Towards an Automatic Source Detection Pipeline in the Galactic Plane Survey by CTAO using Deep Learning

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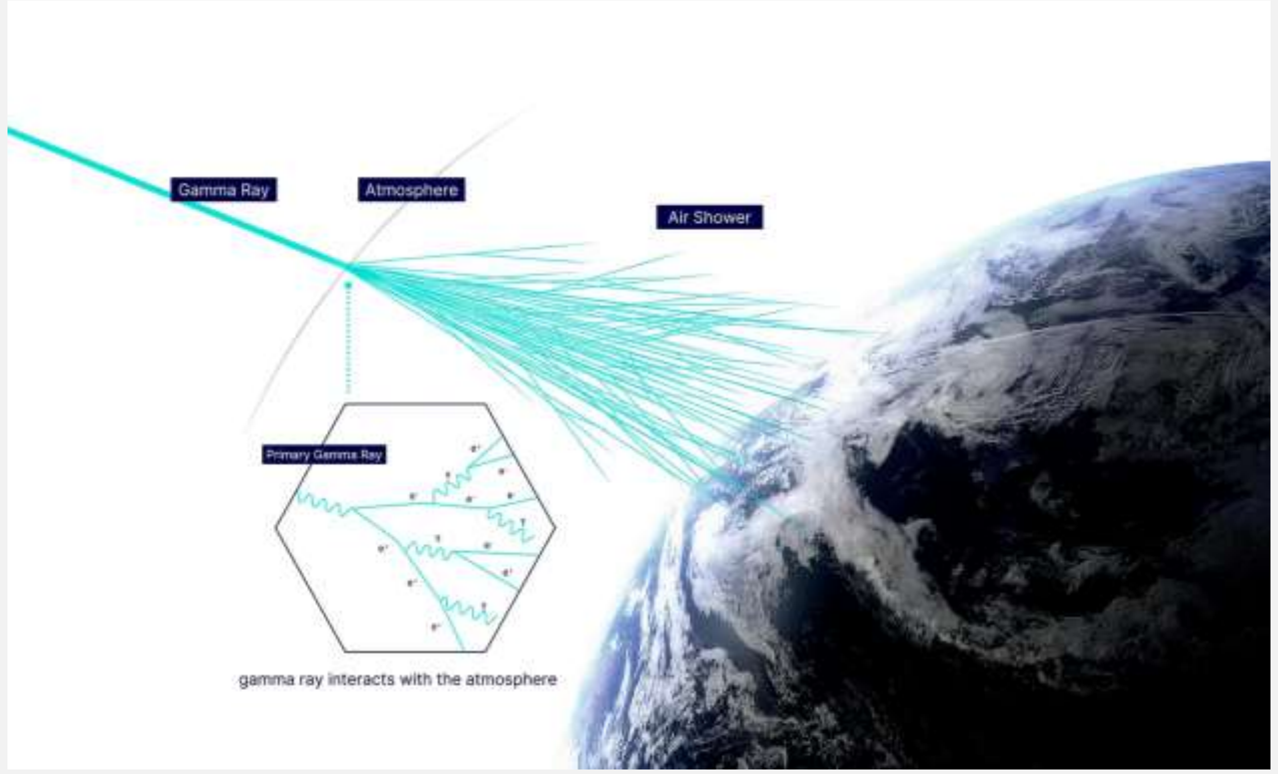
The CTAOs Galactic Plane Survey (GPS)

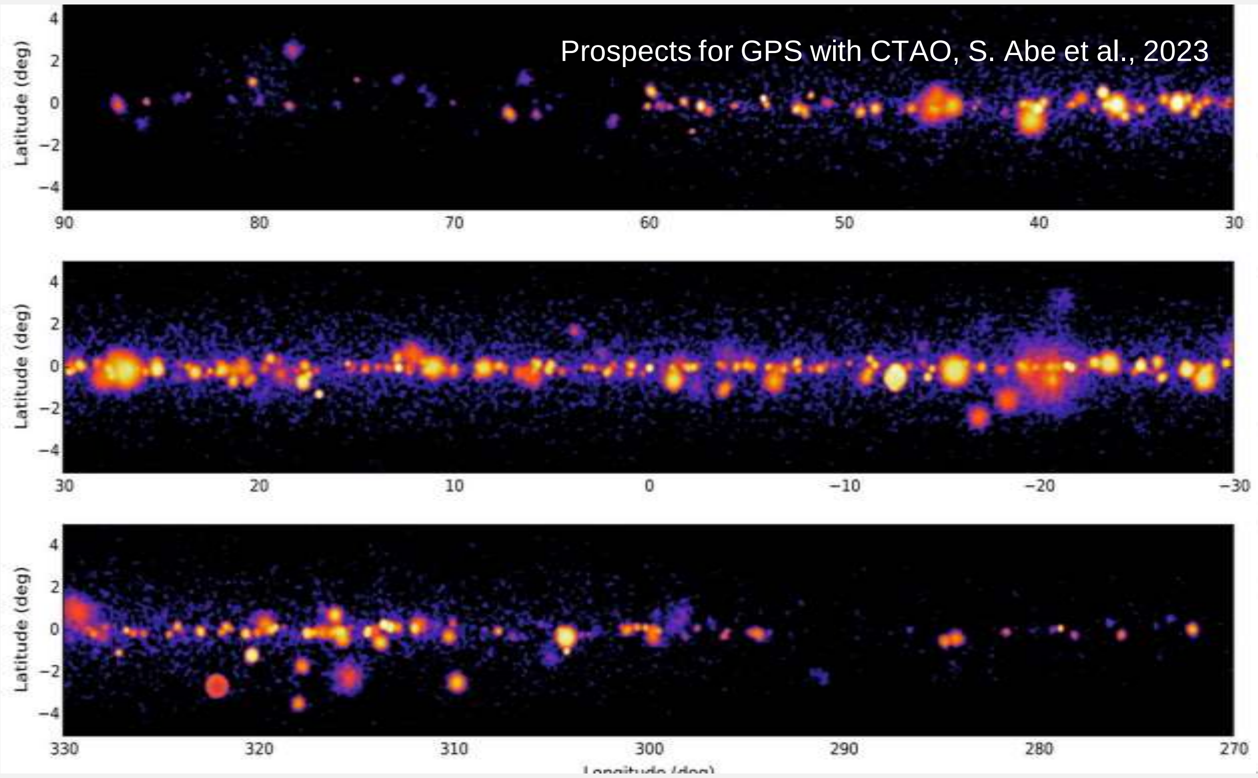
CTAO:

- Next generation ground-based observatory for very-high-energy gamma-ray astronomy (20 GeV - 300 TeV)
- Factor 10 higher sensitivity than existing instruments

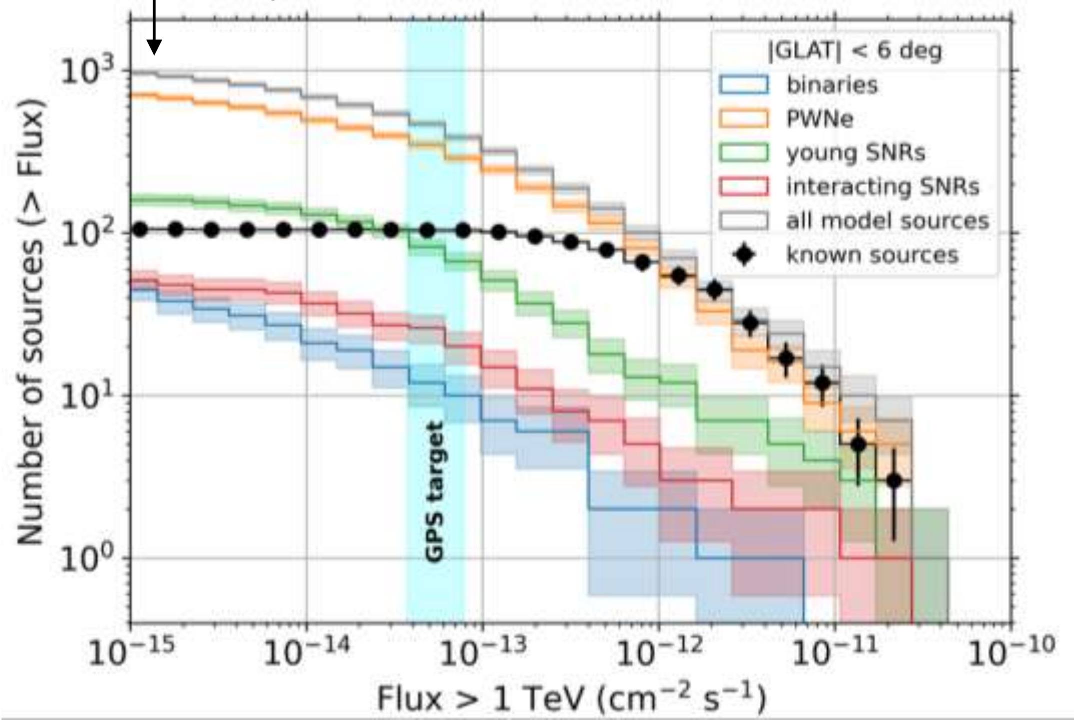
GPS:

- A detailed map of gamma-ray sources in the Galactic Plane (GP)
- Expected to detect 2-5 times more (and fainter) sources than current surveys





Prospects for GPS with CTAO, S. Abe et al., 2023



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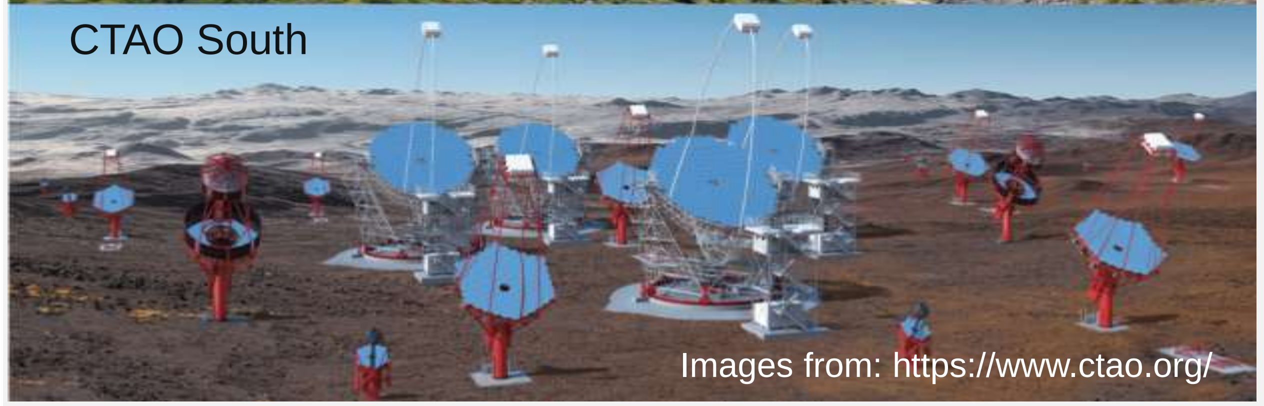


Images from: https://www.ctao.org/

Main idea

Goal: Improve detection of faint gamma-ray sources using Machine Learning (ML)

Method:

- Simulate toy model of CTAO GPS data
- Apply ML to detect and localize sources – AutoSourceID framework
- Explore three transformations of training data (counts, square root of counts, log of counts) for optimal flux sensitivity and localization accuracy
- Compare ML results with traditional likelihood-based approach

Machine learning architecture - AutoSourceID (ASID)

Identification of point sources in gamma rays using U-shaped convolutional neural networks and a data challenge

Boris Panes[1], Christopher Eckner[2][3], Luc Hendriks[4], Sacha Caron[4][5], Klaas Dijkstra[6], Guðlaugur Jóhannesson[7][8], Roberto Ruiz de Austri[9], and Gabrijela Zaharijas[2]

