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# Generative Neural Networks for Simulating Radio Emission from Air Showers

Pranav Sampathkumar<sup>a1</sup>,  
Tim Huege<sup>a</sup>, Andreas Haungs<sup>a</sup>, Ralph Engel<sup>a</sup>

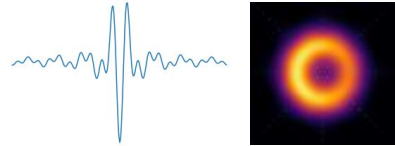
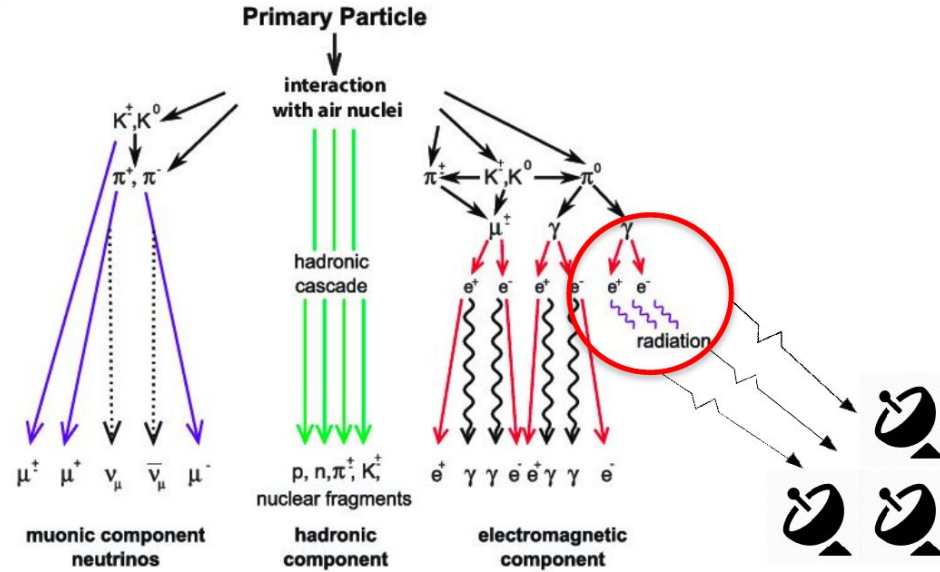
Workshop on Machine Learning for Analysis of High-Energy  
Cosmic Particles, University of Delaware

29/01/2025

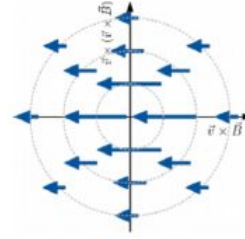
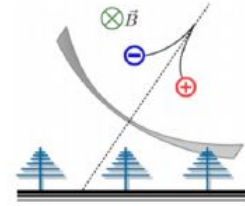
<sup>1</sup>[pranav.sampathkumar@kit.edu](mailto:pranav.sampathkumar@kit.edu)

<sup>a</sup> Institute for Astroparticle Physics, Karlsruhe Institute of Technology

# Radio Showers

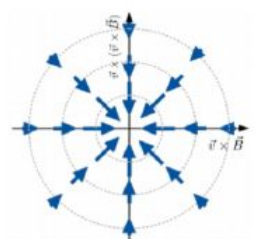
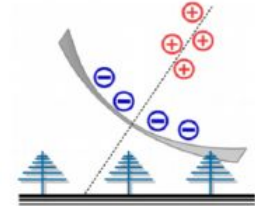


## Geomagnetic



Charges deflected in magnetic field

## Charge excess



Time varying net charge excess

C. Glaser

## Motivation:

- Analysis of data from radio arrays are heavily limited by the computational cost of CoREAS simulations
- There is a need for interpolation techniques which reduce the simulation cost in large arrays.

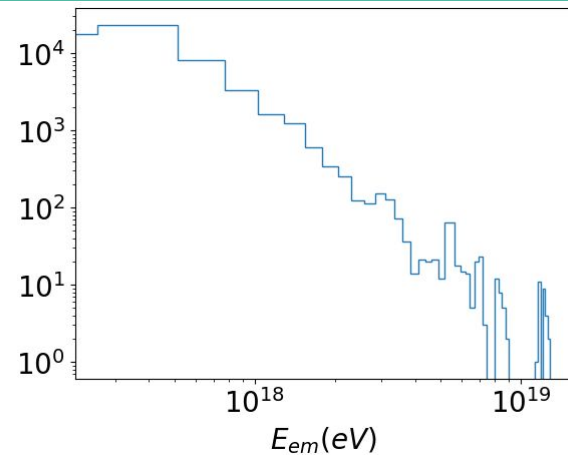
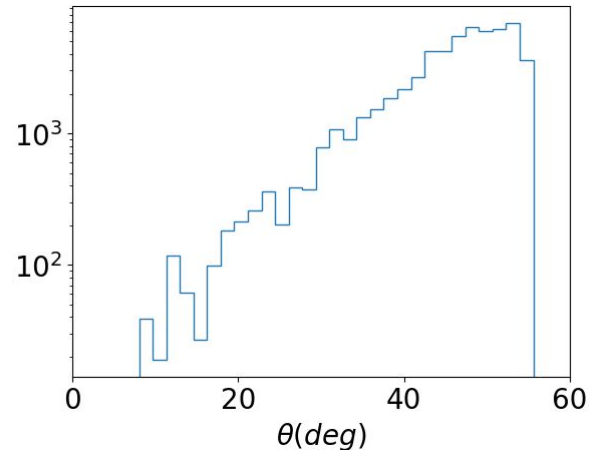
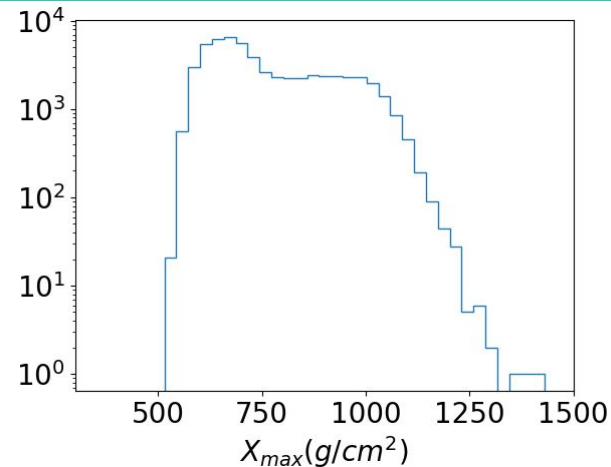
## Our Work:

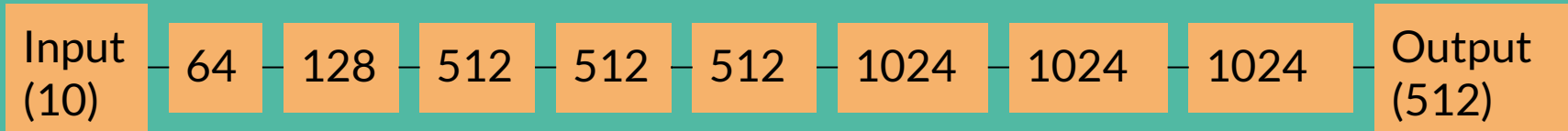
- We present a neural network which can generate pulses from shower parameters in the 30-80MHz range.
- The network can be used for  $X_{\max}$  reconstruction.

## Training:

- We give as **input**,
  - Cos(Zenith Angle), Azimuthal angle
  - $X_{\max}$  density at  $X_{\max}$ , height at  $X_{\max}$
  - sin(geomagnetic\_angle)
  - Electromagnetic Energy
  - Antenna position in shower coordinates
- We get as **output**,
  - Trace of length 256 time bins. (Shower plane - vB polarization)
  - Trace of length 256 time bins. (Shower plane - vvB polarization)
- Custom Loss Function:
  - We use a L1 norm loss, where the weaker vvB polarization is weighted more.
  - Regularization via weight decay during minimization (Adam)

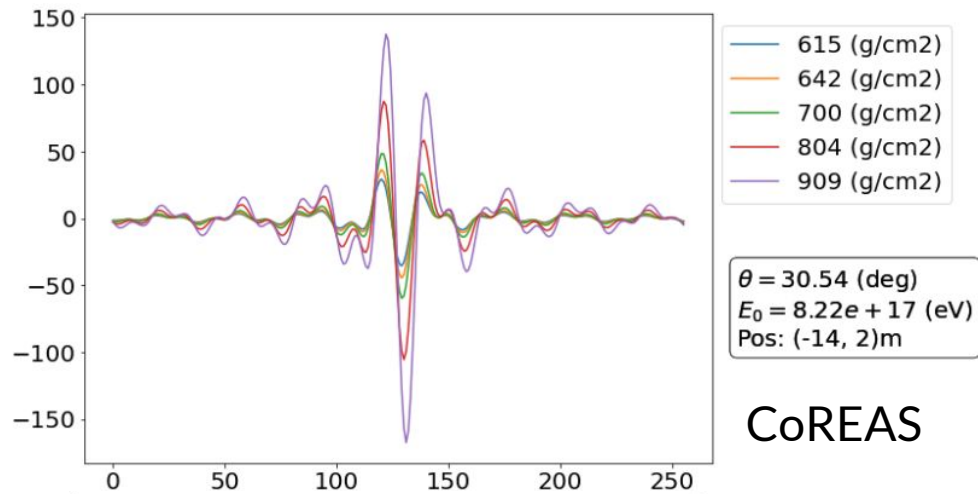
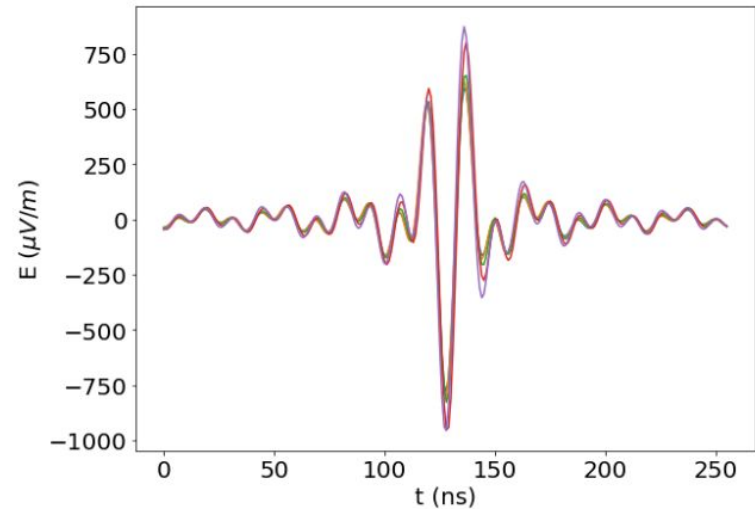
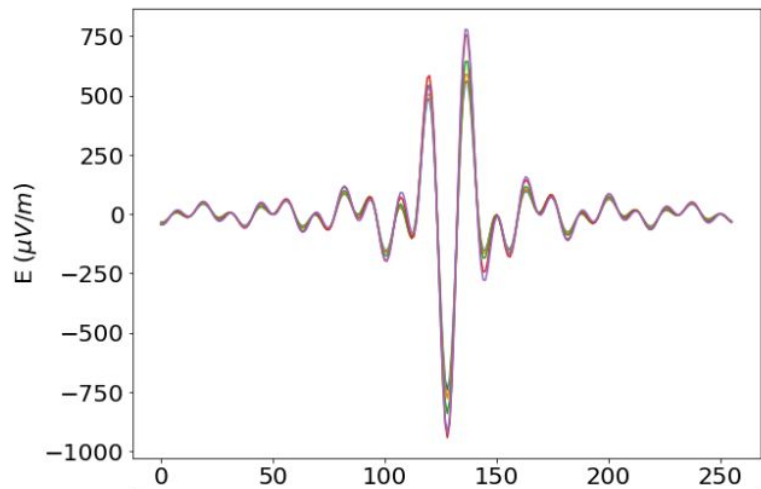
- Trained with the 2158 x 28 showers simulated for the AERA  $X_{\max}$  analysis (Thank you, Auger MC Task!)
- Filter the pulses to 30-80MHz band.
- Train only with 70% (~42000) showers.
- For each shower calculate the radius where pulses are dominated by thinning and train within that radius.



