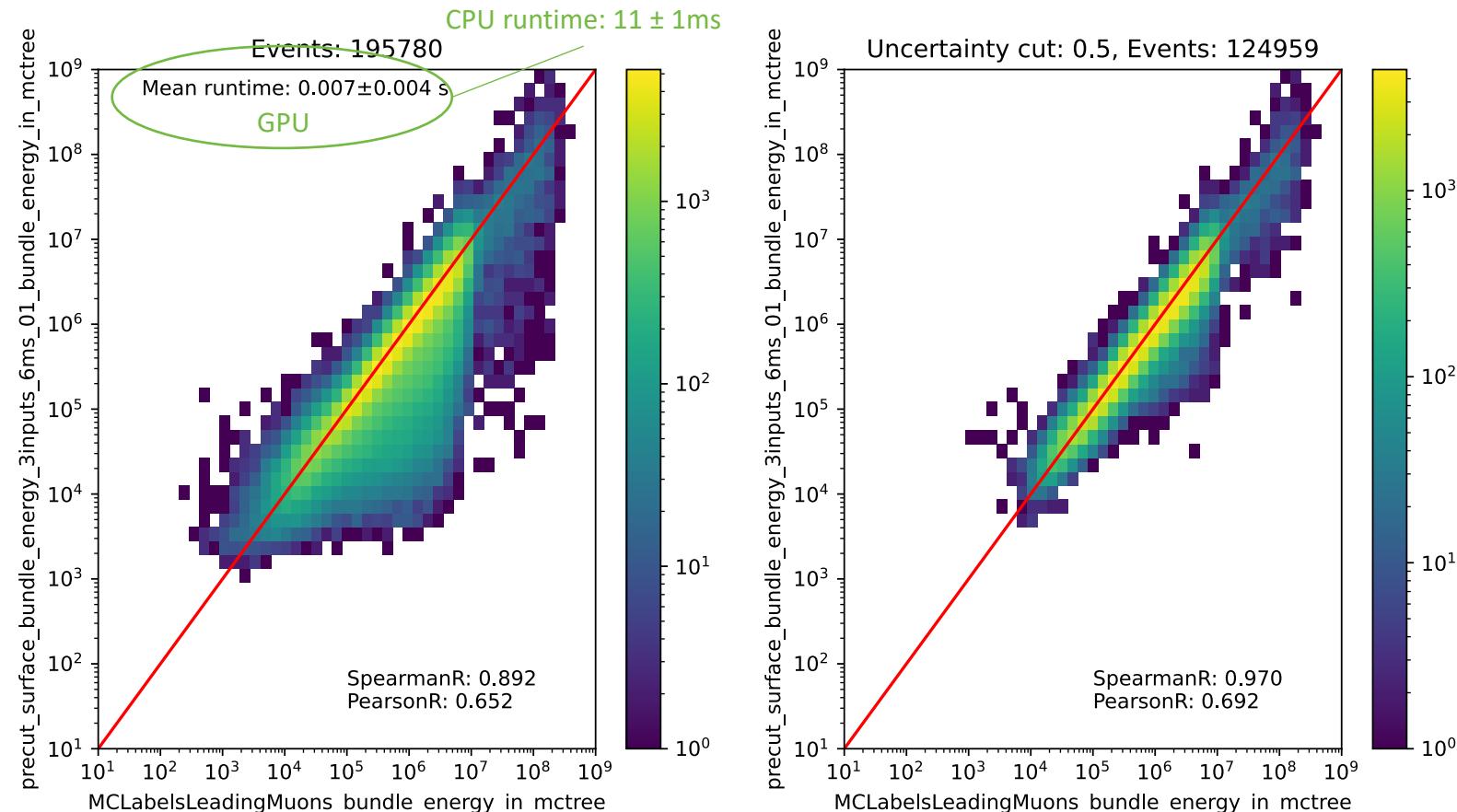
Fraction rejected events	All energies	Leading energy > 10 TeV	Leading energy > 100 TeV
MuonFilter	0.93	0.28	0.06
HQFilter	0.99	0.74	0.18



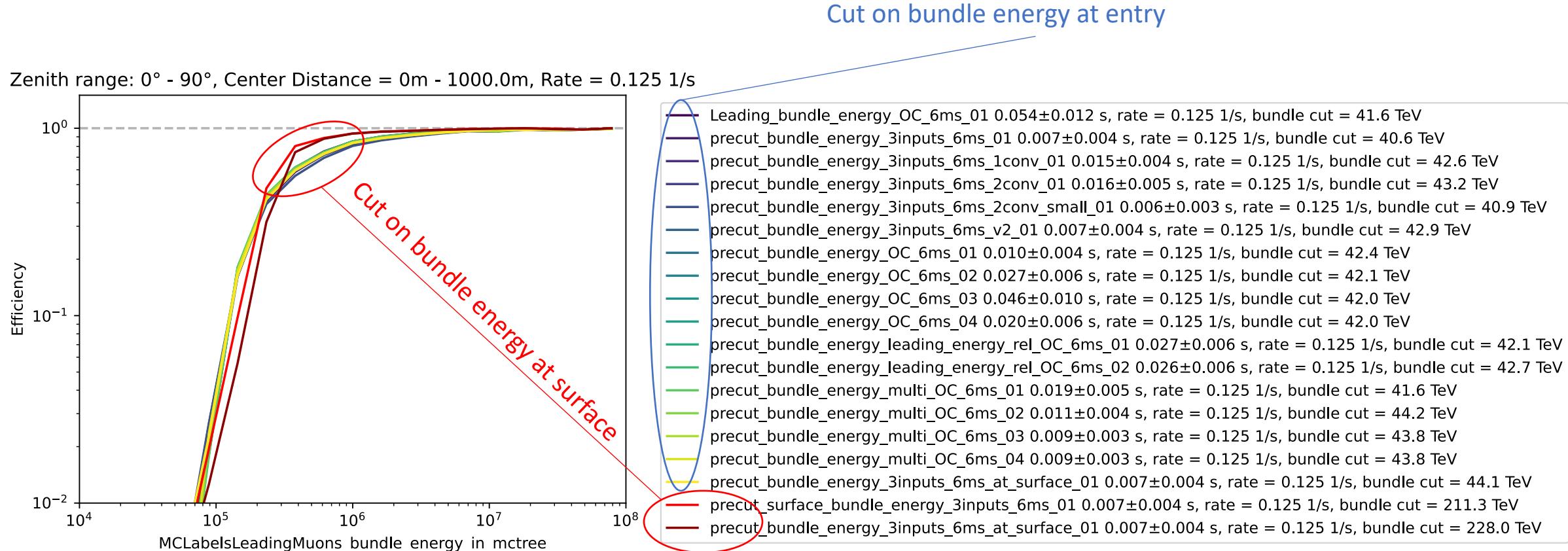
- L2 rate: 369.43 Hz
- Rate after muon filter: 24.62 Hz
- Choose muon filter to remove large amount of statistics at low energies

Bundle energy cut

- Rate after muon filter: 24.62 Hz
- If the process of 1 event needs 1 second, 8h run takes 200h -> needs to be reduced!
- Use small, fast network to remove low energy events -> target rate 125 mHz

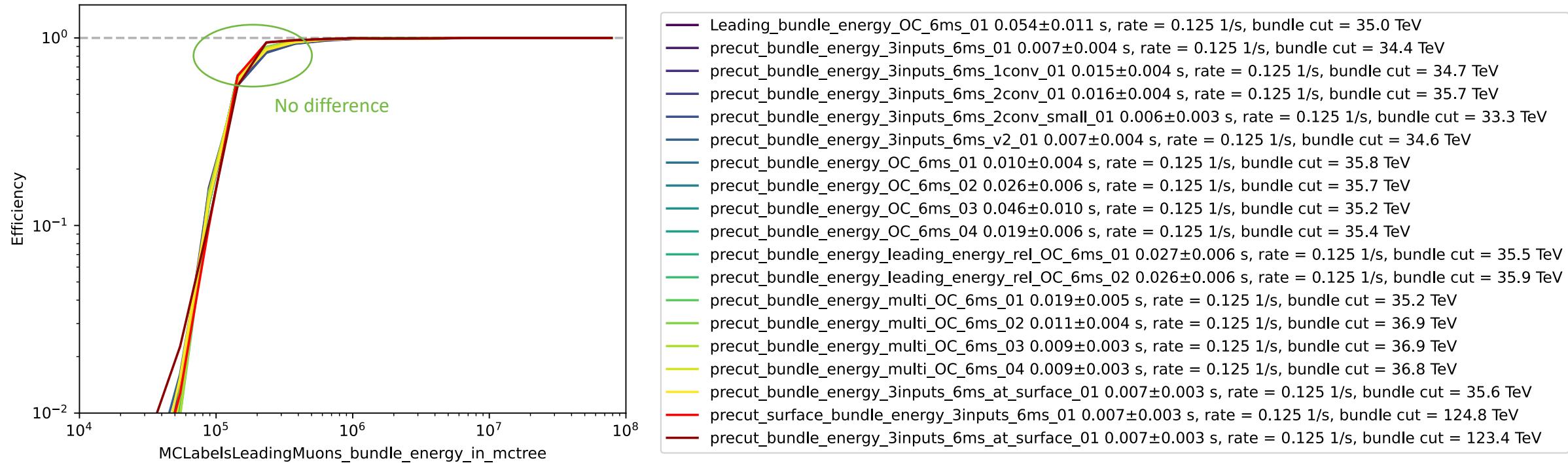


Rejection efficiency - all events



Rejection efficiency – small zenith

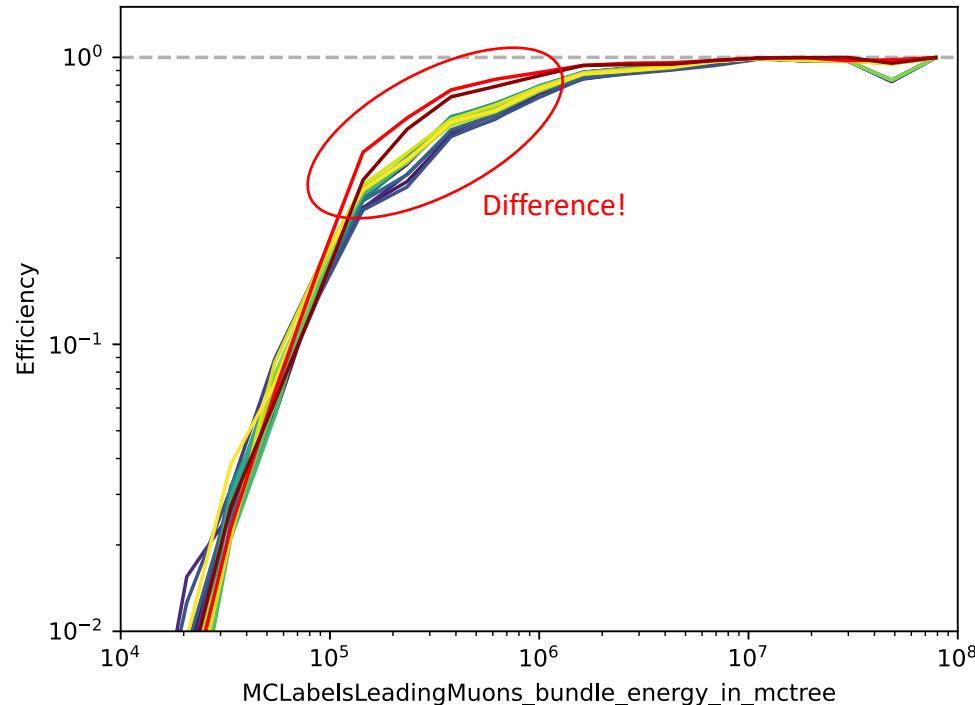
Zenith range: 0° - 45°, Center Distance = 0m - 1000.0m, Rate = 0.125 1/s



Rejection efficiency – high zenith

- At high zenith angles, events with high energies are removed with a cut on the **bundle energy at entry**

Zenith range: 70° - 90°, Center Distance = 0m - 1000.0m, Rate = 0.125 1/s



Leading_bundle_energy_OC_6ms_01	0.054 ± 0.012 s	rate = 0.125 1/s	bundle cut = 8.9 TeV
precut_bundle_energy_3inputs_6ms_01	0.007 ± 0.004 s	rate = 0.125 1/s	bundle cut = 9.3 TeV
precut_bundle_energy_3inputs_6ms_1conv_01	0.015 ± 0.004 s	rate = 0.126 1/s	bundle cut = 9.6 TeV
precut_bundle_energy_3inputs_6ms_2conv_01	0.017 ± 0.005 s	rate = 0.121 1/s	bundle cut = 8.6 TeV
precut_bundle_energy_3inputs_6ms_2conv_small_01	0.006 ± 0.003 s	rate = 0.125 1/s	bundle cut = 9.8 TeV
precut_bundle_energy_3inputs_6ms_v2_01	0.007 ± 0.004 s	rate = 0.125 1/s	bundle cut = 9.6 TeV
precut_bundle_energy_OC_6ms_01	0.010 ± 0.004 s	rate = 0.125 1/s	bundle cut = 9.0 TeV
precut_bundle_energy_OC_6ms_02	0.027 ± 0.007 s	rate = 0.125 1/s	bundle cut = 8.7 TeV
precut_bundle_energy_OC_6ms_03	0.046 ± 0.011 s	rate = 0.125 1/s	bundle cut = 8.5 TeV
precut_bundle_energy_OC_6ms_04	0.020 ± 0.006 s	rate = 0.127 1/s	bundle cut = 8.7 TeV
precut_bundle_energy_leading_energy_rel_OC_6ms_01	0.027 ± 0.007 s	rate = 0.125 1/s	bundle cut = 8.8 TeV
precut_bundle_energy_leading_energy_rel_OC_6ms_02	0.027 ± 0.006 s	rate = 0.125 1/s	bundle cut = 9.0 TeV
precut_bundle_energy_multi_OC_6ms_01	0.019 ± 0.005 s	rate = 0.125 1/s	bundle cut = 8.8 TeV
precut_bundle_energy_multi_OC_6ms_02	0.011 ± 0.004 s	rate = 0.125 1/s	bundle cut = 8.8 TeV
precut_bundle_energy_multi_OC_6ms_03	0.009 ± 0.003 s	rate = 0.125 1/s	bundle cut = 8.6 TeV
precut_bundle_energy_multi_OC_6ms_04	0.009 ± 0.003 s	rate = 0.129 1/s	bundle cut = 8.3 TeV
precut_bundle_energy_3inputs_6ms_at_surface_01	0.007 ± 0.004 s	rate = 0.122 1/s	bundle cut = 8.5 TeV
precut_surface_bundle_energy_3inputs_6ms_01	0.007 ± 0.004 s	rate = 0.125 1/s	bundle cut = 100.9 TeV
precut_bundle_energy_3inputs_6ms_at_surface_01	0.007 ± 0.004 s	rate = 0.125 1/s	bundle cut = 106.5 TeV

- Rate after muon filter: 24.62 Hz
- Rate after bundle cut: 144 mHz
- Perform 200 TeV cut on bundle energy at surface

Selection – Level 4

1. Add DNN network reconstructions

Add DNN networks

- Internal DNN pulse cleaning leads to slightly better results

Network	Preprocess / ms	CPU / ms	GPU / ms
direction_9inputs_uncleaned_medium_01	22 ± 20	106 ± 42	5 ± 38
leading_bundle_surface_leading_bundle_energy_OC_inputs9_large_log_02	22 ± 20	144 ± 56	3 ± 13
track_geometry_9inputs_uncleaned_01	22 ± 20	106 ± 42	3 ± 10
precut_surface_bundle_energy_3inputs_6ms_01 (added in level 3)	22 ± 20	11 ± 1	7 ± 4

What we have discussed today

- Reconstruction
 - Trained networks to reconstruct several properties
- Selection
 - Level 3 (L2MuonFilter + 200 TeV bundle energy cut at surface)
 - Level 4 (add reconstructions)
- Data-MC
 - Check several properties
 - Largest mismatch in z-vertex
- Forward fit
 - Test NNMFit for analysis
- Unfolding
 - Unfold event rate
 - Calculate effective area
- New simulations
 - Preparation for large scale IceProd simulation (latest software, switch some options)
- Wiki
 - Created and uploaded

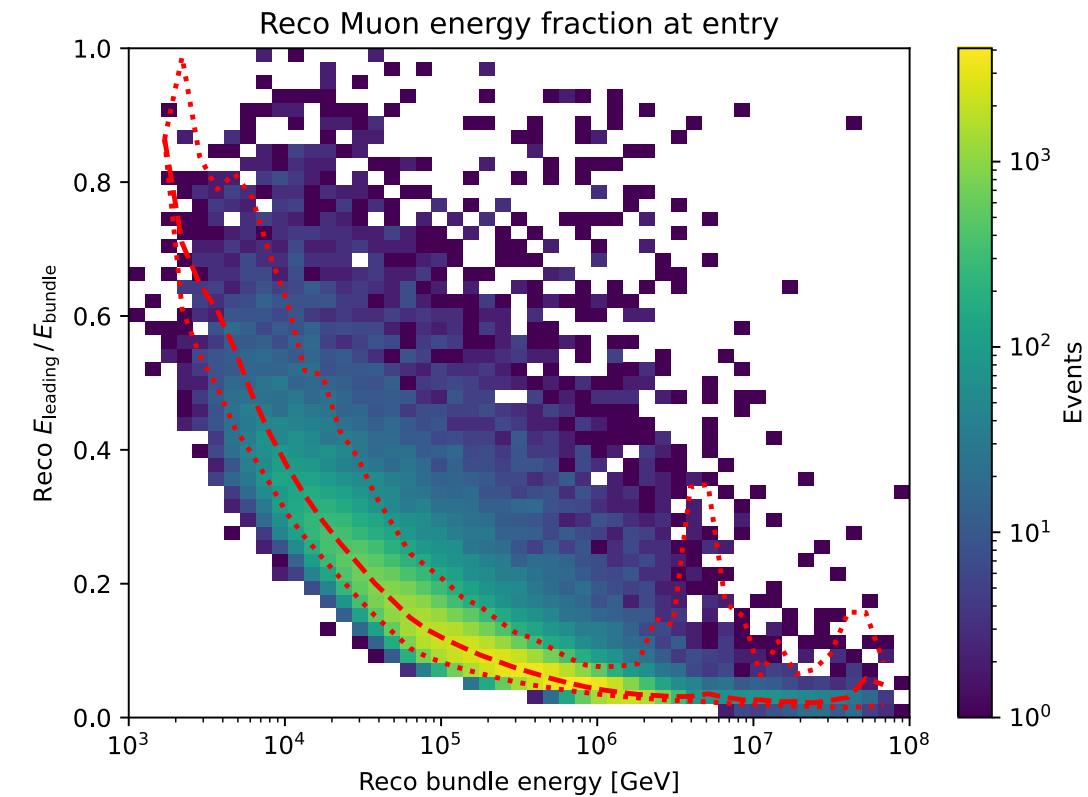
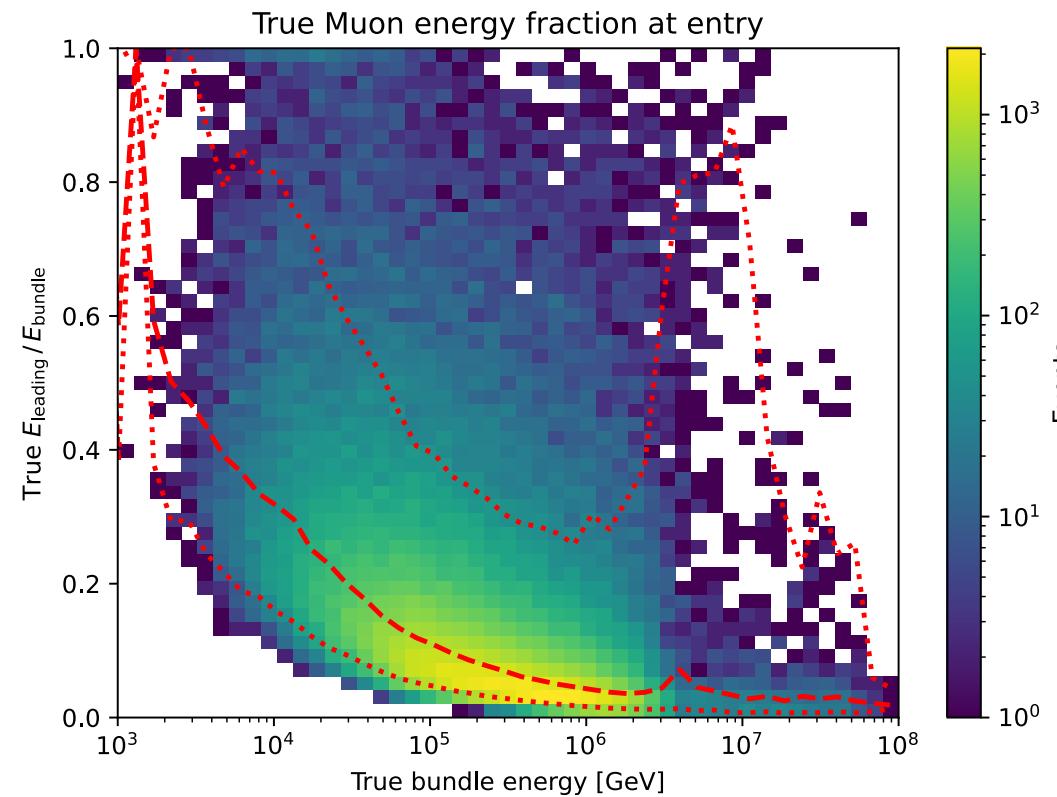
Collaboration meeting

