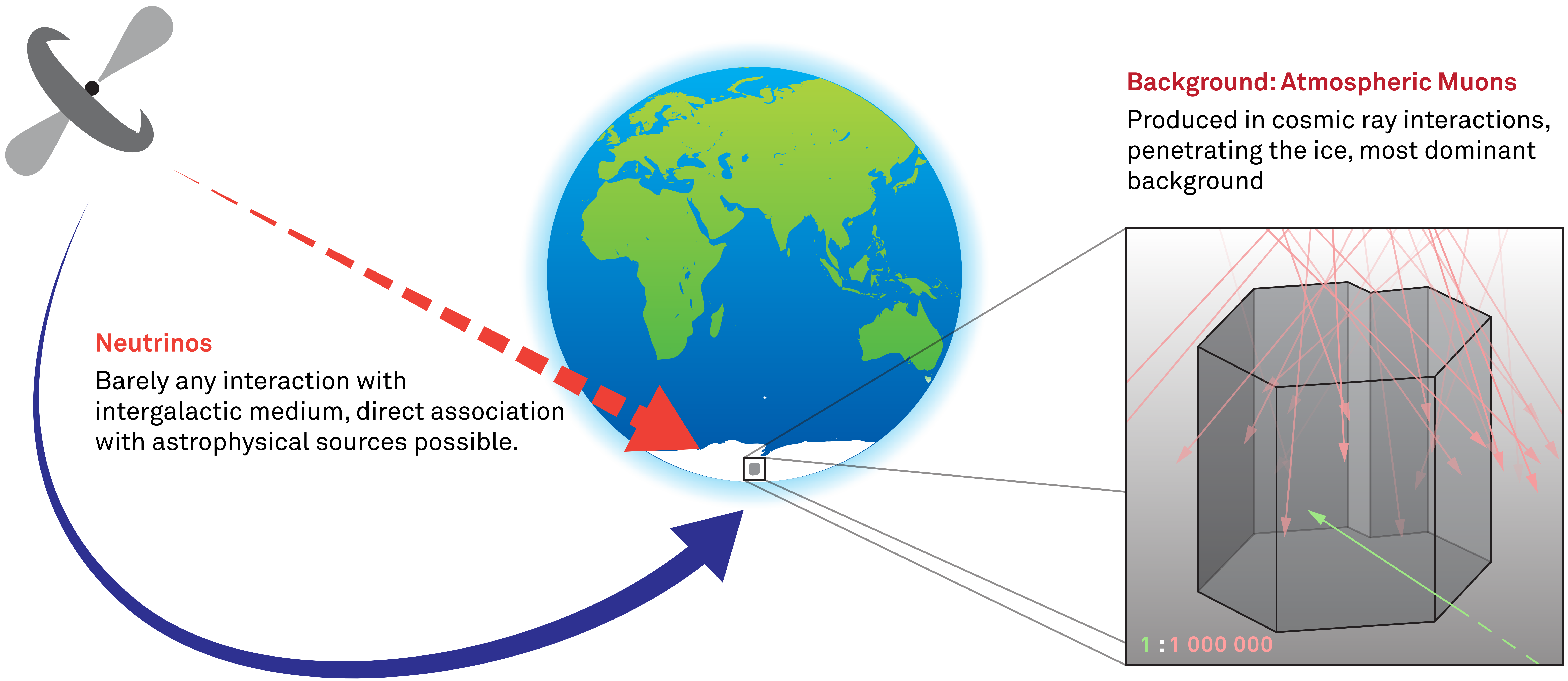
Model-independent Measurement of the Atmospheric Muon Neutrino Energy Spectrum up to 2.5 PeV

J. Soedingrekso, T. Hoinka, M. Börner

International Cosmic Rays Conference 2019

Madison

ICECUBE AND ASTROPHYSICS



Background: Atmospheric Muons

Produced in cosmic ray interactions, penetrating the ice, most dominant background

Neutrinos

Barely any interaction with intergalactic medium, direct association with astrophysical sources possible.

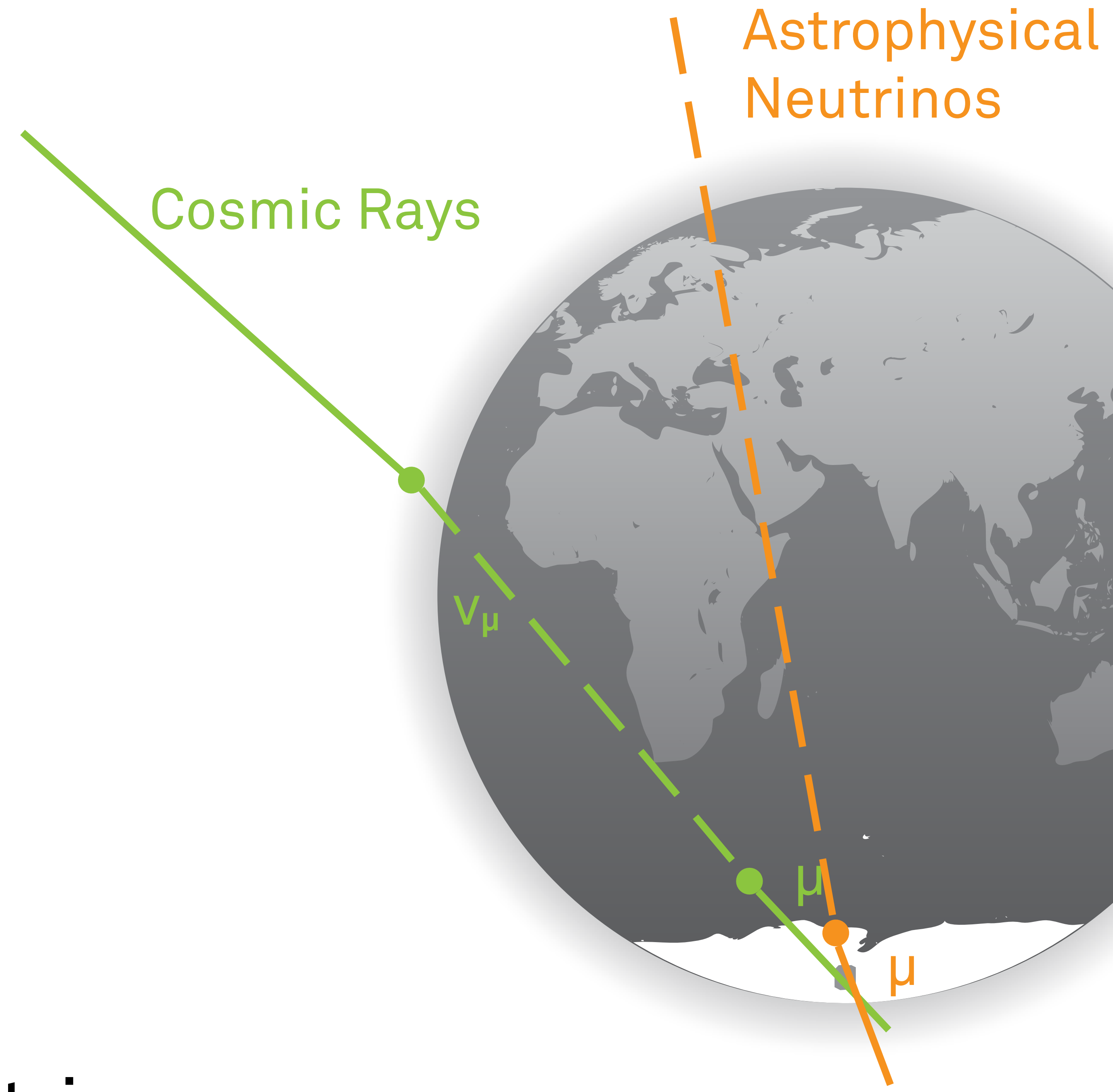
Charged Cosmic Rays

Deflected by magnetic fields, association with sources very difficult.

