

# Determination of cosmic-ray primary mass on an event-by-event basis using radio detection

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# Overview and motivation

- Traditionally,  $X_{max}$  is used as a surrogate for composition
- Large overlap in  $X_{max}$  distributions for different compositions
  - Even a very accurate estimate of  $X_{max}$  cannot lead to an event-by-event composition analysis
- $X_{max}$  radio reconstructions have large uncertainties for inclined events
  - Radio experiments are using less dense but larger arrays, e.g. AERA
  - Larger arrays lead to better UHECR statistics
  - But sparser arrays can only properly sample footprints of inclined events
  - An alternative is needed for composition analysis
- We propose a new method that bypasses  $X_{max}$  reconstructions and infers primary composition directly
  - Based on comparisons between event and simulations of various primary compositions
  - Large event-by-event composition discrimination efficiency, even when taking into account some characteristic detection uncertainties

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- First  $X_{max}$  radio reconstruction technique developed by LOFAR
  - Based on comparisons between the measured electric fields and scintillator data with simulations of proton and iron initiated showers
- Variants of this method currently used by multiple radio experiments
  - Some use only radio data
  - Comparable uncertainties to FD for less inclined showers ( $\sim 20\text{g}/\text{cm}^2$ )
- We developed a simplified variant of the LOFAR method
  - Investigate how the uncertainty in  $X_{max}$  varies with zenithal angle
  - Used ZHAIRES simulations along with the “two component” model

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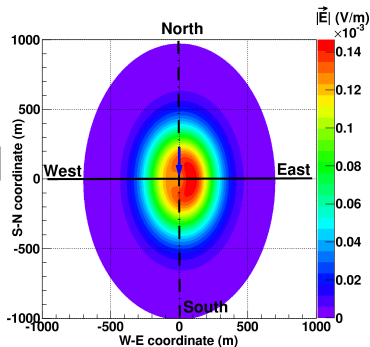
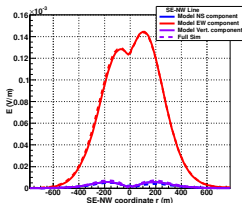
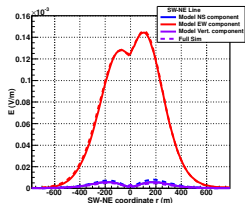
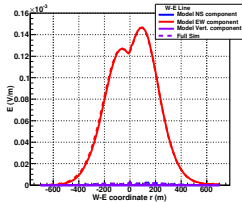
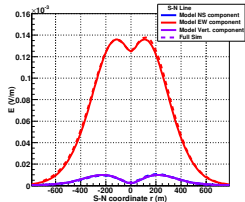
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# ZHAireS and the two component approach

- Superposition model used in lieu of “interpolation”
- Superposition of Askaryan and Geomagnetic components
- Obtain field at any position from simulations at only a few positions along a single direction w.r.t. the core: Very Fast!

Astropar. Phys. 59, 29, 2014



## Simplified Radio $X_{max}$ reconstruction

- $\Sigma_s$  used to quantify the difference between event and simulation

$$\Sigma_s(f_s, \vec{r}_{core}) = \sum_{\text{all antennas}} \left[ |\vec{E}_{ant}| - f_s \cdot |\vec{E}|(x_{ant} - x_{core}, y_{ant} - y_{core}) \right]^2$$

- $|\vec{E}_{ant}|$ : amplitude of measured peak electric field
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- $(x_{core}, y_{core})$ : Core position (core position uncertainty)
- No SD particle data is used in the reconstruction
- For each simulation one can vary the core position and  $f_s$ .
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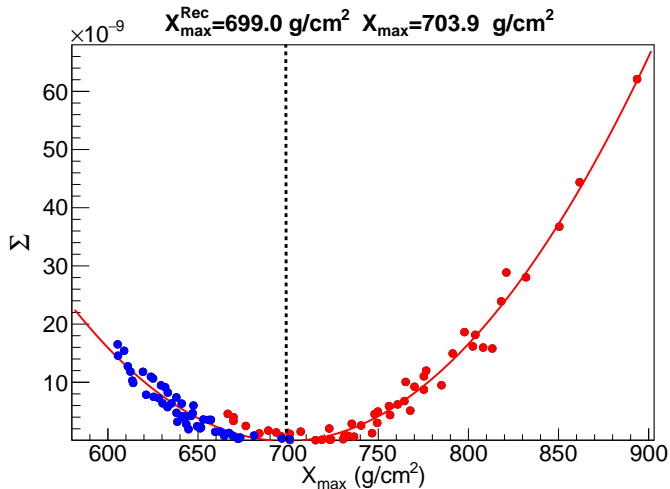
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# $X_{max}$ reconstruction: $\Sigma$ vs $X_{max}$