- Ask for WG Reviewer
- Storage request large-scale simulation

Backup

Leading muon energy fraction - leadingness

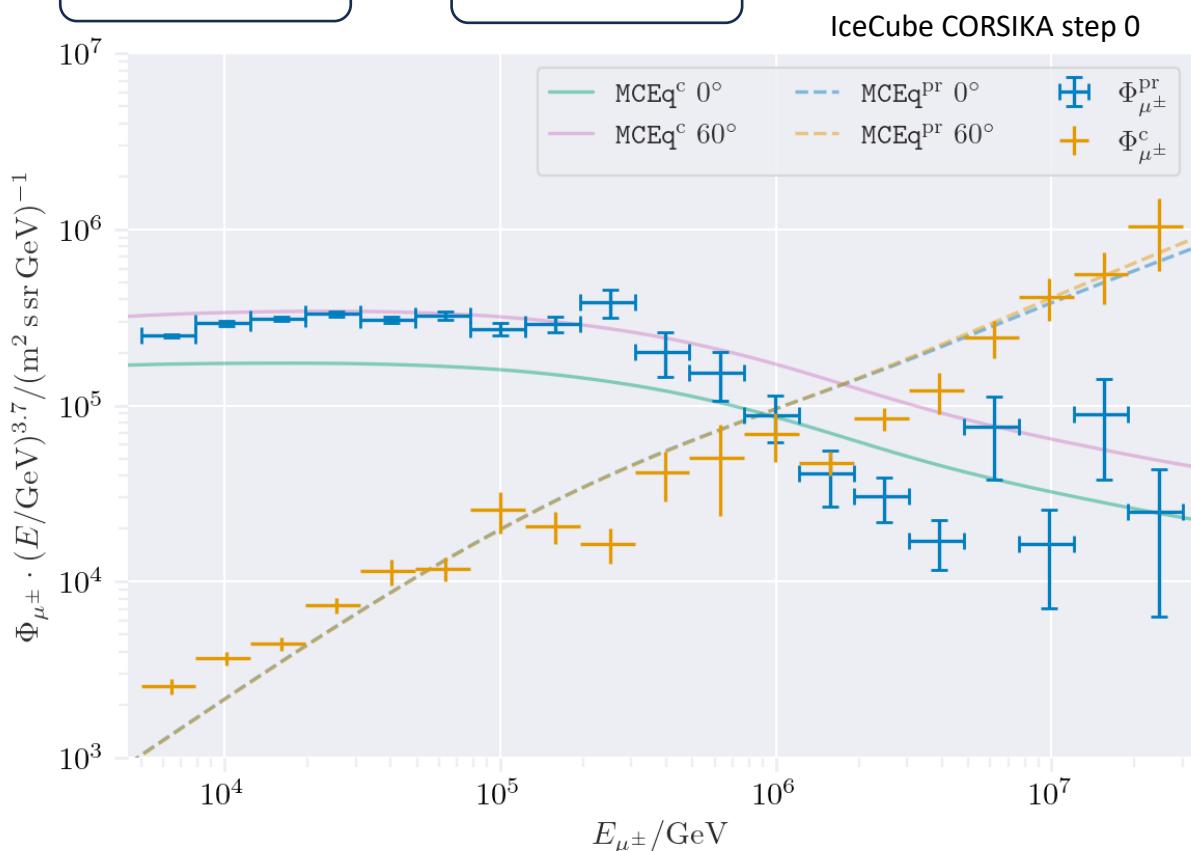
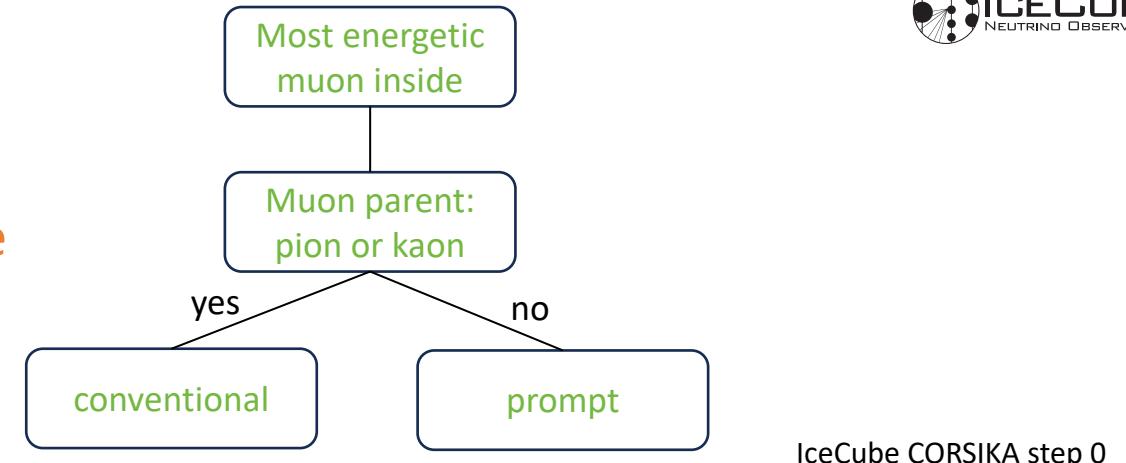
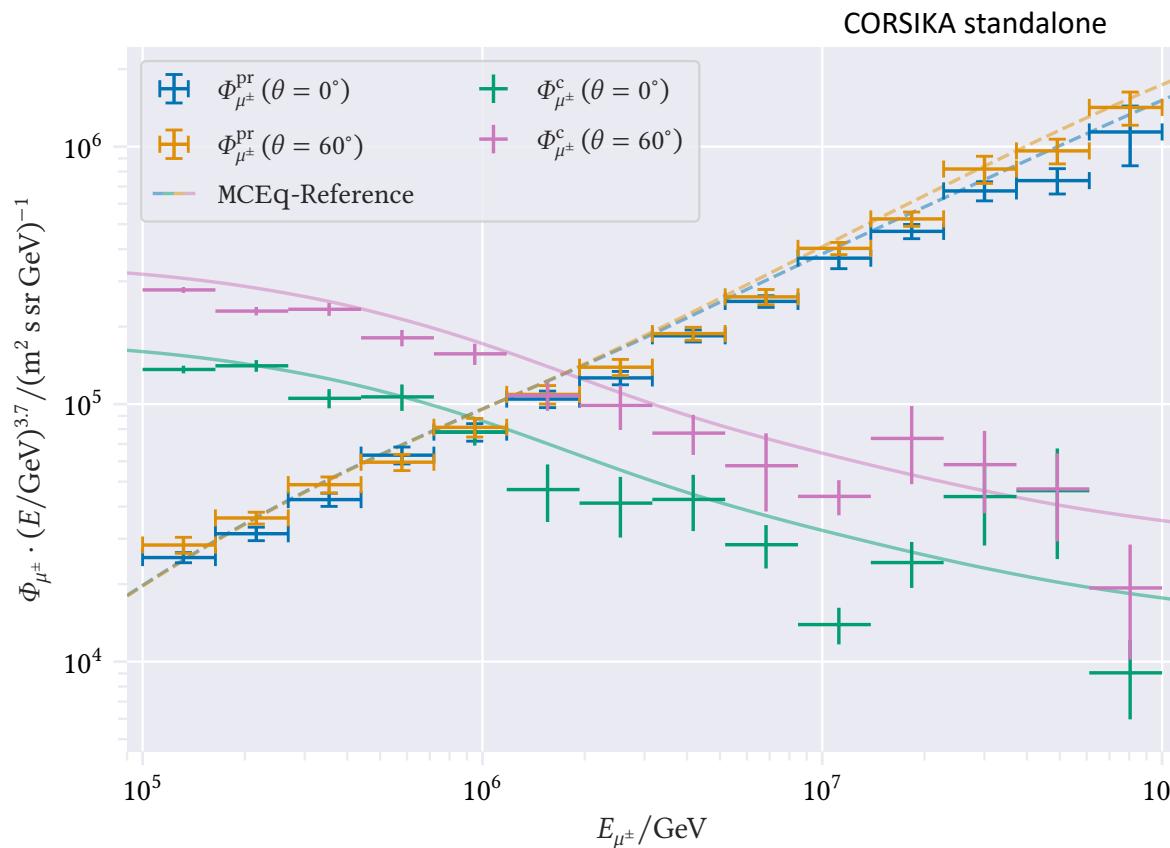
- True muon energy fraction is smeared
- Network tries to predict the median of the distribution



CORSIKA vs. MCEq

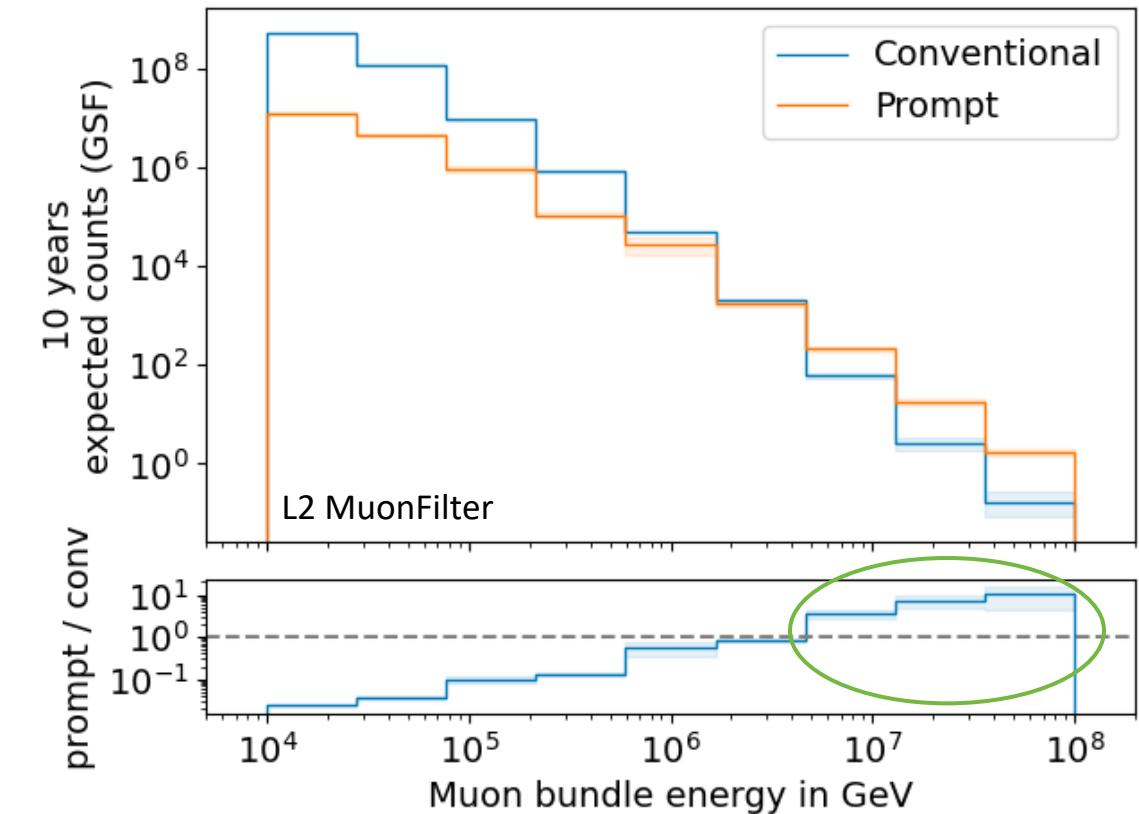
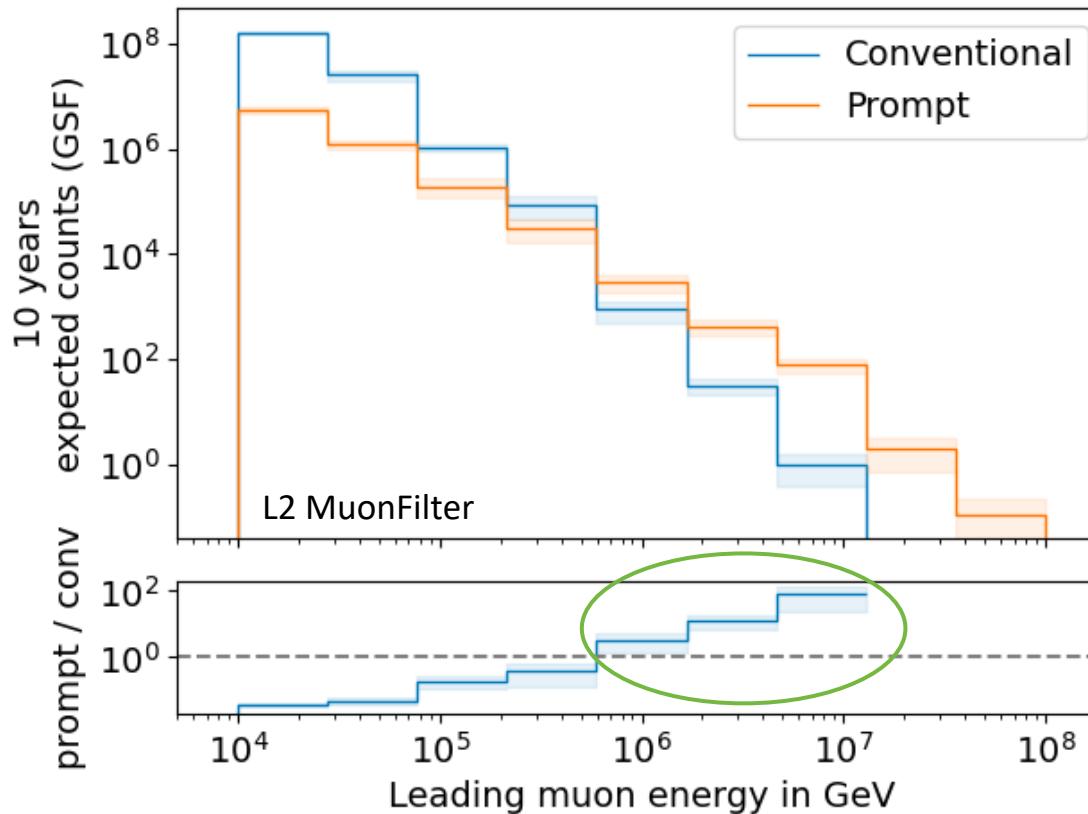
➤ Presented by Ludwig Neste

➤ Good agreement



MC data exploration

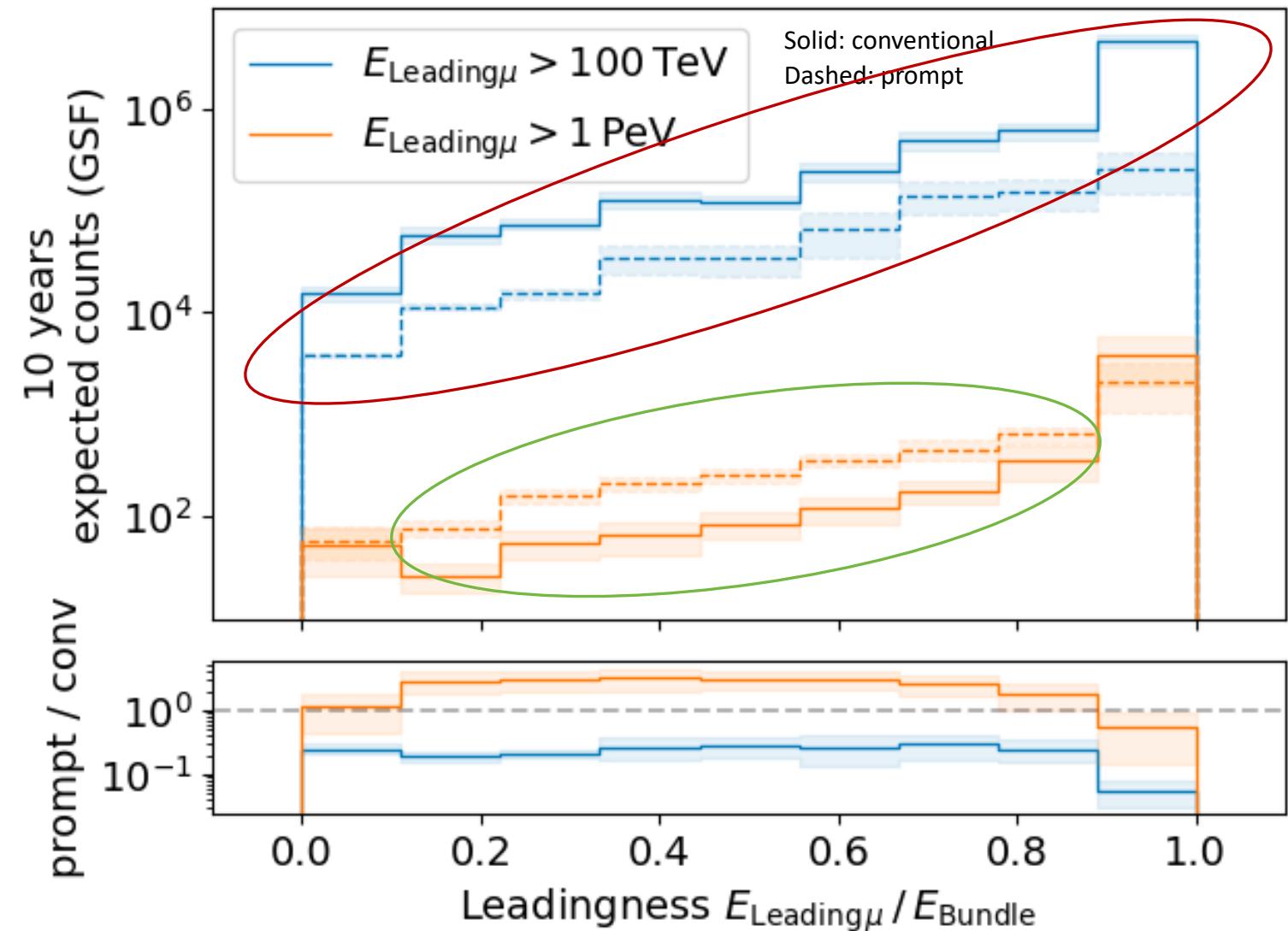
Expected muons for 10 years: leading vs. bundle energy (GSF)



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

Leading muon energy fraction

- Prompt dominates for energies $> 1 \text{ PeV}$
- Leading energy sweet spot: $0.1 - 0.9$



Leading muon contribution

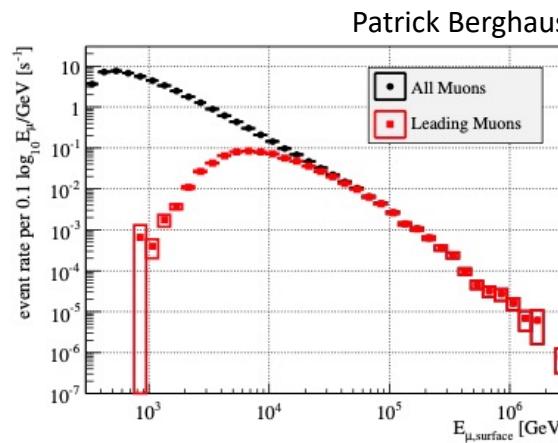
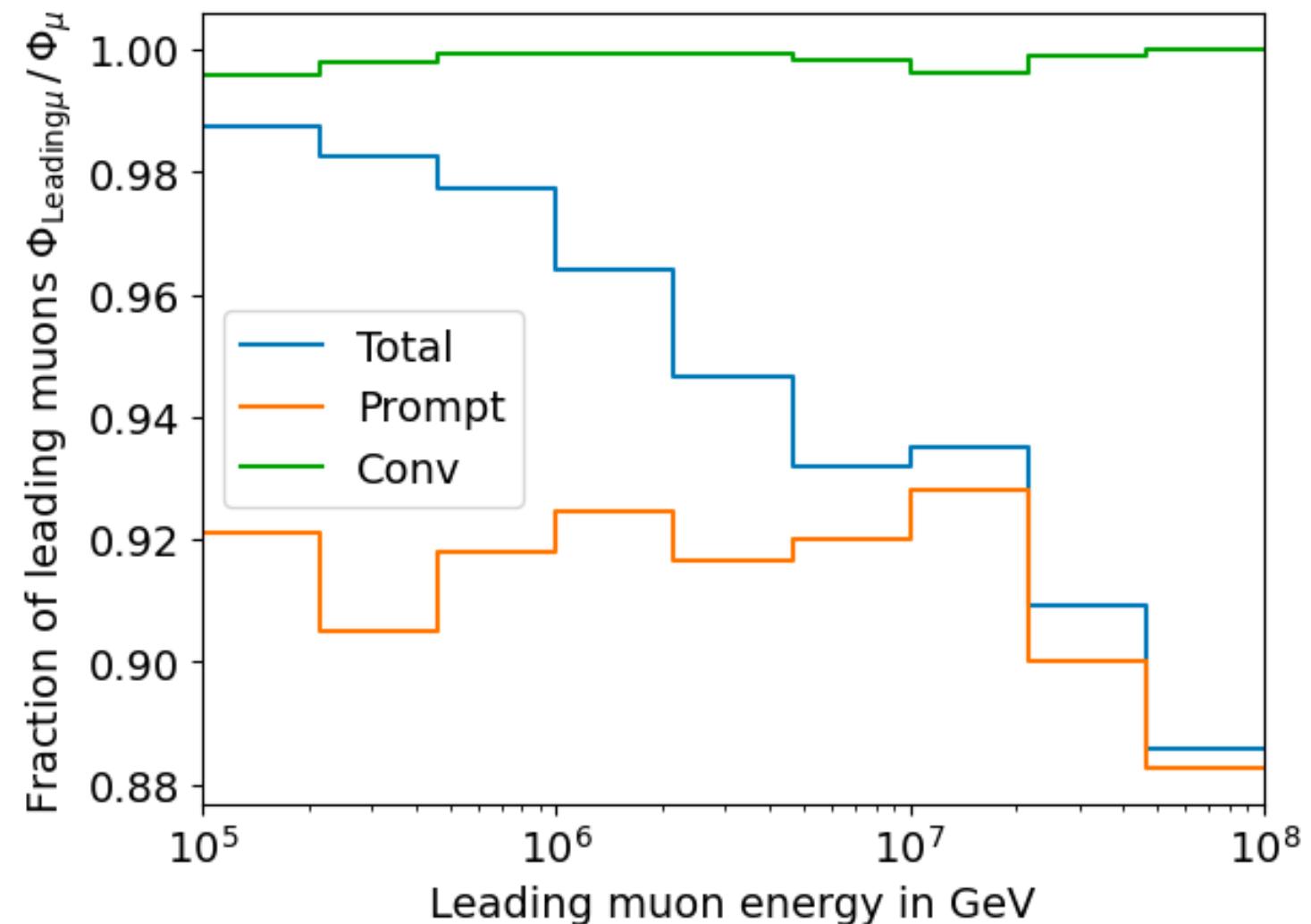