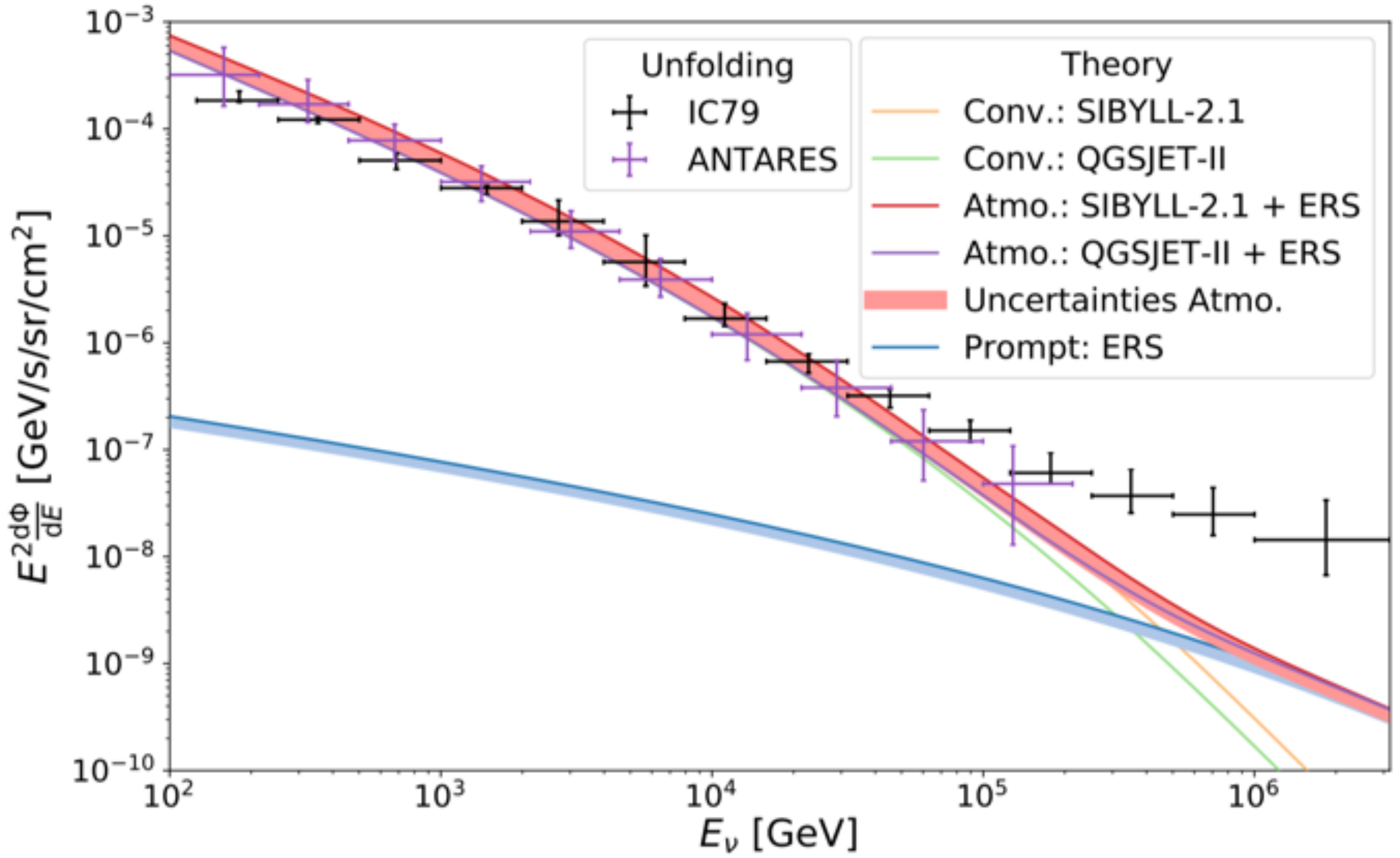
Signal: Upgoing Muon Neutrinos

All background is absorbed by Earth,
Event rate of few per hour

ICECUBE AND ASTROPHYSICS



[10.1140/epjc/s10052-017-5261-3]



- Resulting diffuse muon neutrino spectrum is composed of different components
- Steepening of the atmospheric spectrum indicates excess of astrophysical neutrinos at high energies

EVENT SELECTION

technische universität dortmund

EVENT SELECTION

ICECUBE PRELIMINARY

- Goal: Selecting a set of upgoing muon neutrinos
- Background mostly mis-reconstructed atmospheric muons and cascades
- Estimate resulting event rate for different definitions of signal and background in the event selection pipeline
- Atmospheric muons as background, well-reconstructed upgoing neutrinos as signal results in best event rate

μ_{atm}	$\nu^{\uparrow}_{\mu,\Delta_\theta<5^\circ}$	$\nu^{\uparrow}_{\mu,\Delta_\theta>5^\circ}$	$\nu^{\downarrow}_{\mu}$	ν^{nc}_{μ}	ν_e	**Event Rate**
🔴	🟢	⚪	⚪	⚪	⚪	3.50 mHz
🔴	🟢	🔴	⚪	⚪	⚪	2.32 mHz
🔴	🟢	⚪	🔴	⚪	⚪	3.30 mHz
🔴	🟢	🔴	🔴	⚪	⚪	2.37 mHz
🔴	🟢	⚪	⚪	🔴	🔴	3.30 mHz
🔴	🟢	🔴	🔴	🔴	🔴	2.61 mHz
🔴	🟢	🟢	⚪	⚪	⚪	3.49 mHz
🔴	🟢	🟢	🔴	⚪	⚪	3.36 mHz
🔴	🟢	🟢	🟢	🔴	🔴	3.27 mHz
🔴	🟢	🟢	🟢	🟢	⚪	3.36 mHz

🟢 Included in the training set as signal

🔴 Included in the training set as background

⚪ Not included in training set

FEATURE SELECTION

Initially
1224

↓

Constant,
Correlation > 0.95
323

↓

Mismatches
311

↓

mRMR
61

- Reduce dimensionality of data
- Keep most relevant attributes in the sense of a high neutrino event rate
- Remove attributes that feature disagreements between simulations and data

FEATURE SELECTION

Initially
1224

↓

Constant, Correlation > 0.95
323

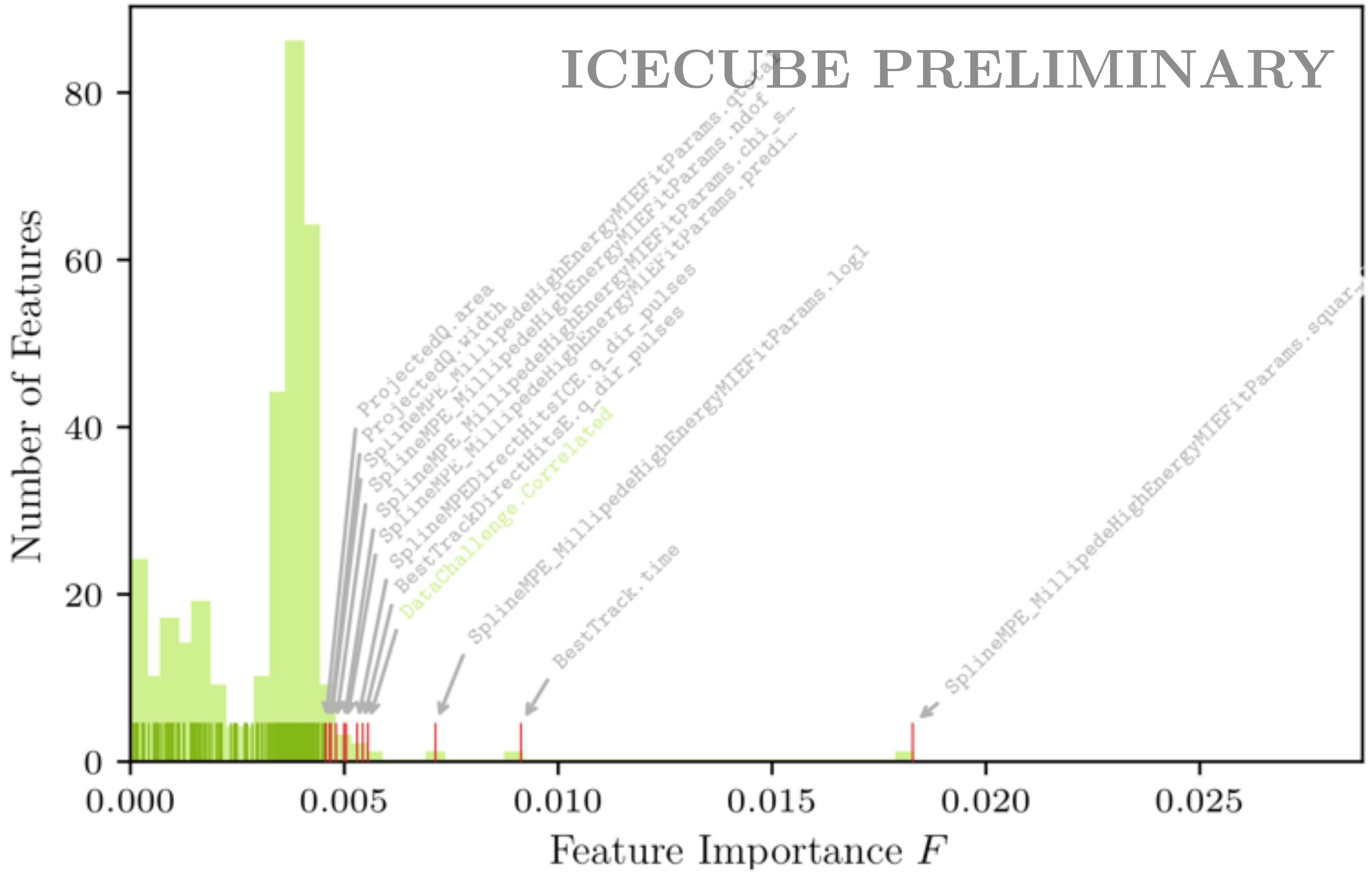
↓

Mismatches
311

↓

mRMR
61

- Reduce dimensionality of data
- Keep most relevant attributes in the sense of a high neutrino event rate
- Remove attributes that feature disagreements between simulations and data



Separate data from simulations using Random Forest, remove features that are identified as outliers, i.e. contribute most significantly to the mismatches