30°, ideal square array with  $D=500$  m.





## Dependance of $\sigma_{X_{max}}$ on zenithal angle

- Obtain lower limit for uncertainty in  $X_{max}$  (intrinsic to the method)
- No detection uncertainties folded into simulated events
- Ideal square array with  $D=500$  m
- Large increase in  $\sigma_{X_{max}}$  for  $\theta > 60^\circ$
- 50 reconstructions per zenith angle

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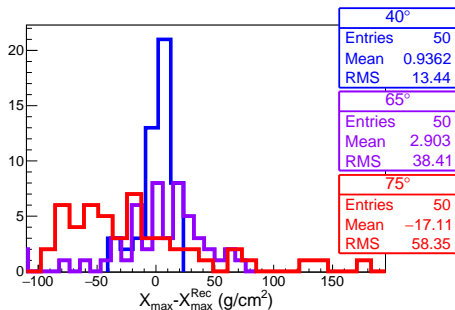
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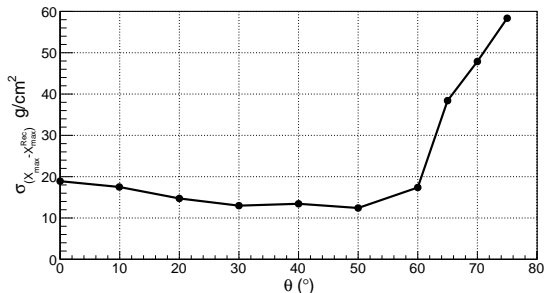
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## Increase in $\sigma_{X_{max}}$ for large $\theta$

- Increase in  $\sigma_{X_{max}}$  due to intrinsic characteristics of the radio footprint
- Radio footprint becomes less sensitive to  $X_{max}$  at large  $\theta$
- Reconstruction becomes more difficult
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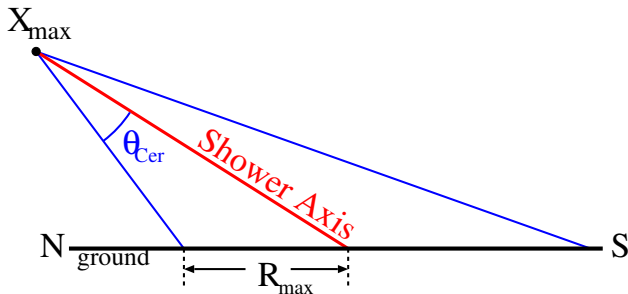
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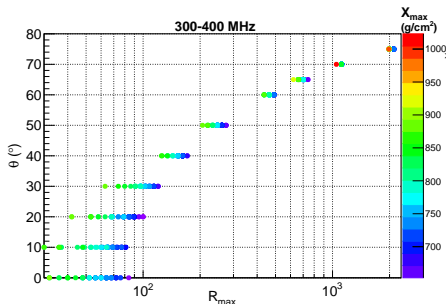
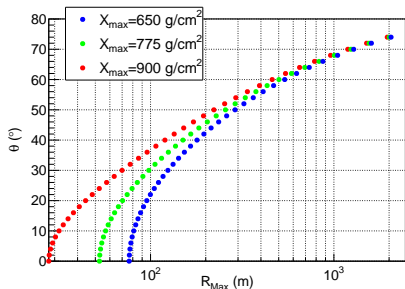
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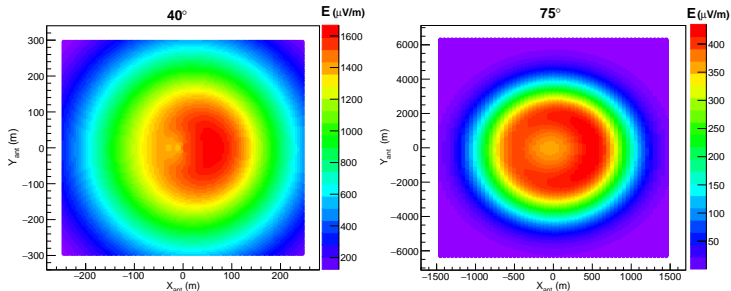
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- Sum over each component  $i = x, y, z$  of the peak electric field