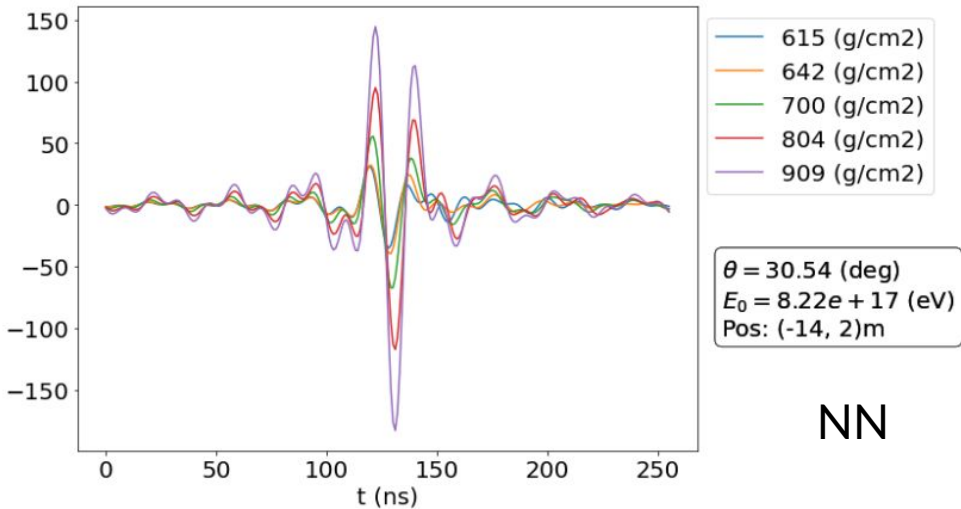


### Network:

- We use a deep fully connected network.
- The inputs are scaled to make all the parameters dimensionless and vary in similar ranges.
- The gradients are well in control, and we didn't need skip connections for such a network.



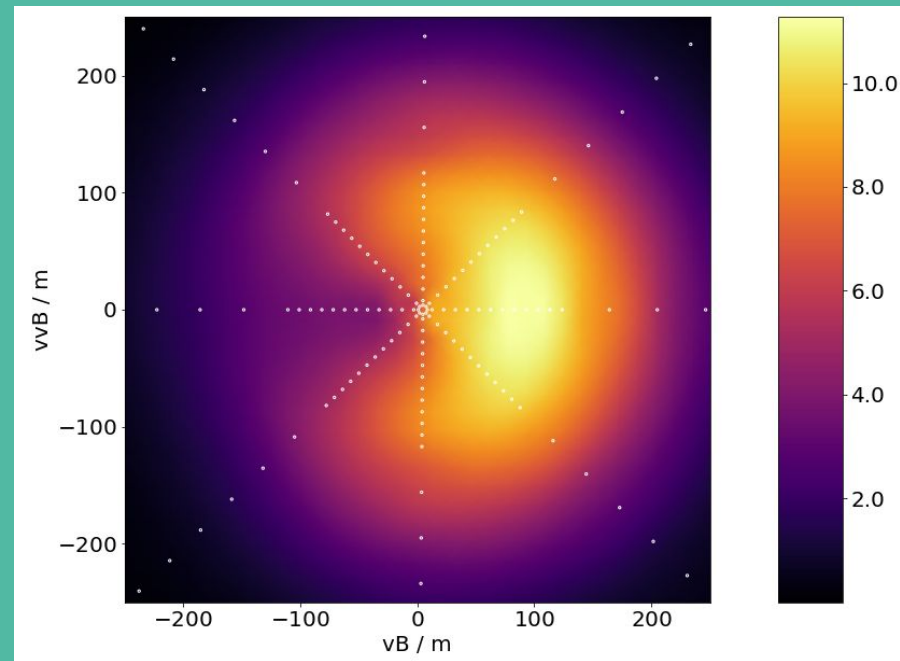
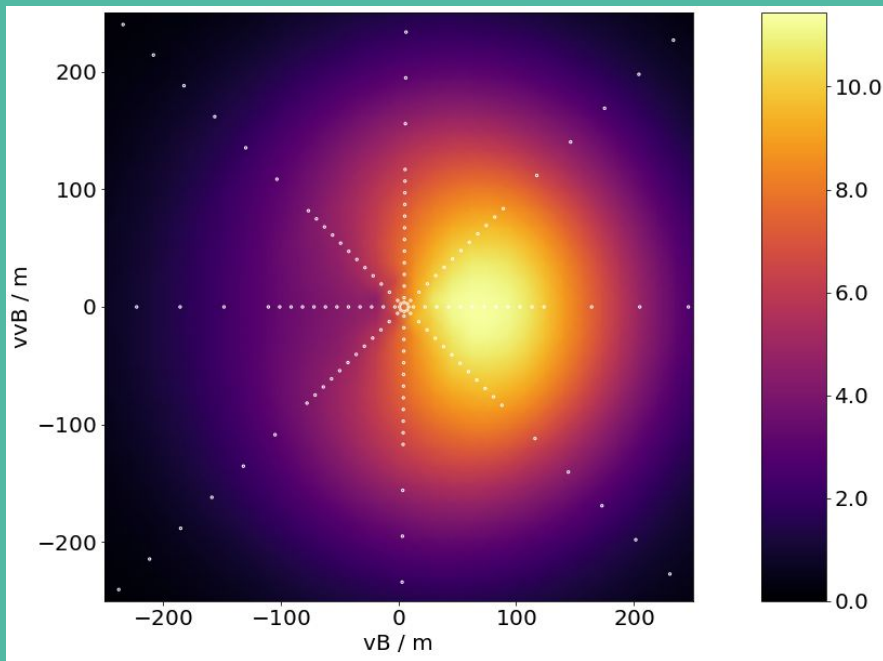
CoREAS



NN

# vB Polarization fluence ( $\text{eV}/\text{m}^2$ )

$\theta = 50.58$   
 $X_{max} = 693.61$   
 $E_0 = 3.15e + 17$

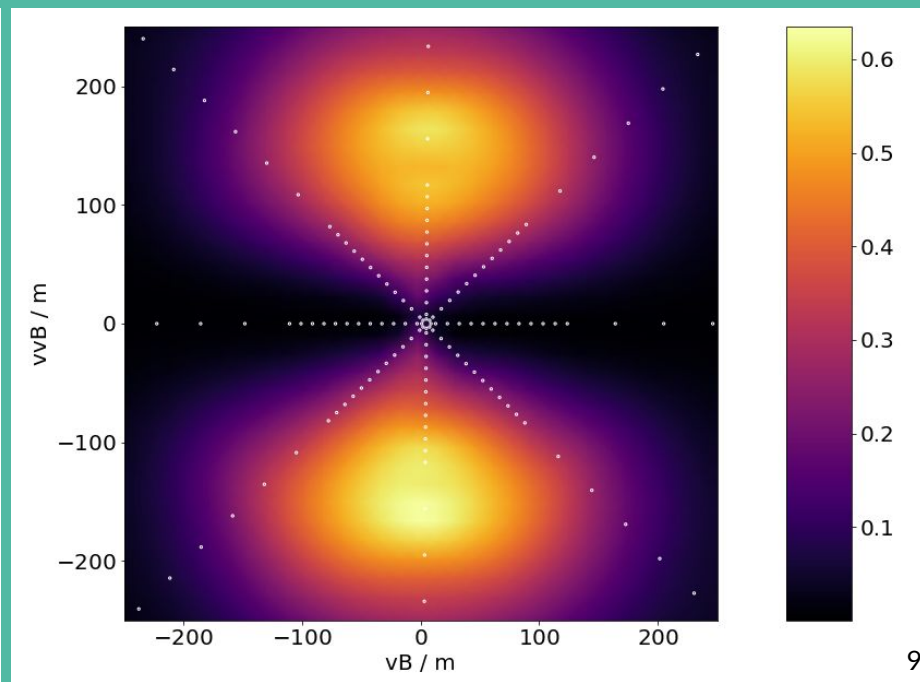
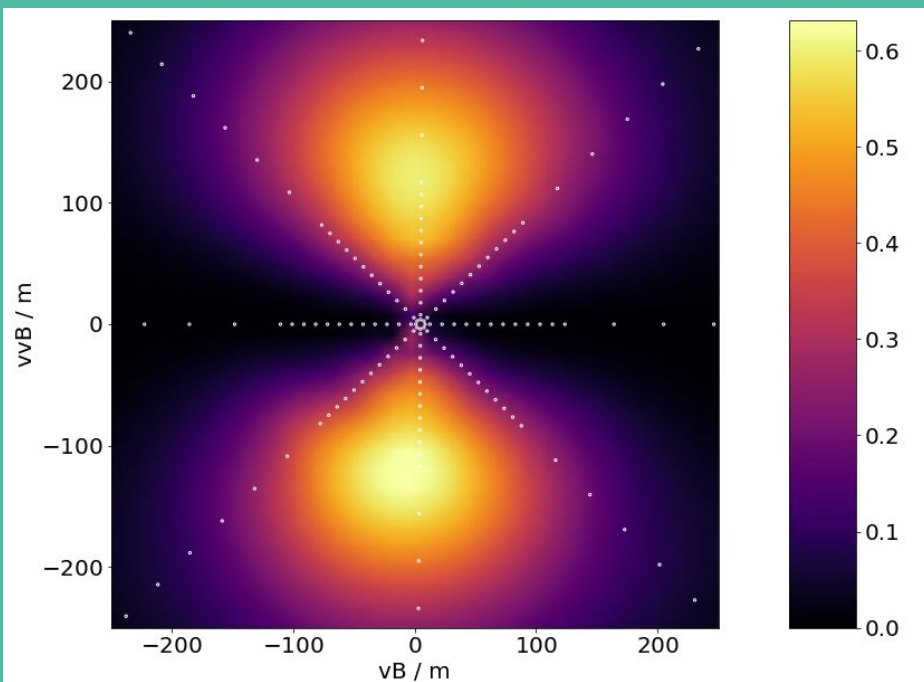