AutoSourceID-Light

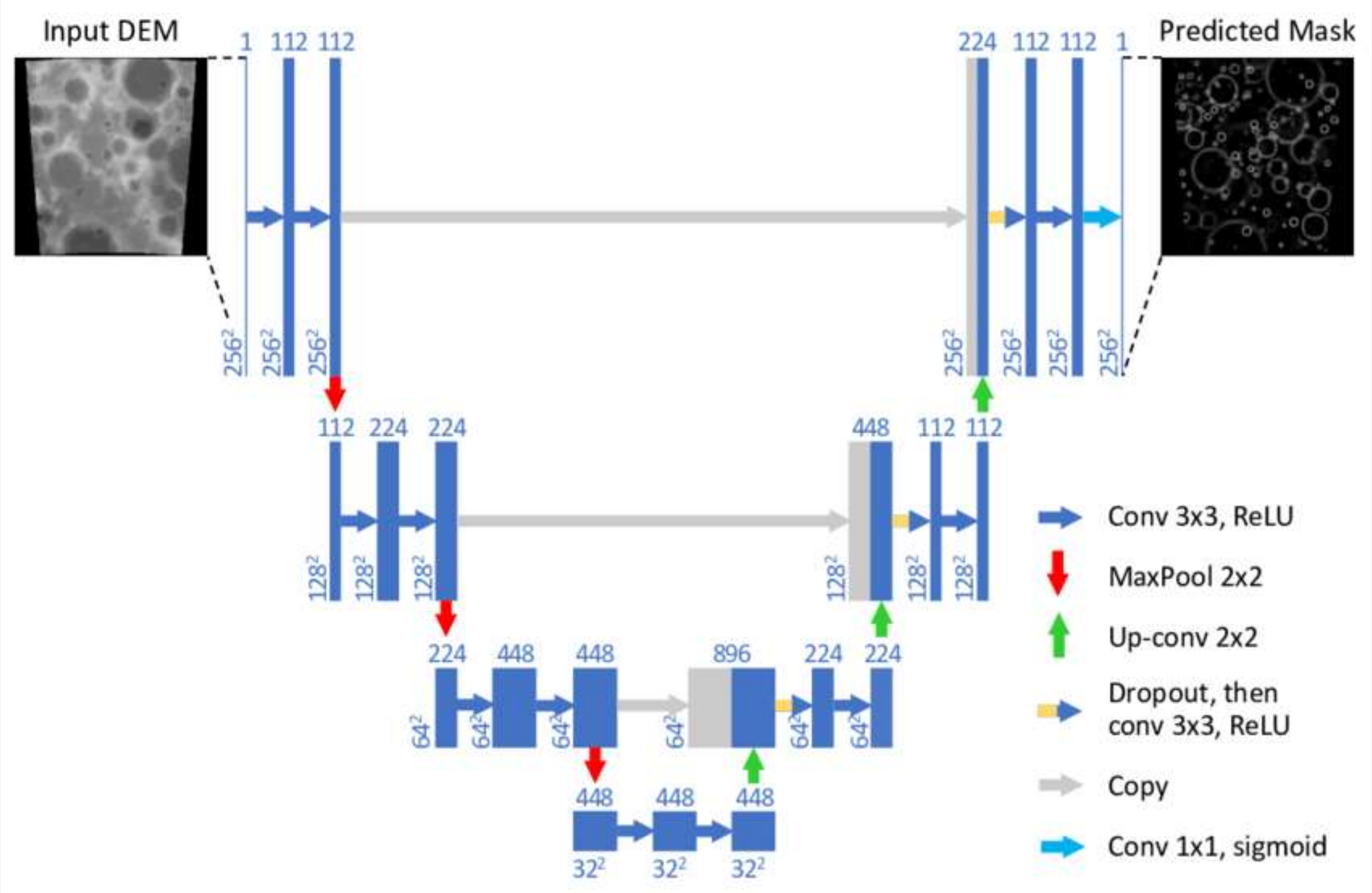
Fast optical source localization via U-Net and Laplacian of Gaussian

F. Stoppa[1,7], P. Vreeswijk[1], S. Bloemen[1], S. Bhattacharyya[2], S. Caron[3,4], G. Jóhannesson[5], R. Ruiz de Austri[6], C. van den Oetelaar[3], G. Zaharijas[2,13], P. J. Groot[1,8,9,10], E. Cator[7], and G. Nelemans[1,11,12]

- Source detection and localization
- So far applied to (mock) Fermi LAT and MEERLICHT (optical) data
- U-shaped convolutional networks (U-Nets) + clustering algorithms

k-means & Centroid-Net

Laplacian of Gaussian



+

$$\mathrm{LoG}(x, y; \sigma^2) = -\frac{1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

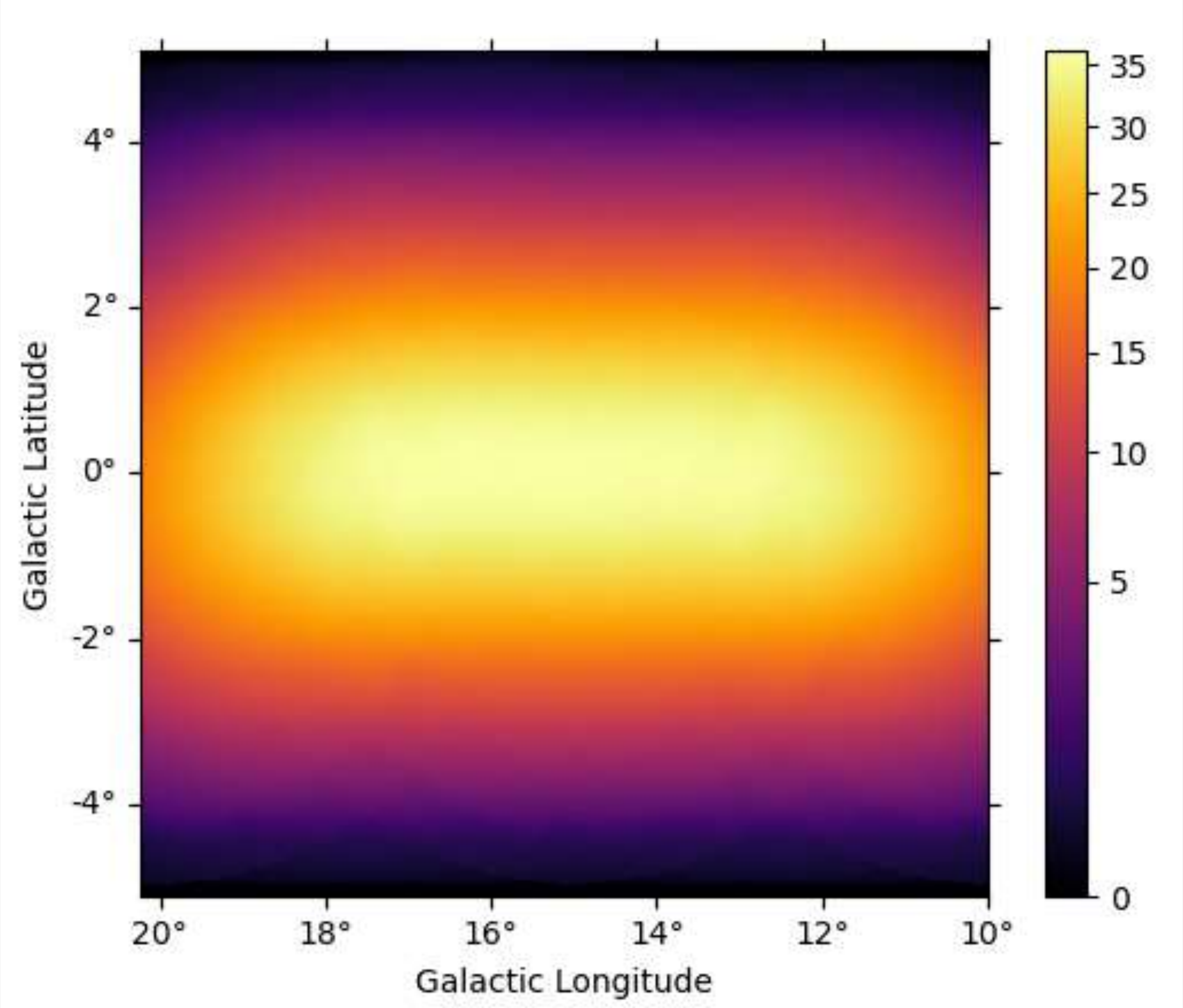
Segmentation: classify every pixel belonging either to source or background - (0: background pixel, 1: source pixel)