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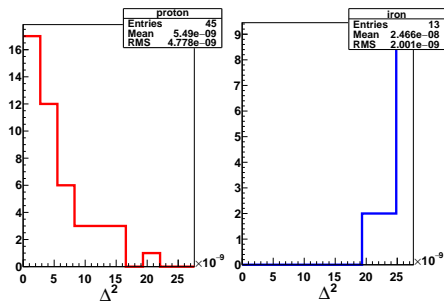
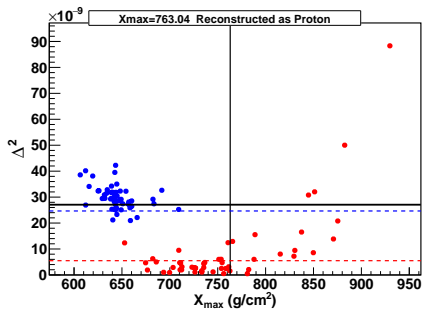
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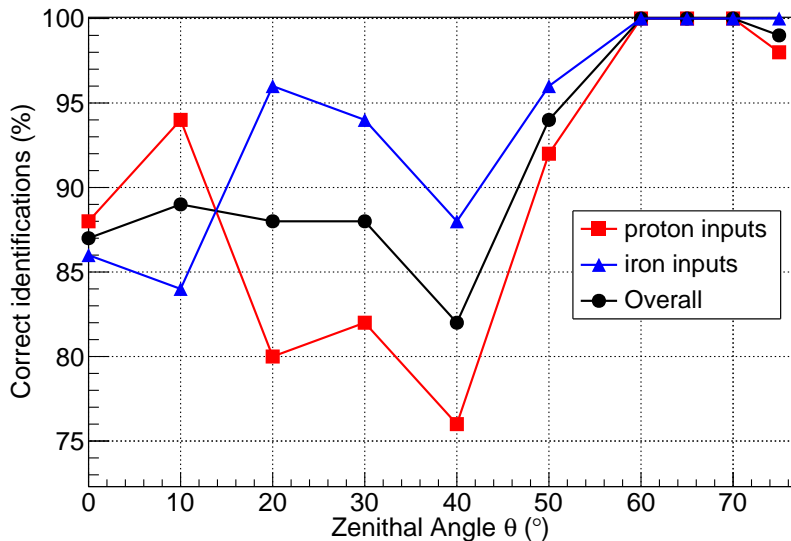


# Example composition Reconstruction: Ideal array

- Input event: proton,  $\theta = 65^\circ$
- Simulations: 50 p and 50 Fe, same energy and direction as input event
- Ideal square array with  $D = 500$  m
- Different  $\Delta^2$  for different compositions, even with similar  $X_{max}$



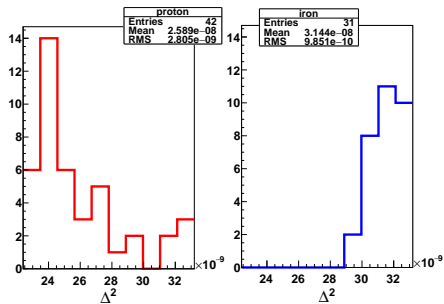
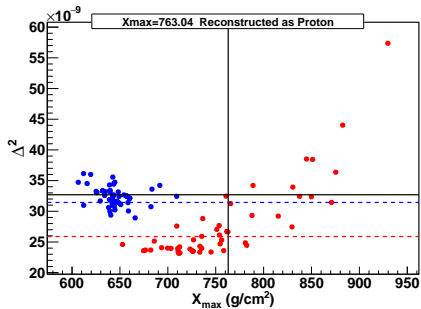
## Results: Ideal array