For the most common case in the training dataset, the fluences match reasonably well



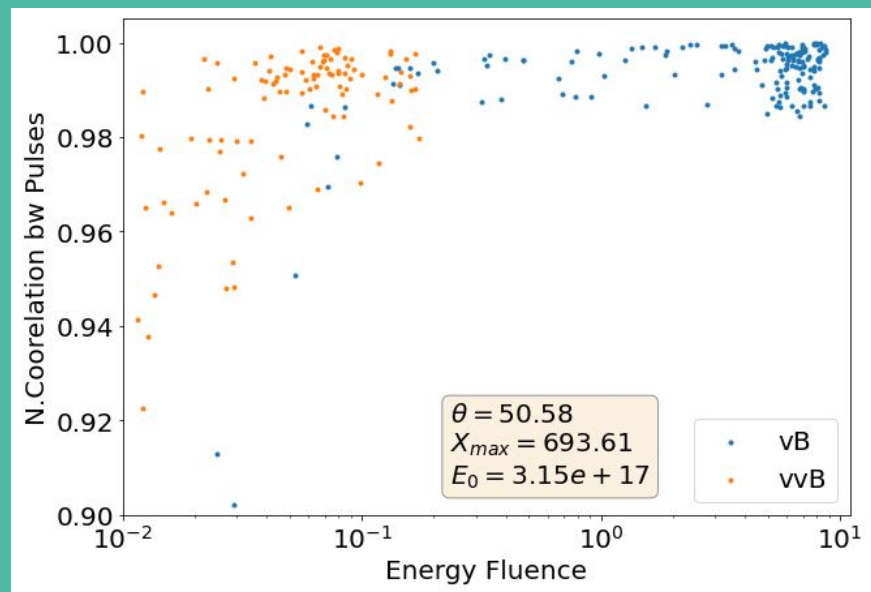
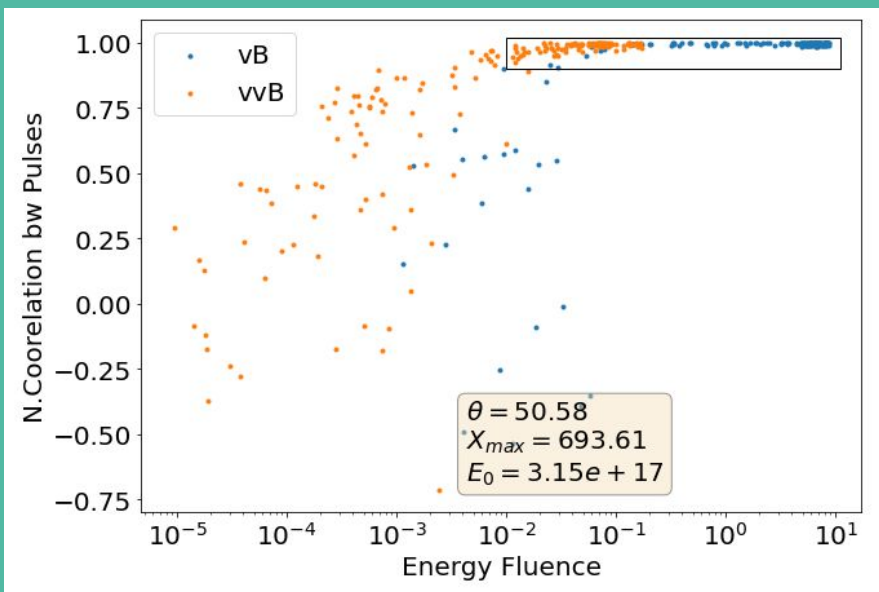
## vvB Polarization fluence ( $\text{eV}/\text{m}^2$ )

We see the same in the vvB polarization too.



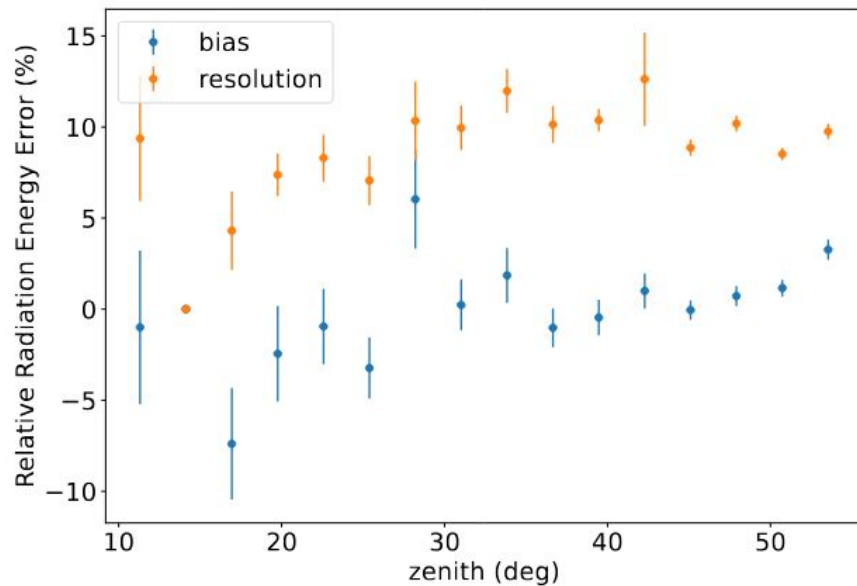
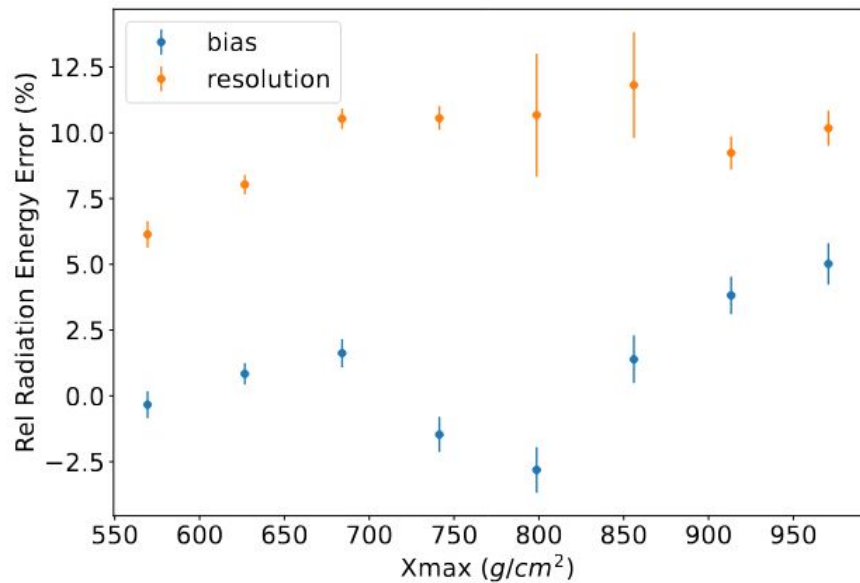
## Normalized Correlation between Pulses.

When we plot normalized correlation with respect to energy fluence of the pulse. The pulse correlation is very good for high fluences.

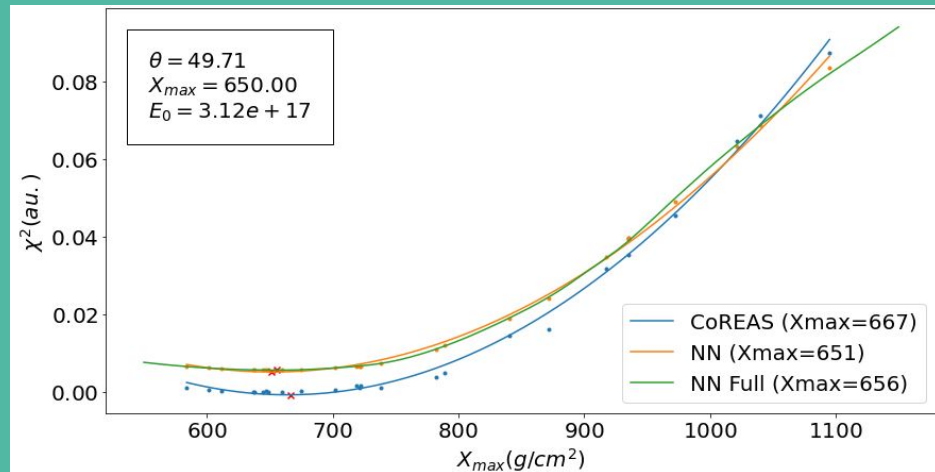


The plot on the right is a zoomed in version of the plot, and the fluences on the x-axis are the true fluences.

## Error in Radiation Energy:



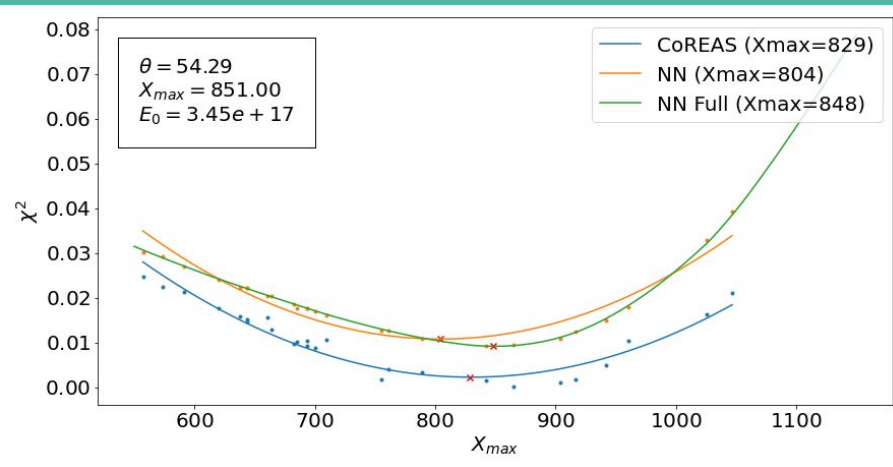
## $X_{\max}$ reconstruction:



NN - The same shower parameters as the CoREAS simulation

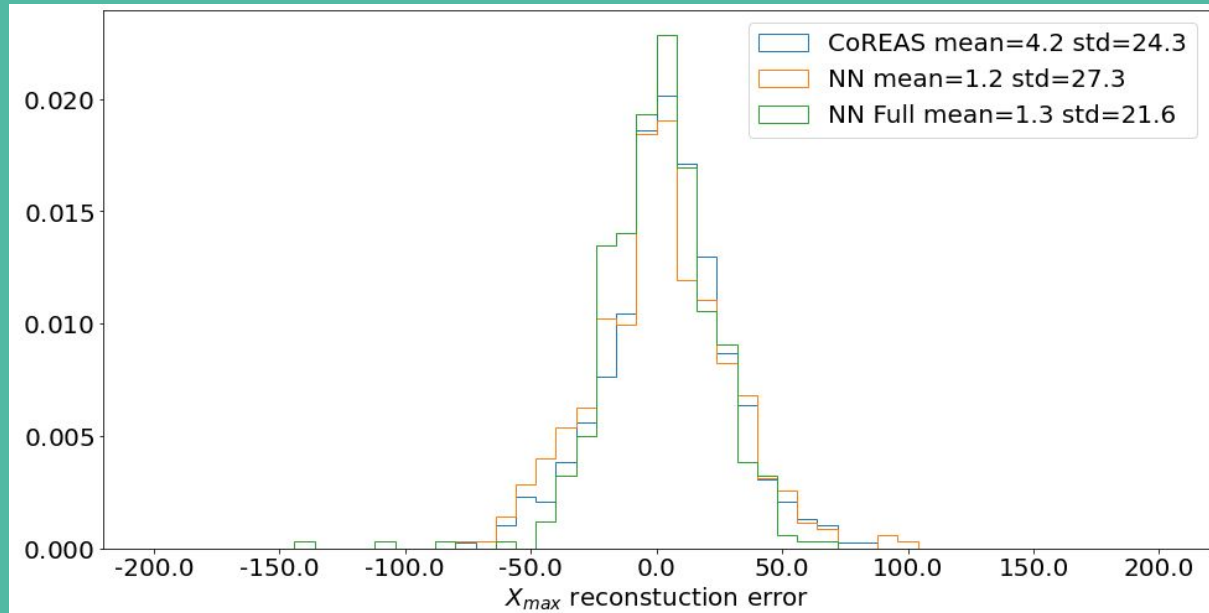
NN Full - Scan the entire  $X_{\max}$  range with a lot of simulations.