Data generation

Set up:

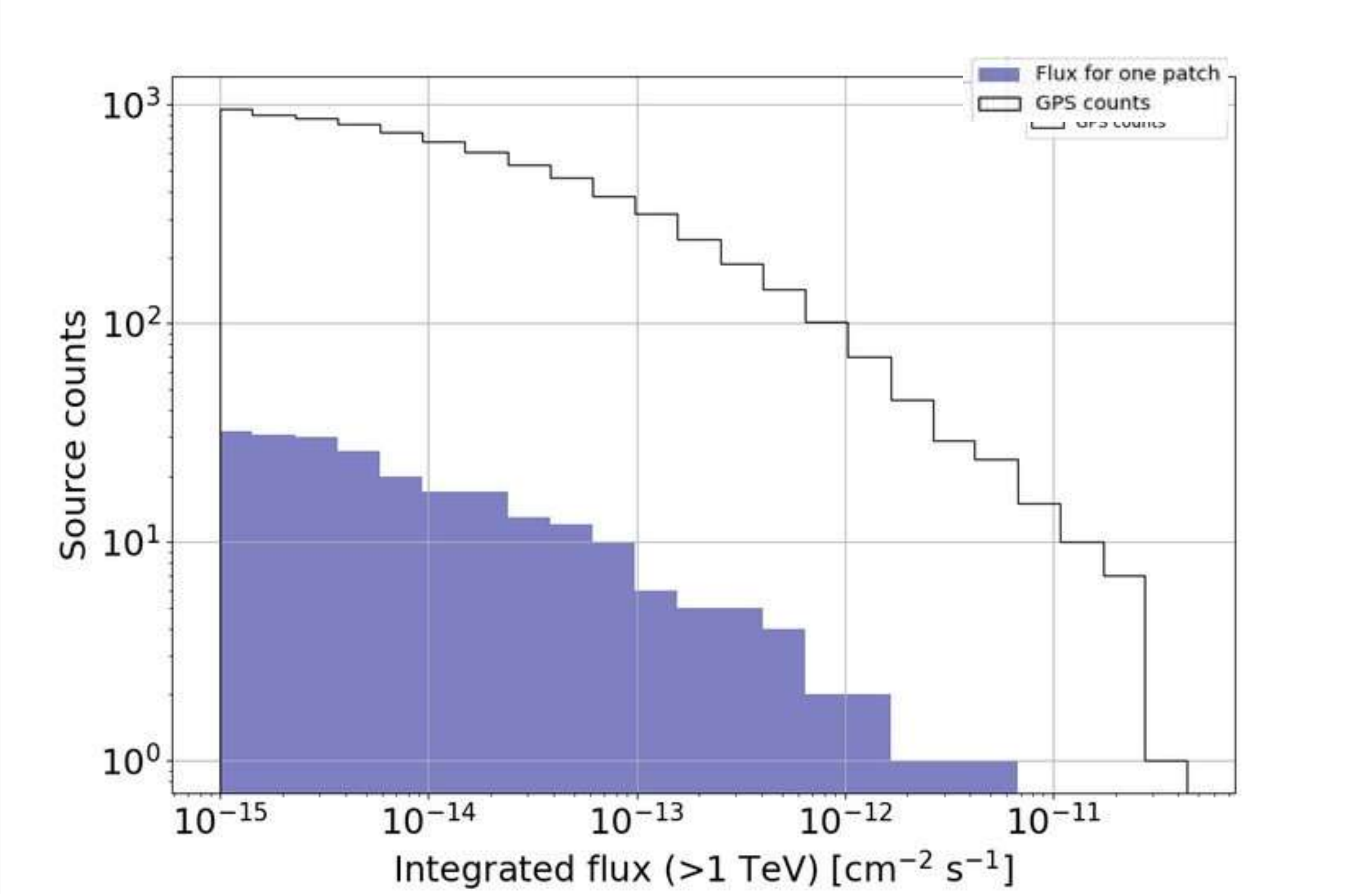
- ROI: 10.24° × 10.24° centered at l = 15.12°, b = 0°
- 0.02° × 0.02° spatial resolution
- 3 logarithmically-spaced energy bins

Instrumental (cosmic-ray) background:



Source parameter distribution:

- Follow Gamma-cat catalog of know TeV gamma-ray sources with well defined spectral parameters (https://github.com/gammapy/gamma-cat)