FEATURE SELECTION

Initially
1224

↓

Constant, Correlation > 0.95
323

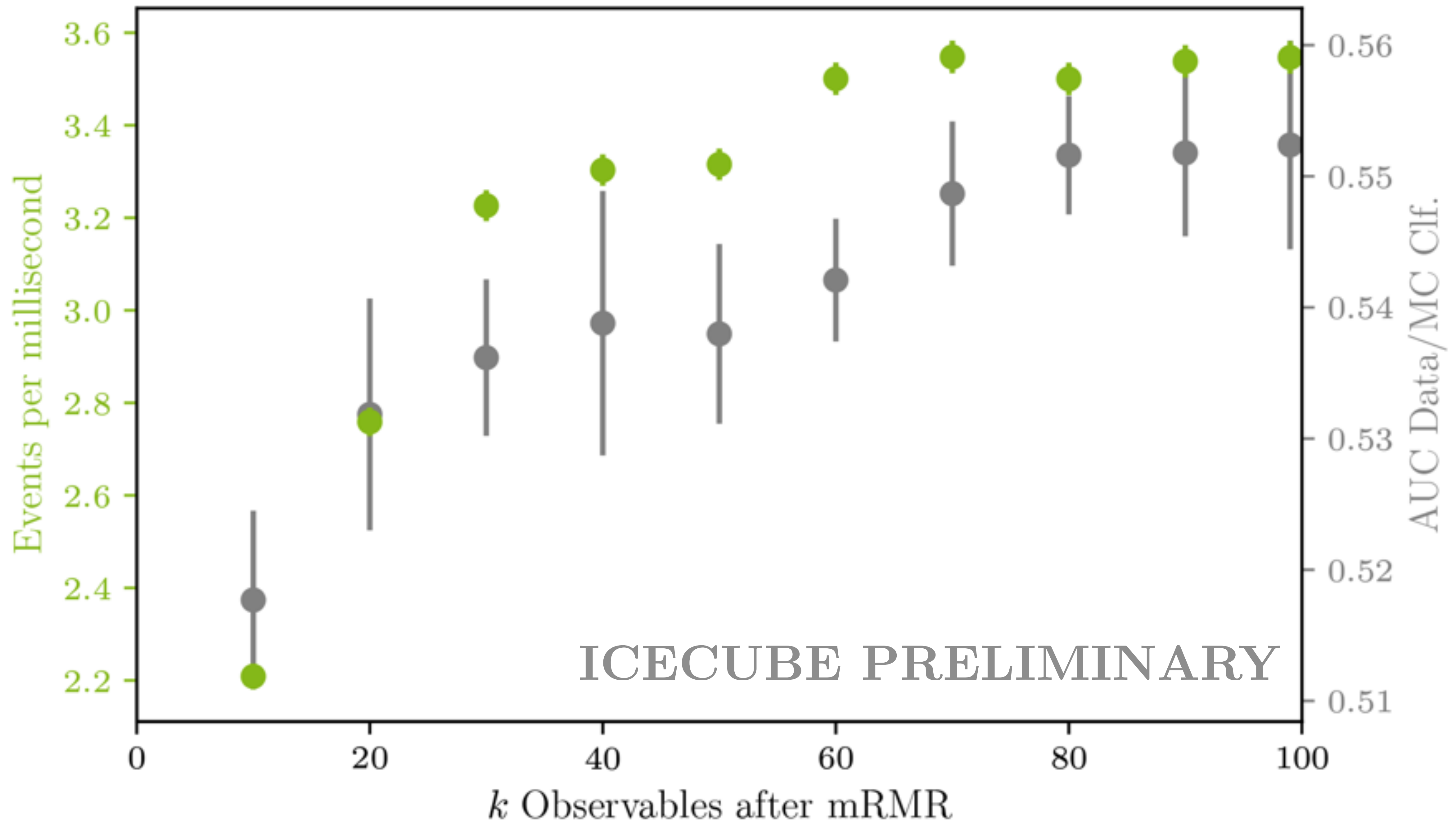
↓

Mismatches
311

↓

mRMR
61

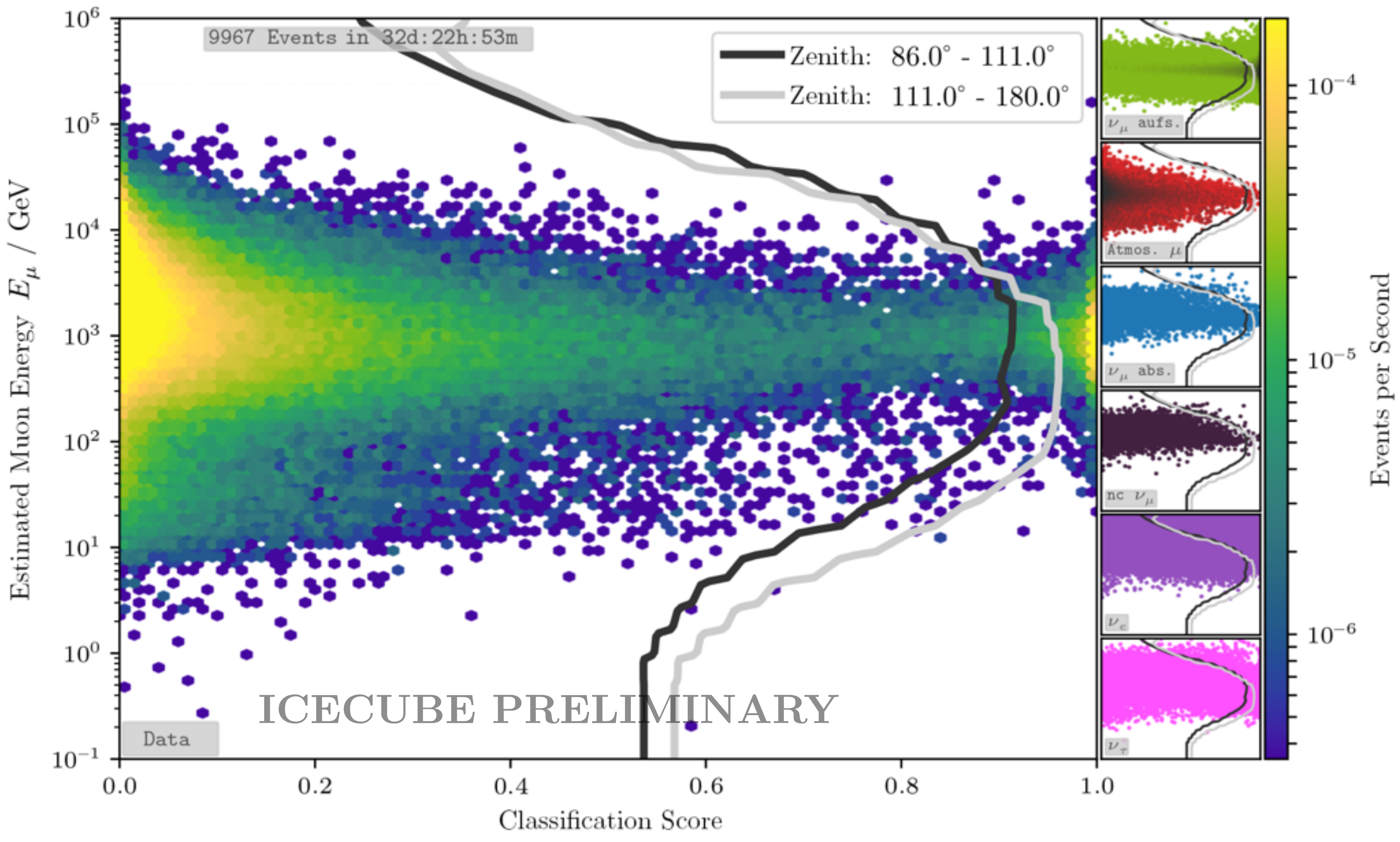
- Reduce dimensionality of data
- Keep most relevant attributes in the sense of a high neutrino event rate
- Remove attributes that feature disagreements between simulations and data



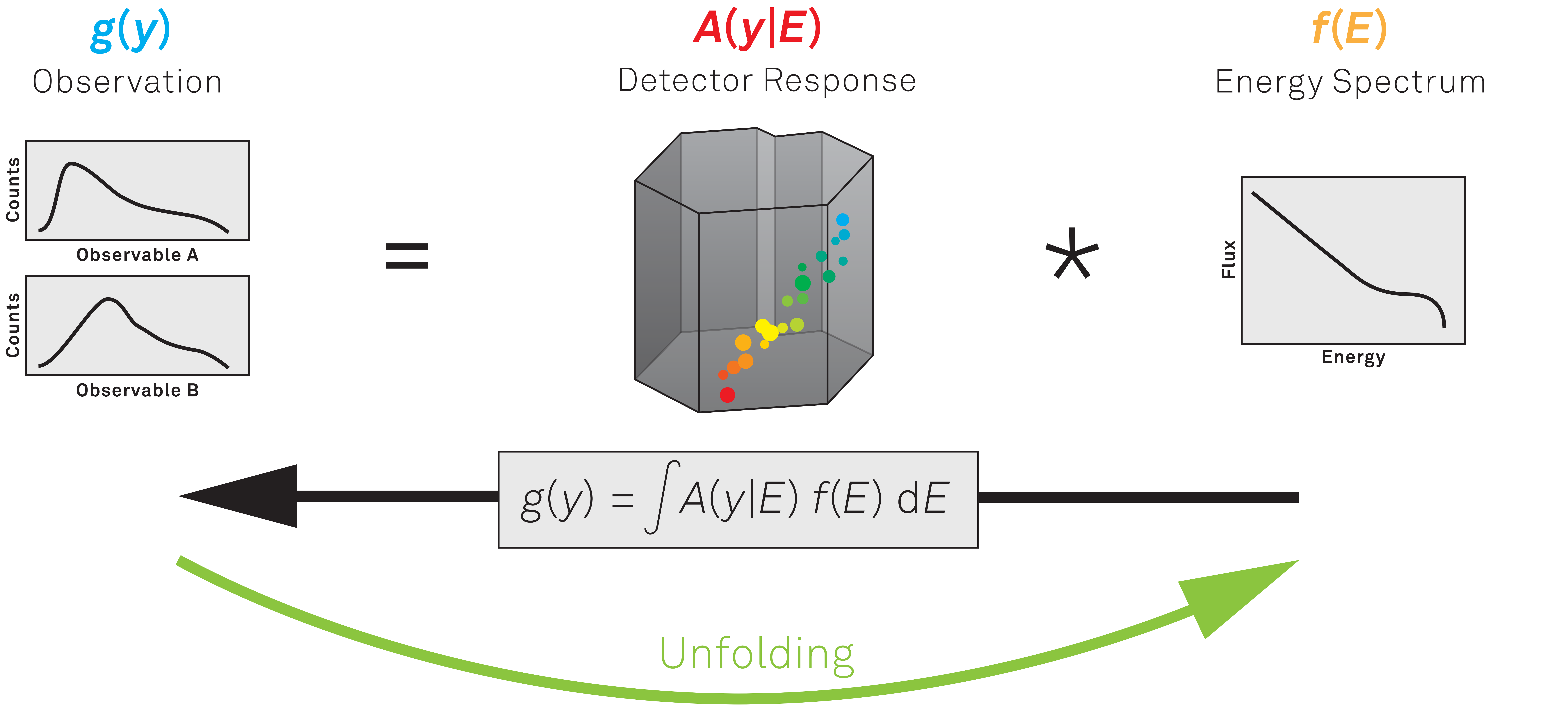
mRMR (minimum Redundancy maximum Relevance)
Calculate resulting expected event rate and mismatches to determine
number of attributes to be used.