Using the same network for a simplistic  $\chi^2$  minimization procedure for  $X_{\max}$  reconstruction.



## $X_{\max}$ reconstruction:

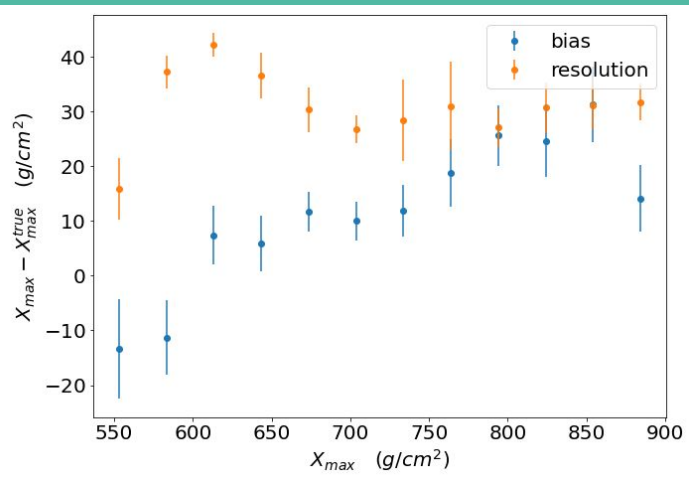
We can see that the  $X_{\max}$  distribution is very similar between the reconstruction methods using the neural network and using the CoREAS simulations.



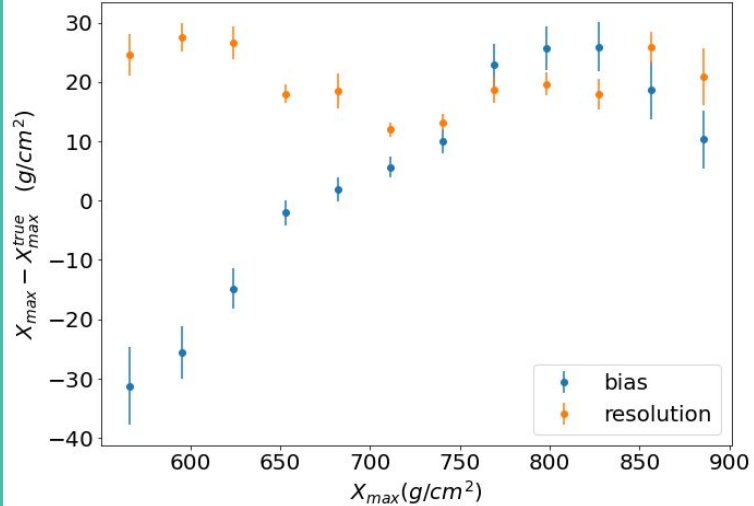
# $X_{\max}$ reconstruction:

Comparing the  $X_{\max}$  reconstruction resolution across various  $X_{\max}$

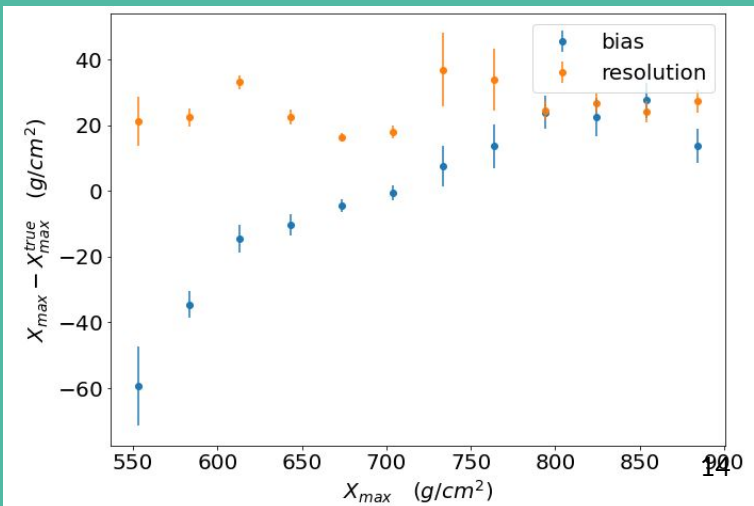
NN Full



CoREAS



NN



## Results:

- The networks seems to **perform reasonably well** in the initial tests.
- High amplitude/High Fluence pulses are **accurate**.
- Total radiation energy is accurate **within 10%** for shallow showers.
- Total radiation energy is wrong in deeper showers.
- A quick  $X_{\max}$  reconstruction is comparable with CoREAS using the network.
- **~100ms** for simulating an entire star shape array, memory footprint of the model is **~20MB**.

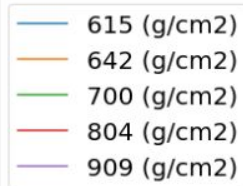
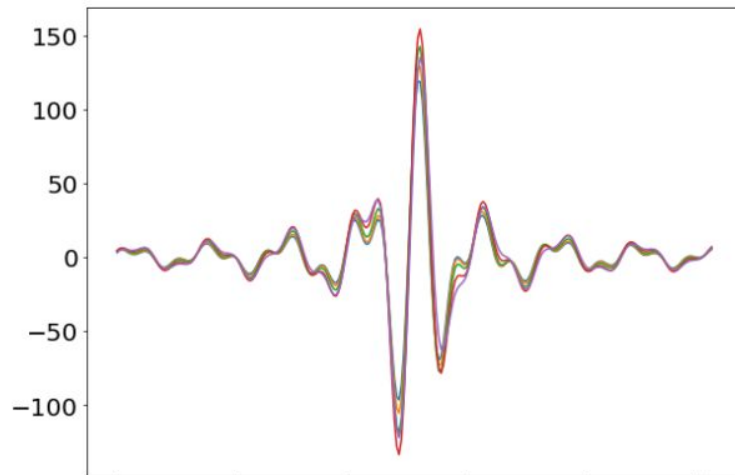
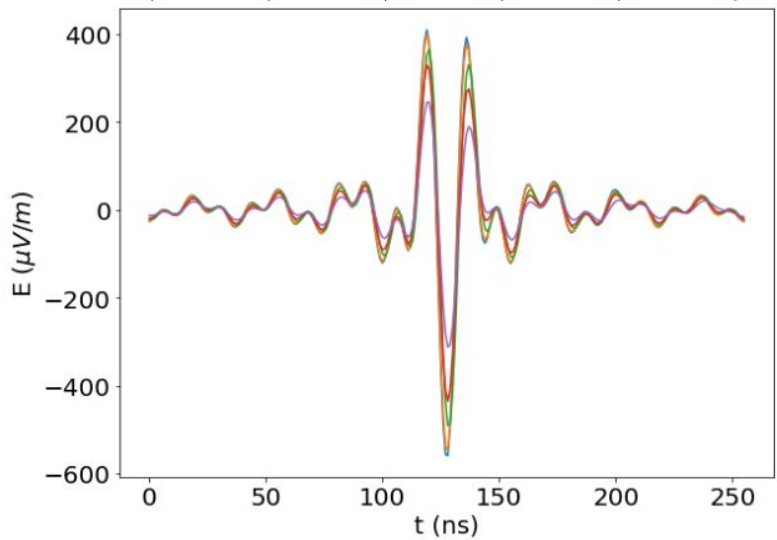
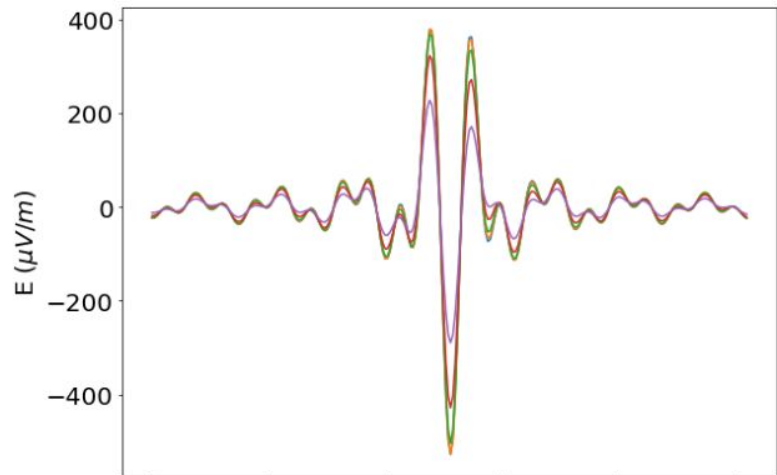
## Todo:

- Do a  $X_{\max}$  reconstruction along with the noise model. Similar to the AERA  $X_{\max}$  Reconstruction pipeline. (PhysRevD.109.022002)
- Manuscript in preparation!