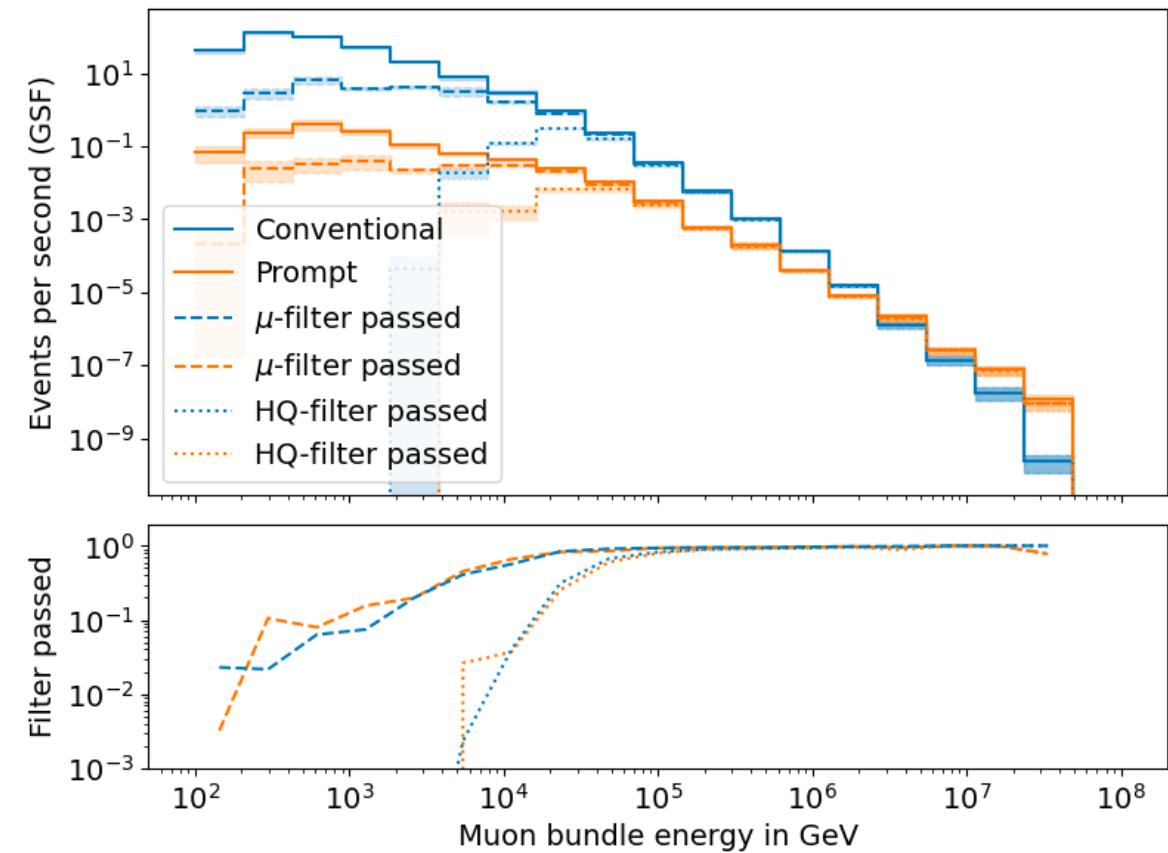
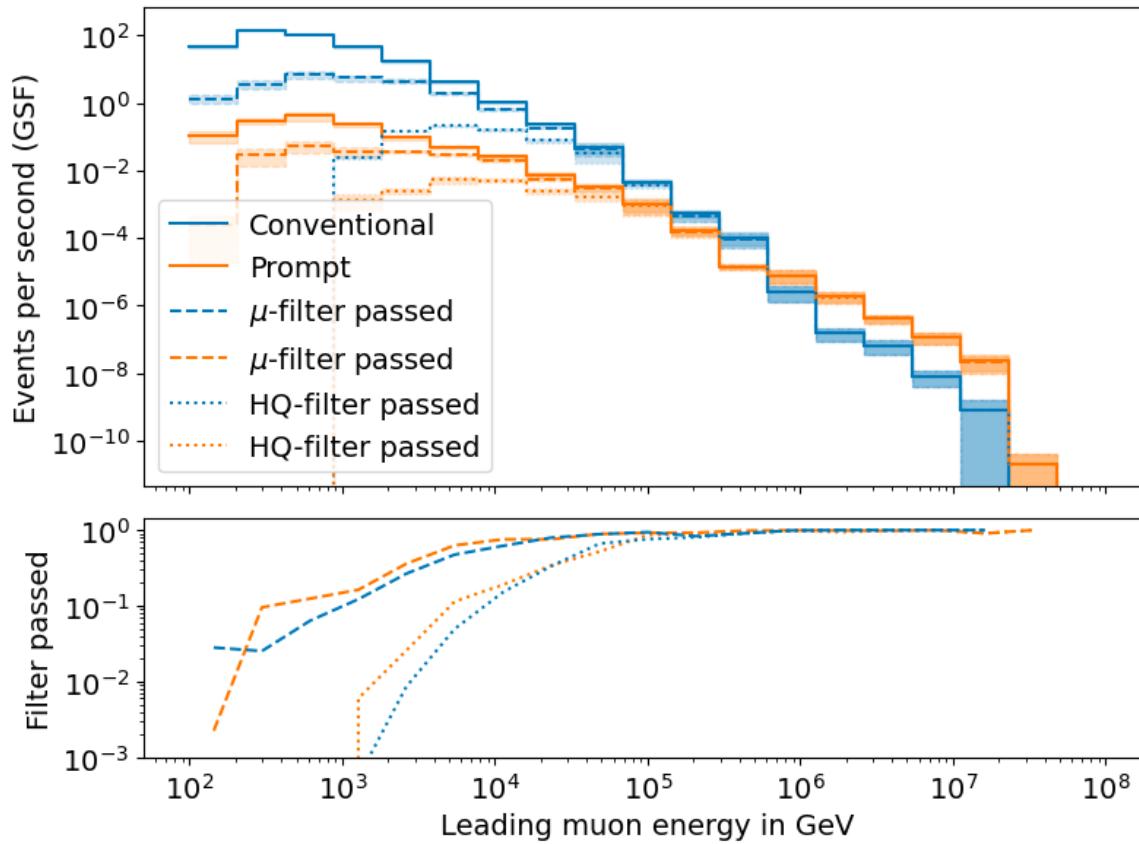
Figure 10: Surface energy distribution for all and most energetic (“leading”) muons in simulated events with a total of more than 1,000 registered photo-electrons in IceCube.

- 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

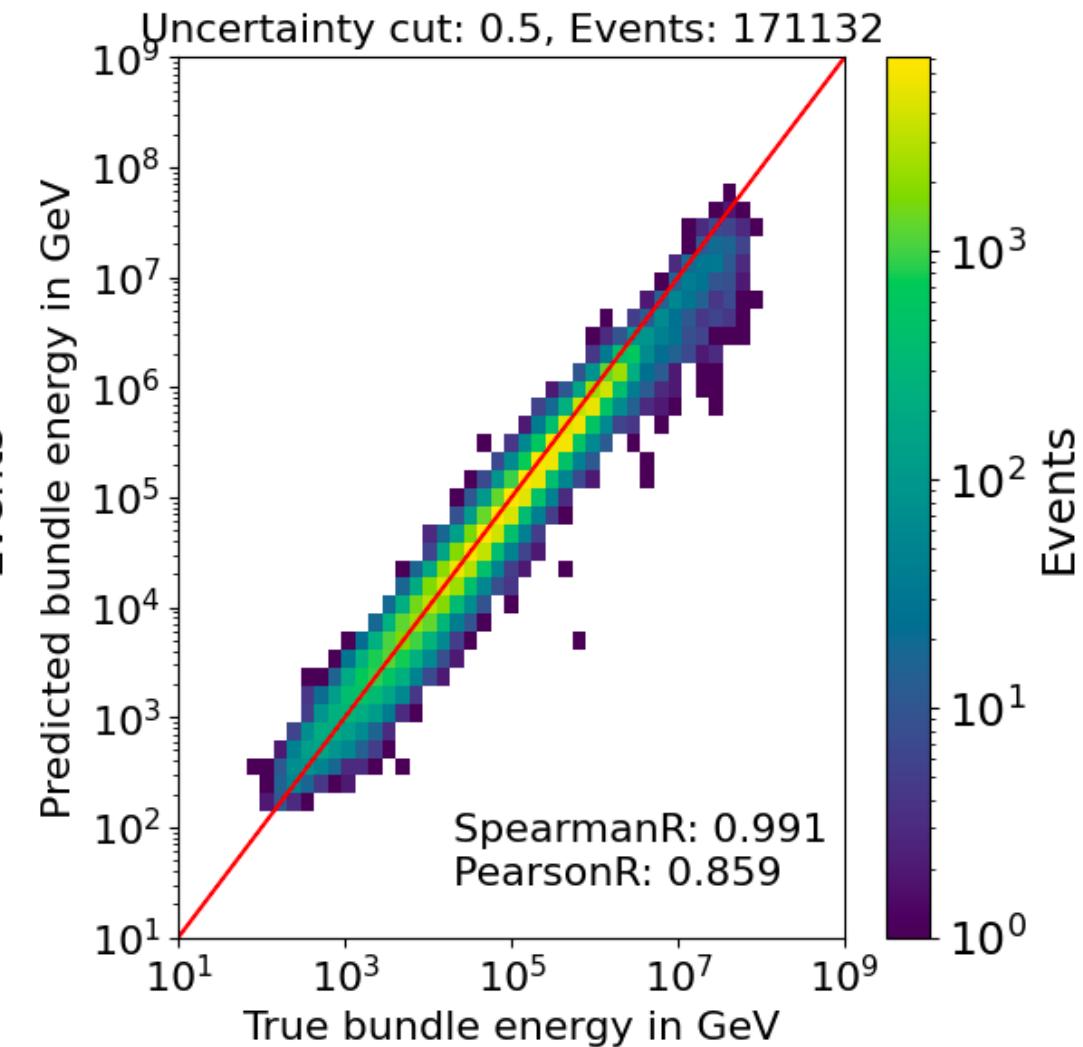
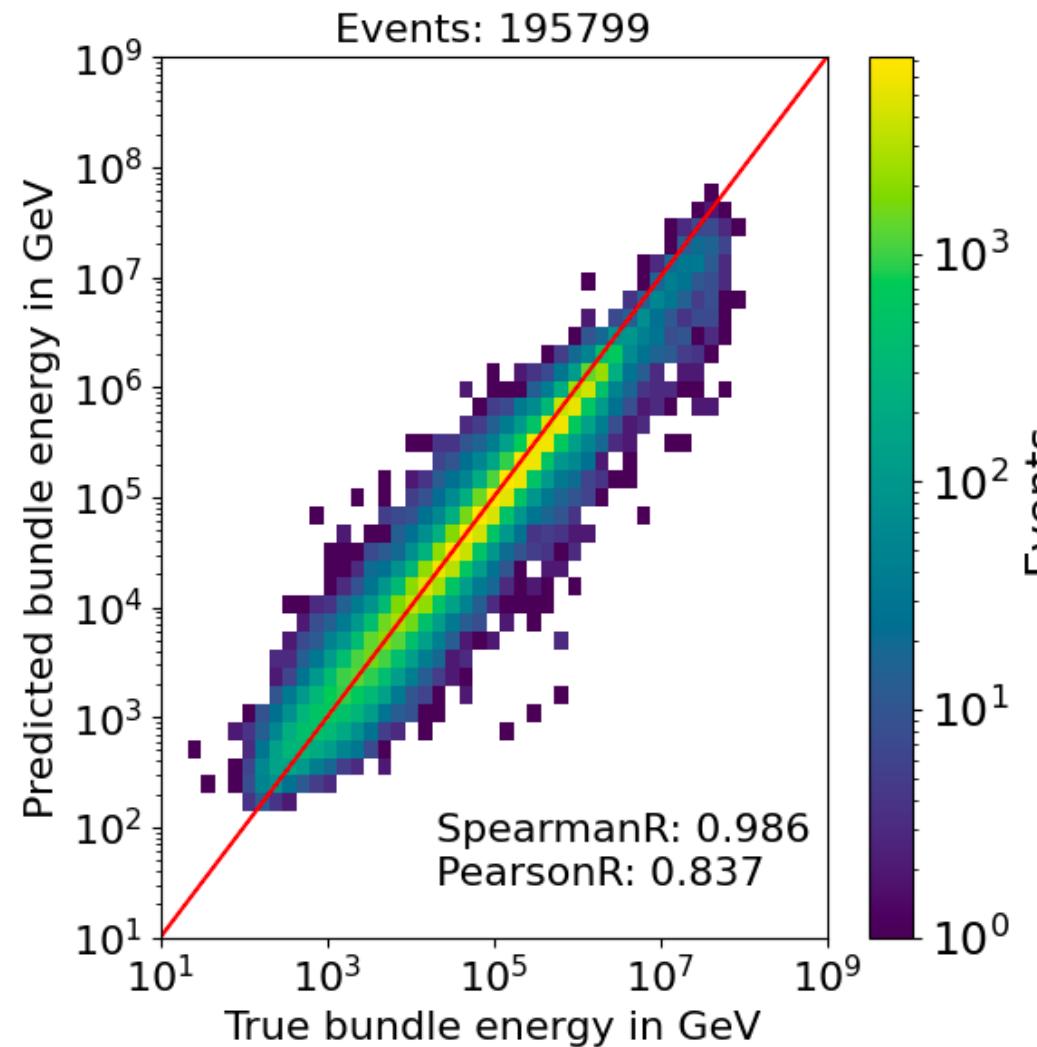


L2 Filters

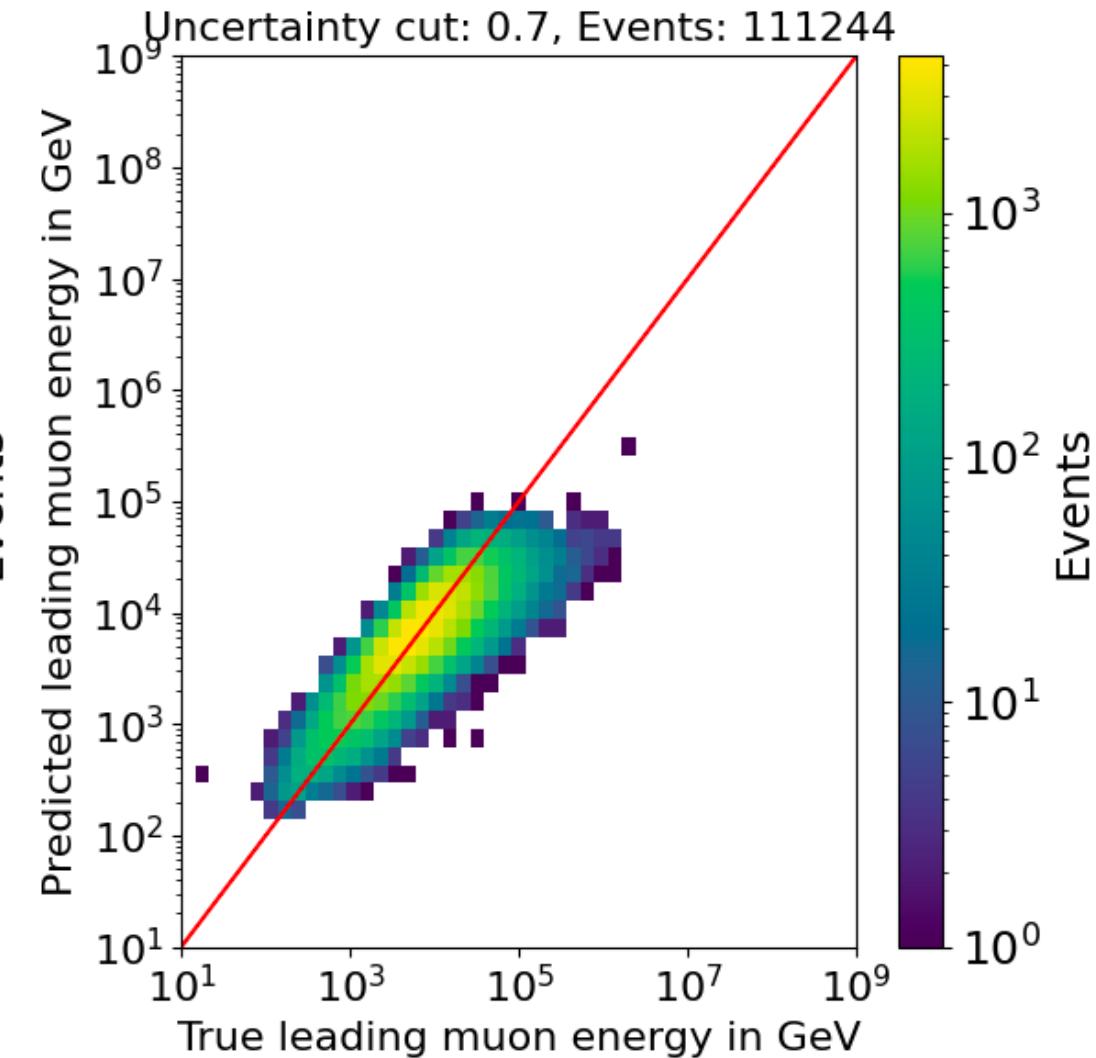
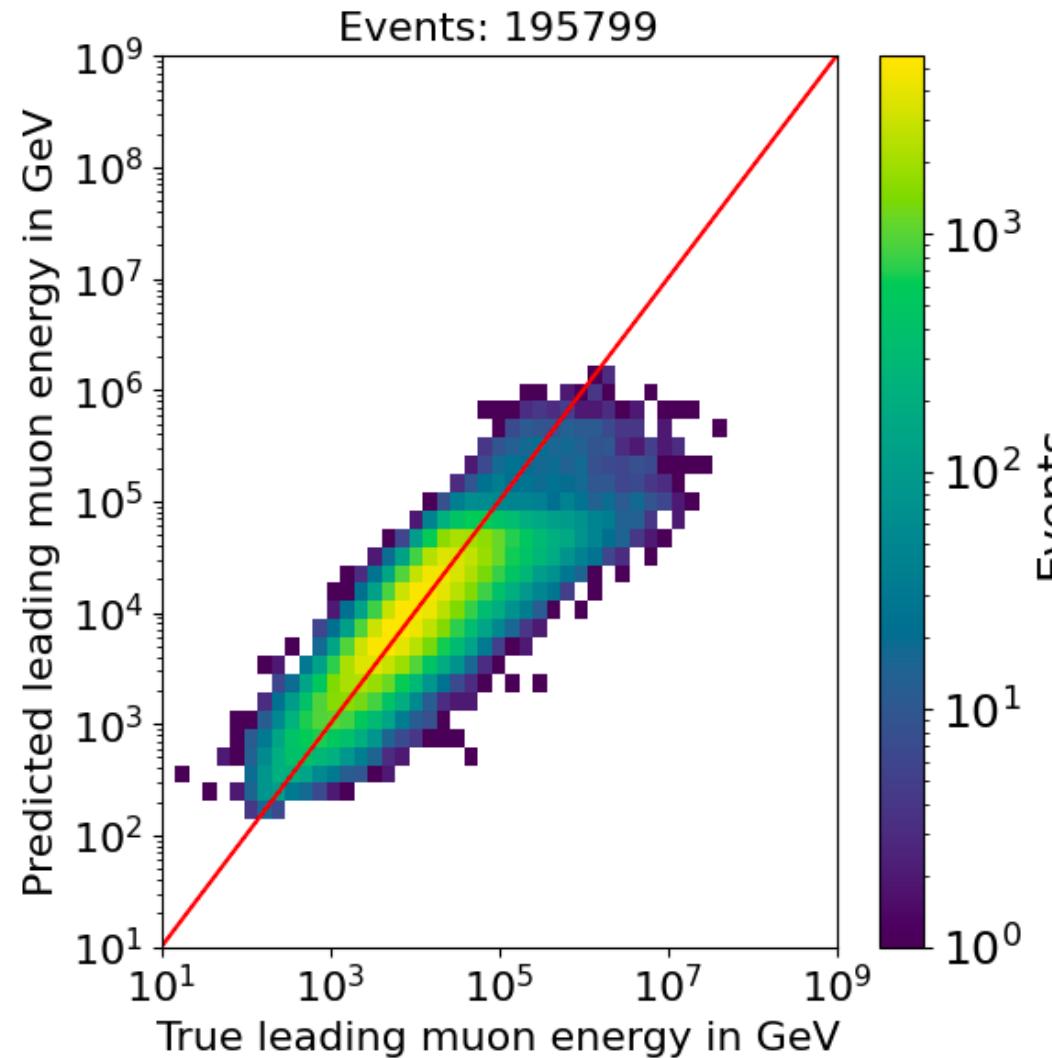
Fraction events rejected	All energies	Leading energy > 10 TeV	Leading energy > 100 TeV
MuonFilter	0.93	0.28	0.06
HQFilter	0.99	0.74	0.18



Bundle energy reconstruction

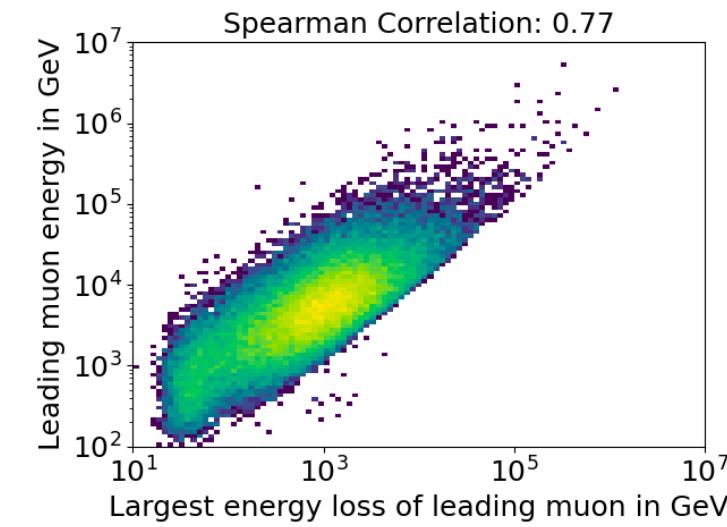
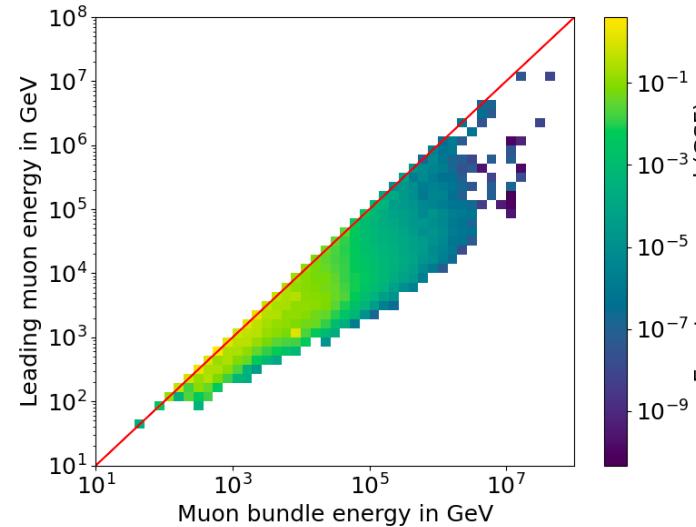
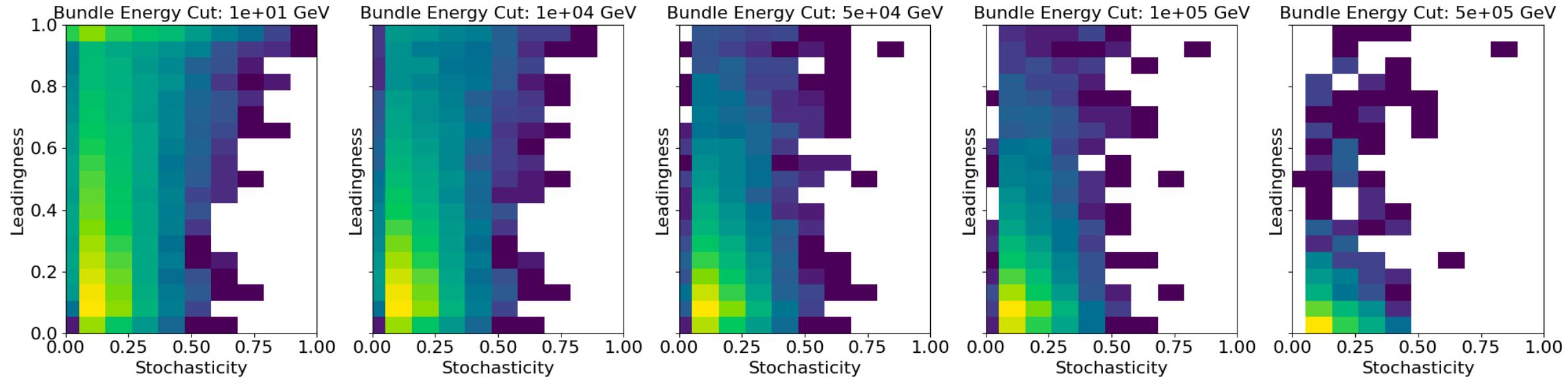