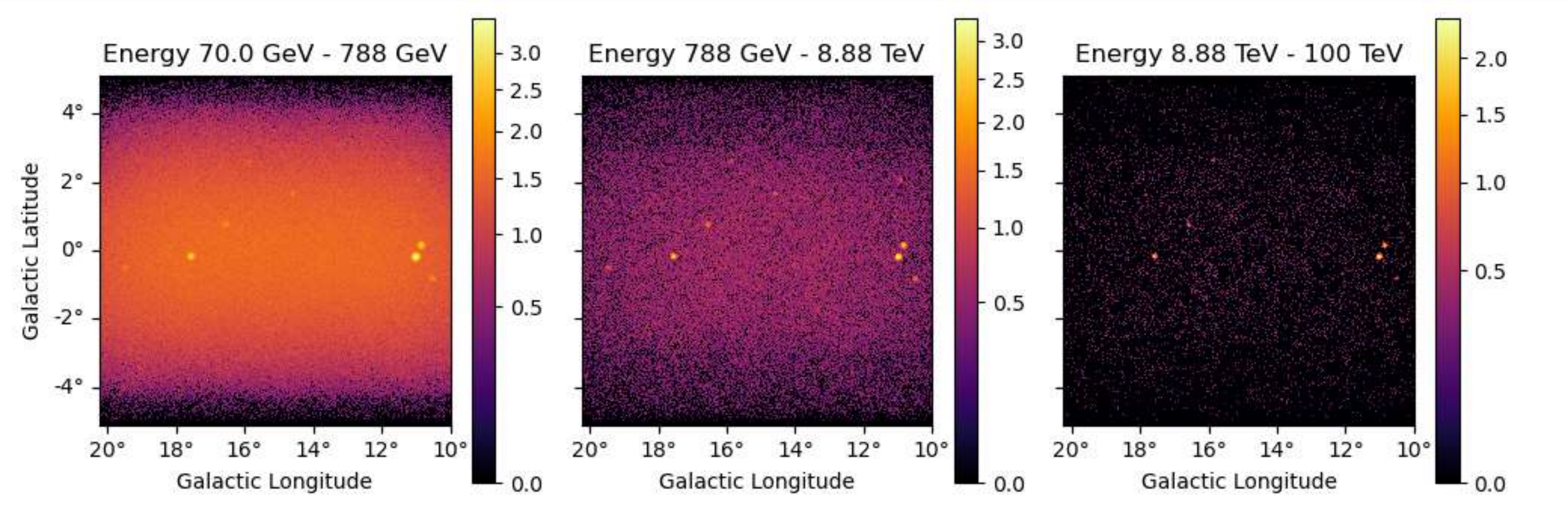


Flux distribution of sources in our RoI compared to expected flux distribution over whole GP

Data generation

Point sources + instrumental (CR) background

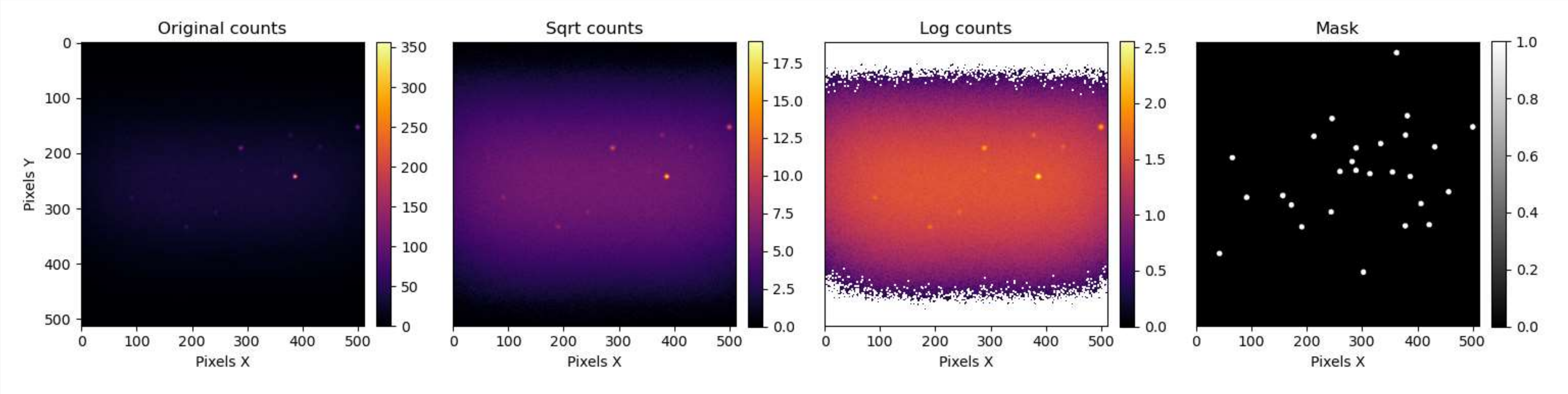
512 x 512 x 3



One realization of the simulated (log) counts map representing the number of detected events per pixel

Data preparation

- 700 realizations split into: 50% training, 30% validation and 20% testing
- Counts scaling - original counts, square root of counts and log of counts
- 0.1° radius mask centered on each source