# THANK YOU!

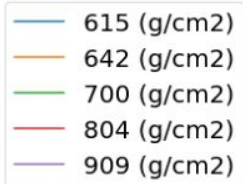
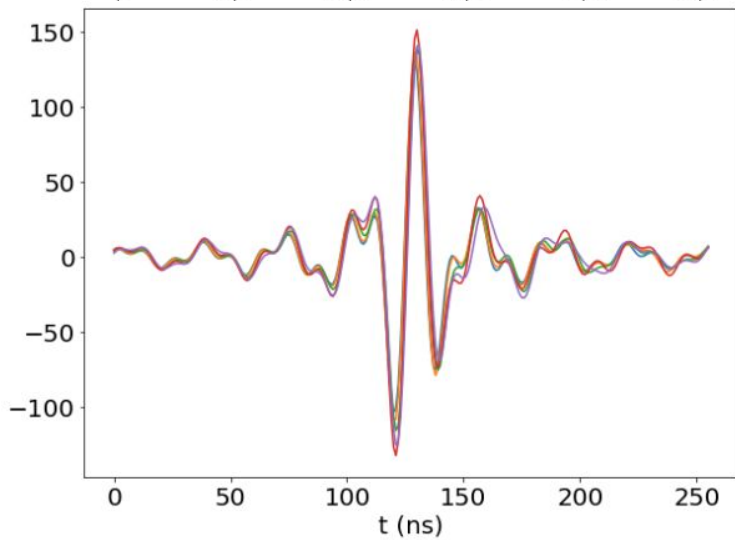
# Backups





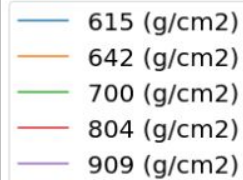
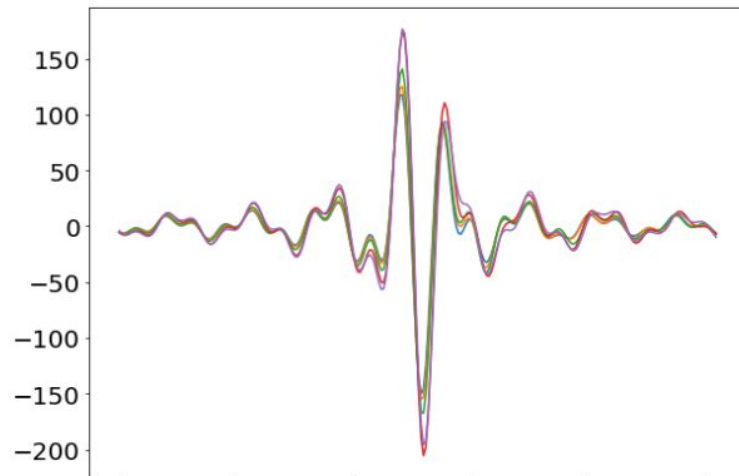
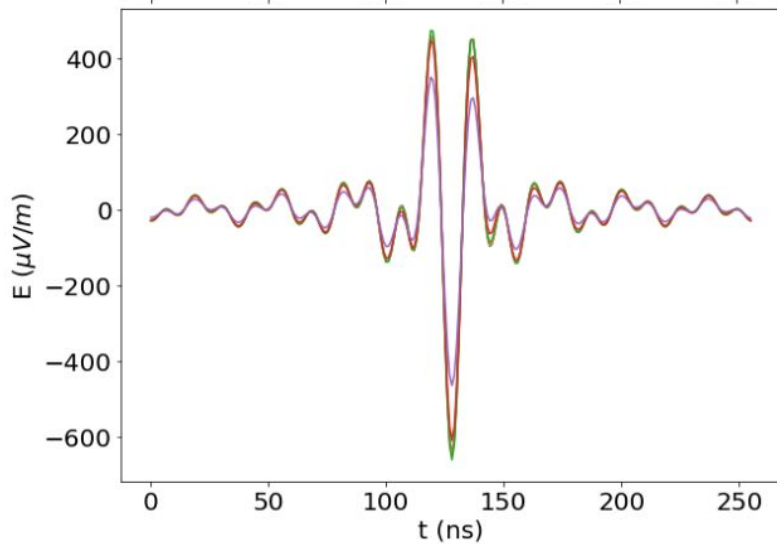
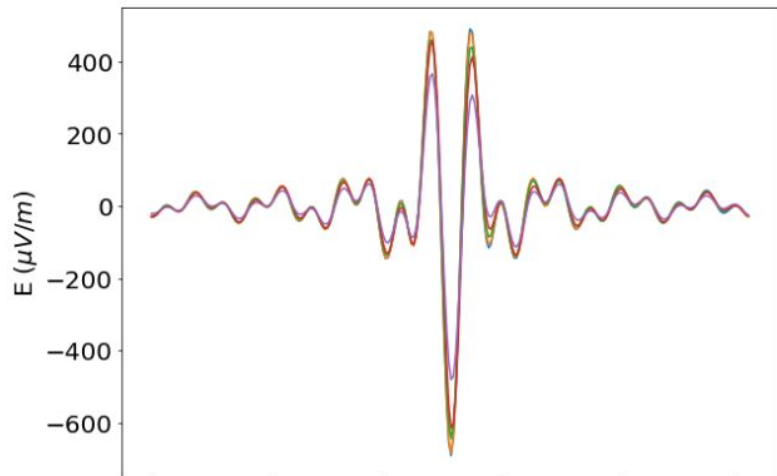
$\theta = 30.54$  (deg)  
 $E_0 = 8.22e + 17$  (eV)  
Pos: (-1, -108)m

CoREAS



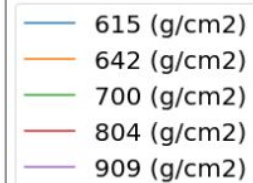
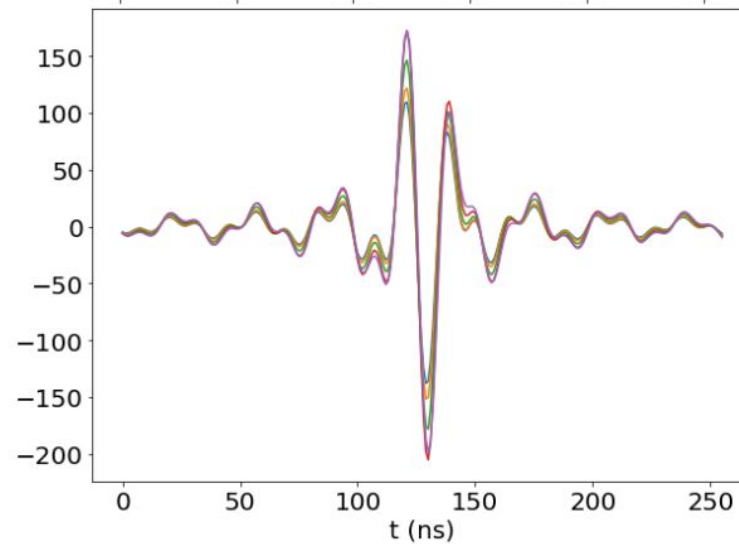
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NN



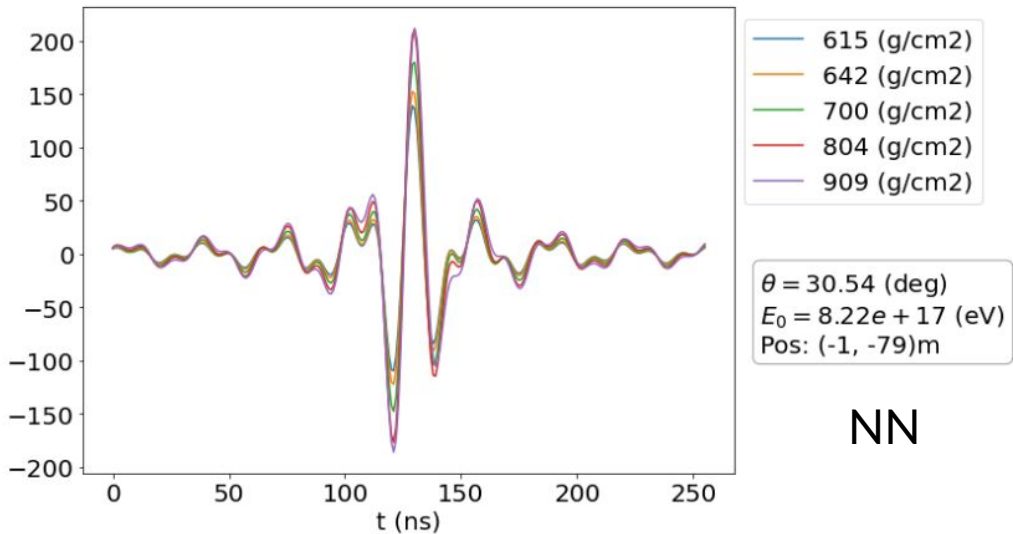
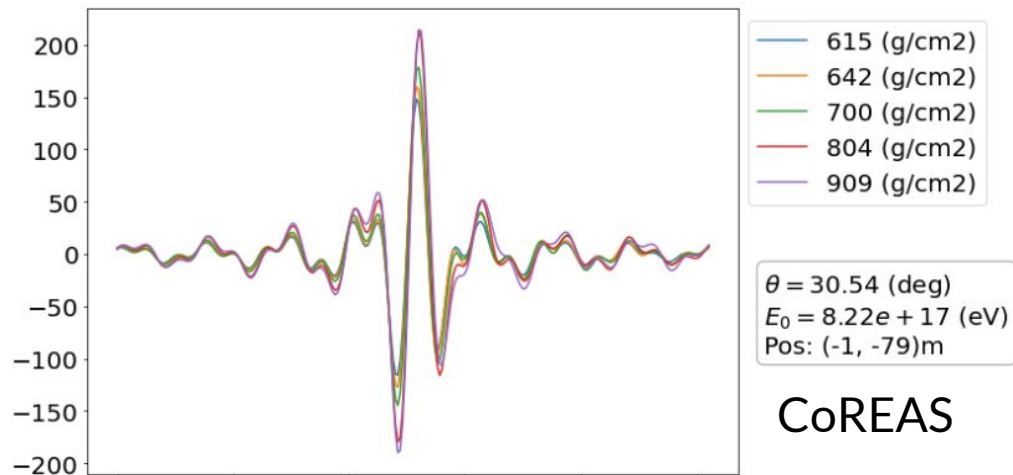
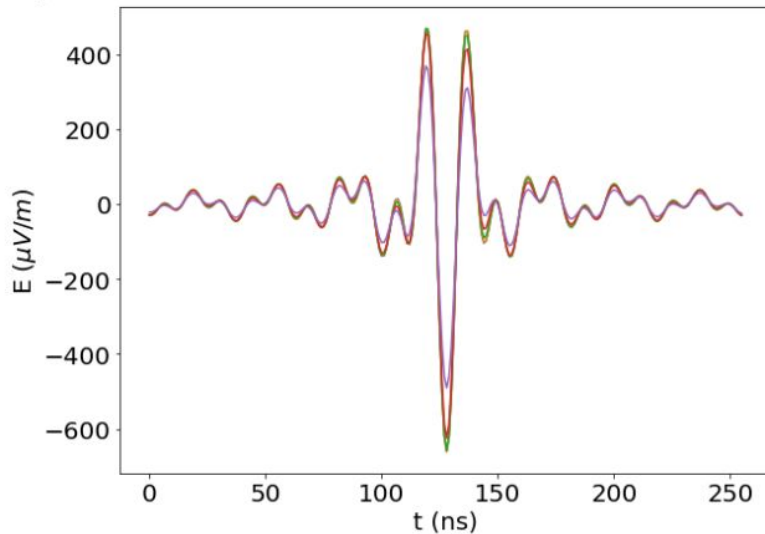
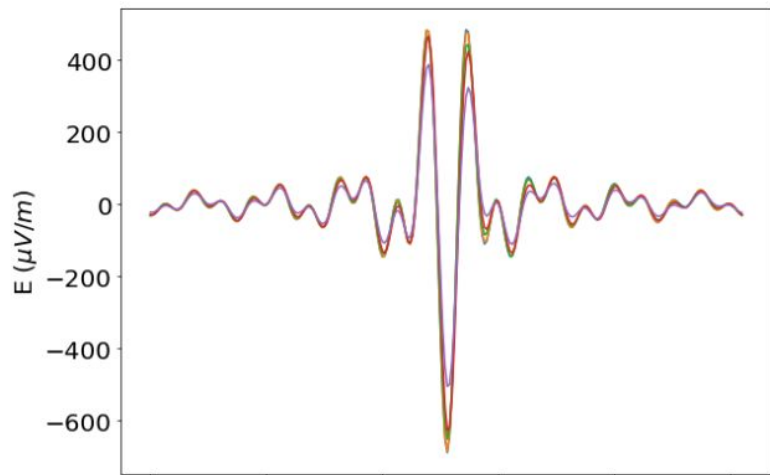
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Pos: (-2, 83)m

