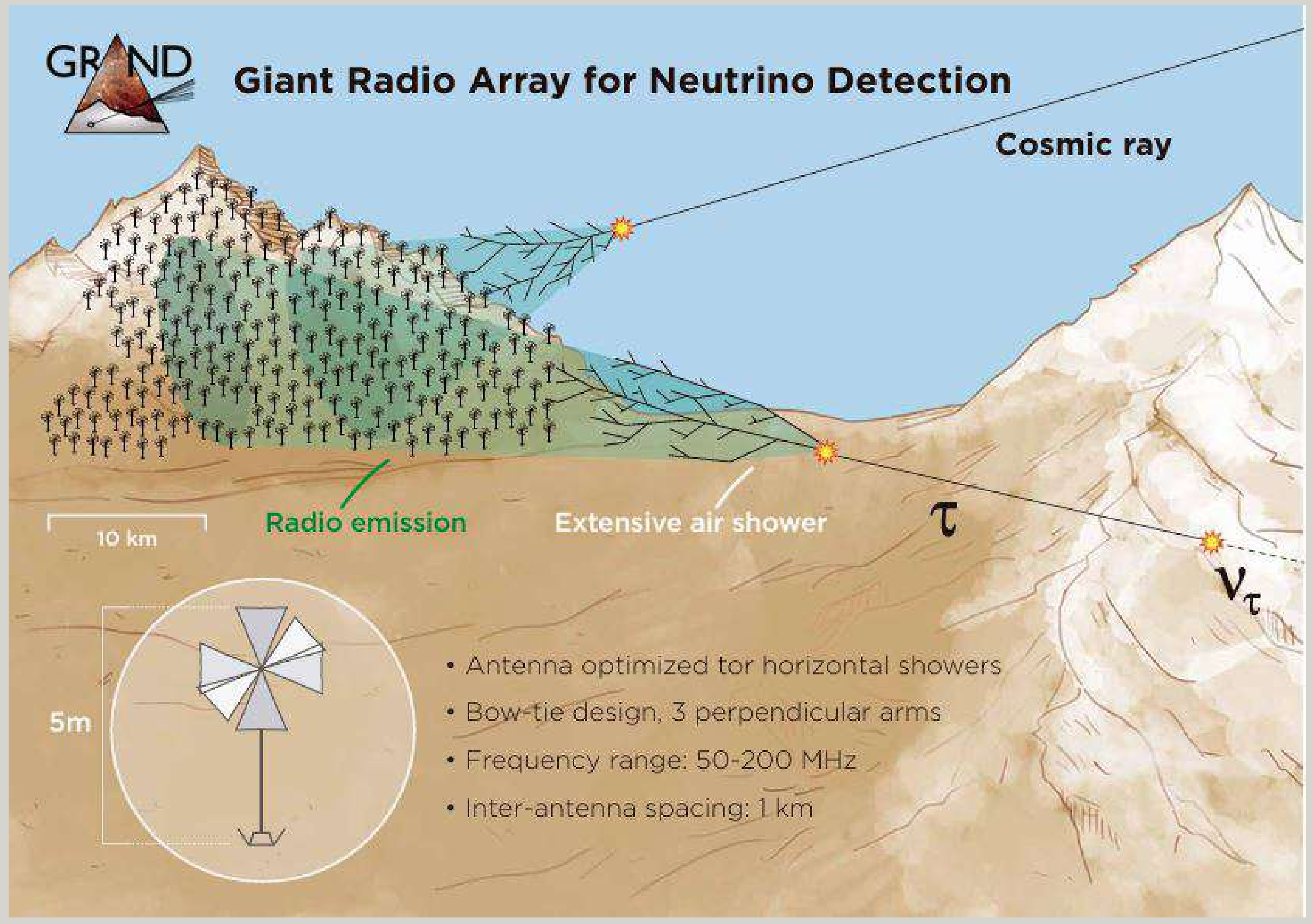
Energy-fluence reconstruction for UHE neutrinos and cosmic rays in GRAND using Rician likelihoods and physics-informed GNNs