U-Net training and evaluation

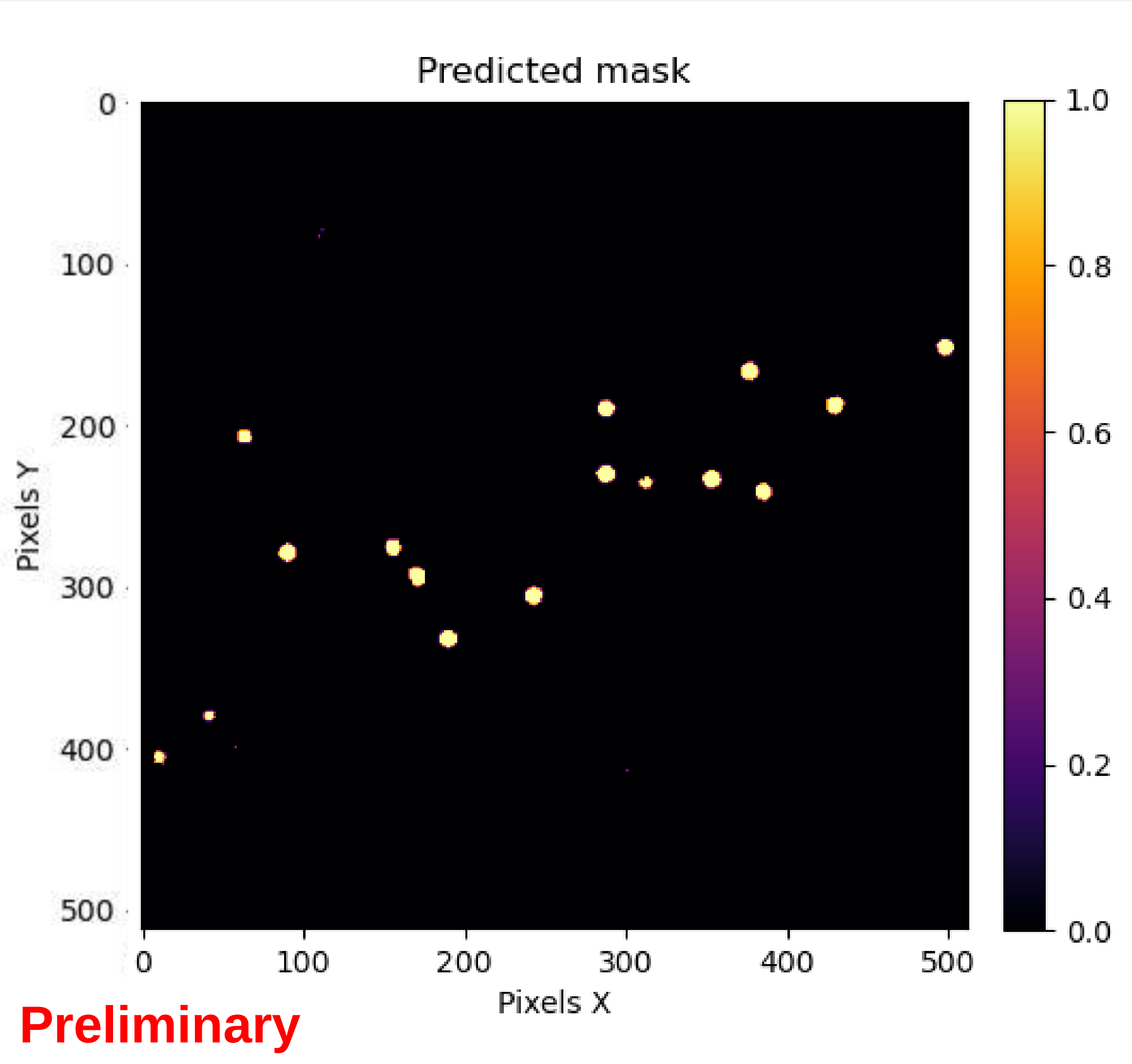
- Binary cross-entropy loss function:

Predicted probability

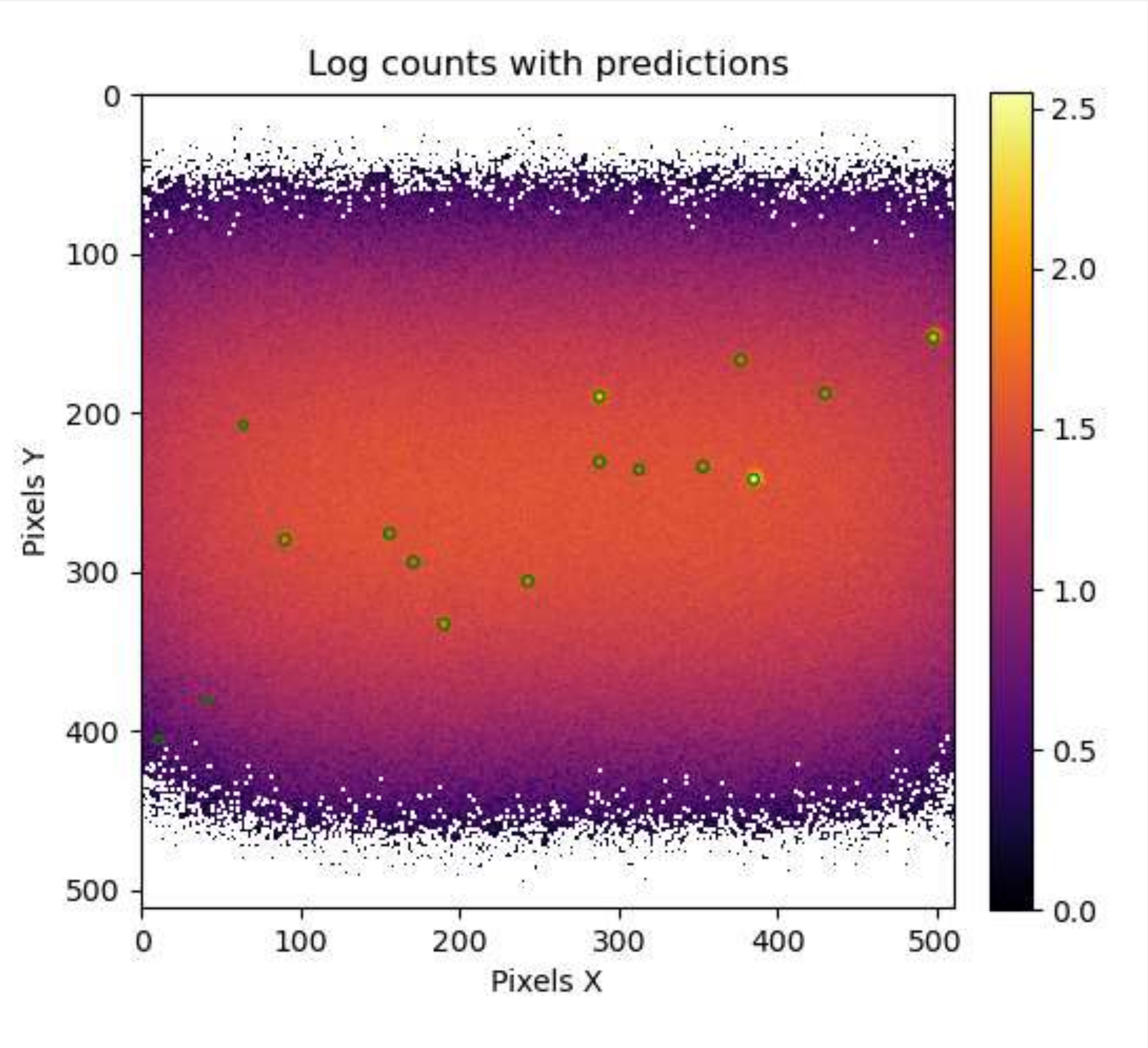
$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