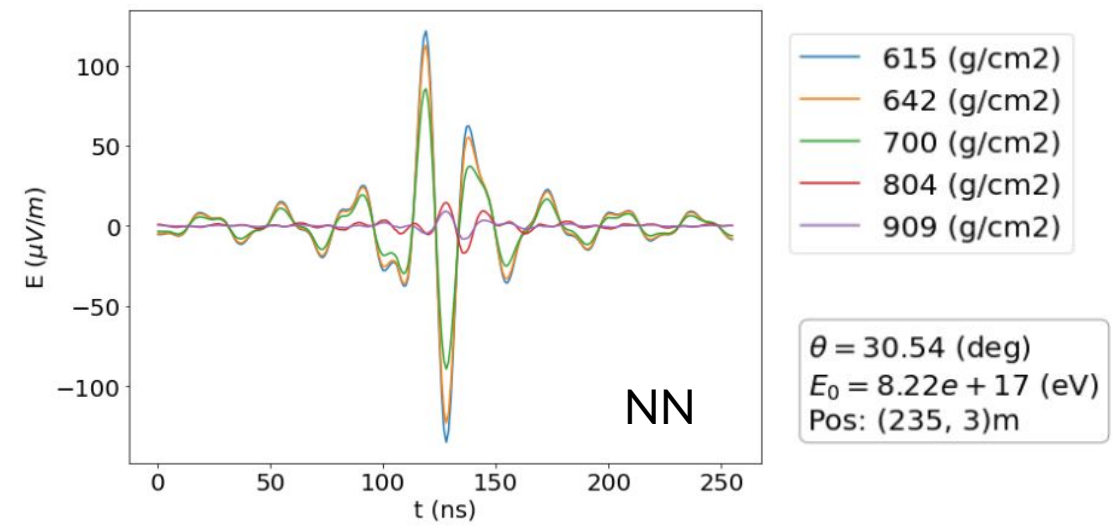
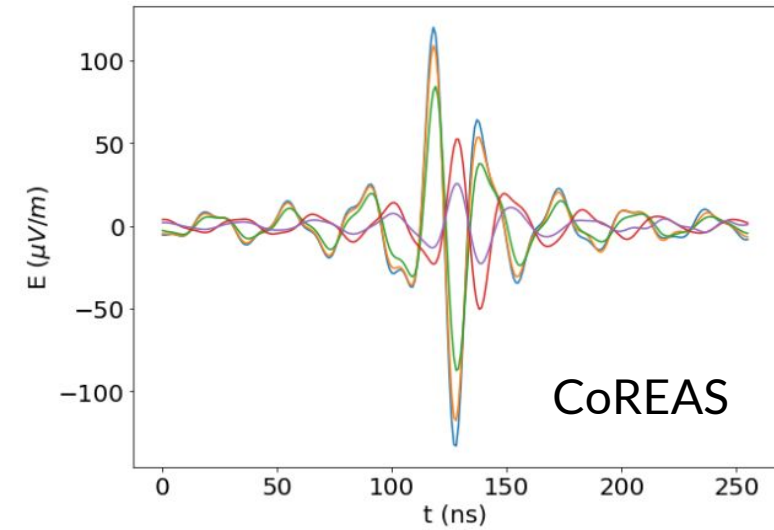
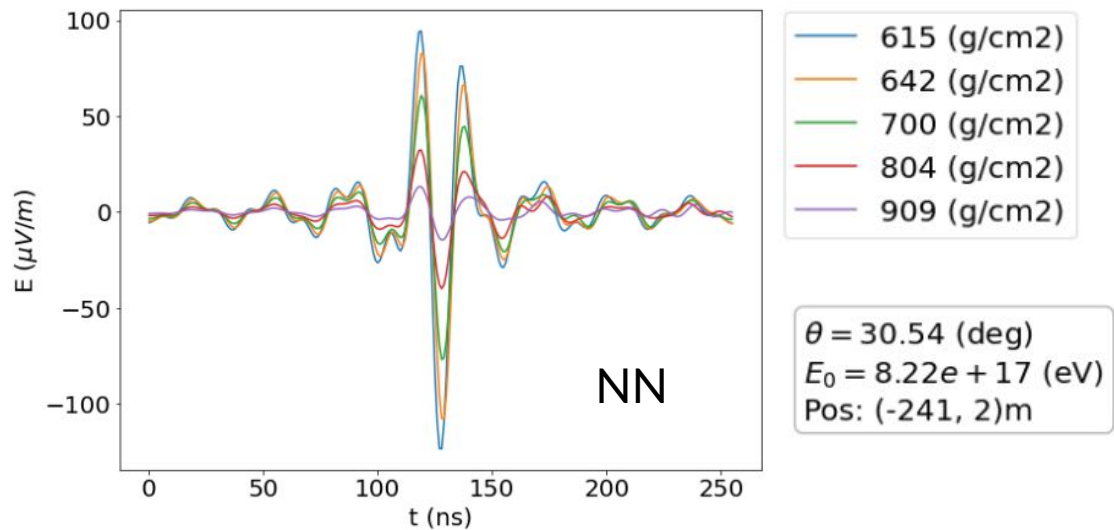
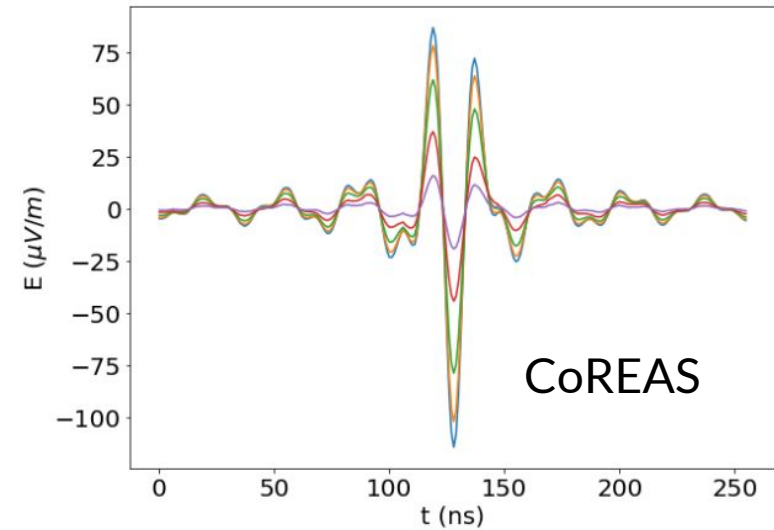
CoREAS

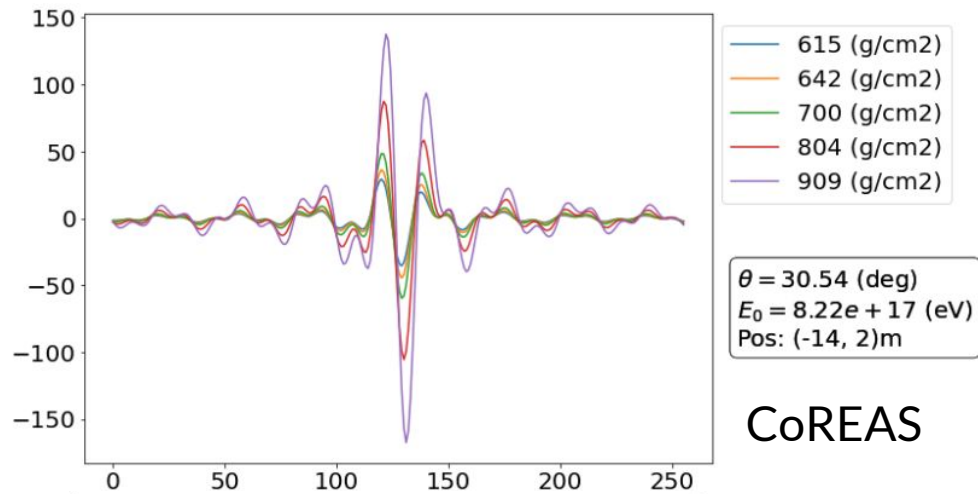
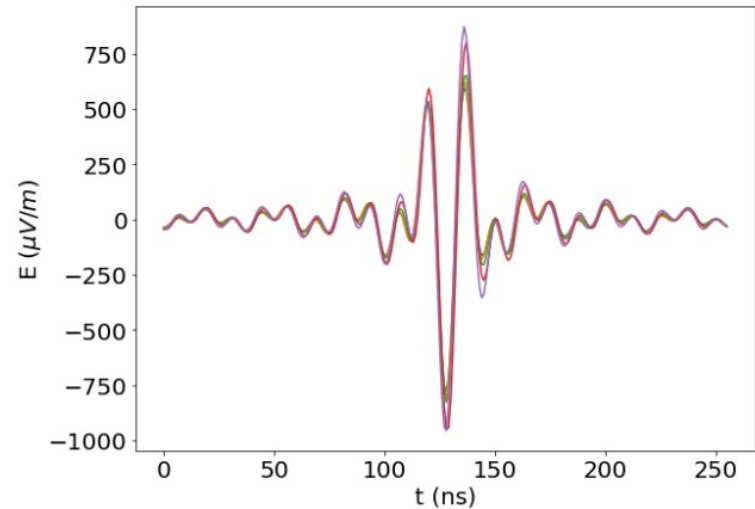
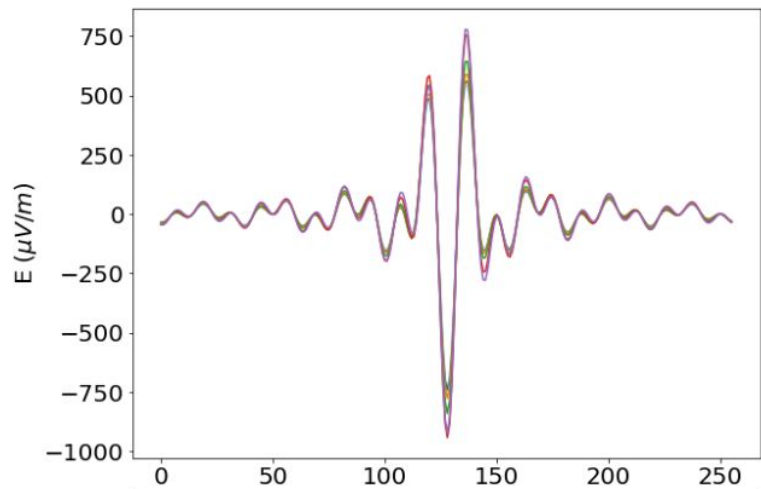