Leading energy reconstruction



Bundle energy cut

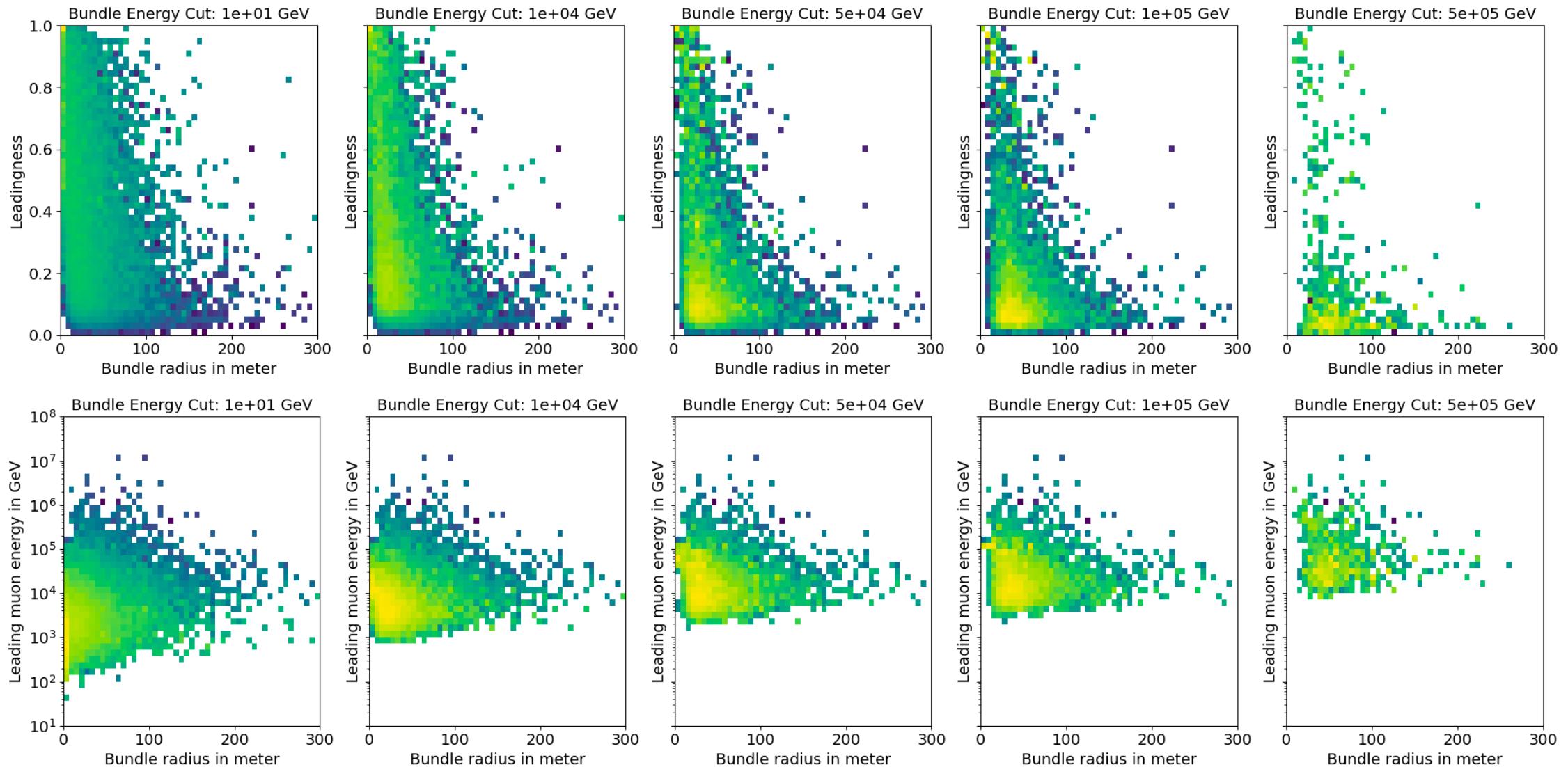
Stochasticity



- High stochasticity leads to high leadingness, but only for a small number of events
- Leading muon energy smears out at large bundle energies
- Largest energy loss of the leading muon correlates with the leading muon energy

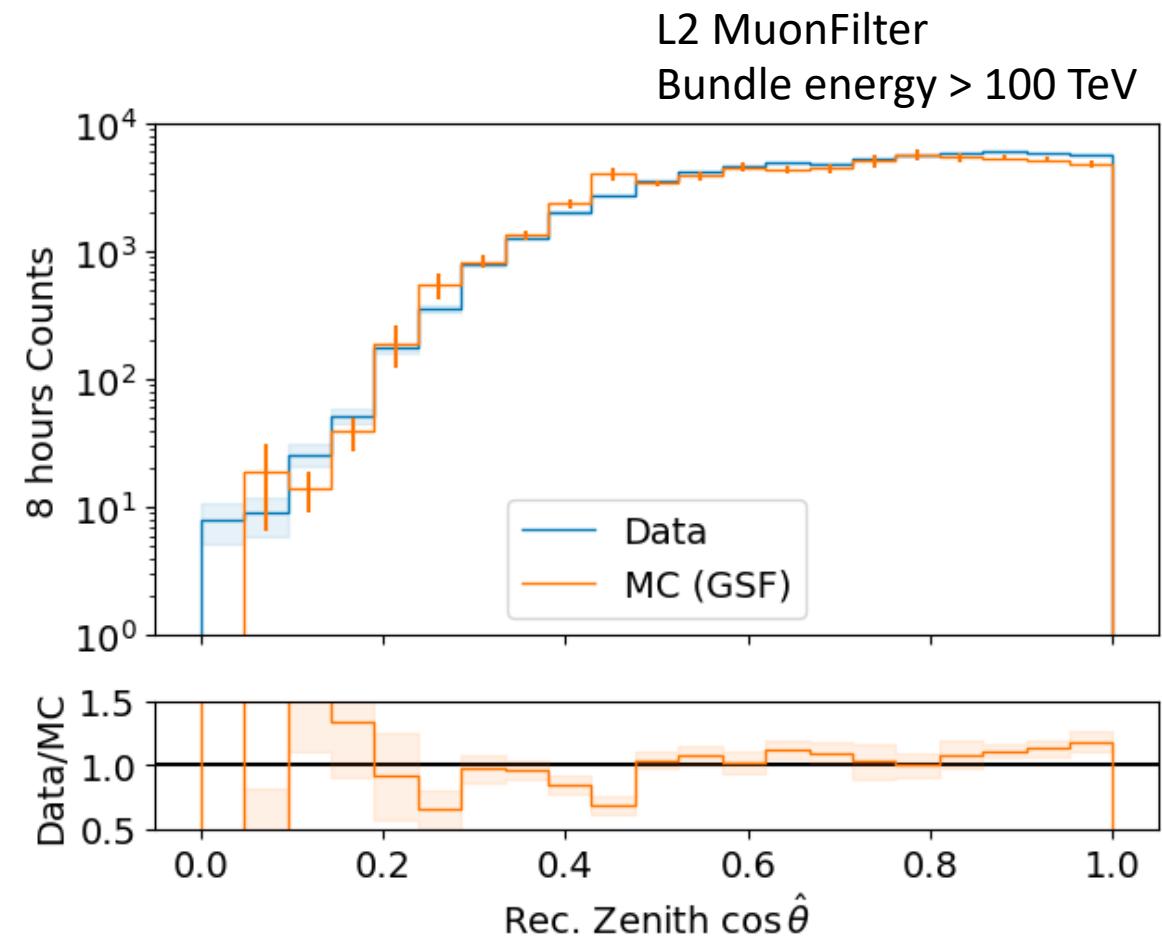
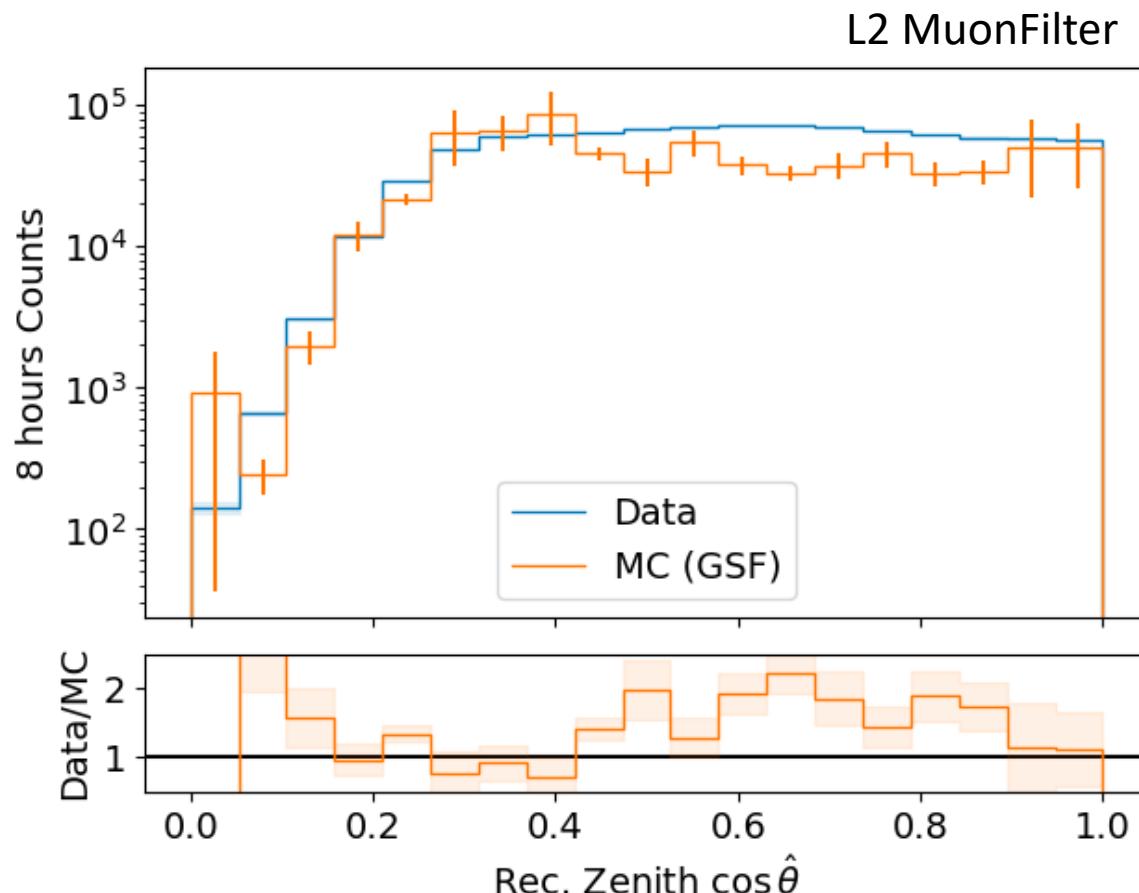
Bundle energy cut

Bundle radius



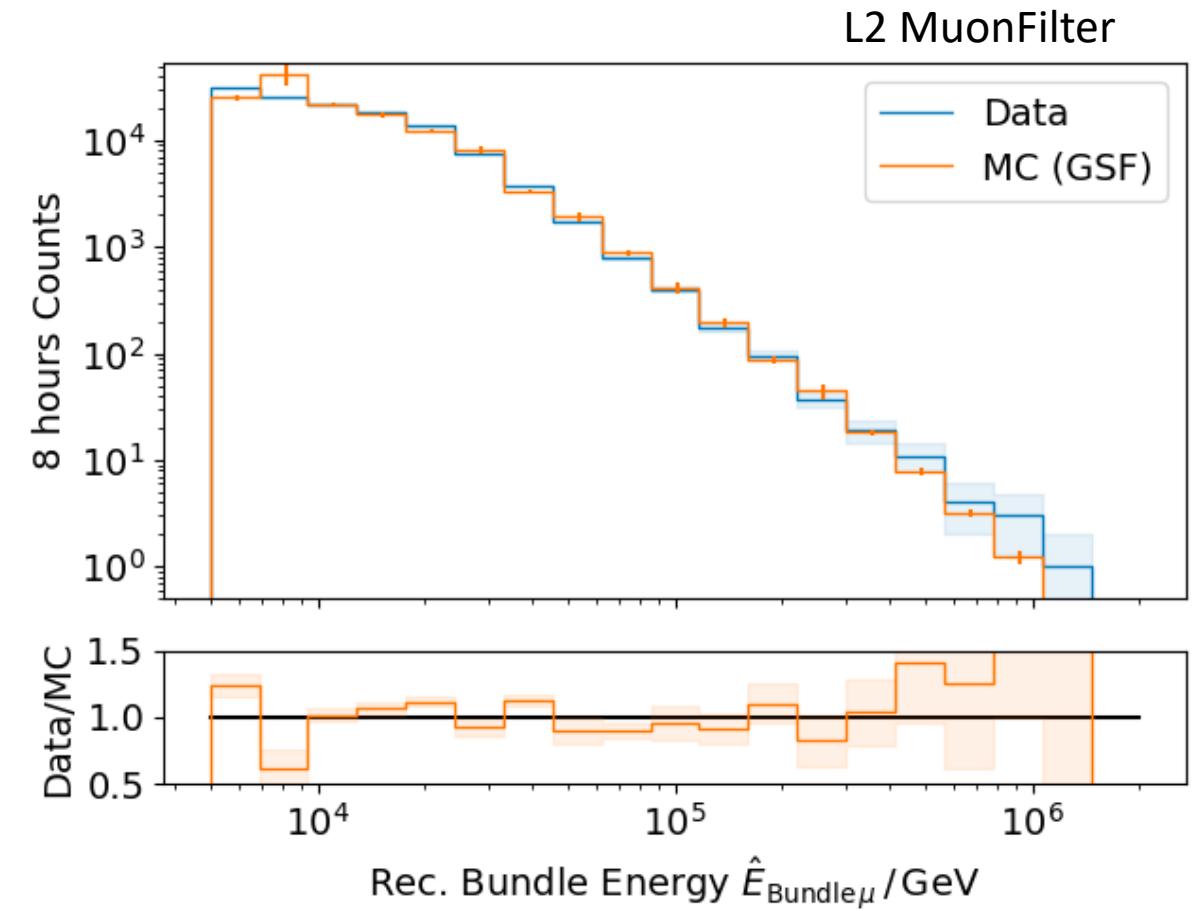
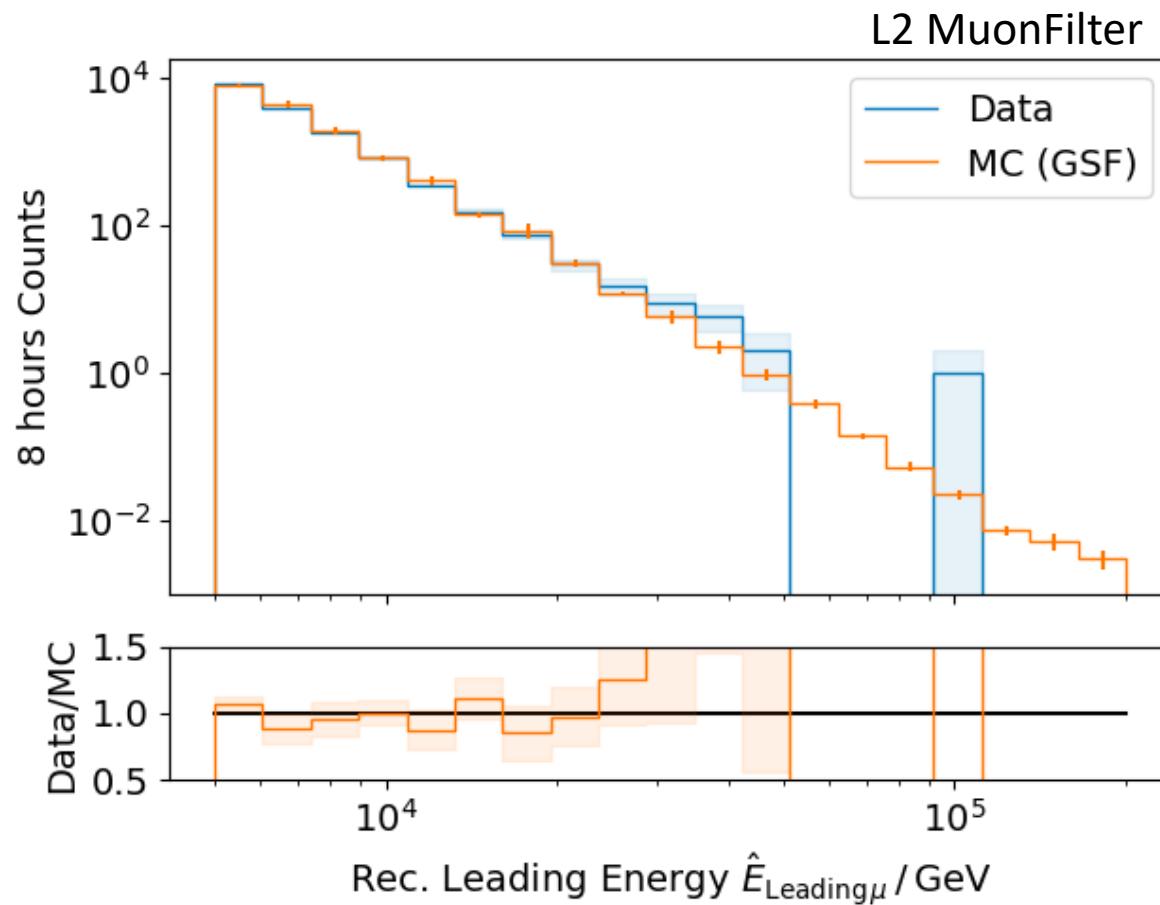
➤ Large bundle radius leads to low leadingness

Data/MC

Data-MC: $\cos(\text{zenith})$ 

- Deviations at low $\cos(\text{zenith})$, but very small statistics
- More data at $\cos(\text{zenith}) > 0.5$
- Less data at $\cos(\text{zenith}) \sim 0.3$

Data-MC: energy spectrum

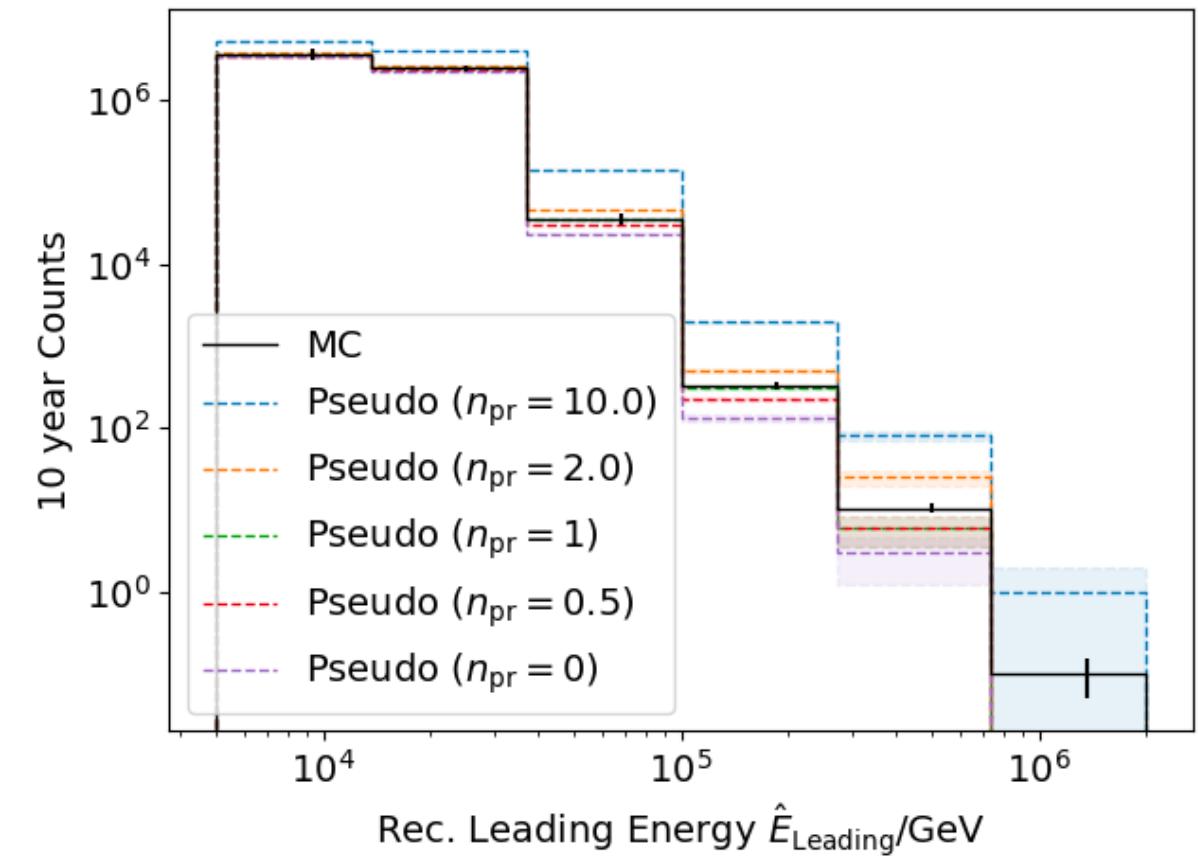
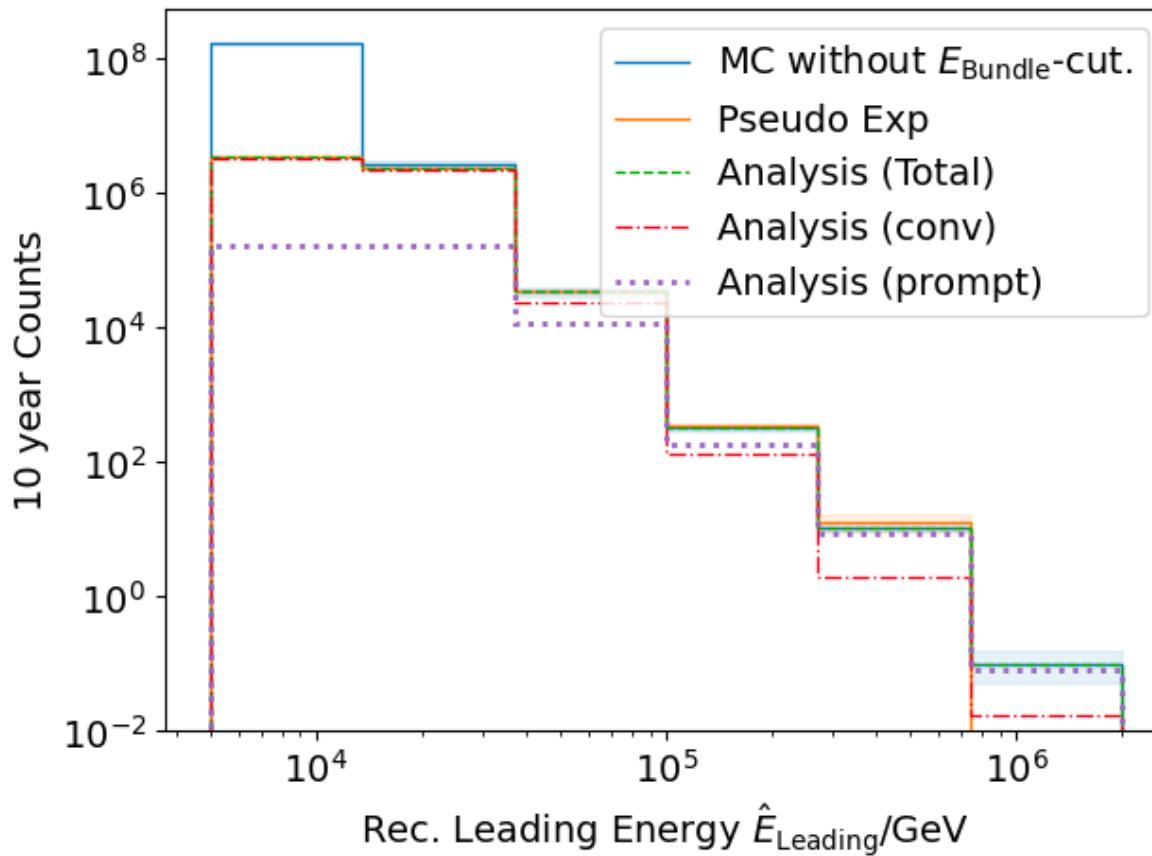