San Francisco State University

Ryan Thong[1], Oscar Macias[1], Zhisen Lai[1], Arsène Ferrière[2]

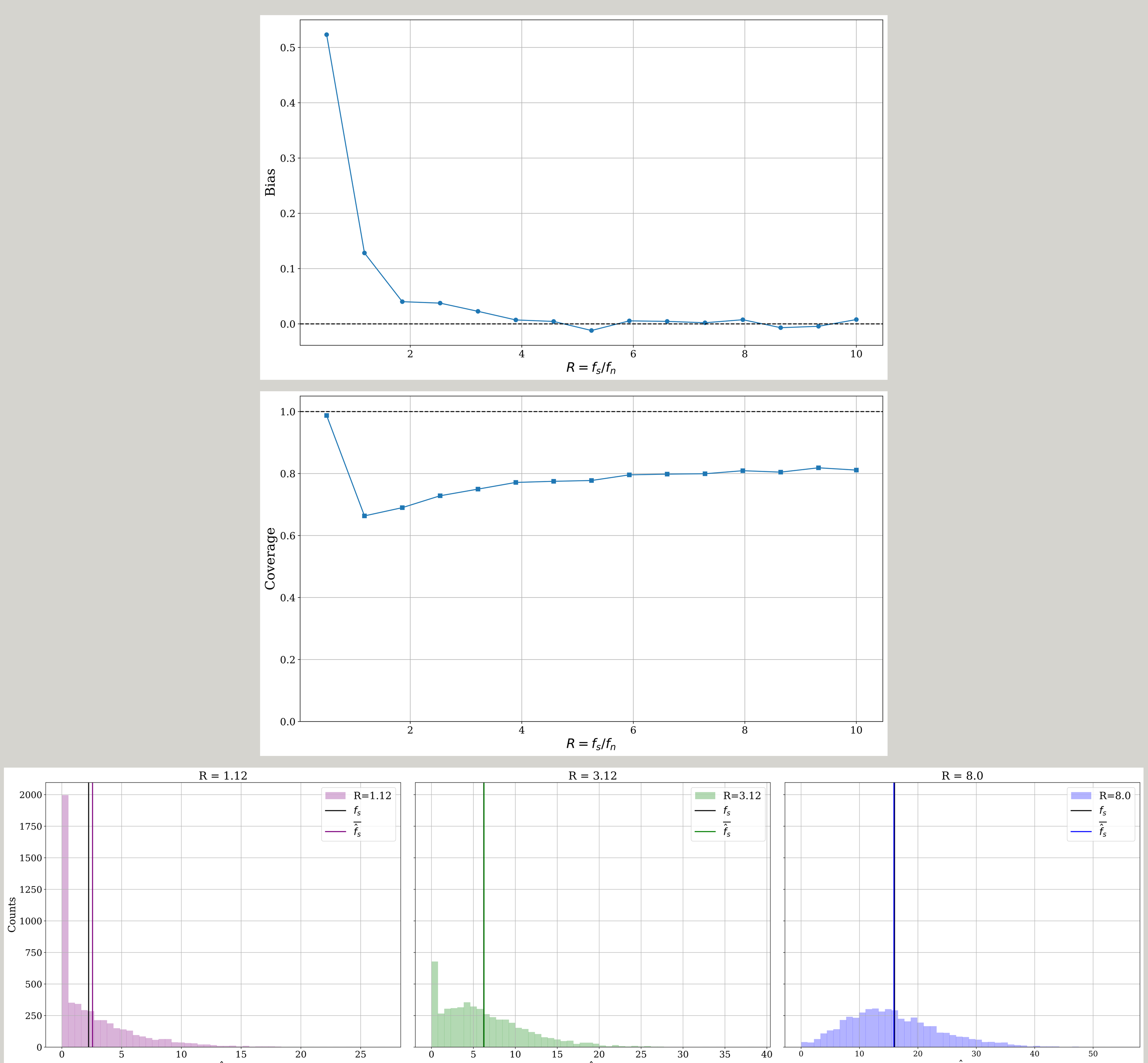
[1] Department of Physics and Astronomy, San Francisco State University
[2] Université Paris-Saclay, CEA

GRAND Detection



For each air-shower event, only some antennas trigger, and the triggered antennas form an irregular radio footprint. GRAND's array of radio antennas detect UHECRs [Credit to arXiv:1810.09994].