CLASSIFICATION

- Random Forest: Classification score
- For the unfolding a purity of 99.7% is demanded
- To ensure purity is the same in all energy and zenith regions, energy cut is a function of both energy and zenith



UNFOLDING


g(y)
Observation
Counts
Observable A
Counts
Observable B
=
A(y|E)
Detector Response
*
f(E)
Energy Spectrum
Flux
Energy
g(y) = ∫ A(y|E) f(E) dE
Unfolding
T. Hoinka

UNFOLDING

$$g(y) = \int A(y|x) f(x) \mathrm{d}x \xrightarrow[\text{Discretization/Binning}]{} \mathbf{g} = \mathrm{A} \cdot \mathbf{f}$$

UNFOLDING

$$g(y) = \int A(y|x) f(x) \mathrm{d}x \xrightarrow[\text{Discretization/Binning}]{} \mathbf{g} = \mathrm{A} \cdot \mathbf{f}$$

$$\mathcal{L}(\mathbf{g}|\mathbf{f}) = \prod_{u=1}^{m} \left[\frac{(\mathrm{A}\mathbf{f})_u^{g_u}}{g_u!} \exp\left(-(\mathrm{A}\mathbf{f})_u\right) \right]$$

Poissonian Statistics

A	Detector Response Matrix
$\mathbf{f}$	Neutrino Energy Spectrum
$\mathbf{g}$	Observable Vector

UNFOLDING

$$g(y) = \int A(y|x) f(x) \mathrm{d}x \xrightarrow[\text{Discretization/Binning}]{} \mathbf{g} = \mathrm{A} \cdot \mathbf{f}$$

$$\mathcal{L}(\mathbf{g}|\mathbf{f}) = \prod_{u=1}^{m} \left[\frac{(\mathrm{A}\mathbf{f})_u^{g_u}}{g_u!} \exp\left(-(\mathrm{A}\mathbf{f})_u\right) \right] \exp\left(-\frac{1}{2\tau} \log_{10}\left(\mathrm{A}_{\mathrm{eff}}^{-1}(\mathbf{f} + d\mathbf{1})^\top\right) \mathrm{C}^2 \log_{10}\left(\mathrm{A}_{\mathrm{eff}}^{-1}(\mathbf{f} + d\mathbf{1})\right) \right)$$

Poissonian Statistics

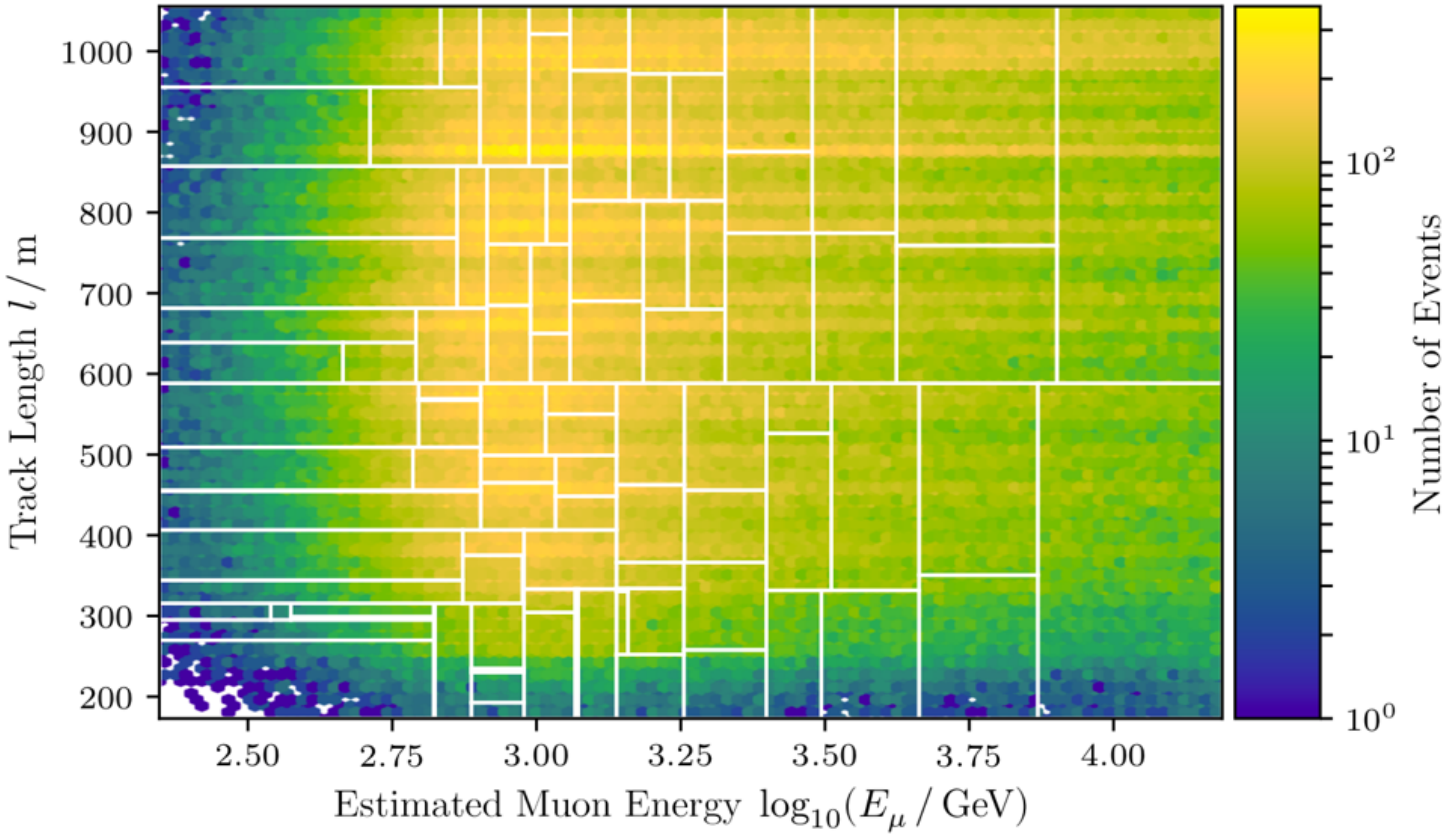
A	Detector Response Matrix
$\mathbf{f}$	Neutrino Energy Spectrum
$\mathbf{g}$	Observable Vector

Regularization Term

τ	Regularization Strength
d	Regularization Offset
C	Regularization Matrix ~***f''***

BINNING OF THE OBSERVABLE SPACE

- Use Decision Tree to define a high-dimensional Binning
- Trained to classify the corresponding bin of **f** for each event
- Each cut is selected to minimize the entropy regarding the energy
- Prune trees to ensure minimal amount of statistics for each bin



technische universität dortmund

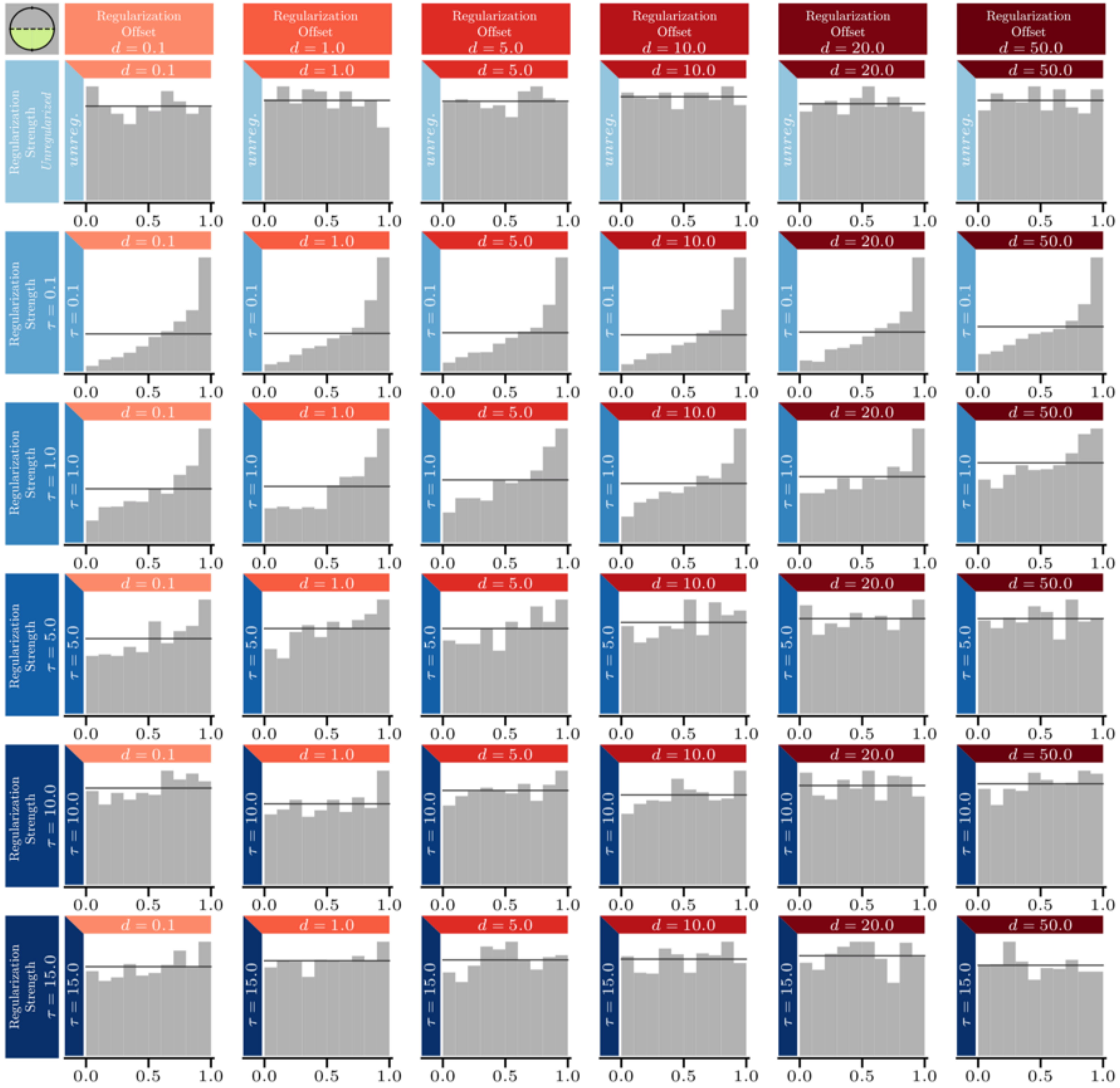
REGULARIZATION PARAMETERS

- Increasing regularization strength will also increase bias of the unfolding
- Calculate test statistic for every unfolding:

$$p'(\mathbf{f}_{\text{test}}) = \frac{1}{N_{\text{MCMC}}} \sum_{i=1}^{N_{\text{MCMC}}} \begin{cases} 1, & p(\mathbf{f}_{\text{test}}|\mathbf{g}) < p(\mathbf{f}_i|\mathbf{g}) \\ 0, & p(\mathbf{f}_{\text{test}}|\mathbf{g}) \geq p(\mathbf{f}_i|\mathbf{g}) \end{cases}$$