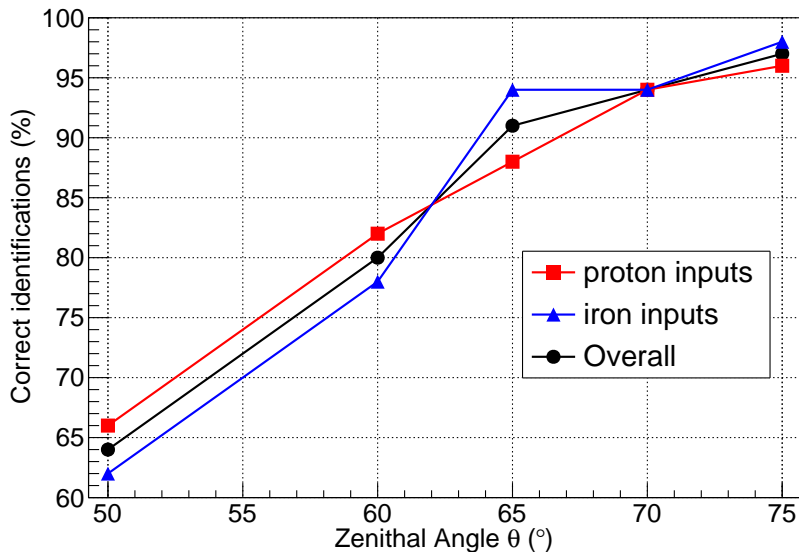
## Detection uncertainties

- Effect of noise and background folded in the peak amplitudes of the input event
- Gaussian Noise:  $\sigma_{noise} = 30\mu V/m$  per component of the electric field
- Background: Fixed at  $3\mu V/m$ , single isotropic direction per event
- Core position error ( $r_{core}, \varphi_{core}$ ):
  - Gaussian  $r_{core}$  with  $\sigma_{core} = 50$  m, equally distributed  $\varphi_{det}$
  - Antenna coordinates of the input event are shifted by  $(r_{core}, \varphi_{core})$  before reconstruction
- Increased distance between antennas in array to  $D = 750$  m
- No energy and arrival direction uncertainties were included ( $f_s = 1$ )

# Example Reconstruction: with detection uncertainties

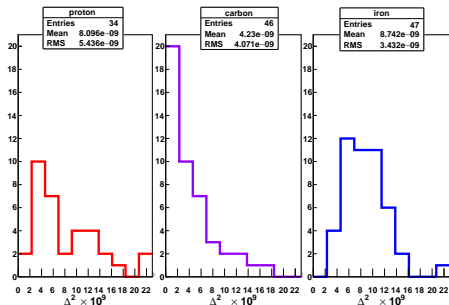
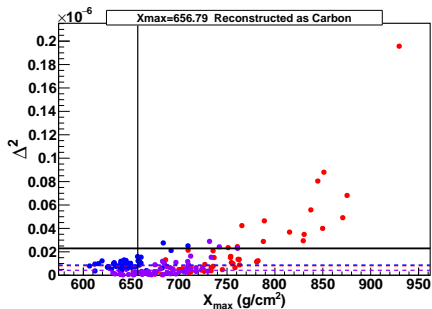


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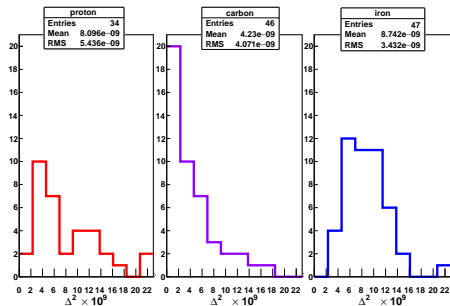
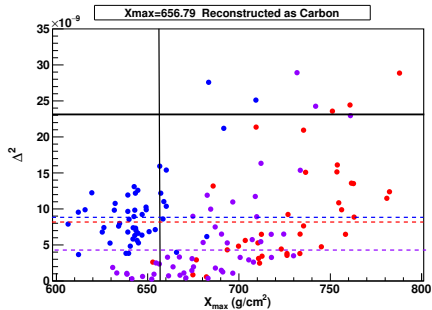
# Including a semi-heavy composition