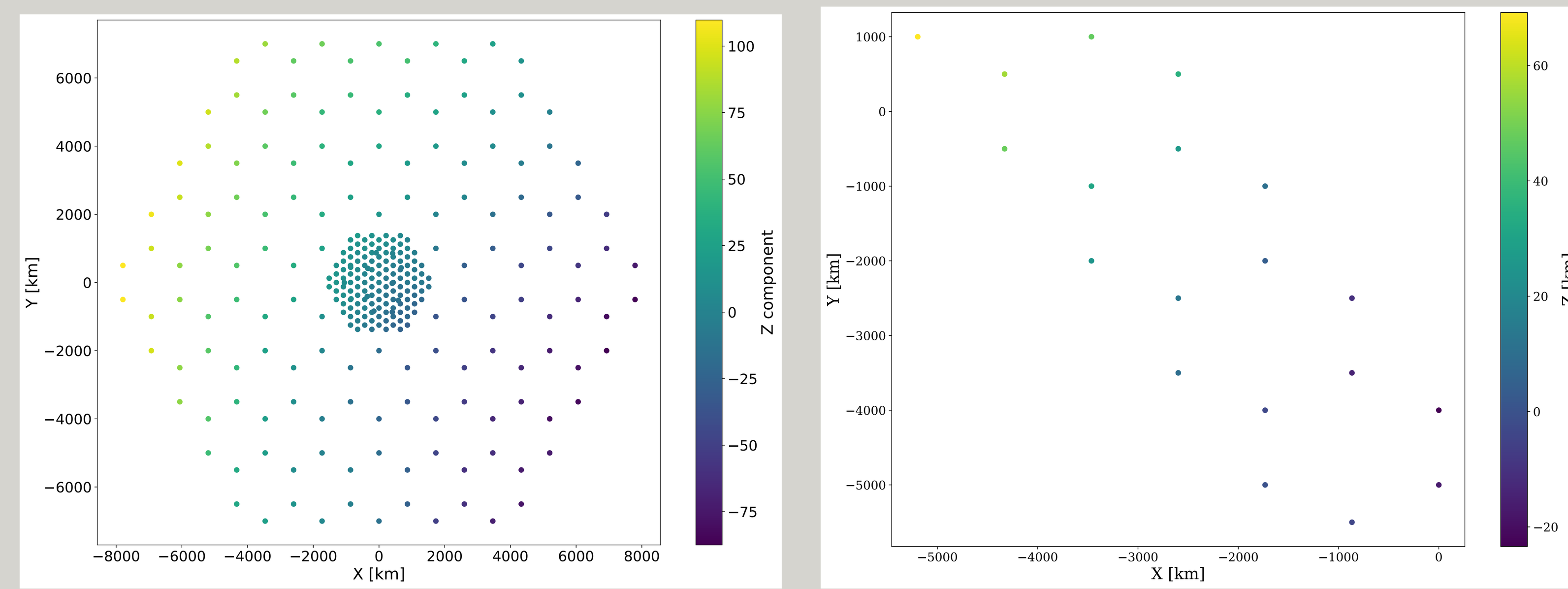
Rician Fluence Estimator



Rician likelihood estimates antenna-level fluence and uncertainty. This method gives access to low-SNR information that would otherwise be discarded by a simple threshold cut.