True label (0: background, 1: source)

- Early stopping
- Learning rate reduction



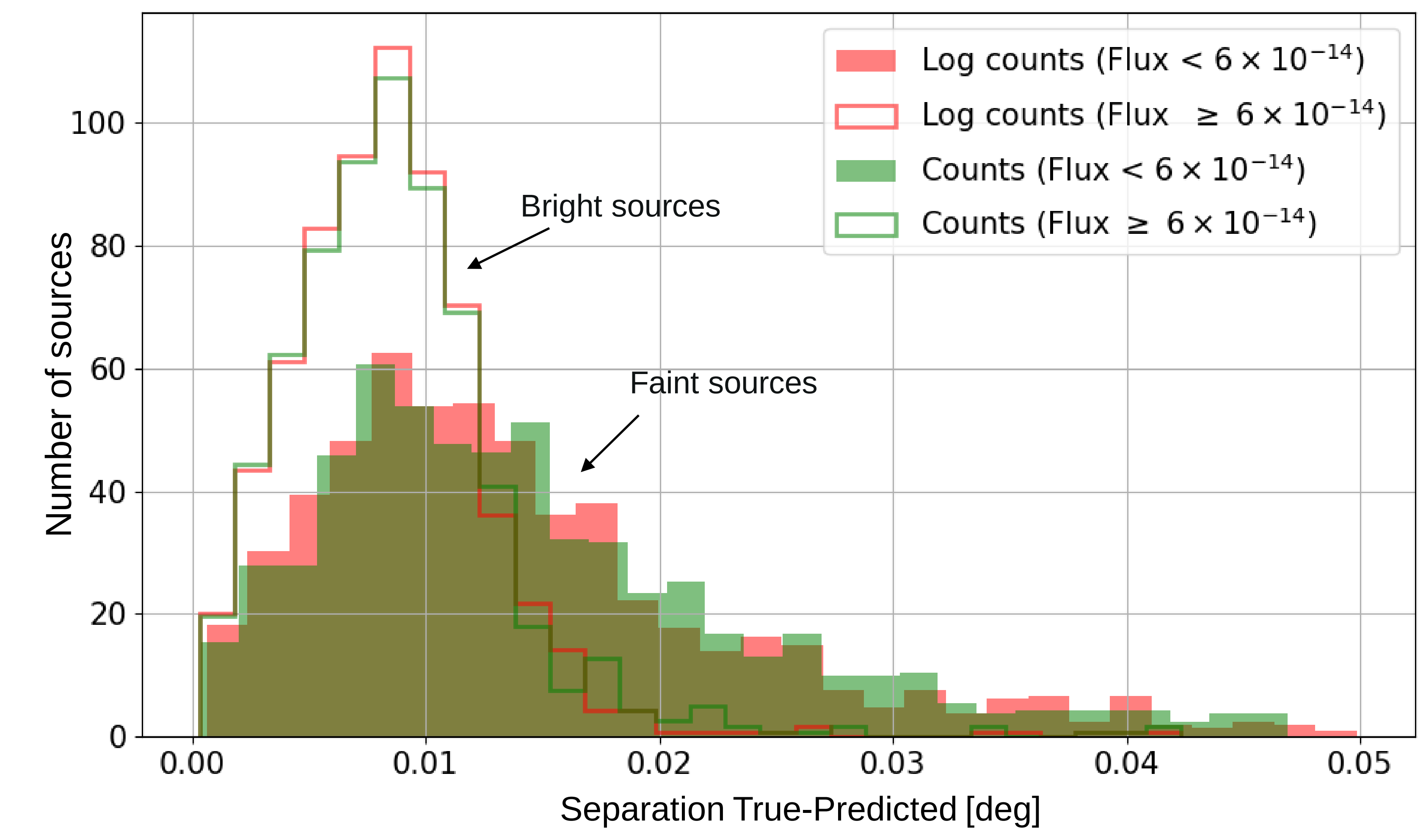
U-net output – per pixel probability map