- Check for different combinations of unfolding parameters
- Final parameter combination:

$$\tau = 5.0 \quad d = 14.0$$



ICECUBE PRELIMINARY

technische universität dortmund

BIAS

- Unfolding has to be unbiased, even when the assumptions for the model disagree with the measurements
- Calculate test statistic for every unfolding:

$$p'(\mathbf{f}_{\text{test}}) = \frac{1}{N_{\text{MCMC}}} \sum_{i=1}^{N_{\text{MCMC}}} \begin{cases} 1, & p(\mathbf{f}_{\text{test}}|\mathbf{g}) < p(\mathbf{f}_i|\mathbf{g}) \\ 0, & p(\mathbf{f}_{\text{test}}|\mathbf{g}) \geq p(\mathbf{f}_i|\mathbf{g}) \end{cases}$$

- Check for different combinations of models

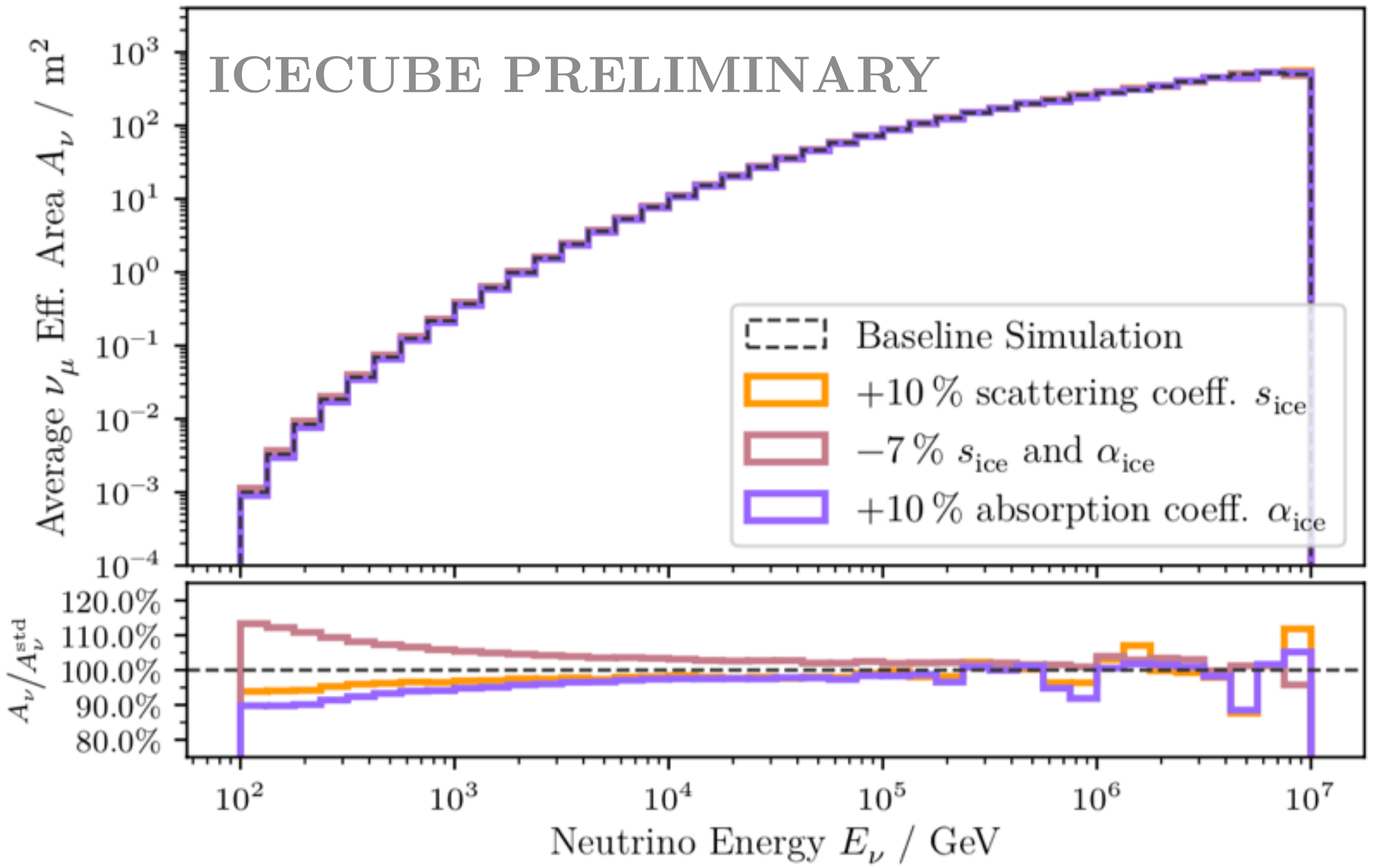
ICECUBE PRELIMINARY

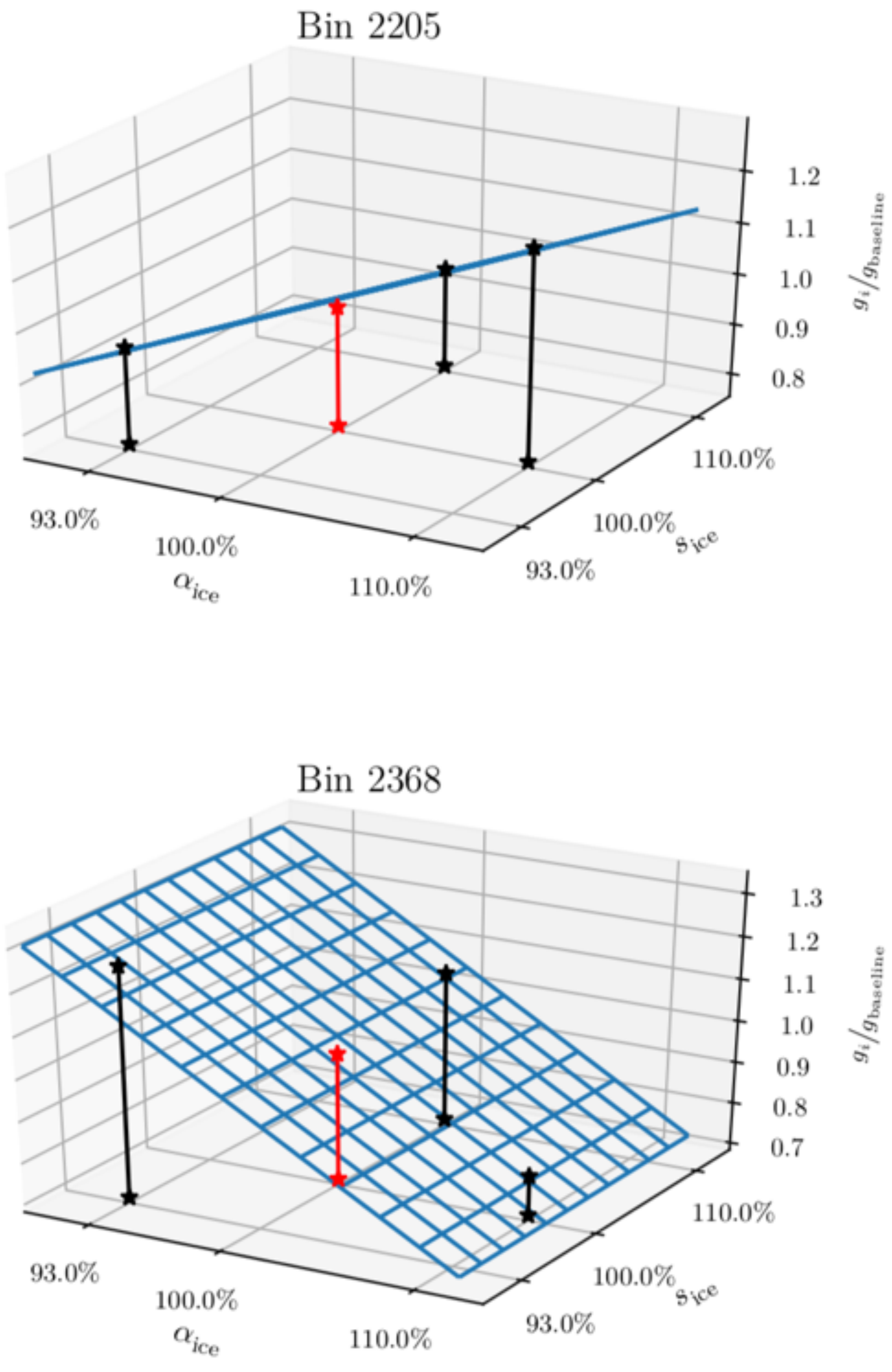
SYSTEMATICS

- DOM efficiency, ice scattering and ice absorption

$$A_{\mathrm{eff}} \to A_{\mathrm{eff}}(\epsilon_{\mathrm{DOM}}, \alpha_{\mathrm{ice}}, s_{\mathrm{ice}})$$