- Bundle energy: good agreement with GSF up to 300 TeV
- But insufficient statistics

Pseudo analysis

Pseudo data sampling

Cuts:
L2 MuonFilter
Bundle energy > 100 TeV



➤ Tagging allows scaling of prompt by factor n_{pr}

Poisson likelihood fit performed in leading muon energy

Prompt scaling/normalization

MC counts per bin i

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

Conv norm = 1

Experimental counts

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

Maximize likelihood

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

Easier:
minimize negative
log-likelihood

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

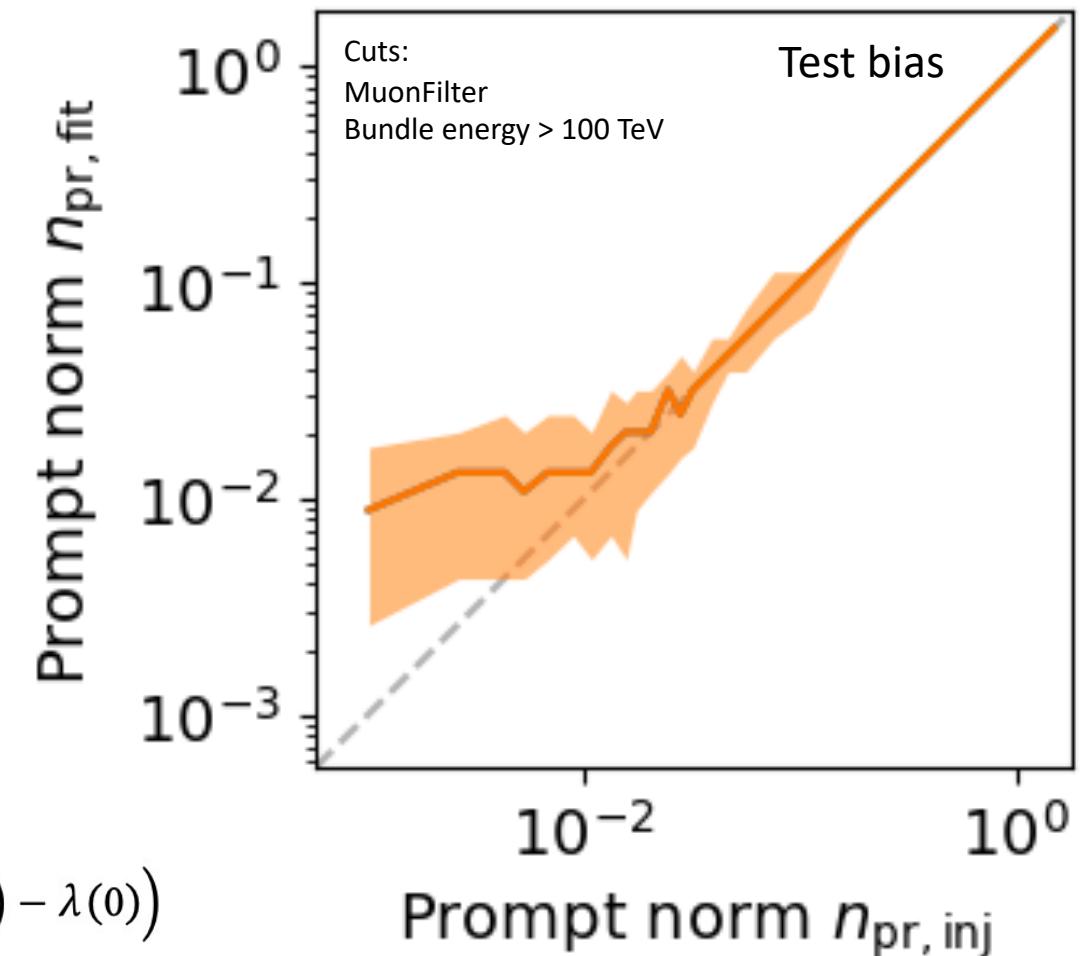
With a constant conv norm:
bin counts depend only on prompt norm
= expectation value per bin

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

Test statistic for Wilks' theorem

Null hypothesis: no prompt

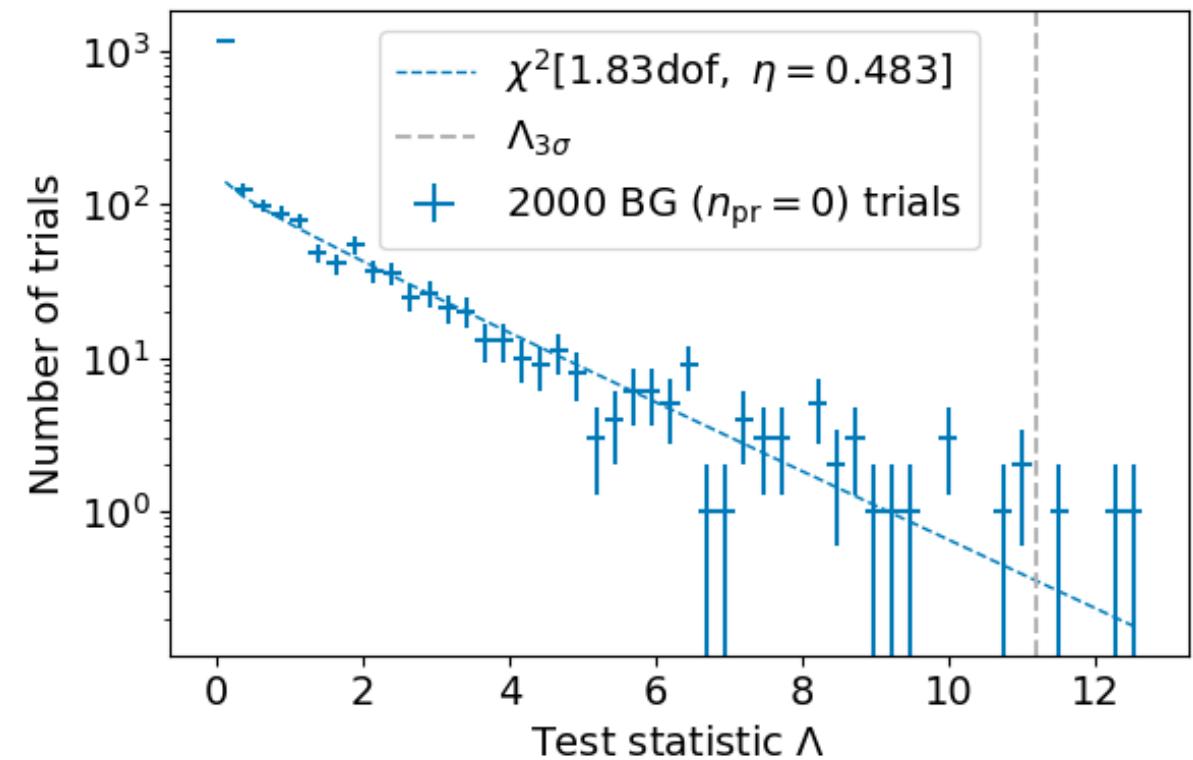
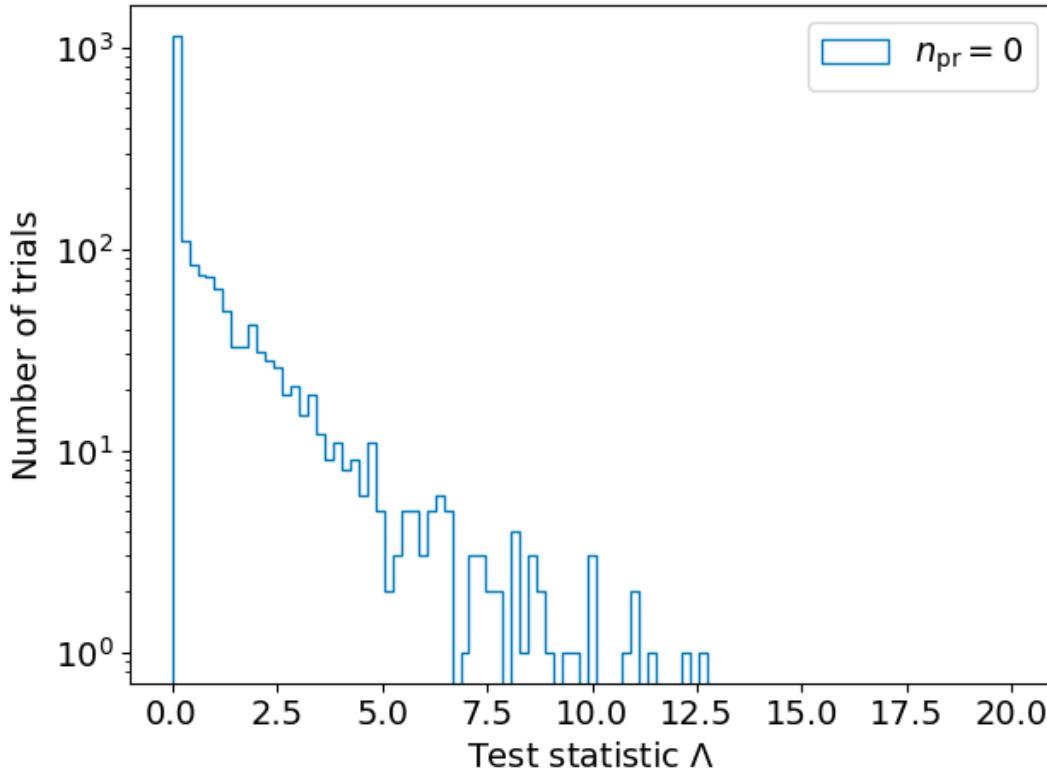
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➤ Bias starts at a prompt normalization of 0.1

Test background statistics

Cuts:
L2 MuonFilter
Bundle energy > 100 TeV



- Background statistic is χ^2 – distributed
- Assume Wilks' theorem for test statistics

Discovery potential and sensitivity

Expectation for 1 year:

- 5 sigma discovery potential: 0.102 ± 0.005
- Sensitivity: 0.024 ± 0.001

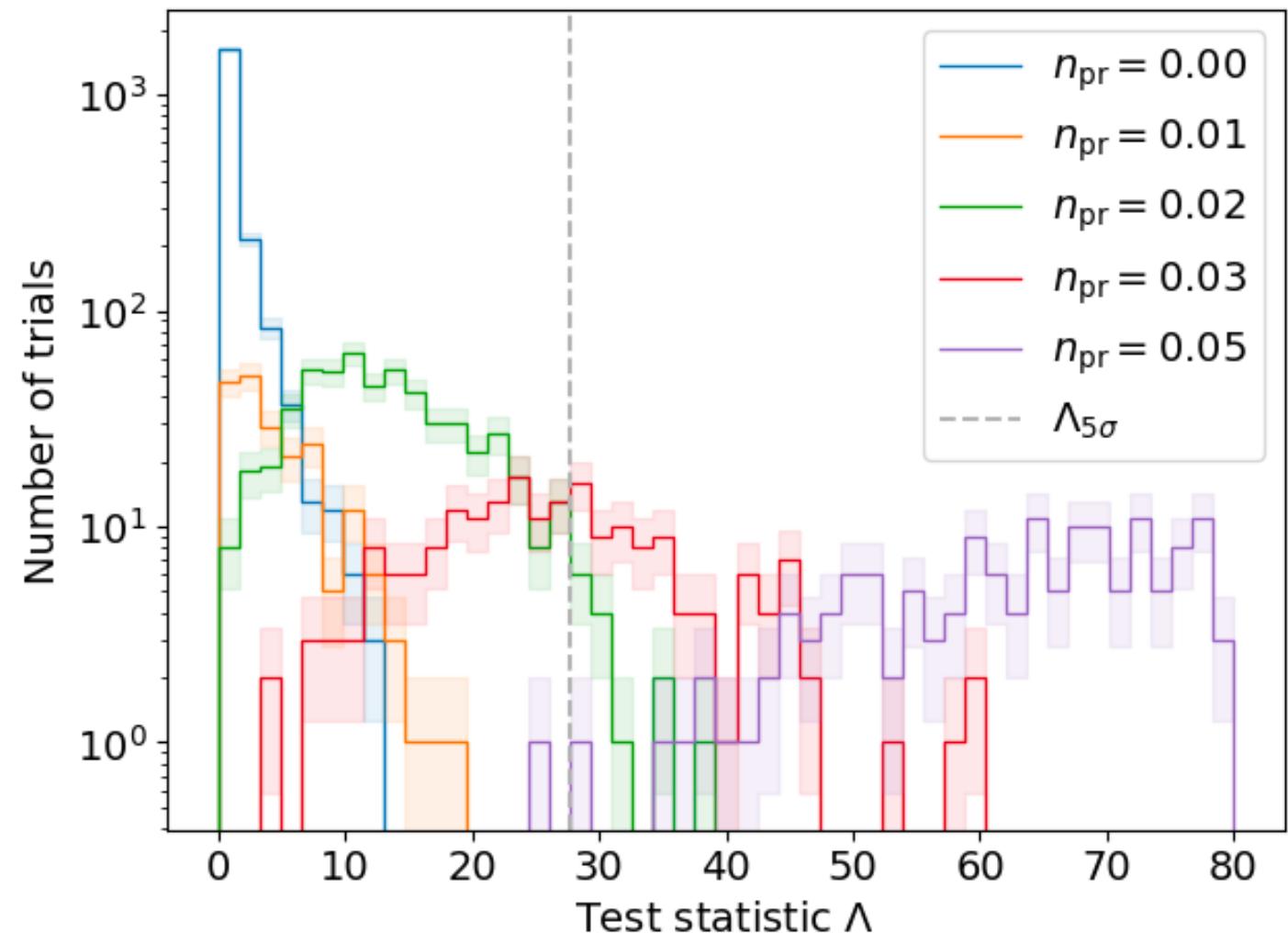
Expectation for 10 years:

- 5 sigma discovery potential: 0.032 ± 0.001
- Sensitivity: 0.007 ± 0.000

Caution:

Limited MC statistics -> events are
oversampled in pseudo dataset

Cuts:
L2 MuonFilter
Bundle energy > 100 TeV



Conclusion and outlook

Next goal

- Measure normalization of the atmospheric prompt muon flux

Steps for normalization

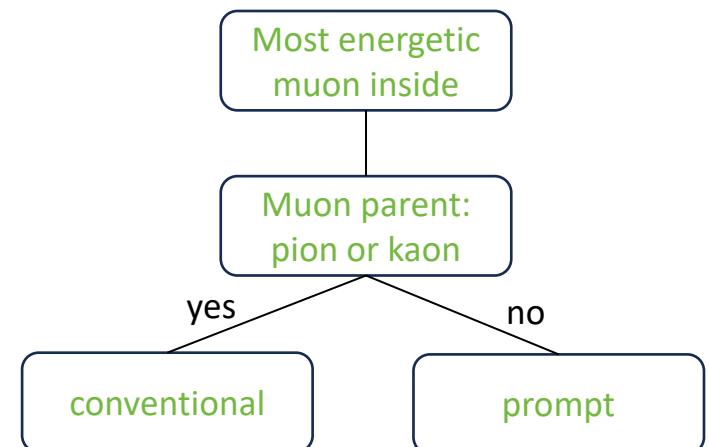
- Verify CORSIKA extended history simulations
- Tag prompt muons (see talk by Ludwig Neste)
- Comparisons to MC Eq (see talk by Ludwig Neste)
- Set up preliminary analysis chain
- Reconstruct muon energy and direction
- Data/MC comparisons
- Include systematics
- Run full statistics simulation

Some definitions and wording...

- Leading muon
 - The most energetic muon inside a bundle (no minimum fraction required)
- Single muon
 - Except for stopping and very low energetic muons, there are never any single muons (almost every event is muon bundle)
- Prompt muon
 - Muon parent is not pion or kaon

Suggestion:

To avoid confusion regarding different leading muon definitions we can introduce a “leadingness”
(For example: Tomasz used a leadingness of 50%, ...)



Intention

- 1) Detect prompt component of the atmospheric muon flux significantly
 - Measure the normalization
 - Get handle on hadronic interaction models
- 2) Unfold an 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

Definition of the muon flux

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

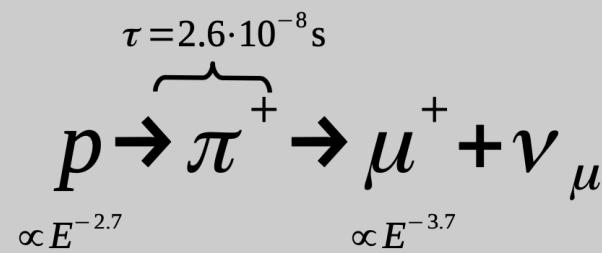


$$\pi, K \propto E^{-3.7}$$

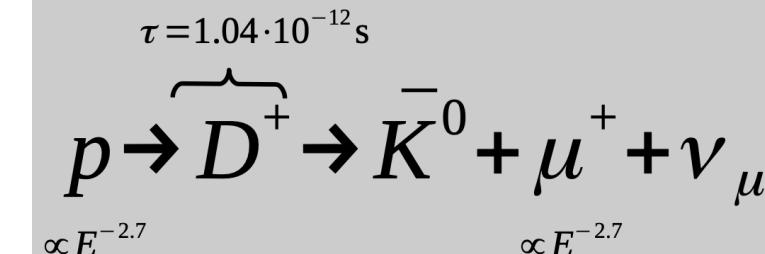


$$\text{"not"} \pi, K \propto E^{-2.7}$$

Conventional component:



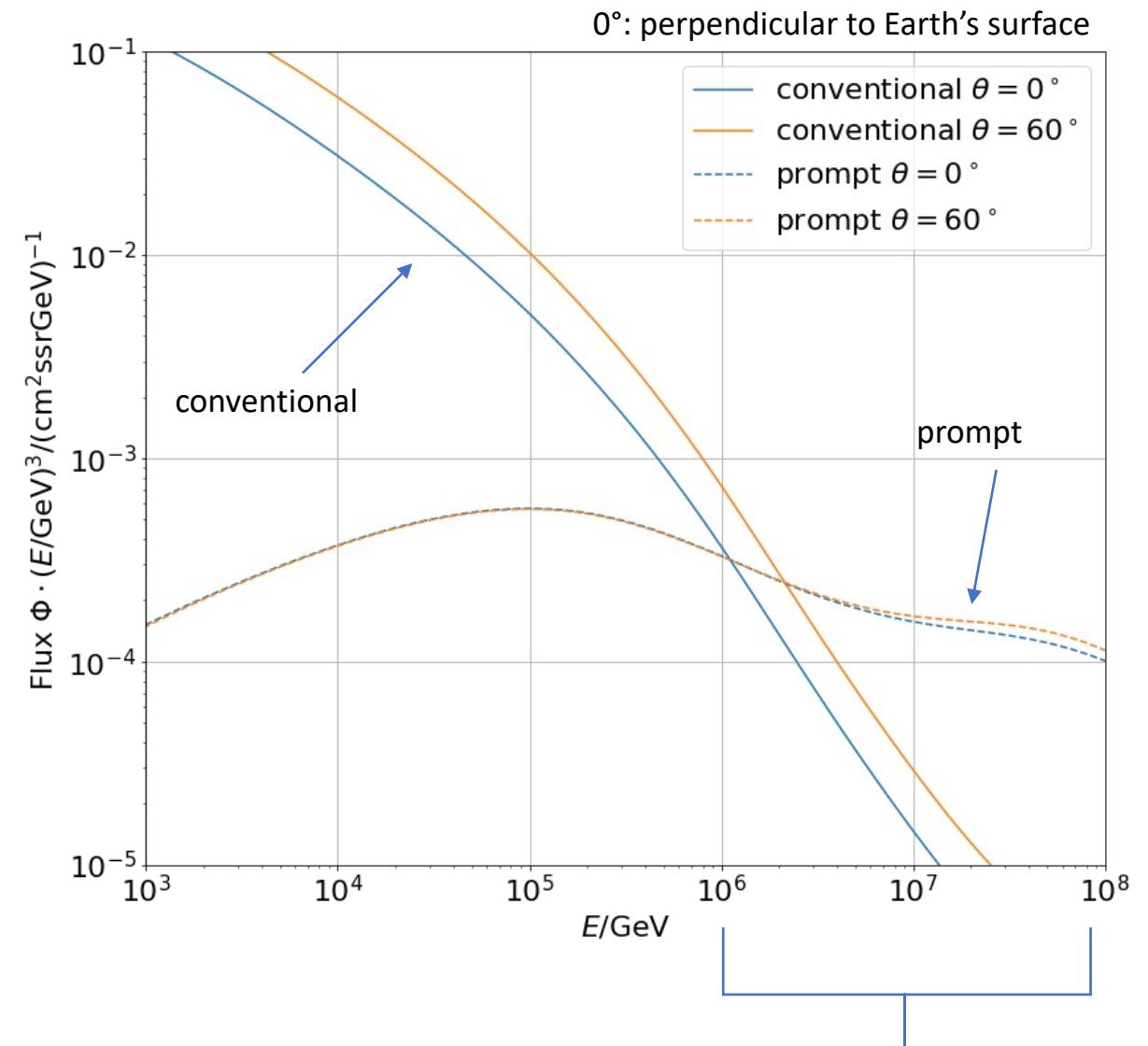
prompt component:



Muon flux

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

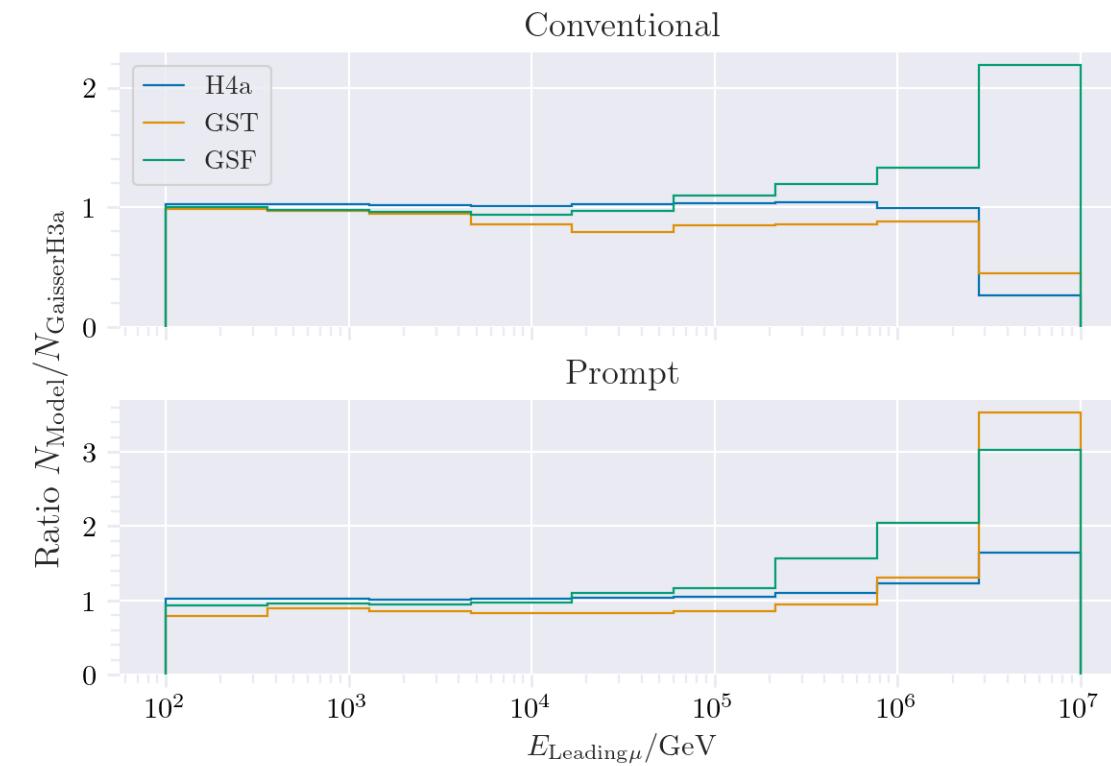
- Prompt dominates at energies larger than PeV
- Conventional particle flux depends on zenith angle



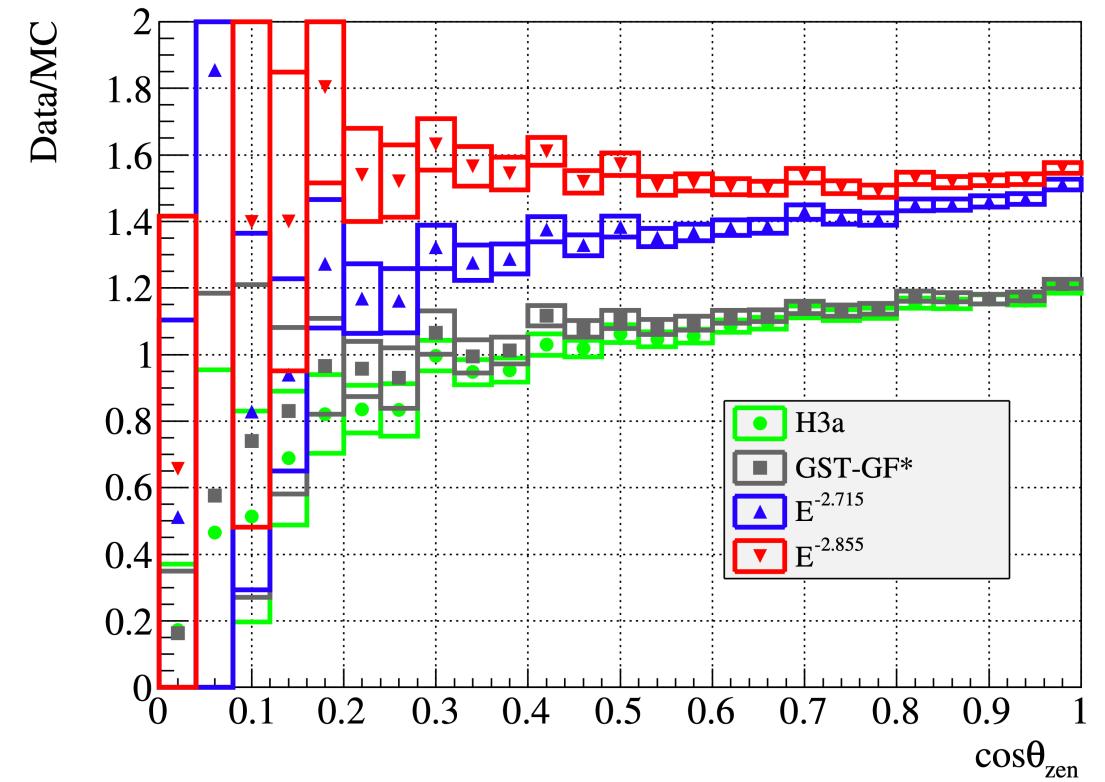
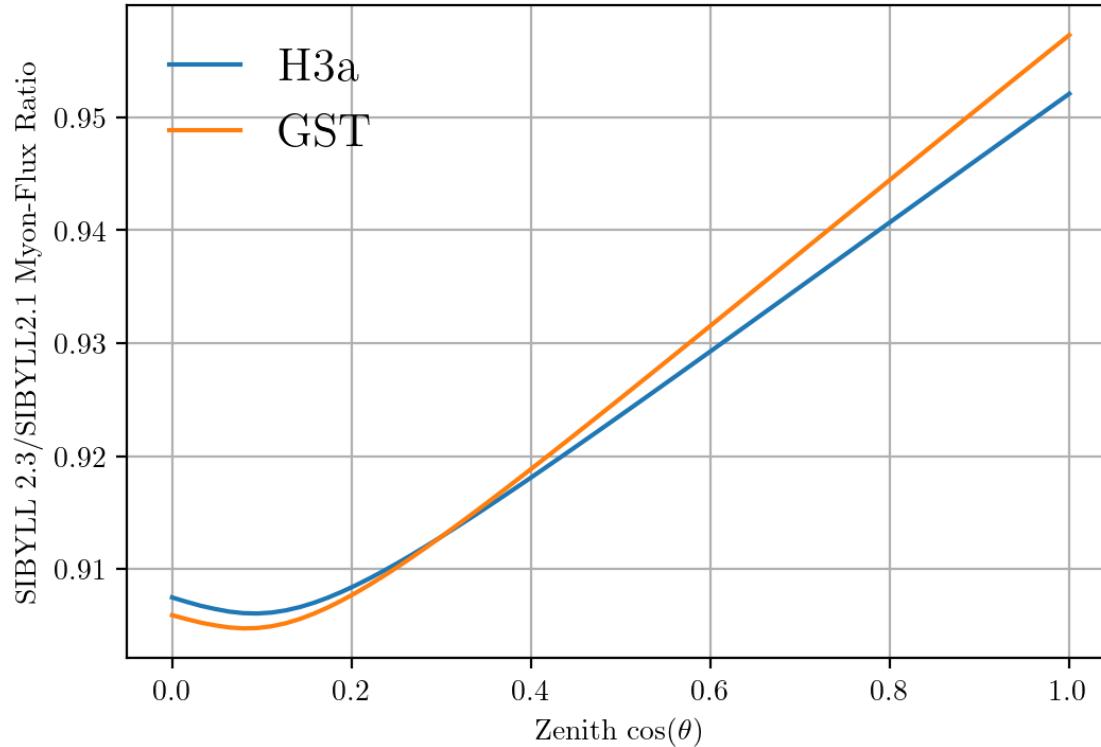
We can measure prompt muon
energies from $\sim 1 \text{ PeV}$ to $\sim 100 \text{ PeV}$

Muon production – different weightings

GST predicts most prompt



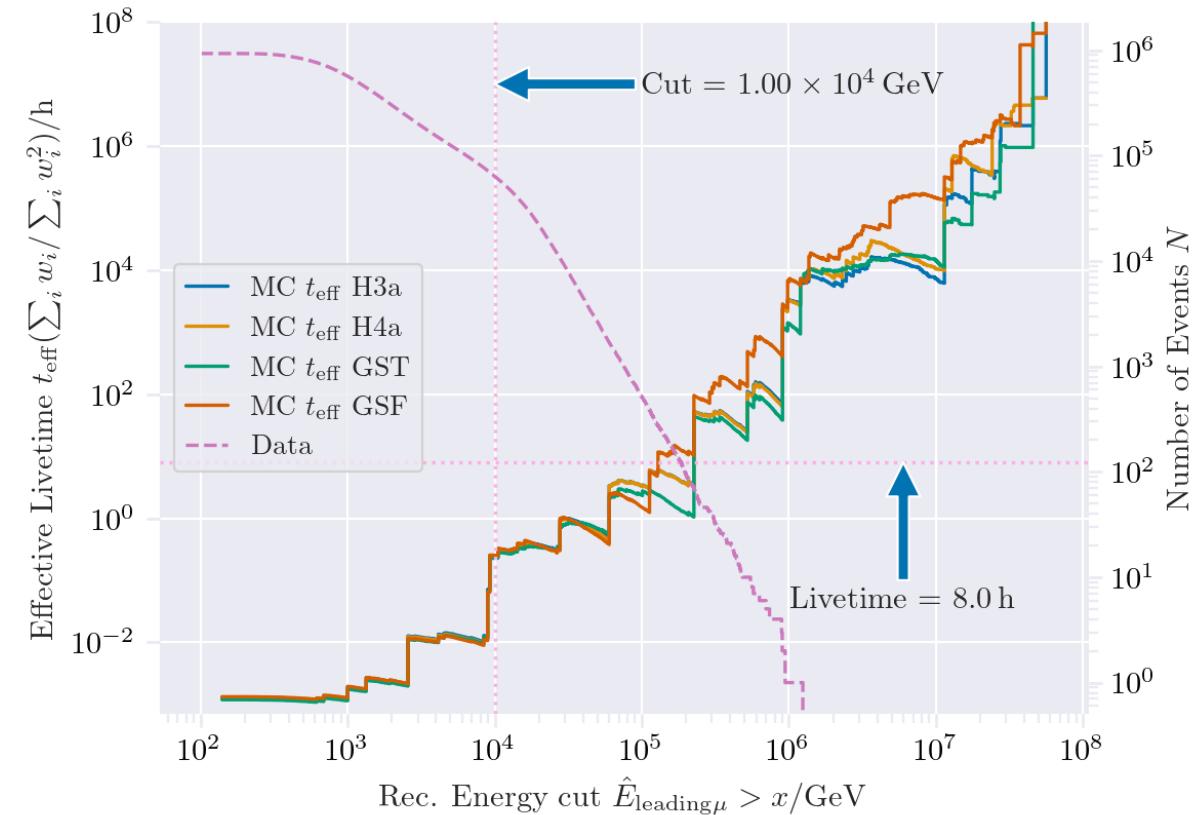
Solution to zenith problem?



- No complete solution, but a step in the right direction

New CORSIKA extended history simulations

- CORSIKA 77420
- SIBYLL 2.3d
- Icetray 1.5.1
- 5 components (p, He, N, Al, Fe)
- Polyplopia: True
- Trimshower: True
- Ecuts1: 273 GeV (hadron min energy)
- Ecuts2: 273 GeV (muon min energy)
- Ecuts3: 10^{20} GeV (electron min energy)
- Ecuts4: 10^{20} GeV (photon min energy)
- 4 datasets:
 - 30010: 600 GeV – 1 PeV
 - 30011: 1 PeV – 100 PeV
 - 30012: 100 PeV – 1 EeV
 - 30013: 1 EeV – 50 EeV
- [/data/sim/IceCube/2023/generated/CORSIKA_EHISTORY/](#)

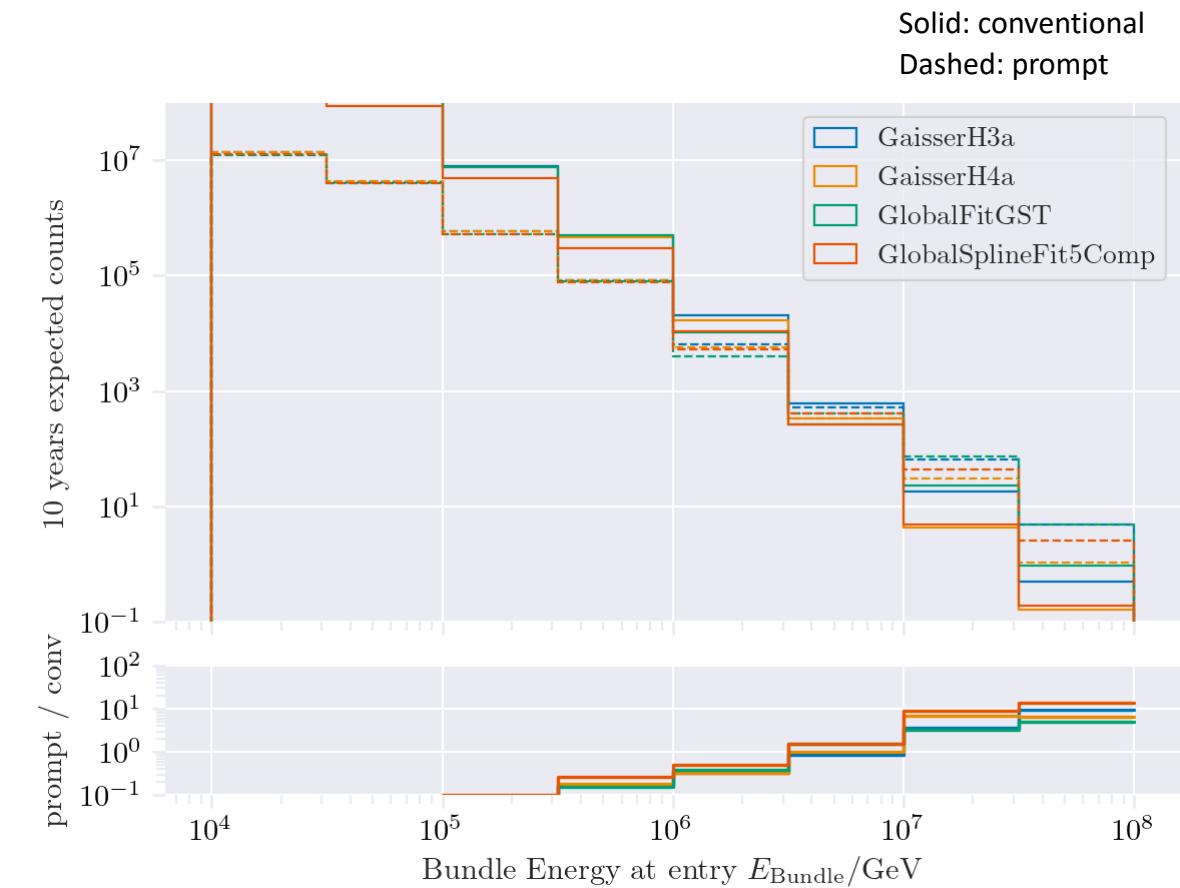
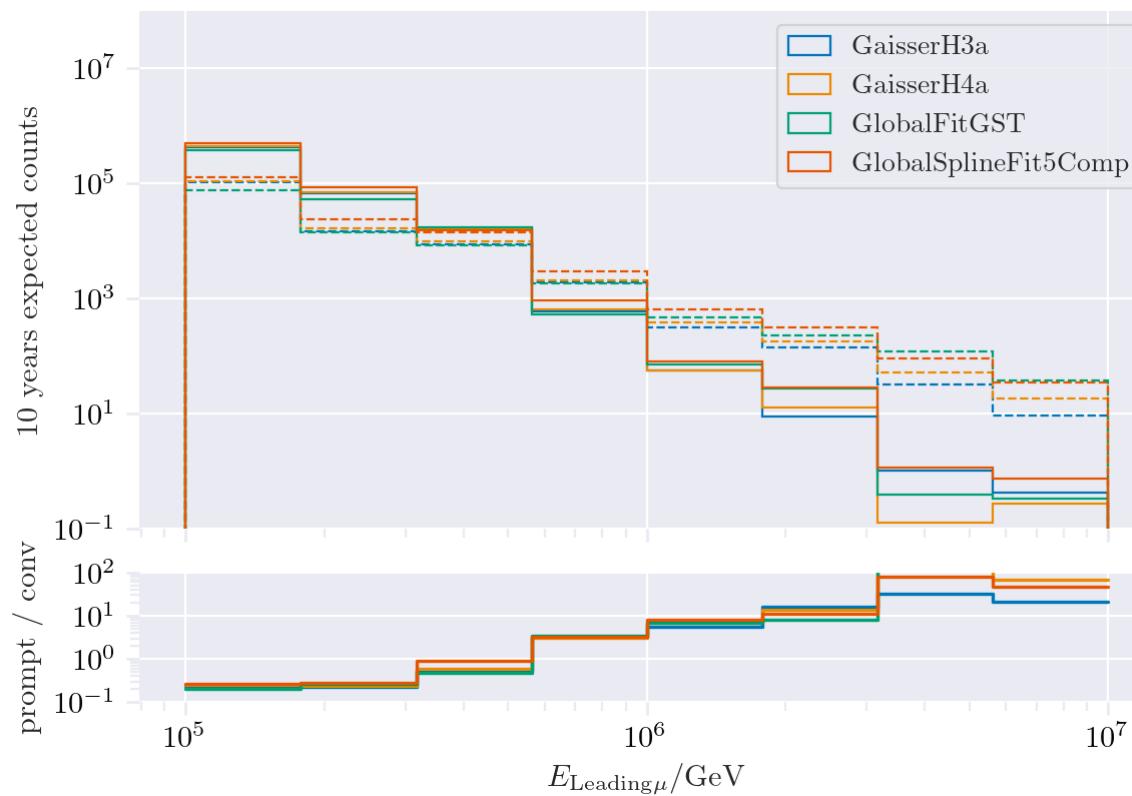


Please go ahead and test the datasets

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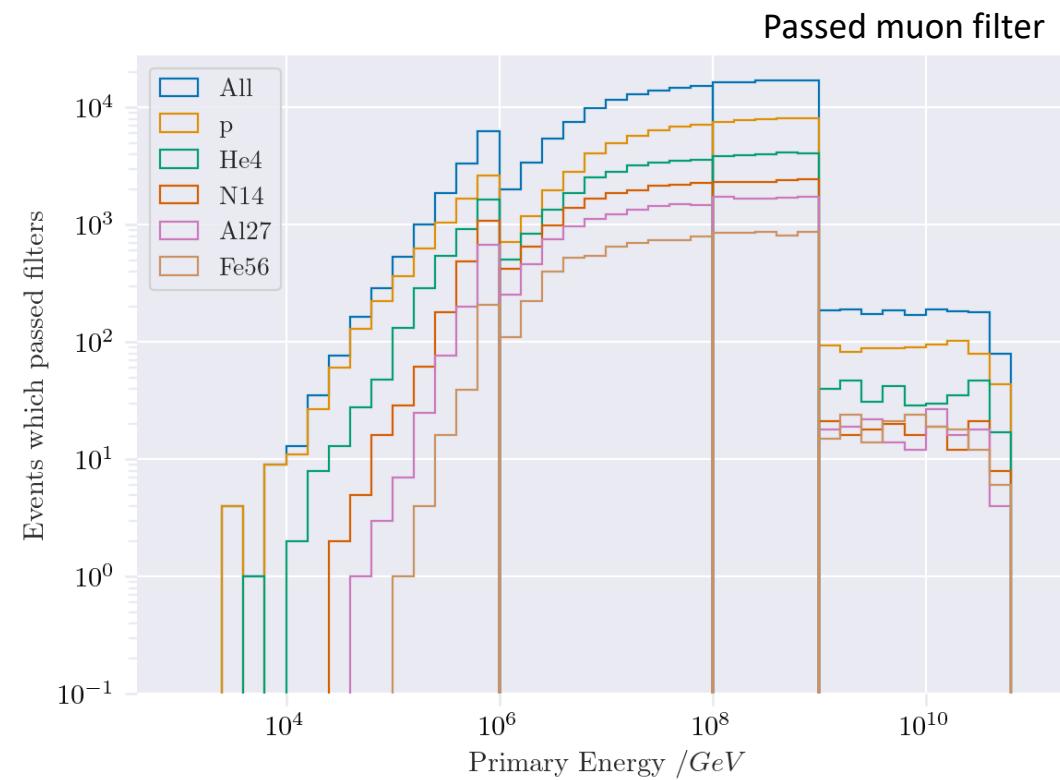
- Sufficient statistics above 1 PeV
- Too few statistics at lower energies

Expected muons for 10 years: leading vs. bundle energy



- Different primary fluxes lead to different prompt fluxes
- Bundle energy extends to higher energies

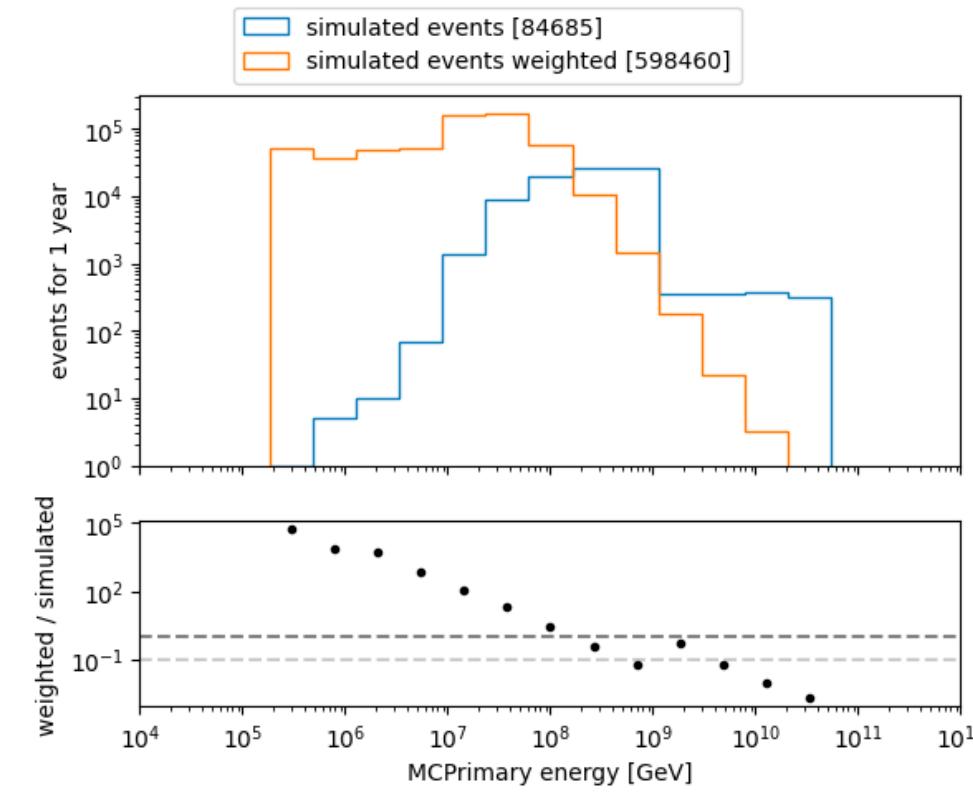
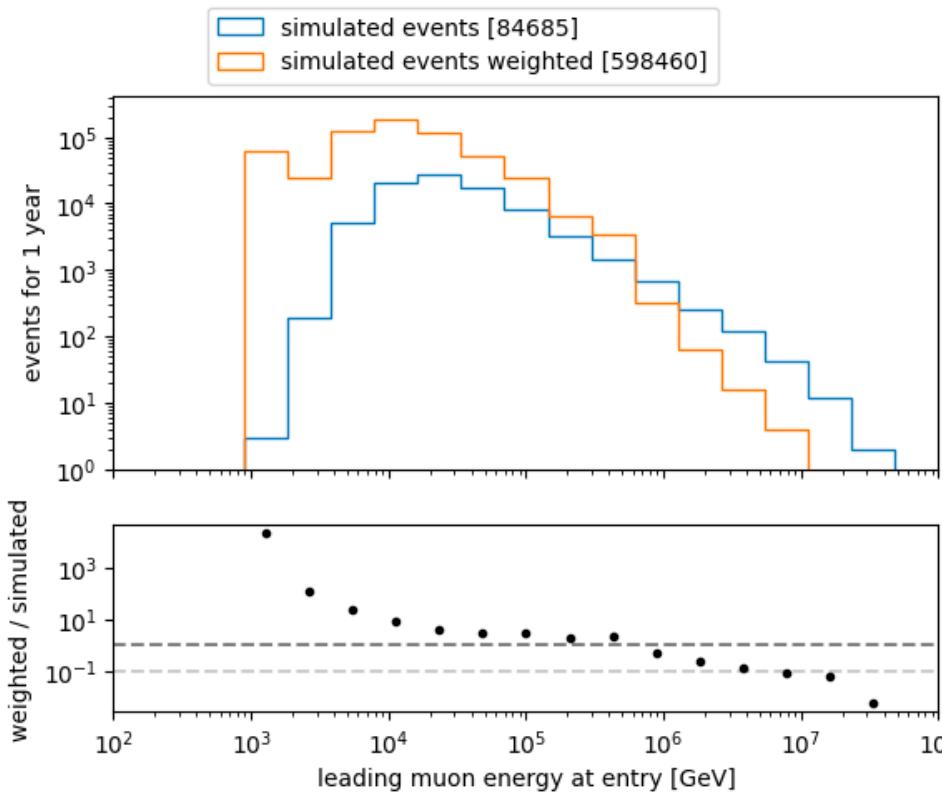
Simulated events