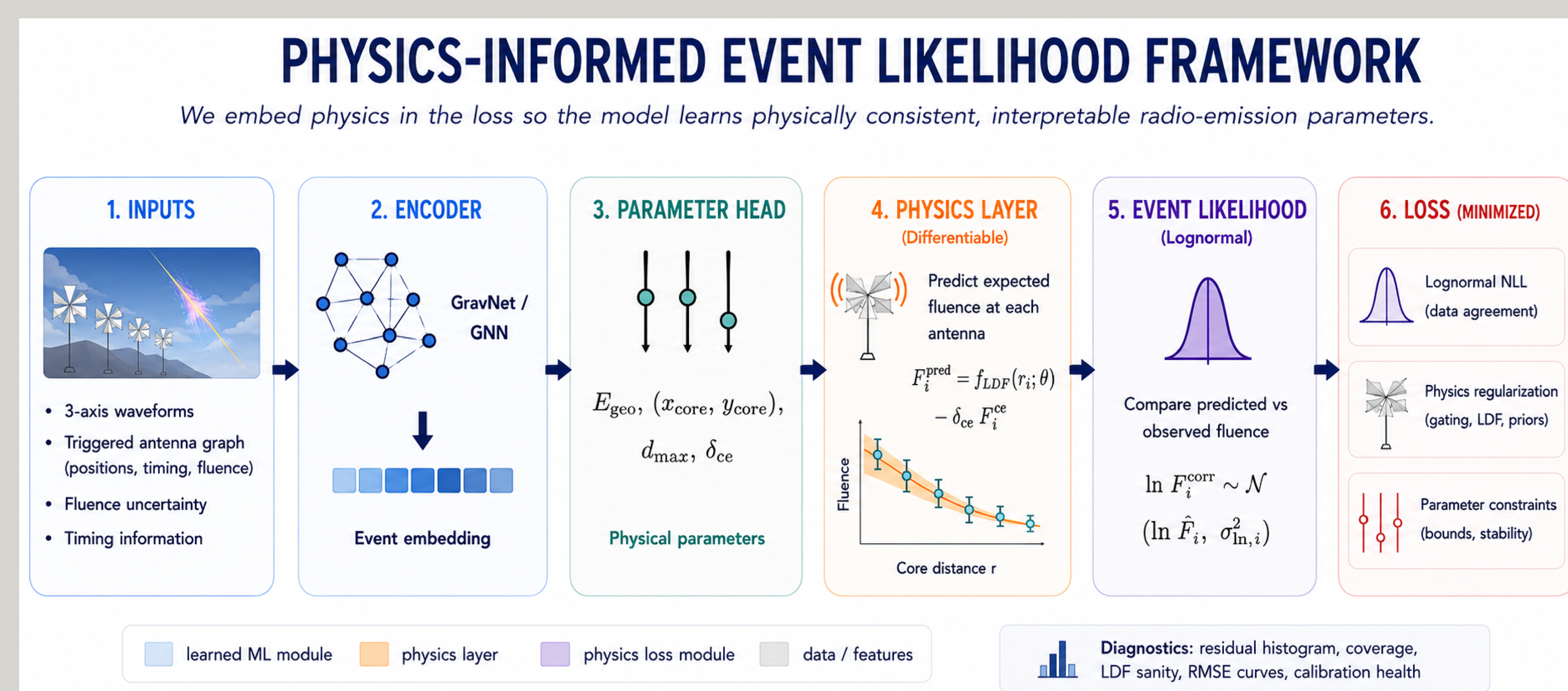
GRAND Event

Simulation: ZHAireS electric-field simulations for GRANDProto300 geometry



Triggered antennas form an irregular graph, not an image. The number of triggered antennas changes from event to event. Each triggered antenna is a node with features including trigger time, polarization information, antenna position, shower-coordinate position, Rician fluence estimate, and fluence uncertainty.

Machine Learning Pipeline



End-to-end architecture of the physics-informed Graph Neural Network model. Per-antenna Rician fluence estimates and geometric features are organized into a $k = 8$ nearest-neighbor graph.