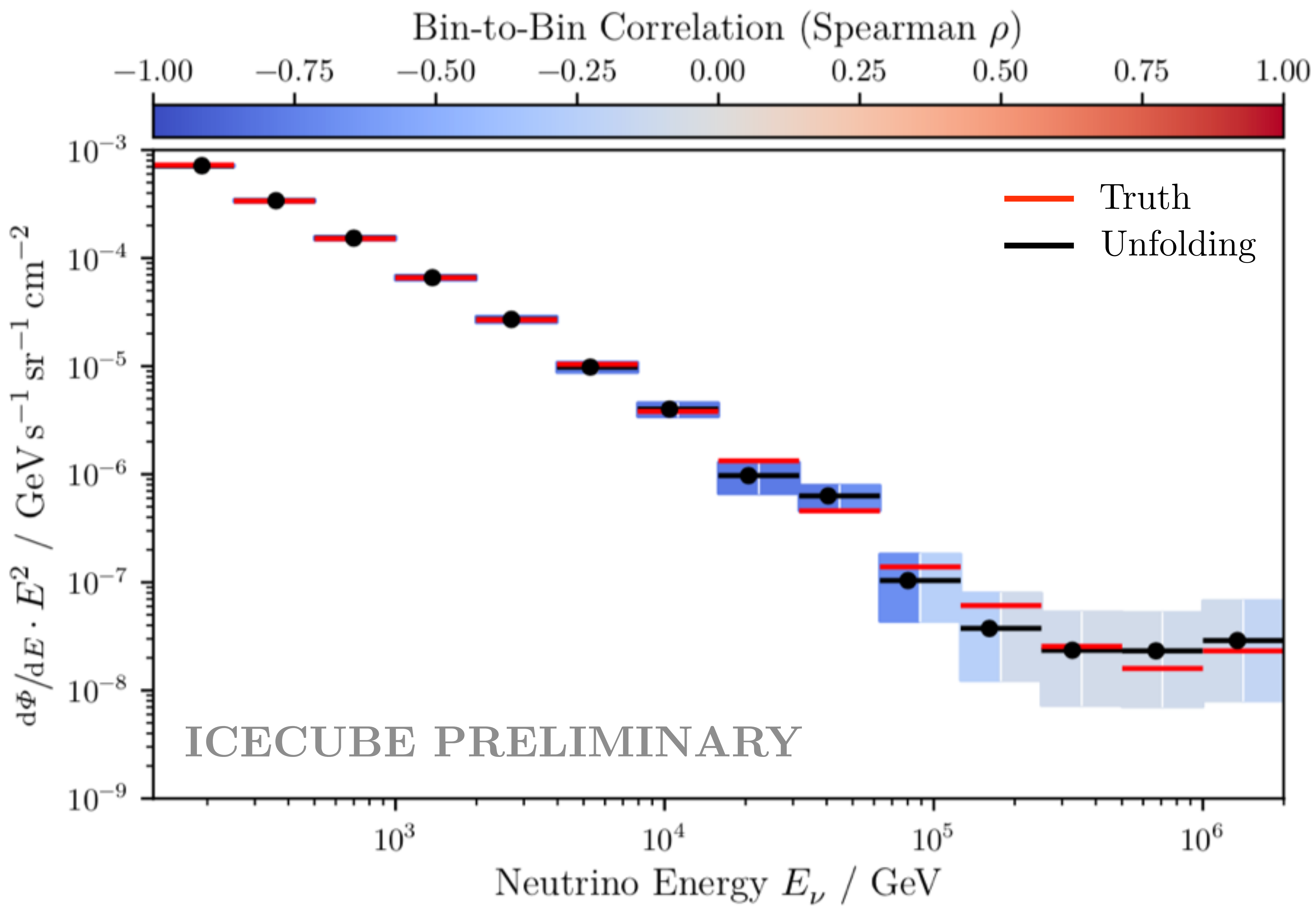
- Linear interpolation of weights for all systematics



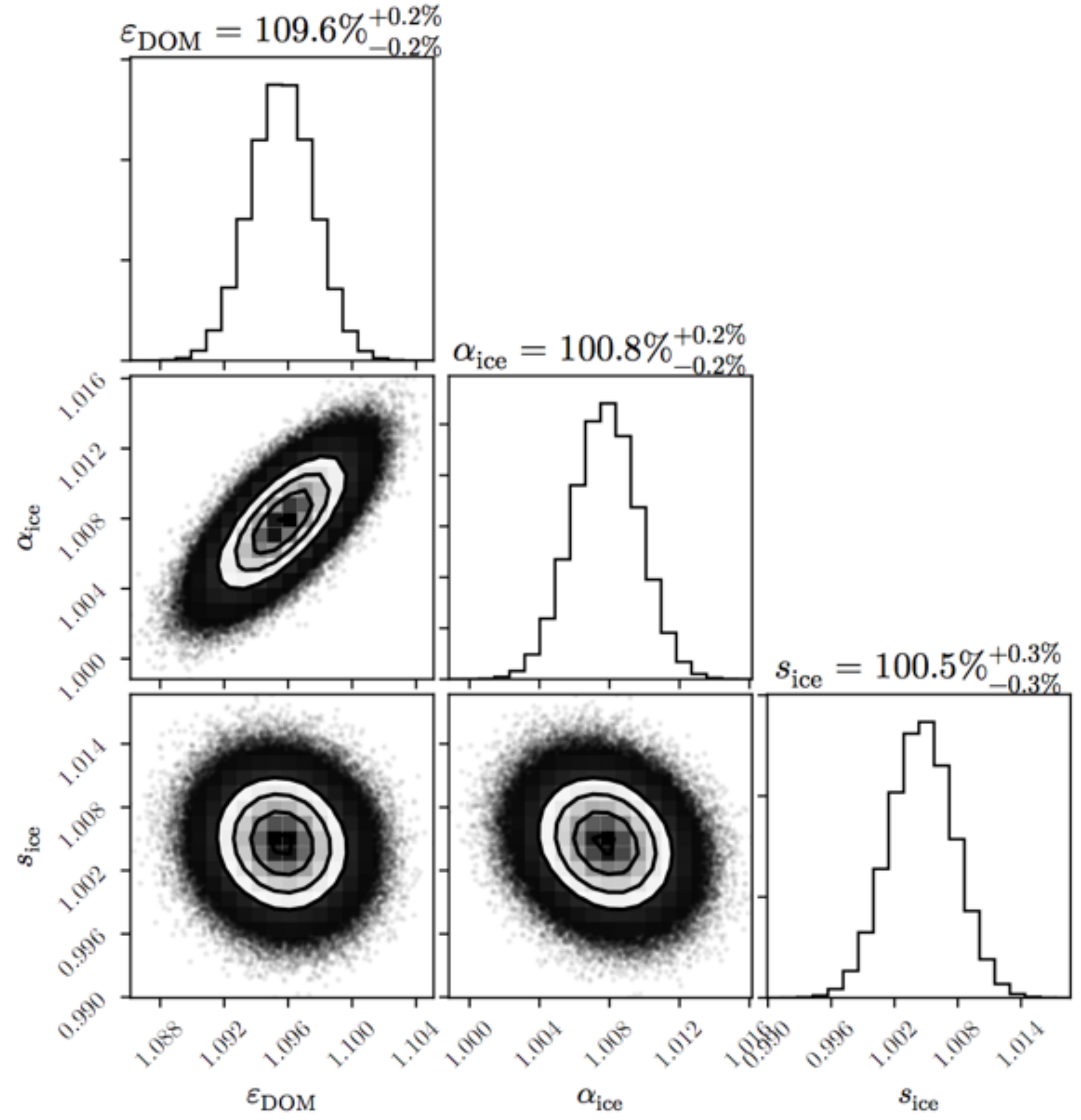


TEST UNFOLDINGS

- Unfolding of different models with different systematics to check whether parameters can be retrieved