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Pos: (-2, 83)m

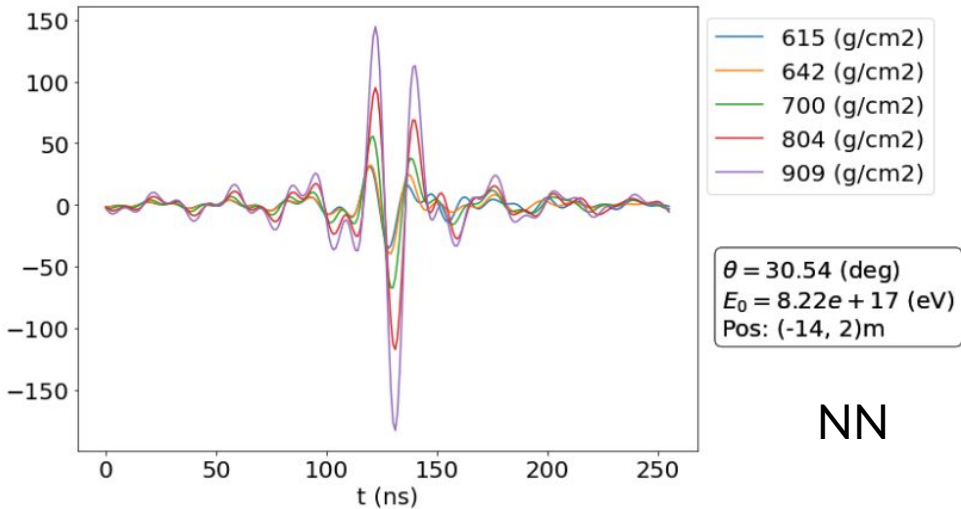
NN



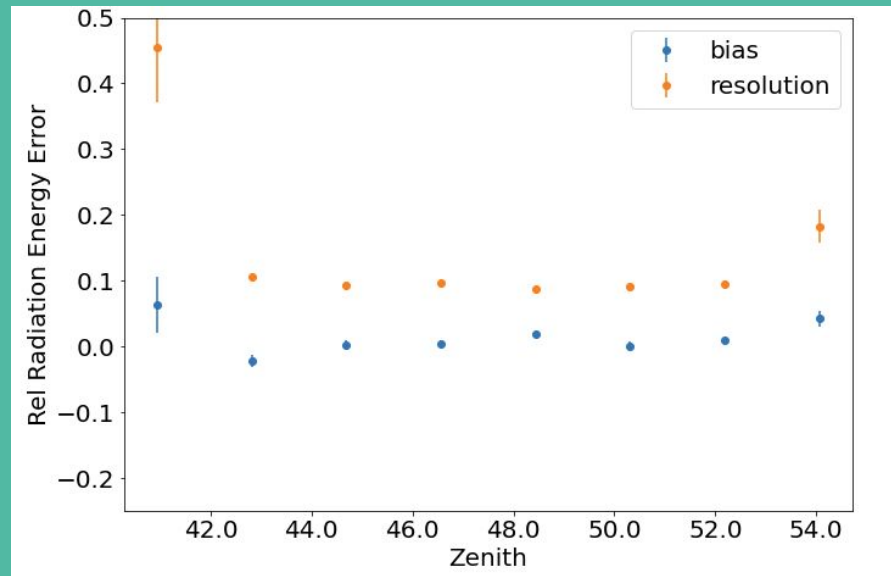
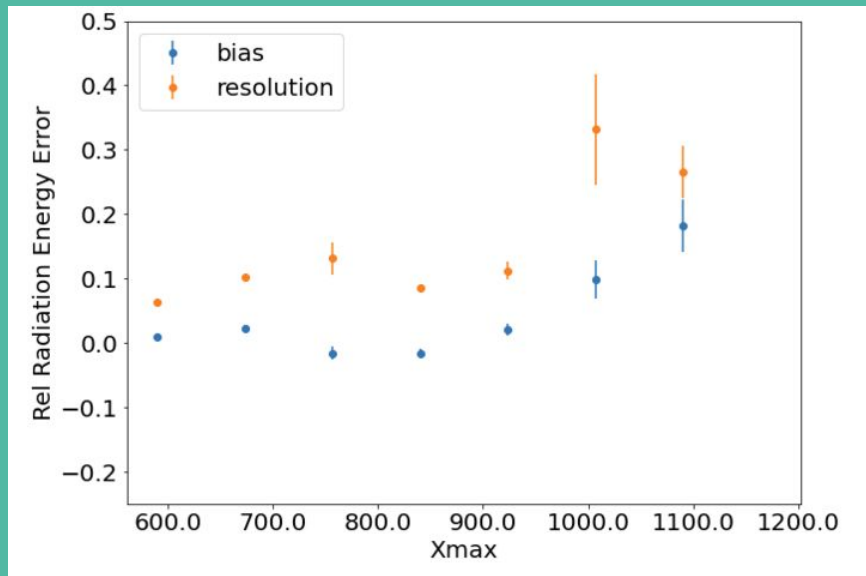


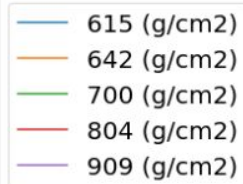
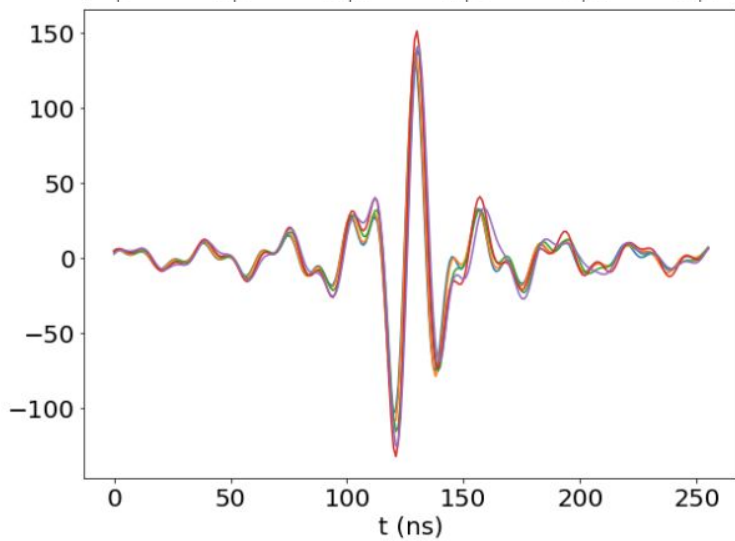
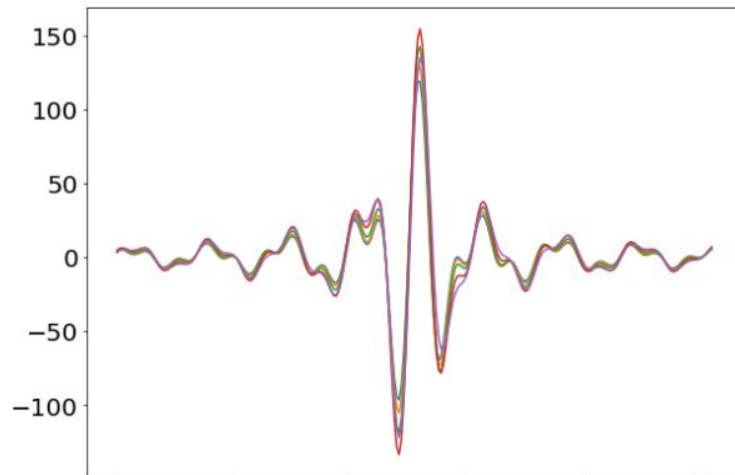
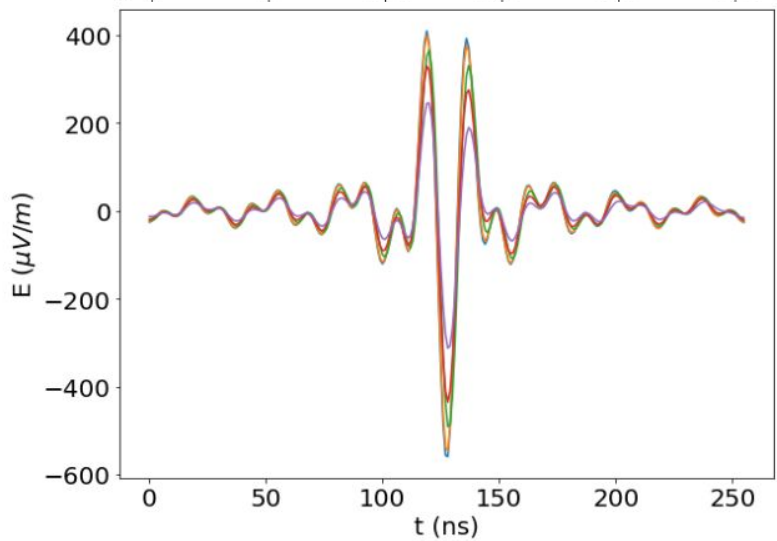
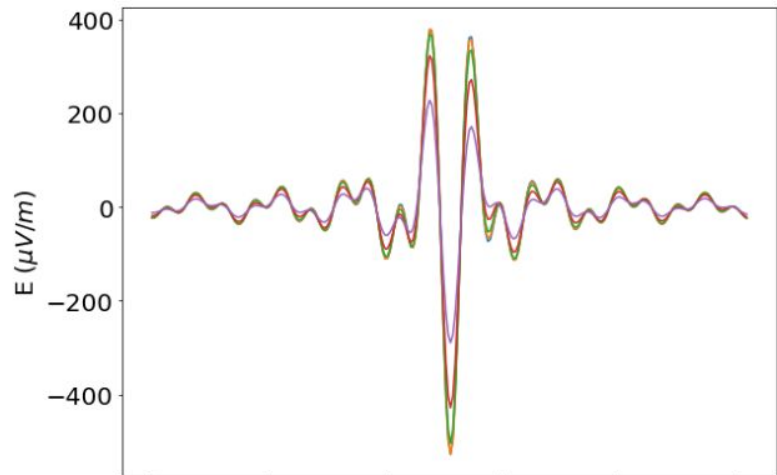