Example Carbon input event,  $65^\circ$ , ideal array with  $D = 500$  m  
No detection uncertainties

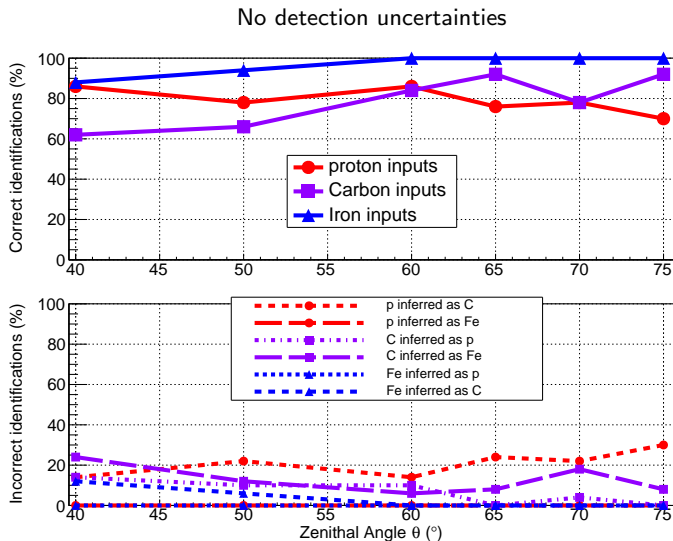


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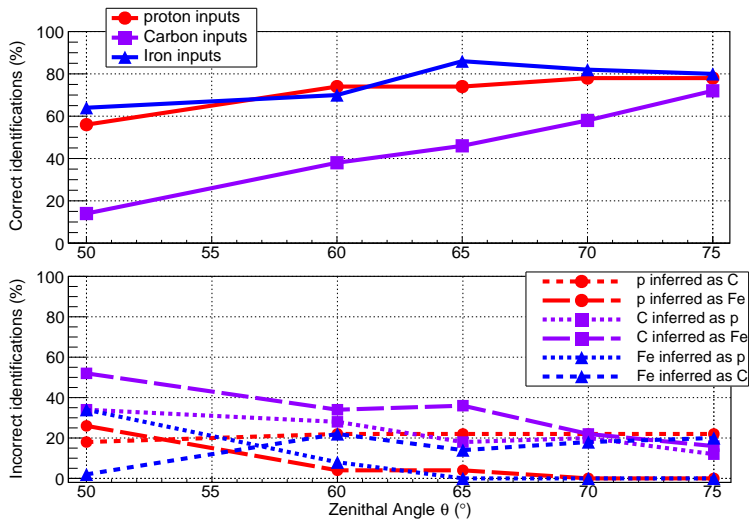
# Results including C: No detection uncertainties





# Results including C: With detection uncertainties

With detection uncertainties: Not good enough for event-by-event analysis



# Conclusions

- Large increase in the intrinsic  $X_{max}$  uncertainty for inclined events
- $\sigma_{X_{max}} \gtrsim 40 \text{ g/cm}^2$  for  $\theta > 60^\circ$ : unsuitable for composition analysis
- An alternative is needed for composition analysis of inclined events
- Do we really need  $X_{max}$  for composition analyses using radio?
- New method: Bypasses  $X_{max}$  and infers composition directly
- In principle capable of discriminating between heavy and light compositions on an event-by-event basis
- More efficient for inclined events: 80% (90%) above  $60^\circ$  ( $65^\circ$ )
  - Even for showers with similar  $X_{max}$  but different compositions
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- $\sigma_{X_{max}} \gtrsim 40 \text{ g/cm}^2$  for  $\theta > 60^\circ$ : unsuitable for composition analysis
- An alternative is needed for composition analysis of inclined events
- Do we really need  $X_{max}$  for composition analyses using radio?
- New method: Bypasses  $X_{max}$  and infers composition directly
- In principle capable of discriminating between heavy and light compositions on an event-by-event basis
- More efficient for inclined events: 80% (90%) above  $60^\circ$  ( $65^\circ$ )
  - Even for showers with similar  $X_{max}$  but different compositions
  - Even when (most) detection uncertainties are included
  - Even when using a simplistic discrimination based only on  $\Delta^2$  averages
- Could be applied to large and sparse arrays suitable for detecting inclined showers (better UHECR statistics)

# Conclusions

- A 3rd semi-heavy composition cannot currently be separated on an event-by-event basis
  - Could be feasible by improving the method further
- Method still in development
  - Maximum-likelihood or Bayesian analysis
  - Use shape of  $\Delta^2$  distributions
  - Investigate other sources of uncertainties (Energy, arrival direction)
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# Questions?