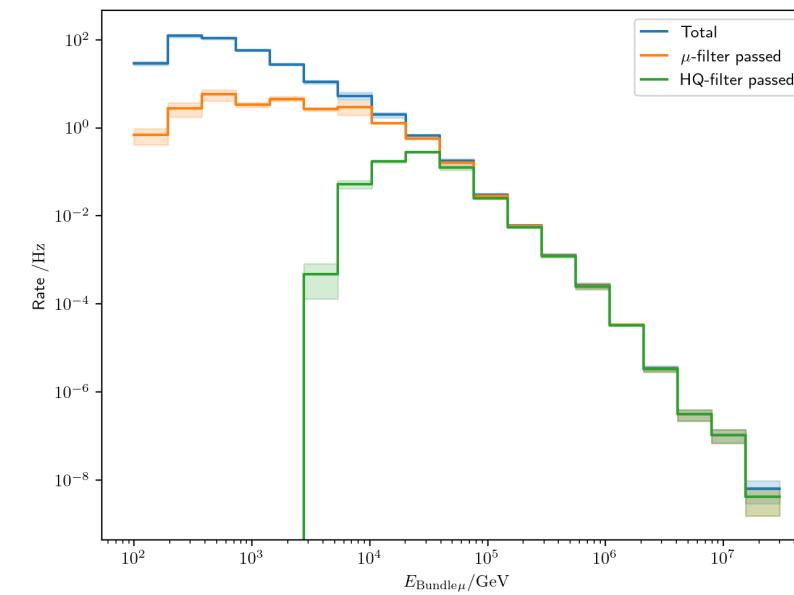
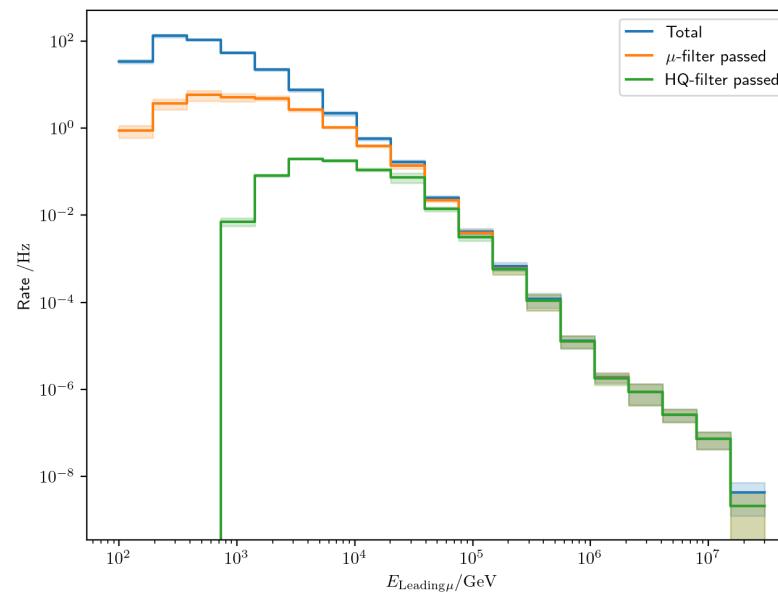
Which energies do we need to simulate?

L2 MuonFilter

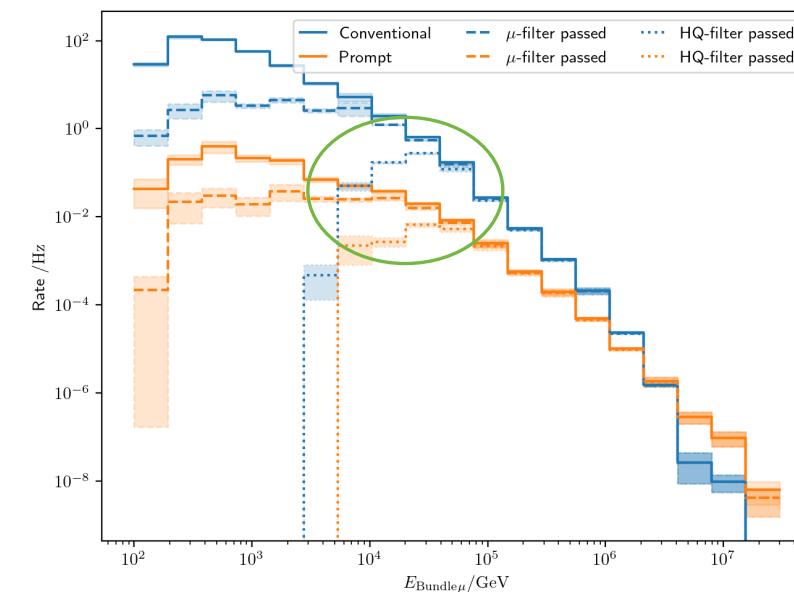
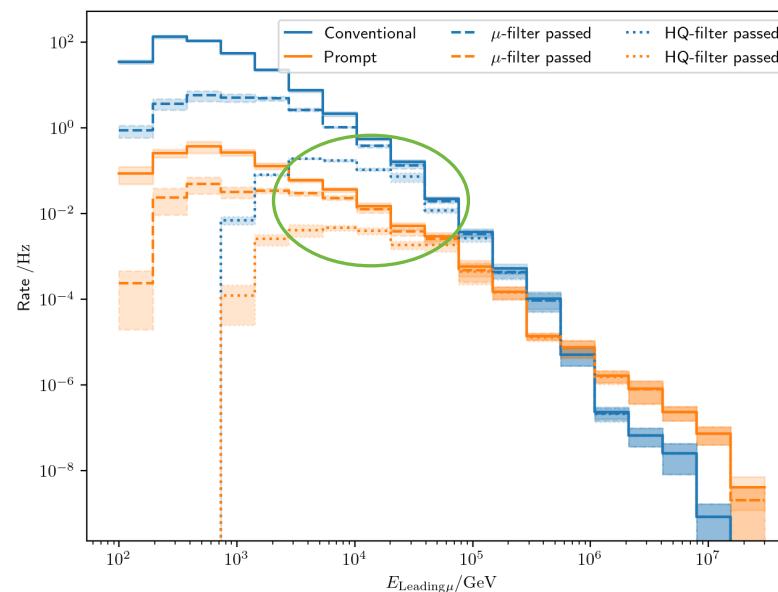
Bundle energy > 100 TeV



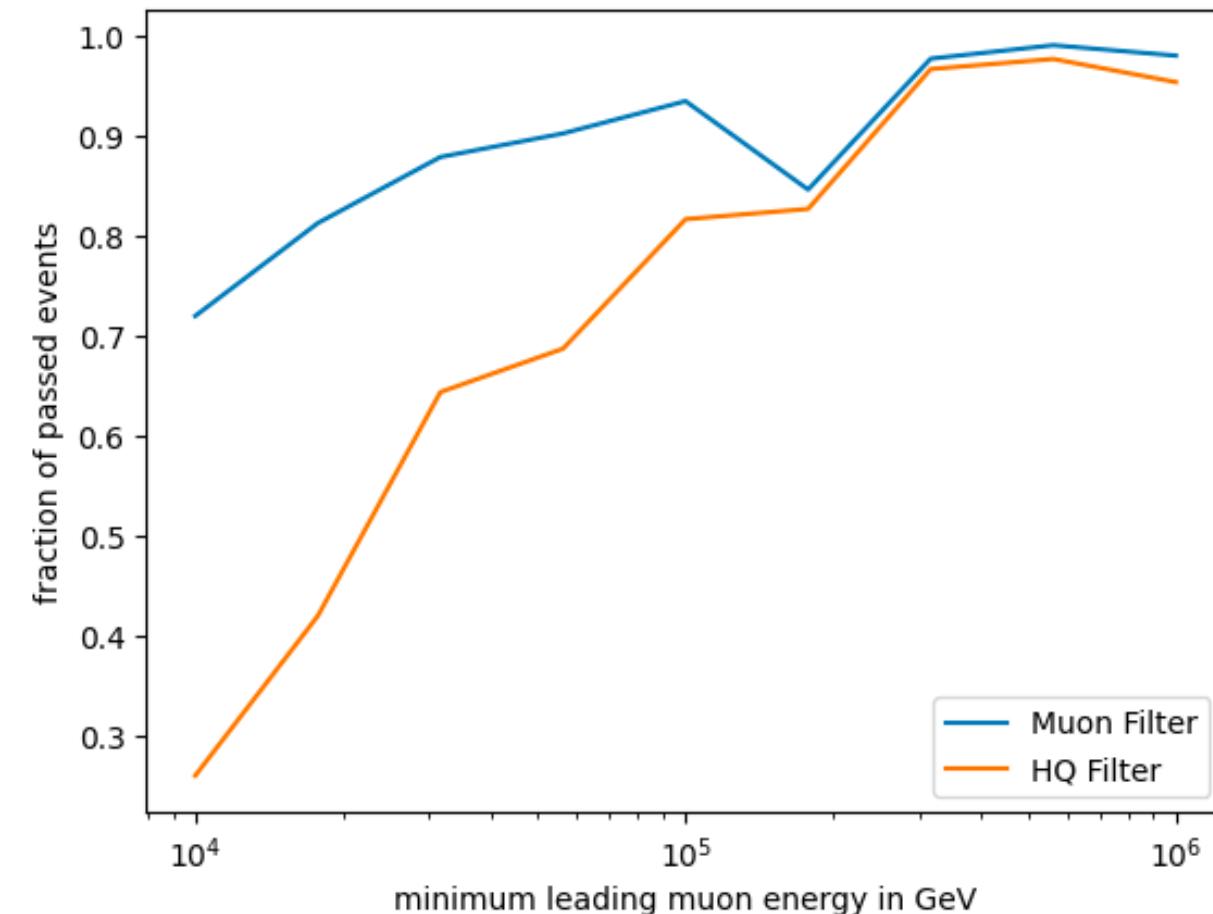
Filters



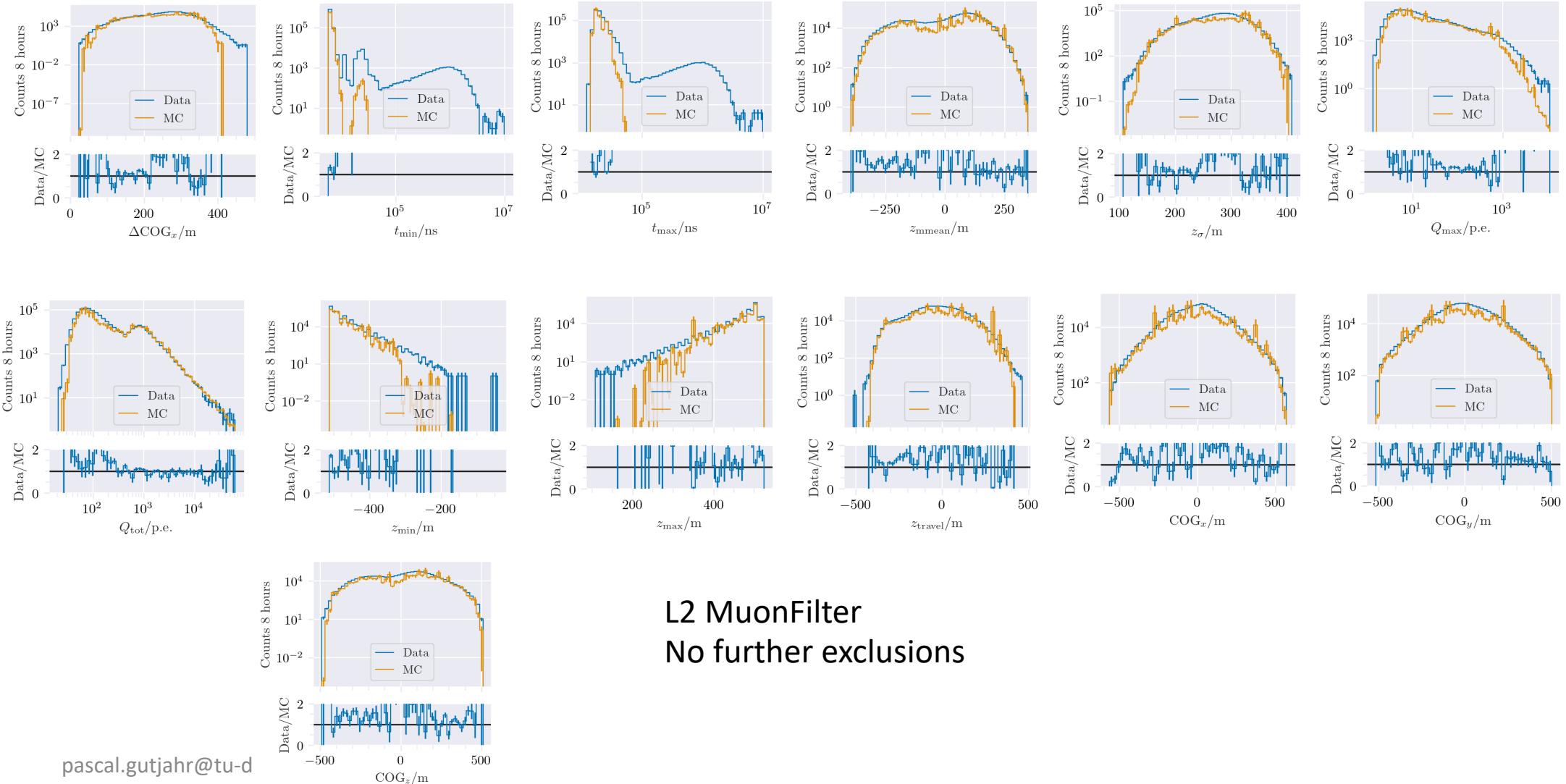
Choose muon filter,
larger statistics at 10 TeV



Filters – passed events per leading energy

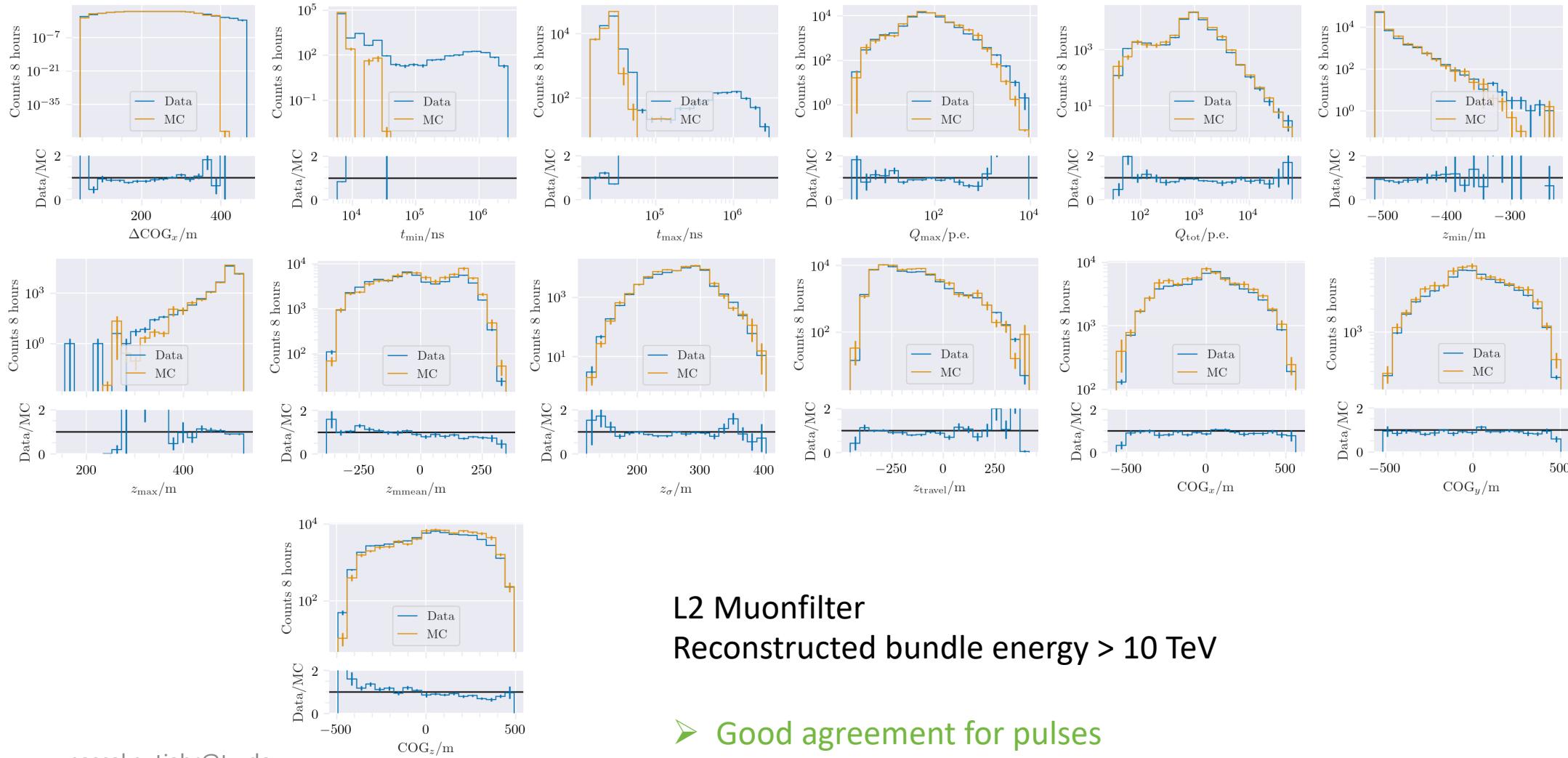


Data-MC: HitStatistics - SplitInIceDSTPulses



L2 MuonFilter
No further exclusions

Data-MC: HitStatistics- SplitInIceDSTPulses



Evaluation of models used in pseudo analysis

- Note: the DNN reconstruction models are still investigated! The models used here are in an early stage. So far, the two bachelor students have trained models with better performance.
- Updates on the models and reconstructions are provided in the near future

Data-MC agreements

- Two bachelor students worked on reconstructions using the dnn_reco framework (thesis available in english):
 - Leander Flottau
 - Benjamin Brandt

Reconstructions:

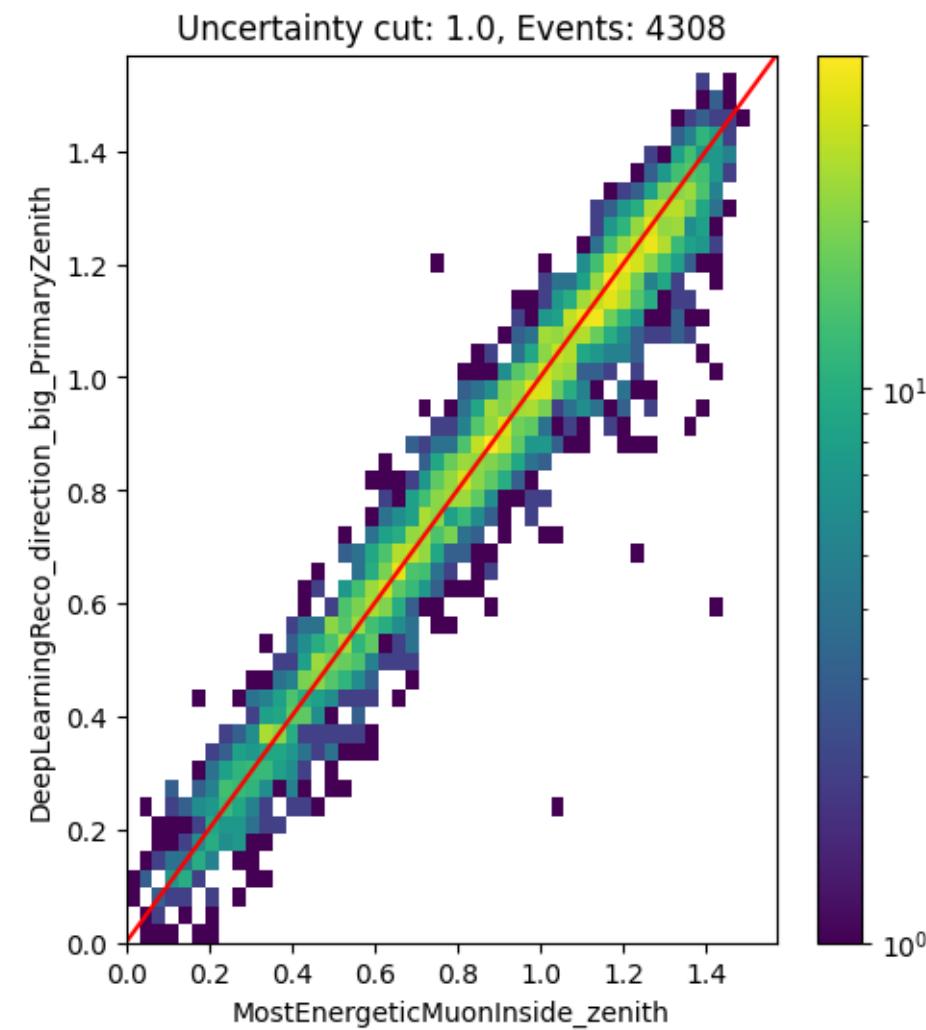
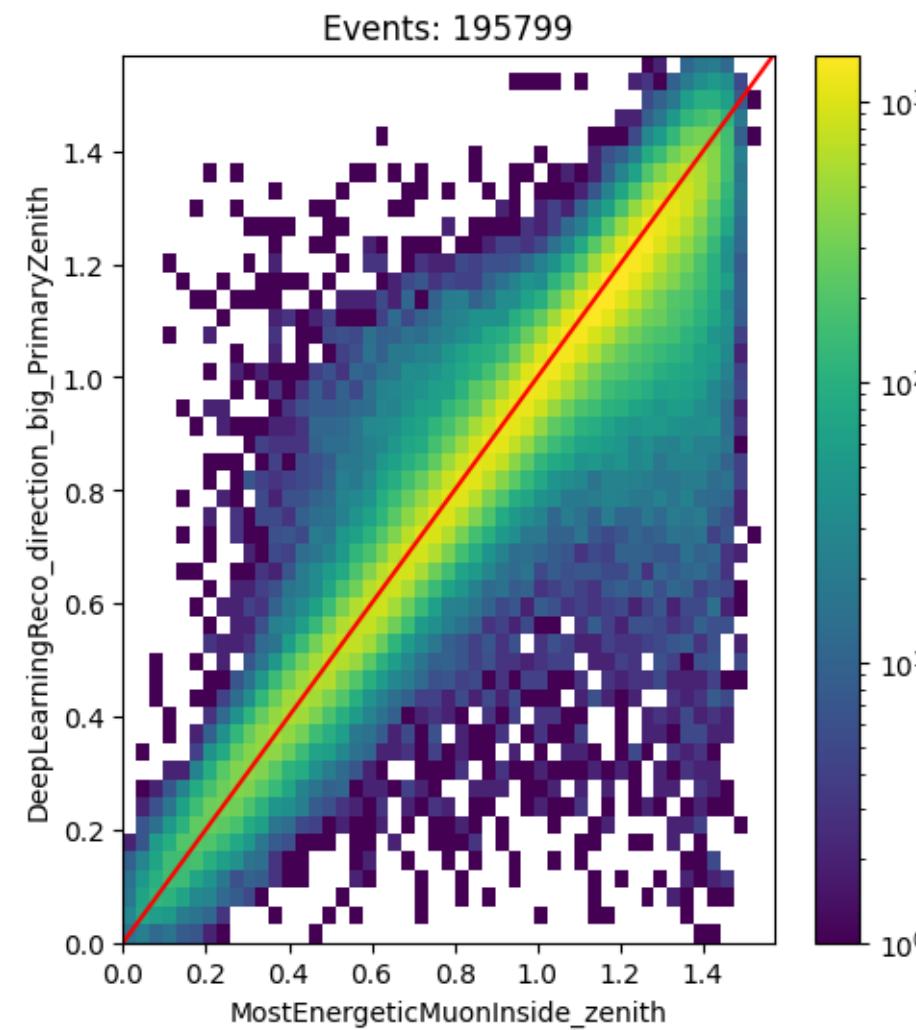
- Leading energy
- Leading fraction
- Bundle energy
- Multiplicity
- Azimuth
- Zenith

Work in progress

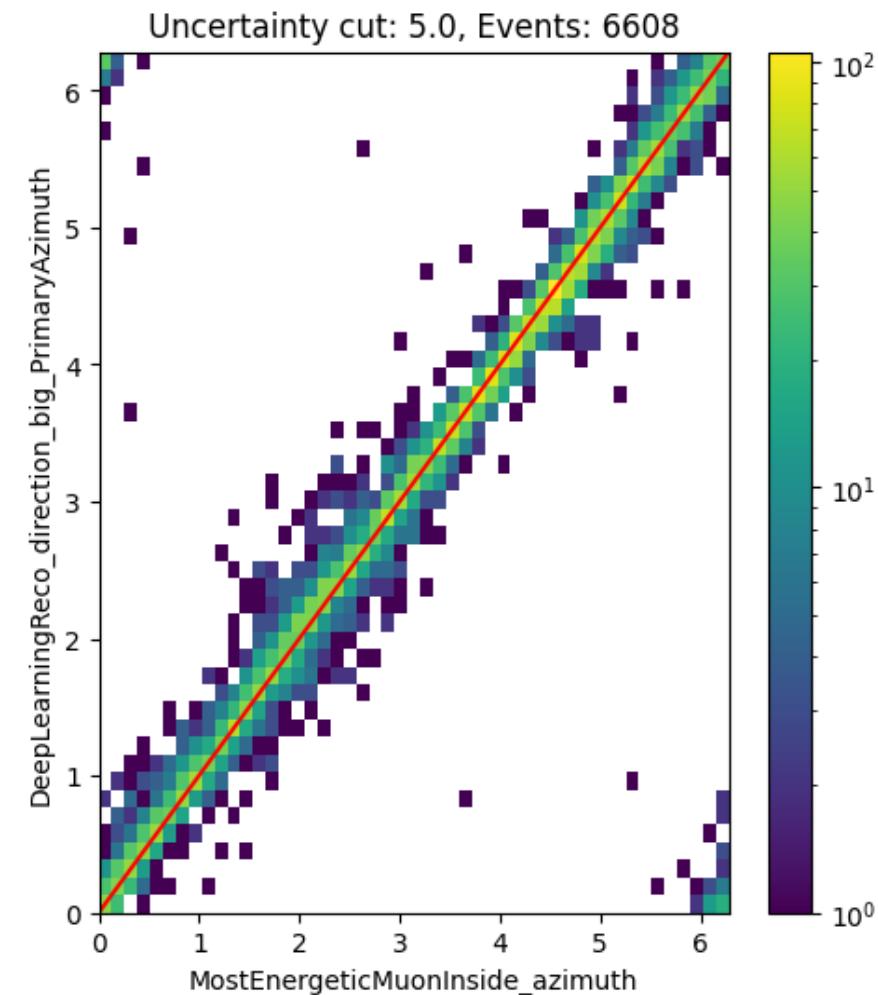
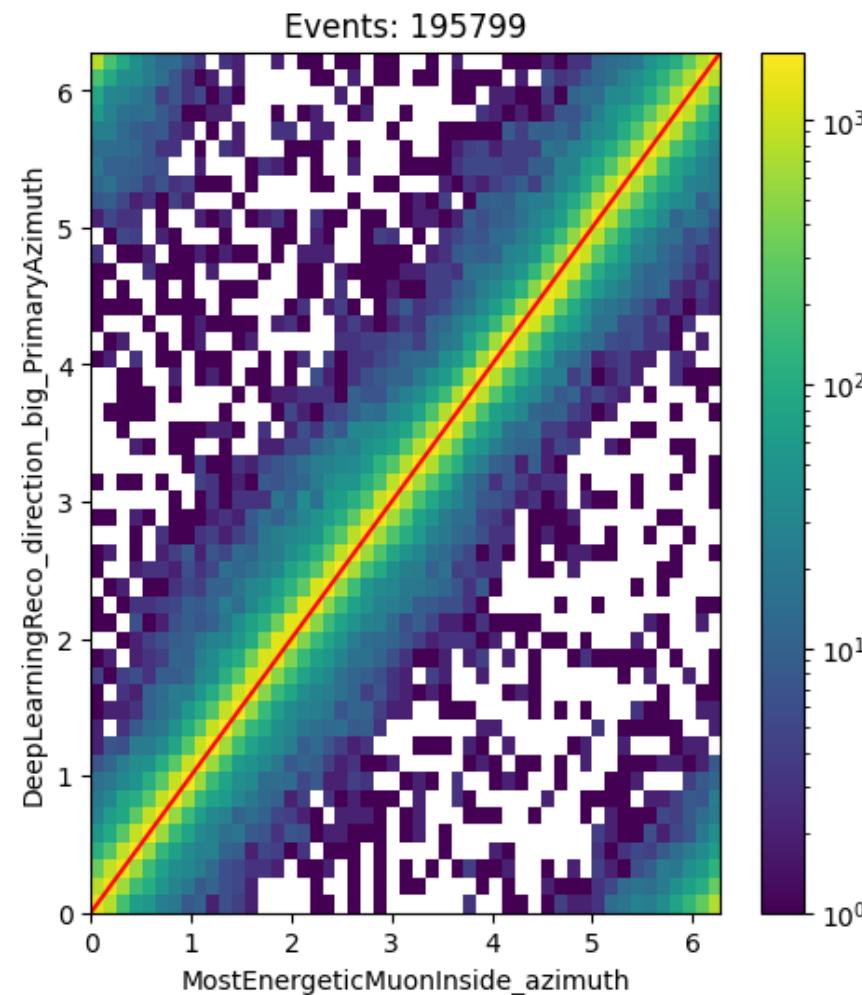
General:

- Trained on uncleaned and $6\mu s$ cleaned muon pulses
- Processed 8h of experimental data (June 4th, 2020)

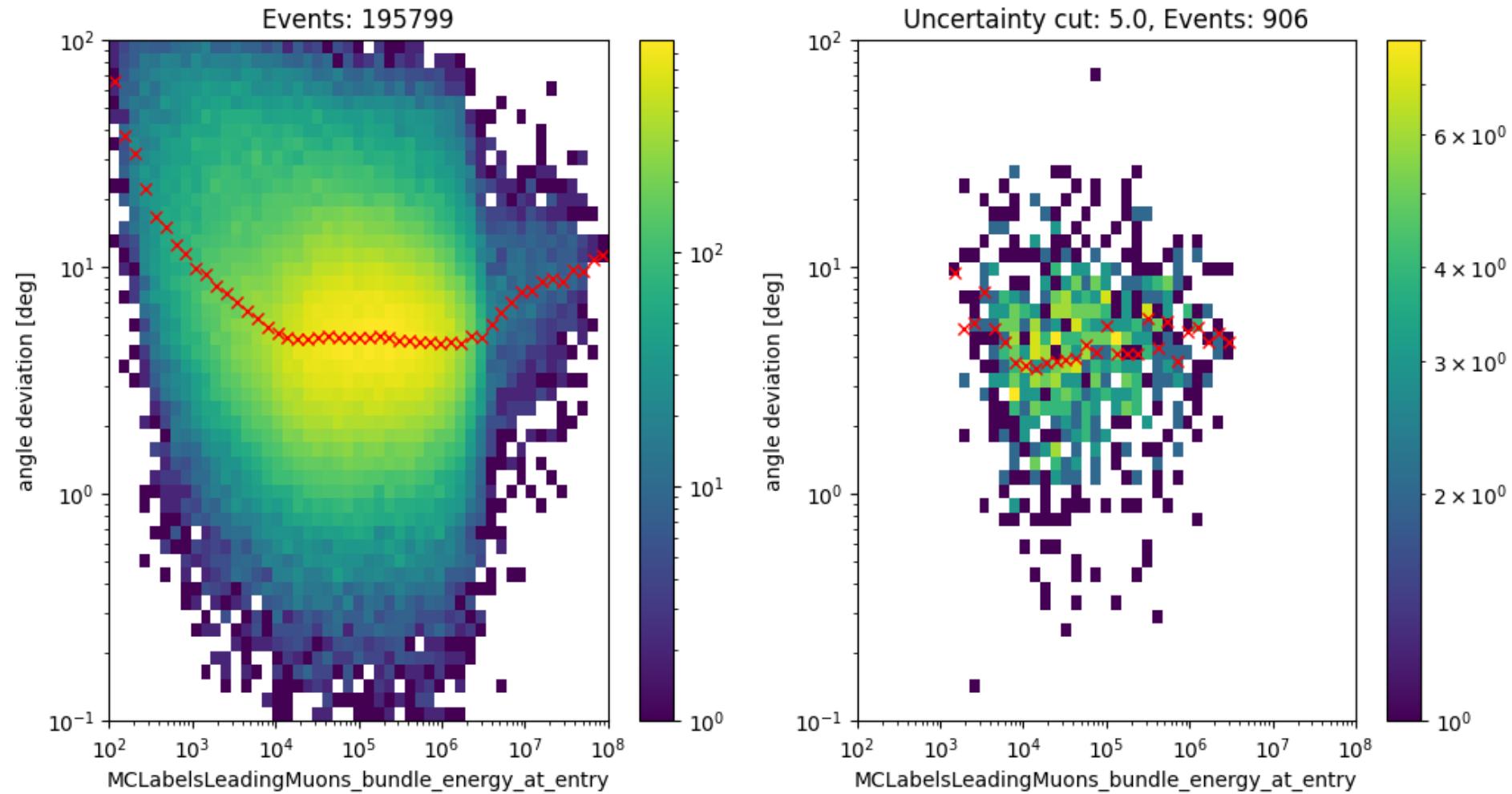
Zenith reconstructions



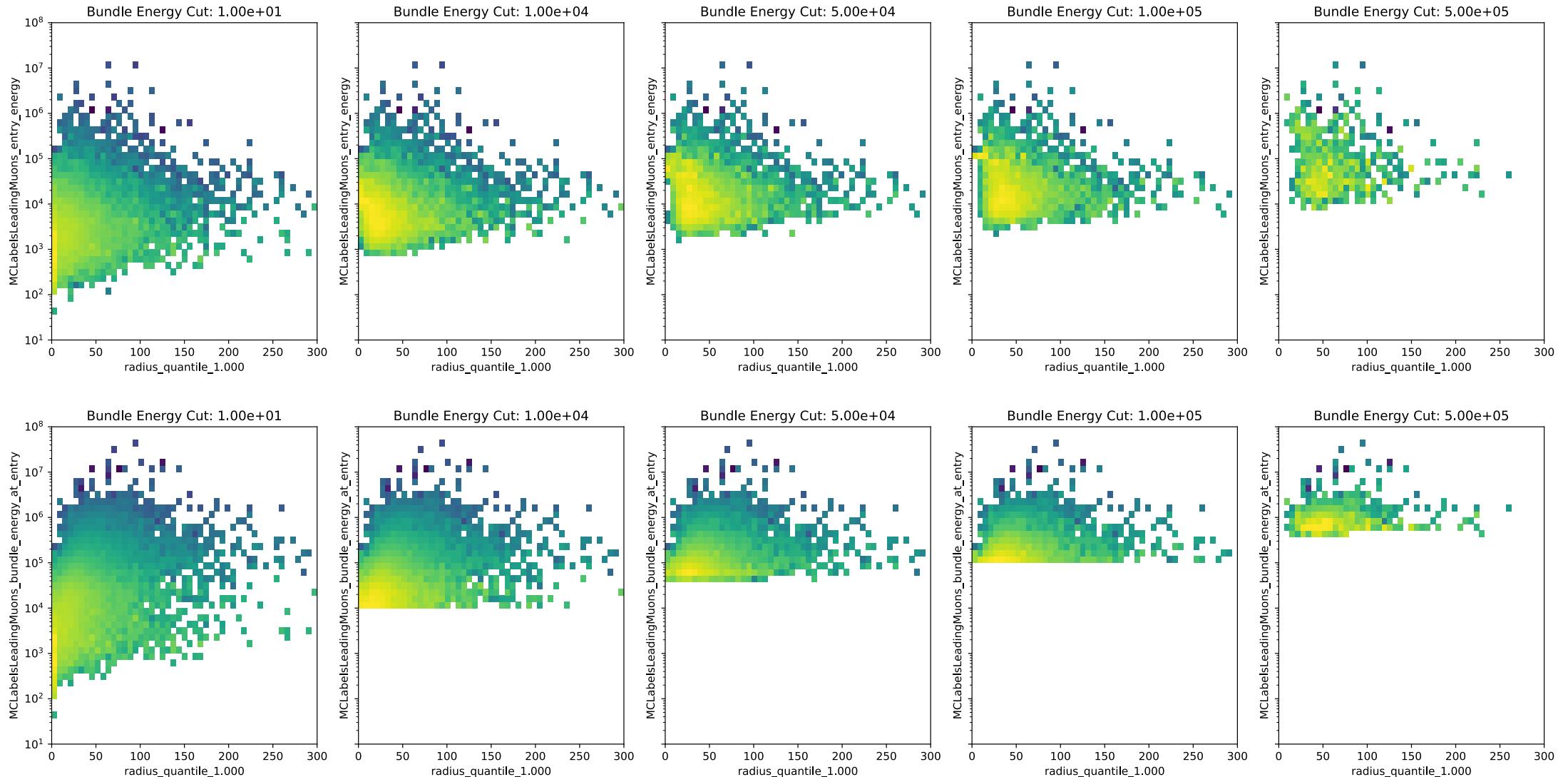
Azimuth reconstructions



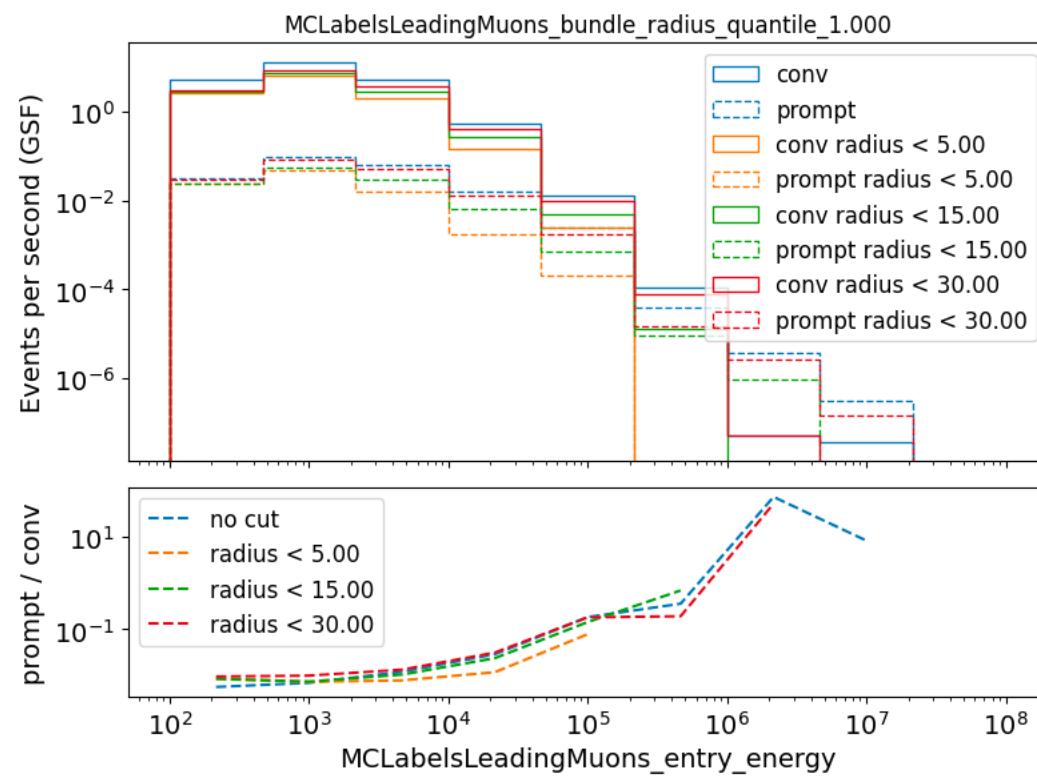
Angular resolution



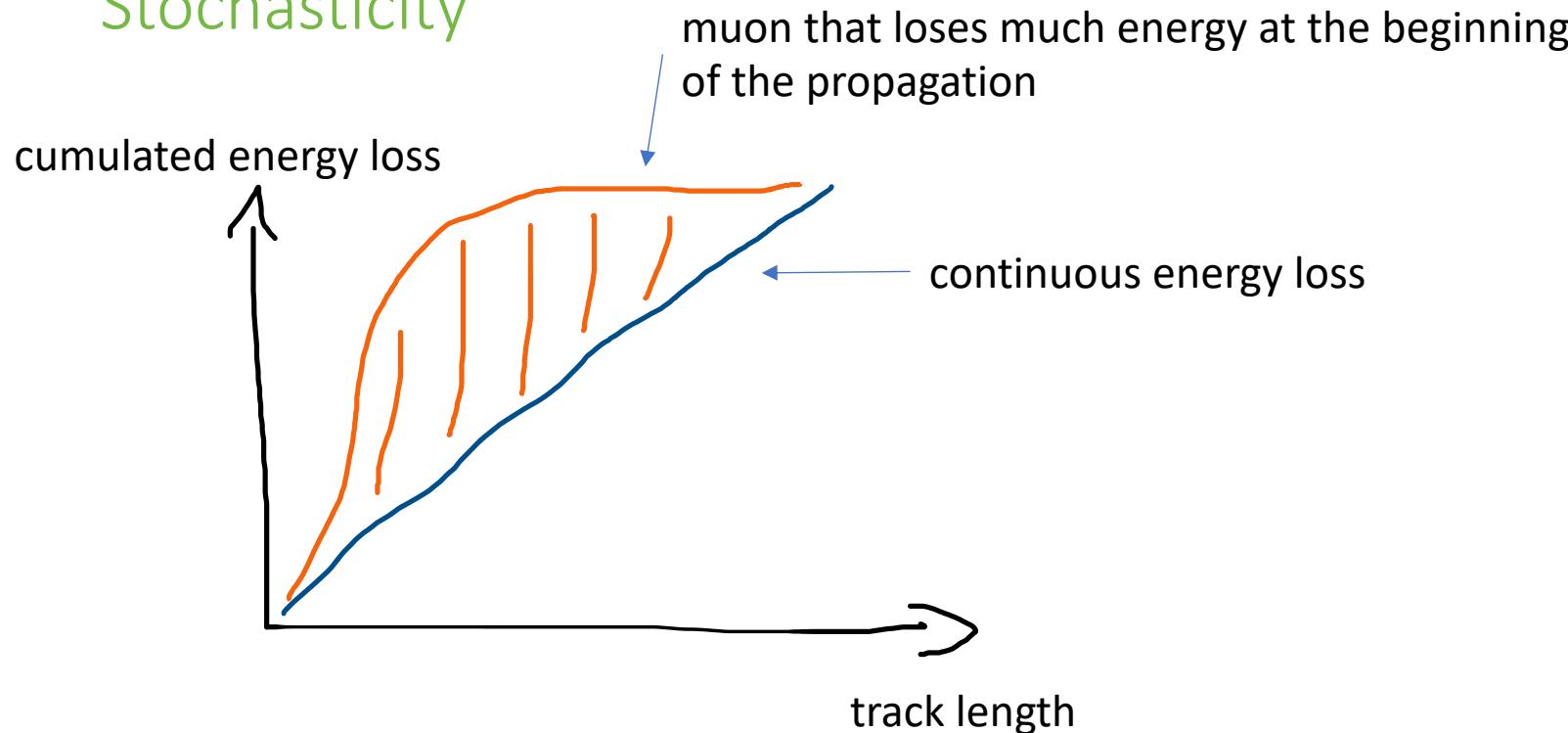
Bundle radius - energy



Muon flux – bundle radius



Stochasticity



- calculate the area between the “continuous muon energy loss” and the accumulated muon energy losses and normalize it
- high stochasticity: area = 1
- no stochasticity: area = 0

Bundle radius

- calculate perpendicular distance between leading muon and closest point to detector center
 - reference point
- calculate the distance between the leading muon and all the other muons at the reference point
- analyze the distances weighted by their energy (100%, 99%, 95%,... energy containment)