CoREAS



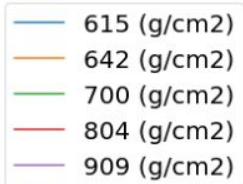
NN





$\theta = 30.54$  (deg)  
 $E_0 = 8.22e + 17$  (eV)  
 Pos: (-1, -108)m

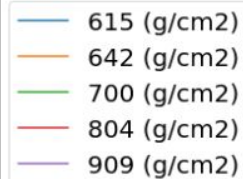
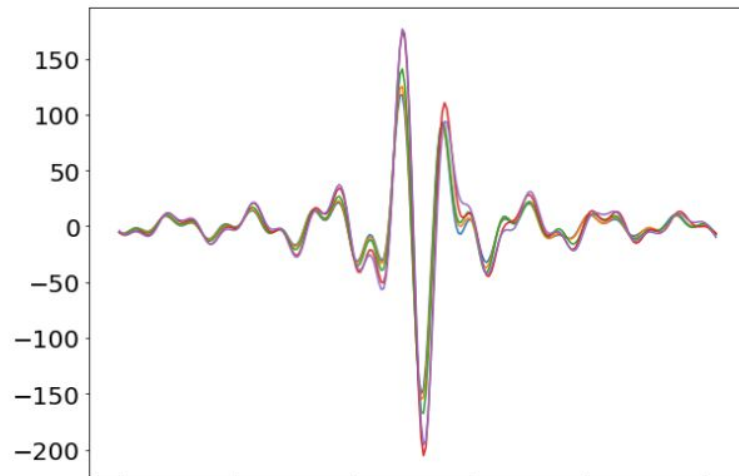
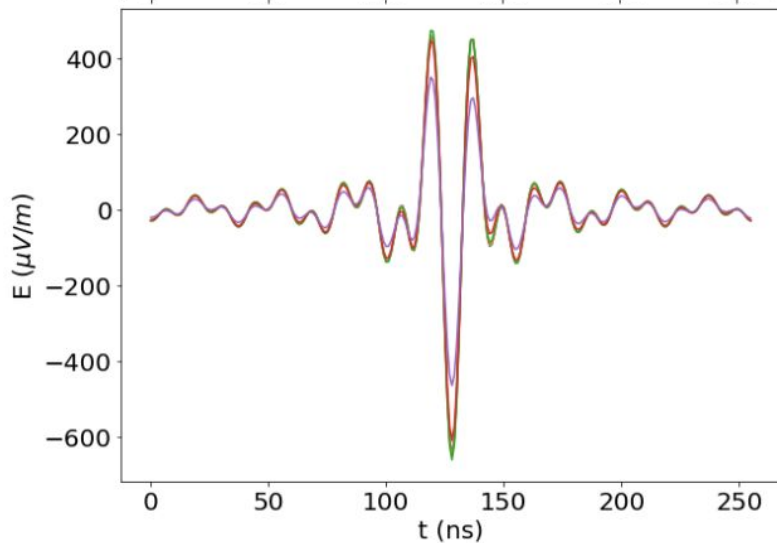
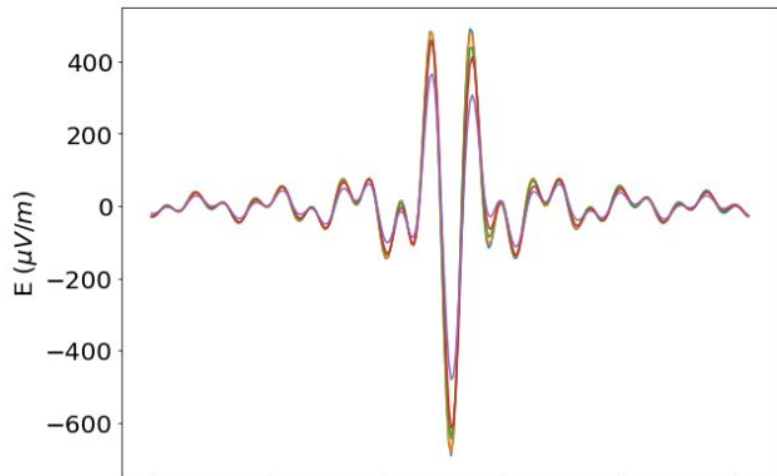
CoREAS



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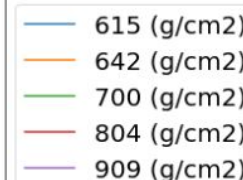
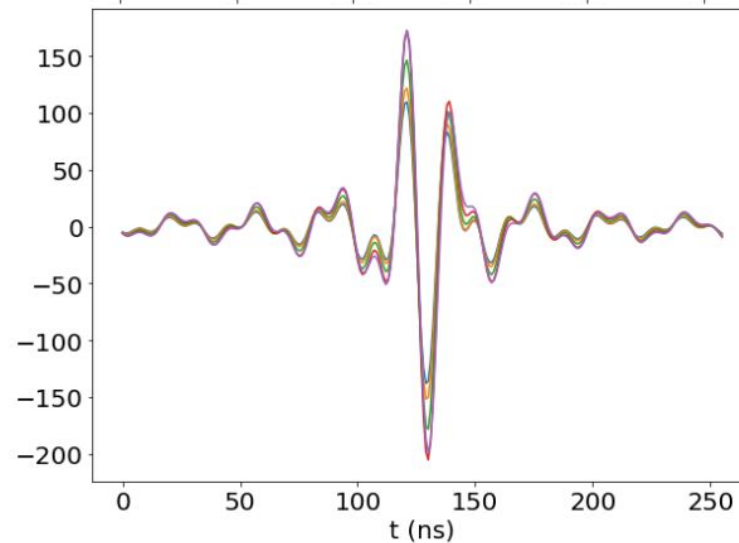
NN





$\theta = 30.54$  (deg)  
 $E_0 = 8.22e + 17$  (eV)  
 Pos: (-2, 83)m

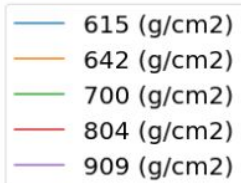
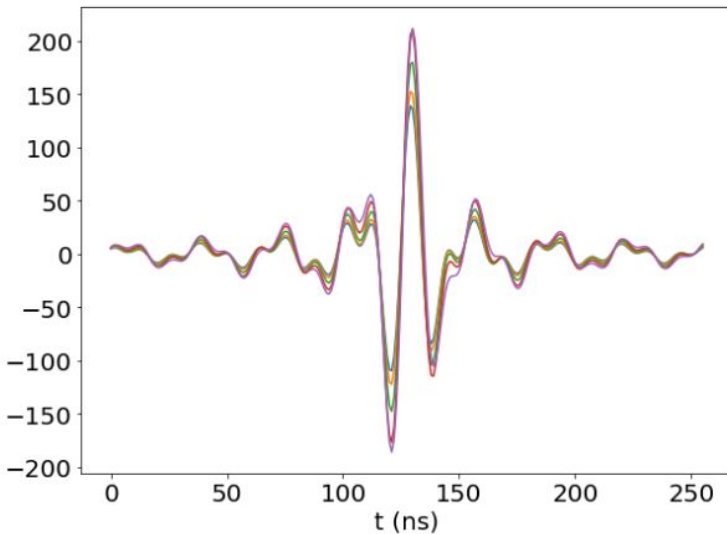
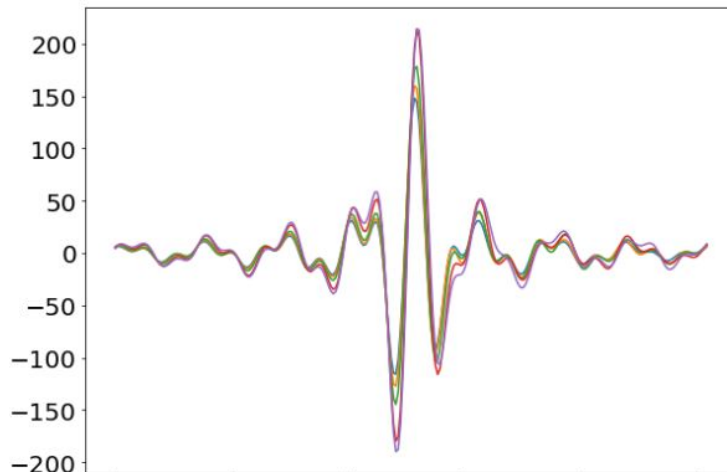
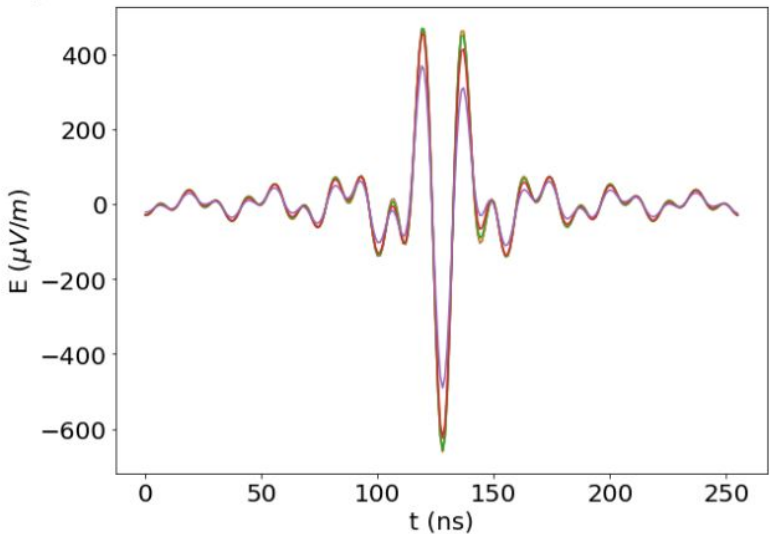
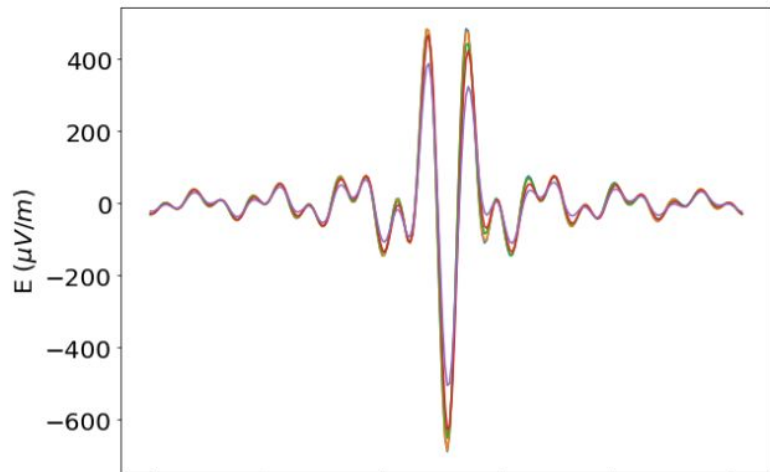
**CoREAS**



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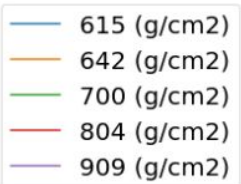
**NN**





$\theta = 30.54$  (deg)  
 $E_0 = 8.22e + 17$  (eV)  
 Pos: (-1, -79)m

CoREAS



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NN