## Other applications of Radio...

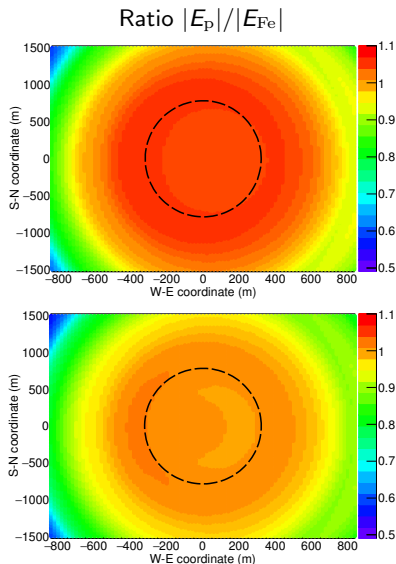
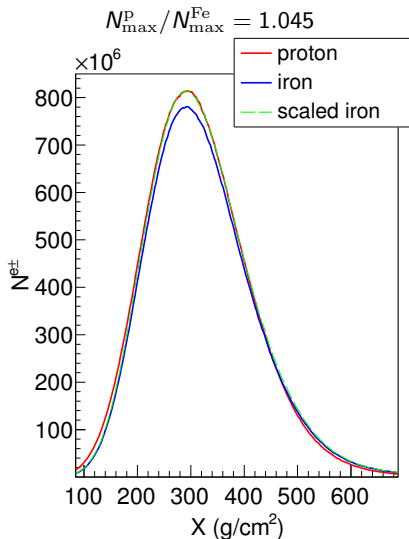


# BACKUP SLIDES

## Pair of events: Similar $X_{max}$ with different compositions

- Pair of events: one p and one Fe with similar  $X_{max}$
- Average number of pairs for  $\Delta X_{max} < 3 \text{ g/cm}^2$ : 14
- Average number of pairs for  $\Delta X_{max} < 20 \text{ g/cm}^2$ : 101
- Investigate the fraction of correctly identified pairs (both p and Fe)
  - Without detection uncertainties:
    - $\sim 0\%$  for  $\theta < 50^\circ$
    - $\sim 65\%$  for  $\theta = 50^\circ$
    - $100\%$  for  $\theta > 60^\circ$
  - With detection uncertainties:
    - $\sim 20\%$  for  $\theta = 50^\circ$
    - $\sim 95\%$  for  $\theta > 70^\circ$
- $X_{max}$  dominates the variation in the radio footprint at lower  $\theta$ 
  - Either p or Fe of the pair is incorrectly discriminated
- As  $\theta$  increases  $X_{max}$  becomes less important
  - $\Delta^2$  becomes sensitive to other degrees of freedom
  - It becomes possible to correctly discriminate both p and Fe of the pair

# Main sources of the differences in the footprint



# Energy uncertainty

- If  $f_s$  used as a free parameter for each simulation
  - Inherent differences in the amplitude of the longitudinal profiles are masked
  - Artificially decreases the differences between proton and iron showers
- Included energy uncertainties on our set of events at  $65^\circ$ 
  - $f_s$  allowed to vary freely between 0.8 and 1.2 in the minimization
  - Minimized  $f_s$  for proton (iron) was 0.95 (1.00)
  - Matches the average difference of  $\sim 5\%$  in  $N_{\max}$  between p and Fe
  - Only small decrease in the overall (p and Fe) discrimination efficiency
  - From 91% (fixed  $f_s$ ) to 83% ( $f_s$  as a free parameter)
- Effect can be mitigated further by enhancing energy estimate
  - e.g. using AERA energy reconstruction
- Impact at other geometries still needs to be investigated