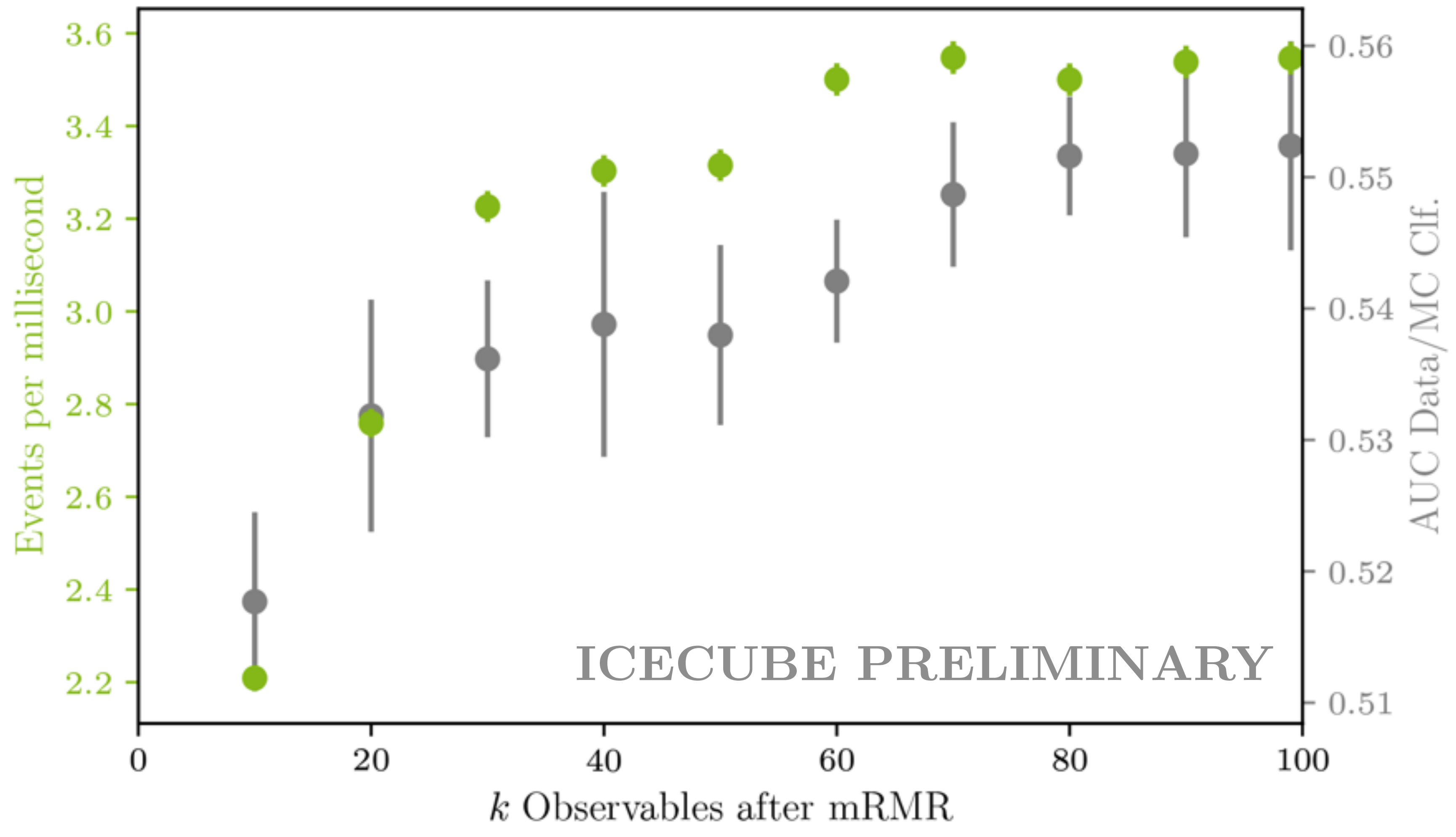


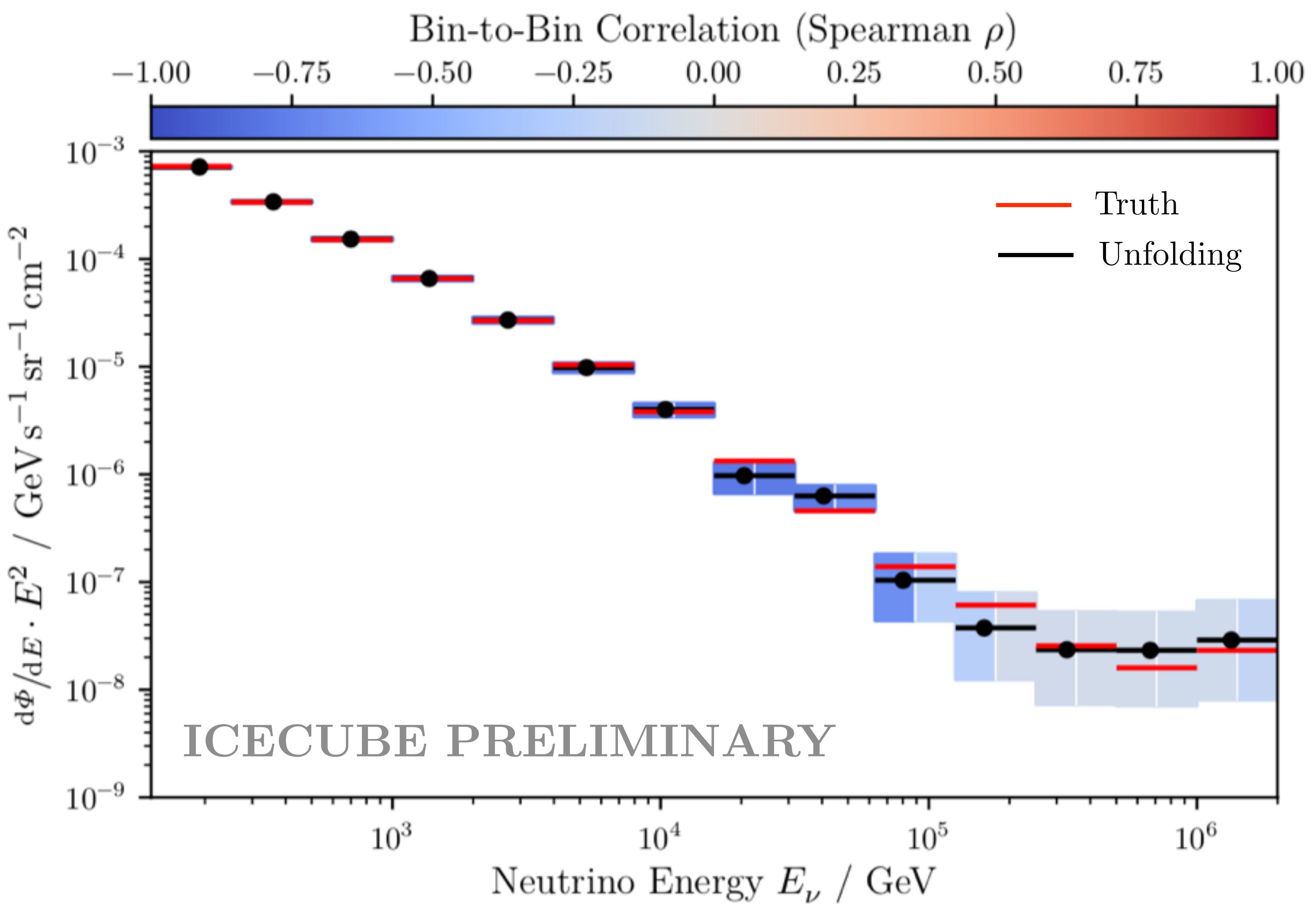
$\epsilon_{\mathrm{DOM}}^{\mathrm{true}} = 110\,\%$ $s_{\mathrm{ice}}^{\mathrm{true}} = 100\,\%$ $a_{\mathrm{ice}}^{\mathrm{true}} = 100\,\%$



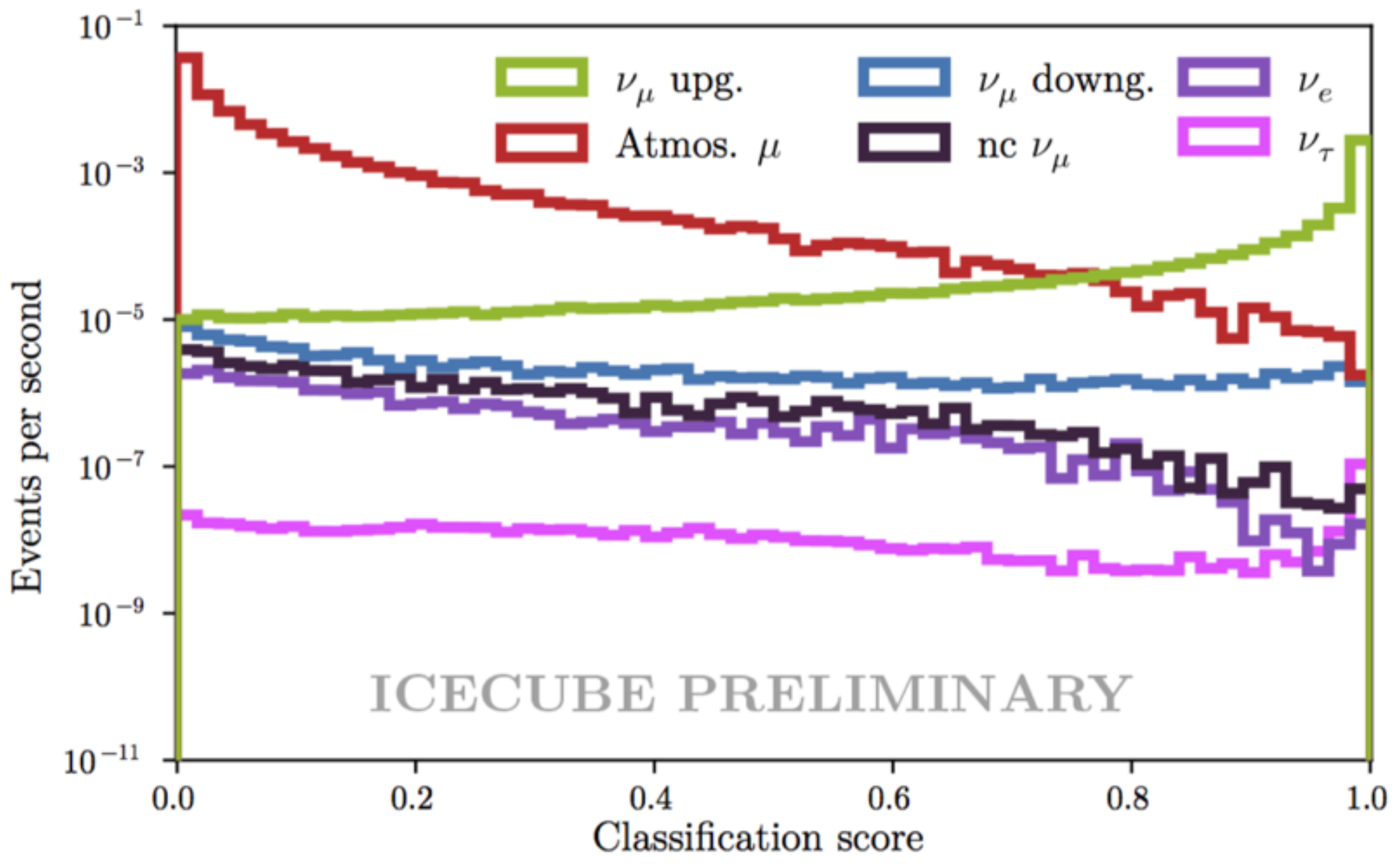
SUMMARY

- High purity sample of >99.7% purity in the whole energy regime, expected event rate of about 3.5 mHz (~110,000 Events/yr)
- Decision tree based binning scheme optimizes observable binning to given analysis goals
- Regularized unfolding scheme shown to exhibit little bias