Loss Function

$$\mathcal{L}_{\text{train}} = \langle \mathcal{L}_{\text{phys}} \rangle_{\text{event}} + s_{\text{reg}} \mathcal{L}_{\sigma} + w_{\text{gate}} \mathcal{L}_{\text{gate}}$$

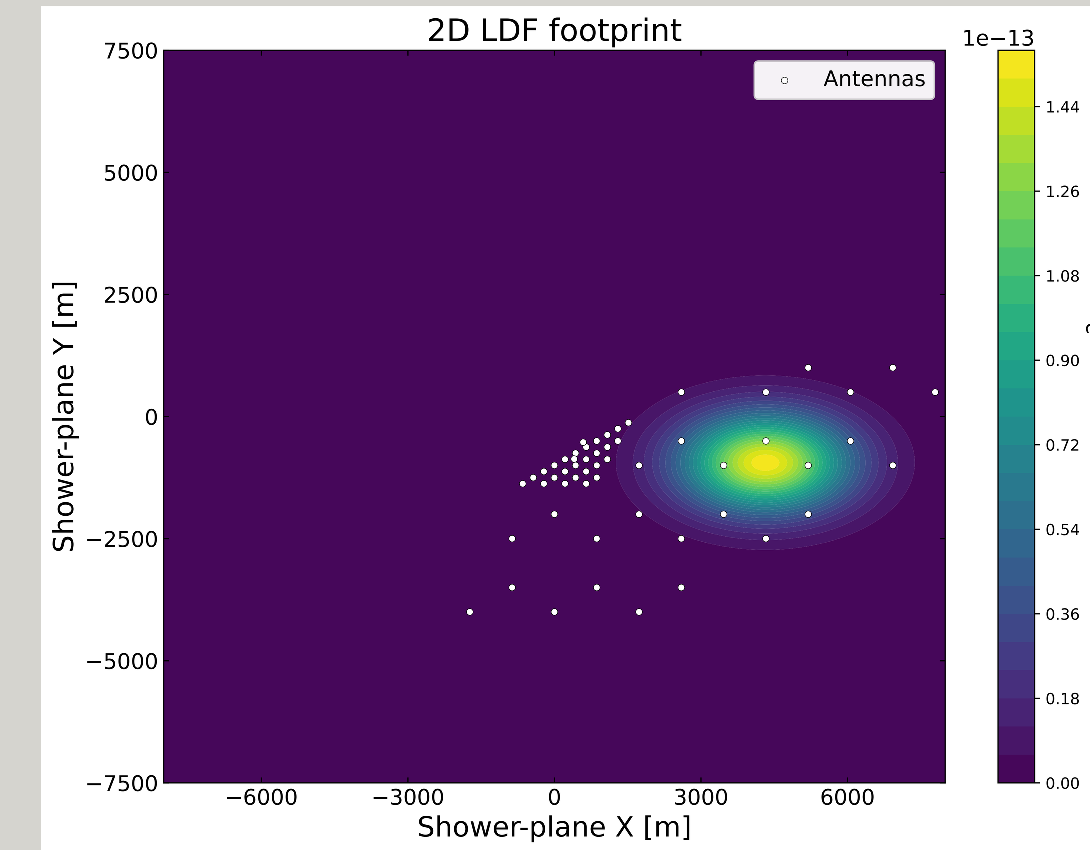
The physics layer converts the encoder output ($E_{\text{geo}}, x_c, y_c, d_{\max}, \delta_{\text{ce}}$) into a shower-plane fluence prediction and scores it against the Rician-derived antenna fluence with a lognormal event likelihood.