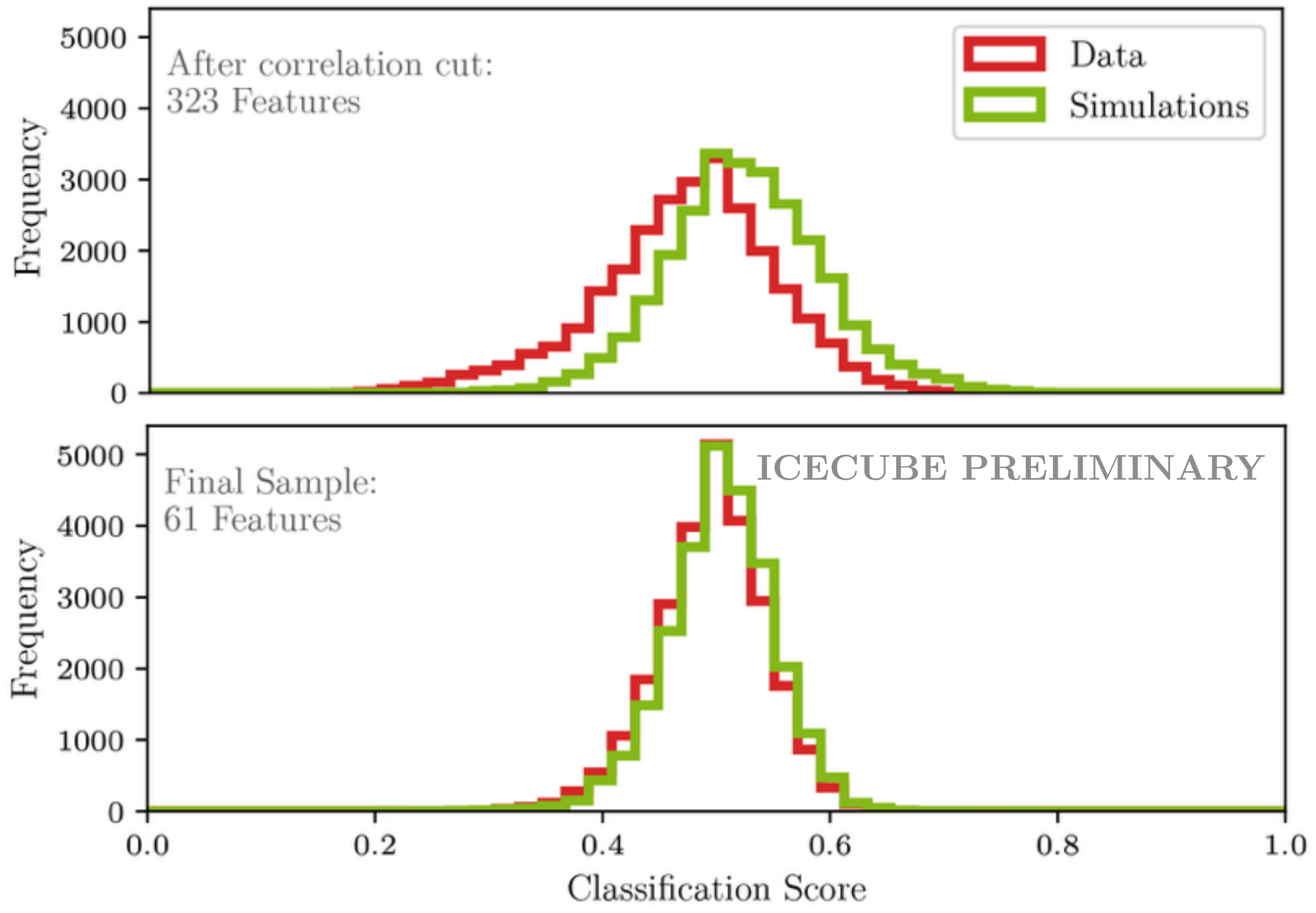




BACKUP



Classification score distribution of event selection for different signal components



Classification score distribution for data/MC separation before and after feature selection

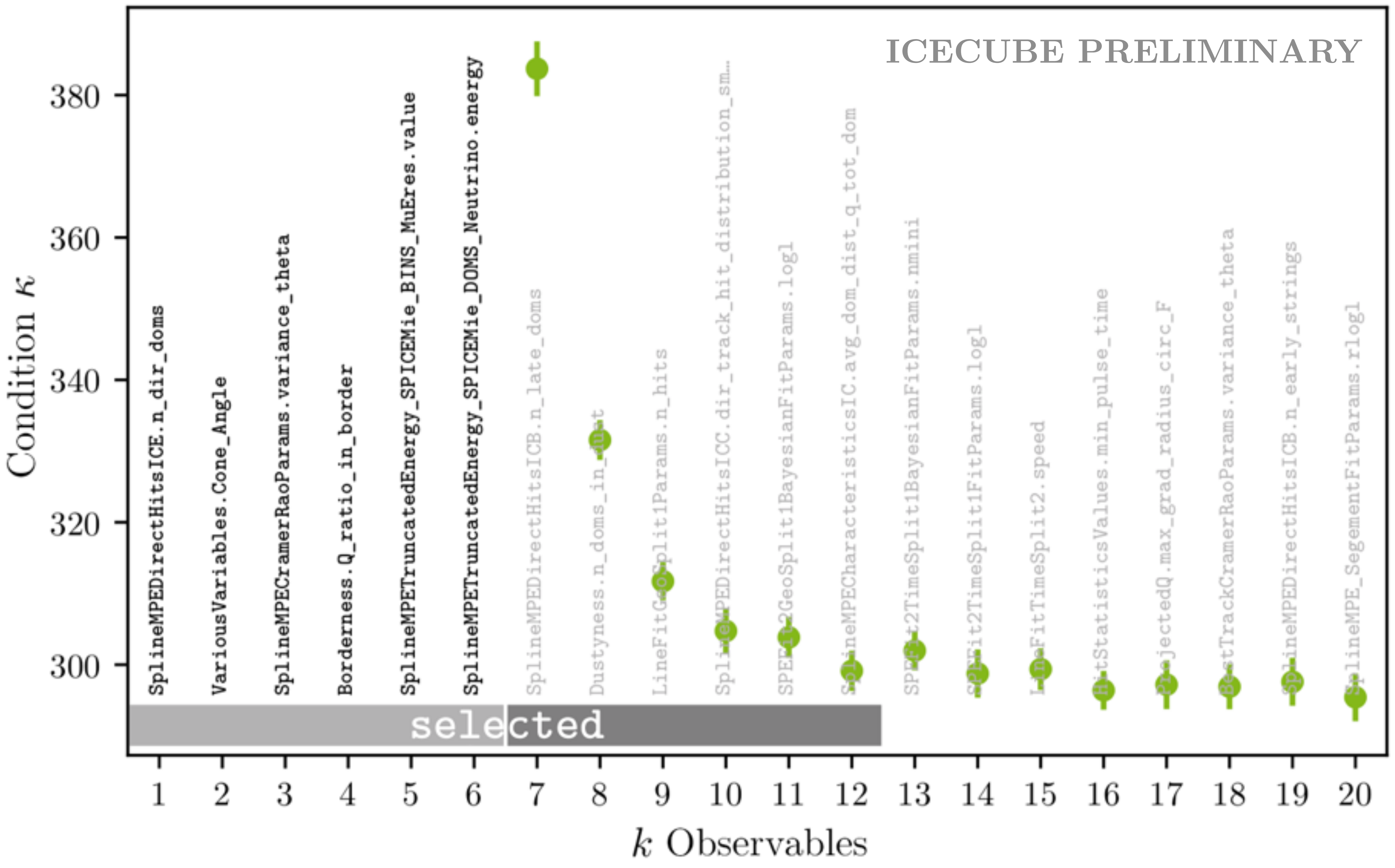
FEATURE SELECTION

Initially
1224

Constant
Correlation > 0.95
300

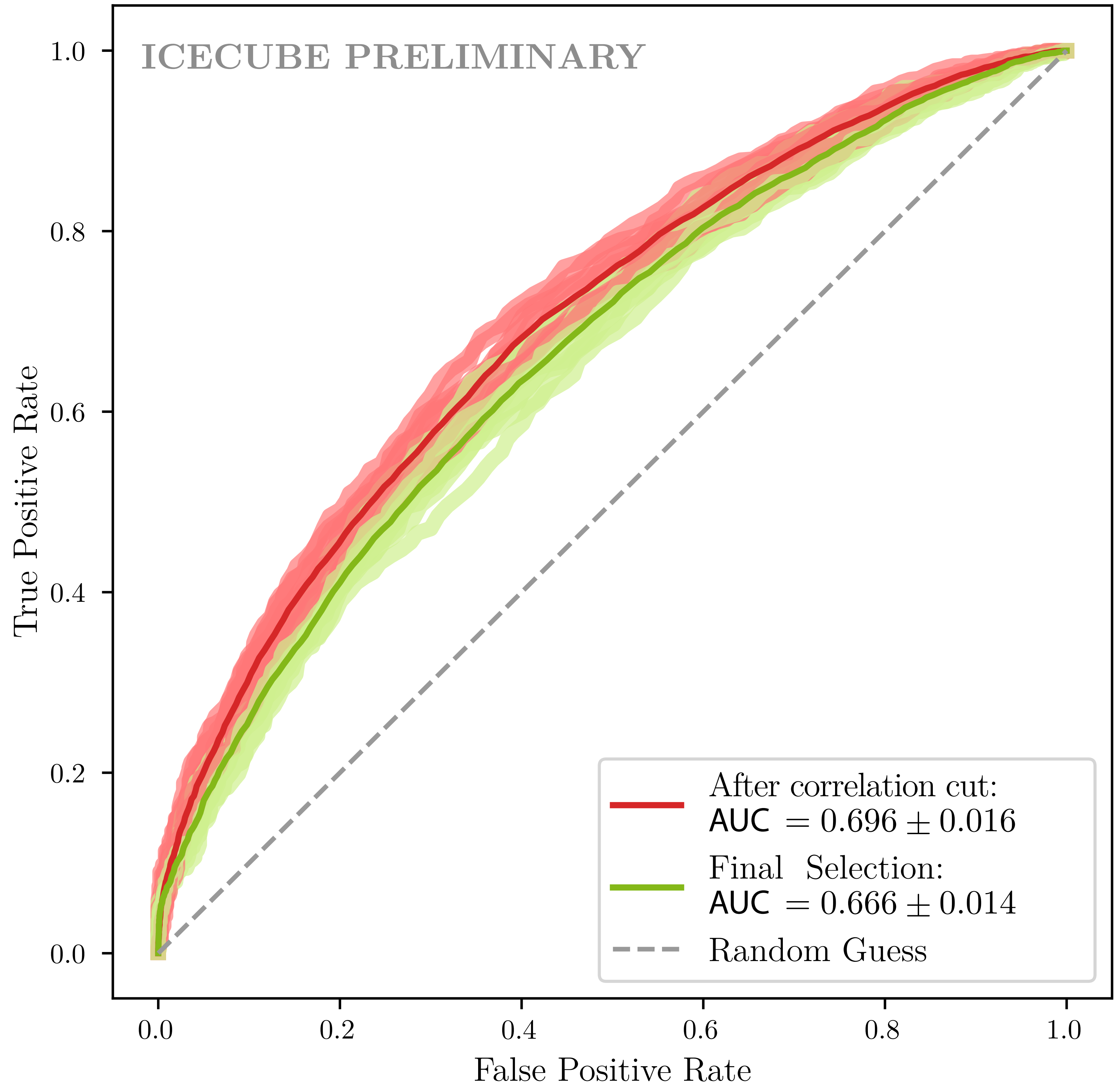
mRMR
60

Forward Selection
12



For all remaining attributes, the condition of the migration Matrix A is calculated.
The attribute that yields the lowest condition is added to the set of attributes.
This is repeated iteratively until 6 features are found. On top of that the 6 best features from the mRMR selection are used.

Event Selection



AUC of data/simulation classification before and after feature selection