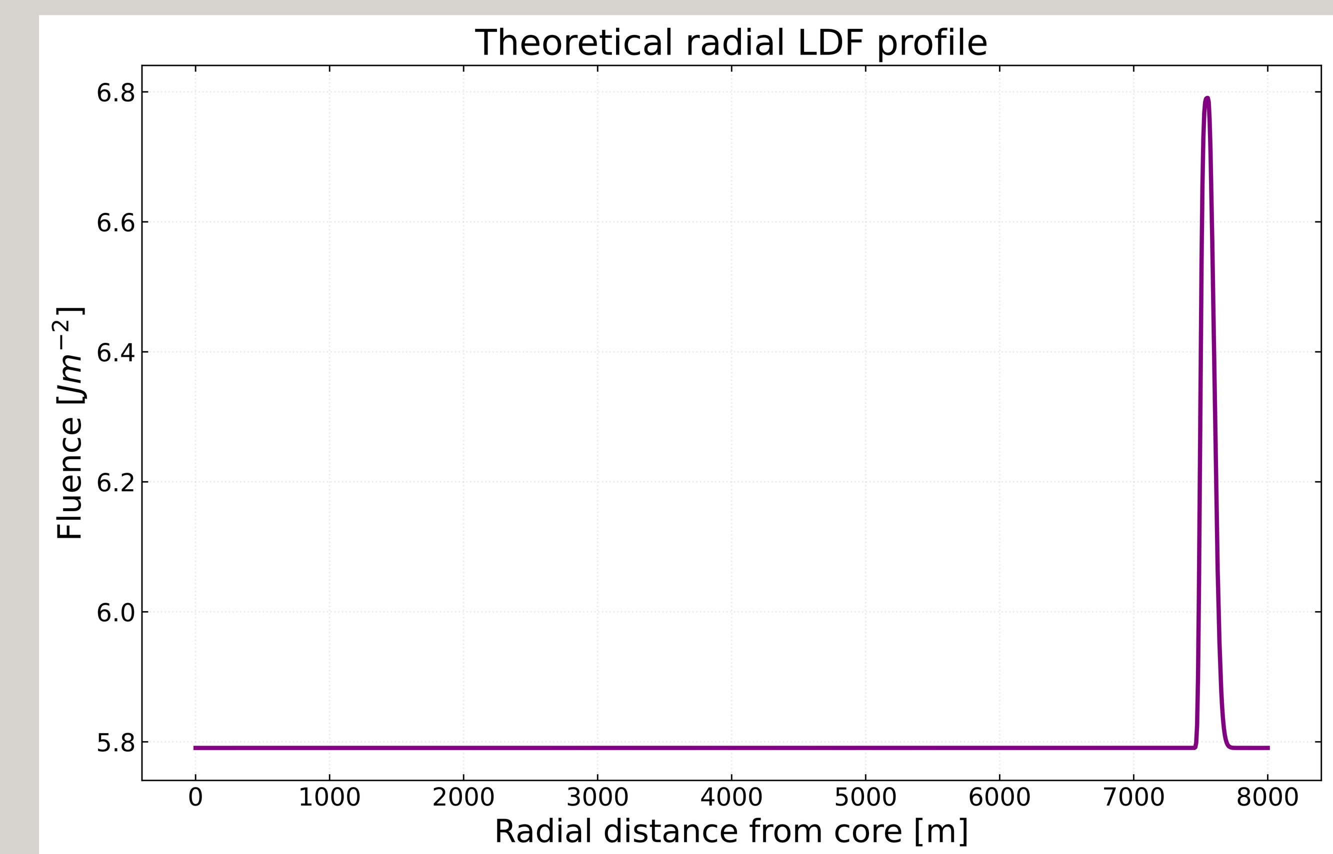
Geomagnetic Fluence

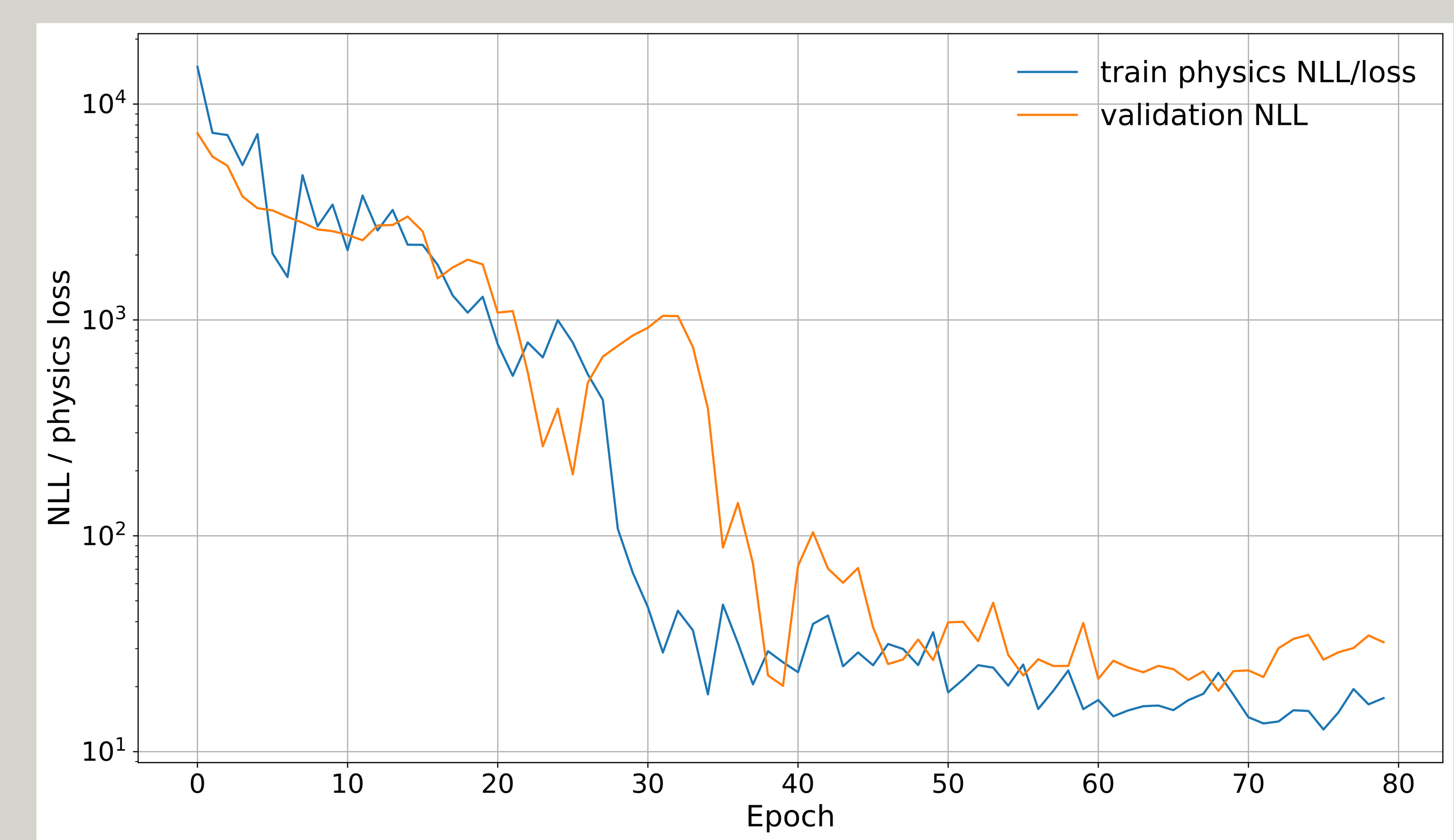
$$f_{\text{LDF}}(r) = \begin{cases} \dfrac{E_{\text{geo}}}{E_0} \left[\exp\left(- \left(\dfrac{|r - r_0|}{\sigma} \right)^{p_{\text{inner}}} \right) + \dfrac{a_{\text{rel}}}{1 + \exp\left(s \left(\dfrac{r}{r_0} - r_{02} \right) \right)} \right], & r < r_0, \\[2ex] \dfrac{E_{\text{geo}}}{E_0} \left[\exp\left(- \left(\dfrac{r - r_0}{\sigma} \right)^{p(r)} \right) + \dfrac{a_{\text{rel}}}{1 + \exp\left(s \left(\dfrac{r}{r_0} - r_{02} \right) \right)} \right], & r \geq r_0. \end{cases}$$

The one-dimensional geomeagnetic LDF supplies the radial template that ties sparse antenna fluences to a physically admissible radio footprint.

Preliminary Validation: Pipeline Is Learning







The pipeline is implemented and learning energy-relevant structure, while bias, resolution, and coverage validation are the next targets.

Next Steps

1. Quantify bias and central 68% residual width
2. Validate uncertainty coverage
3. Test with and without LDF regularization
4. Compare Rician fluence against SNR-cut baseline
5. Compare against standard LDF reconstruction