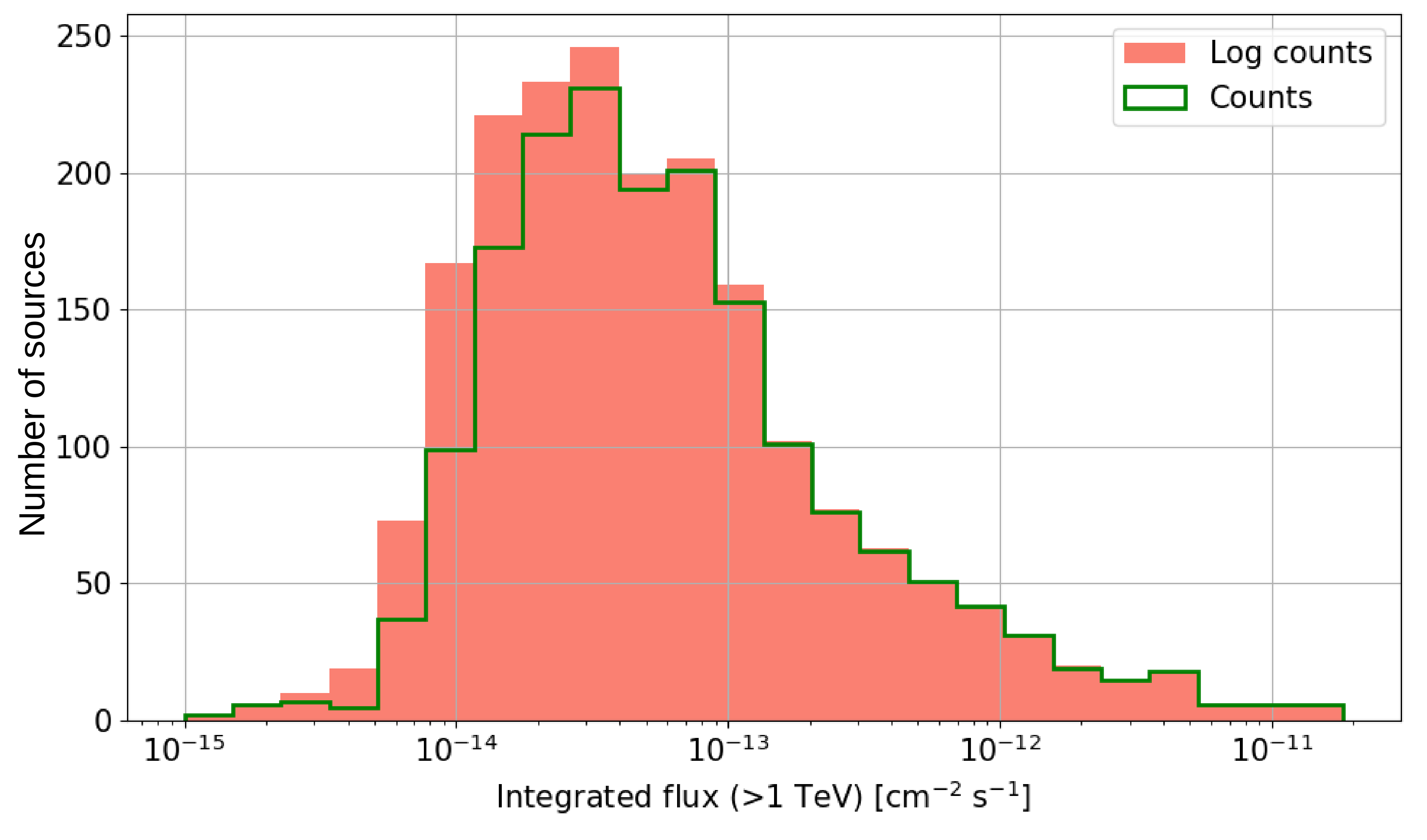


Predicted source locations with LoG filter overlaid on a log scaled test image

Results: Location reconstruction + recovered flux

Preliminary



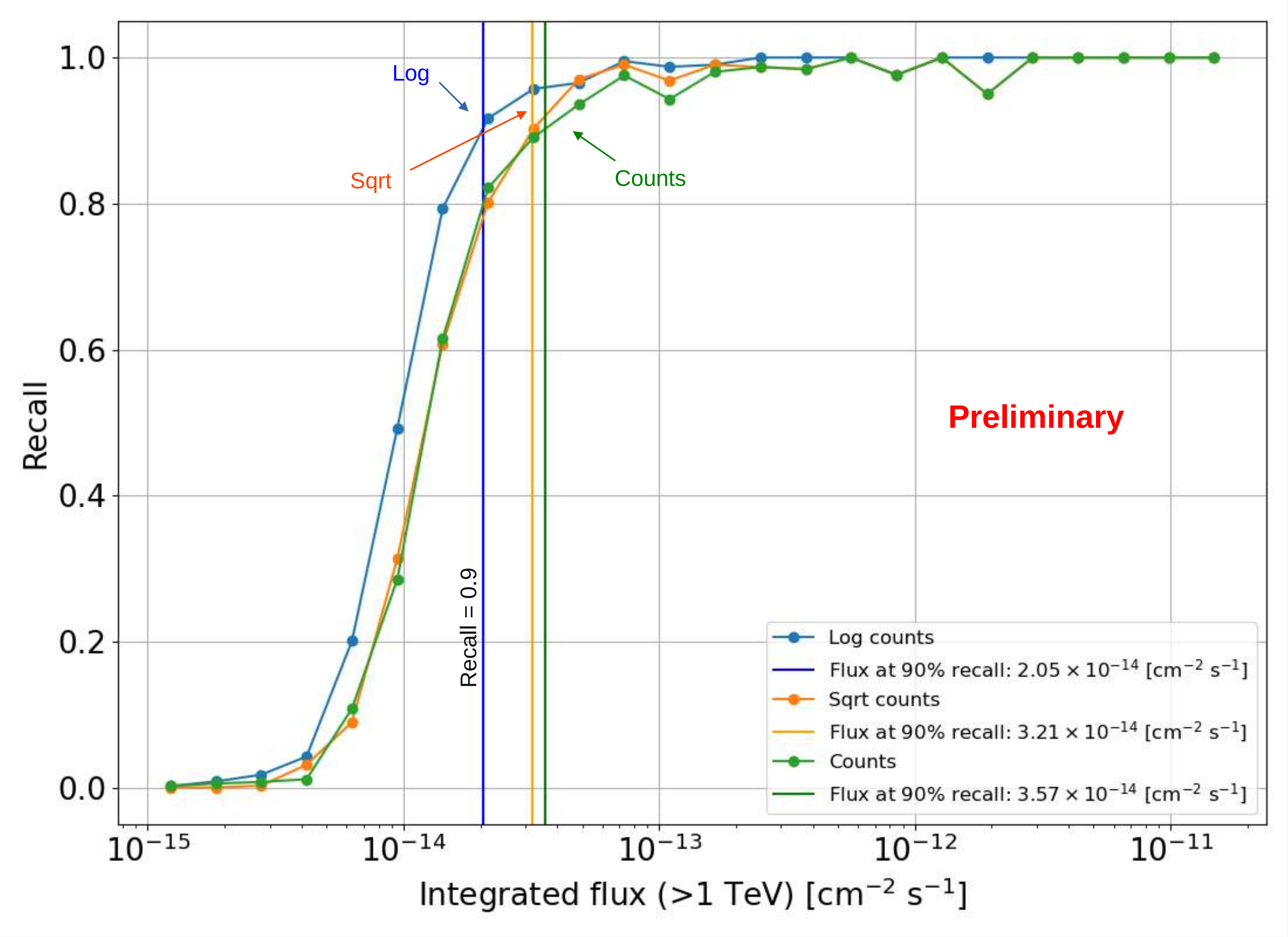


- Angular separation of true positions and predicted positions (TPs)
- No significant difference between counts and log counts in localization accuracy

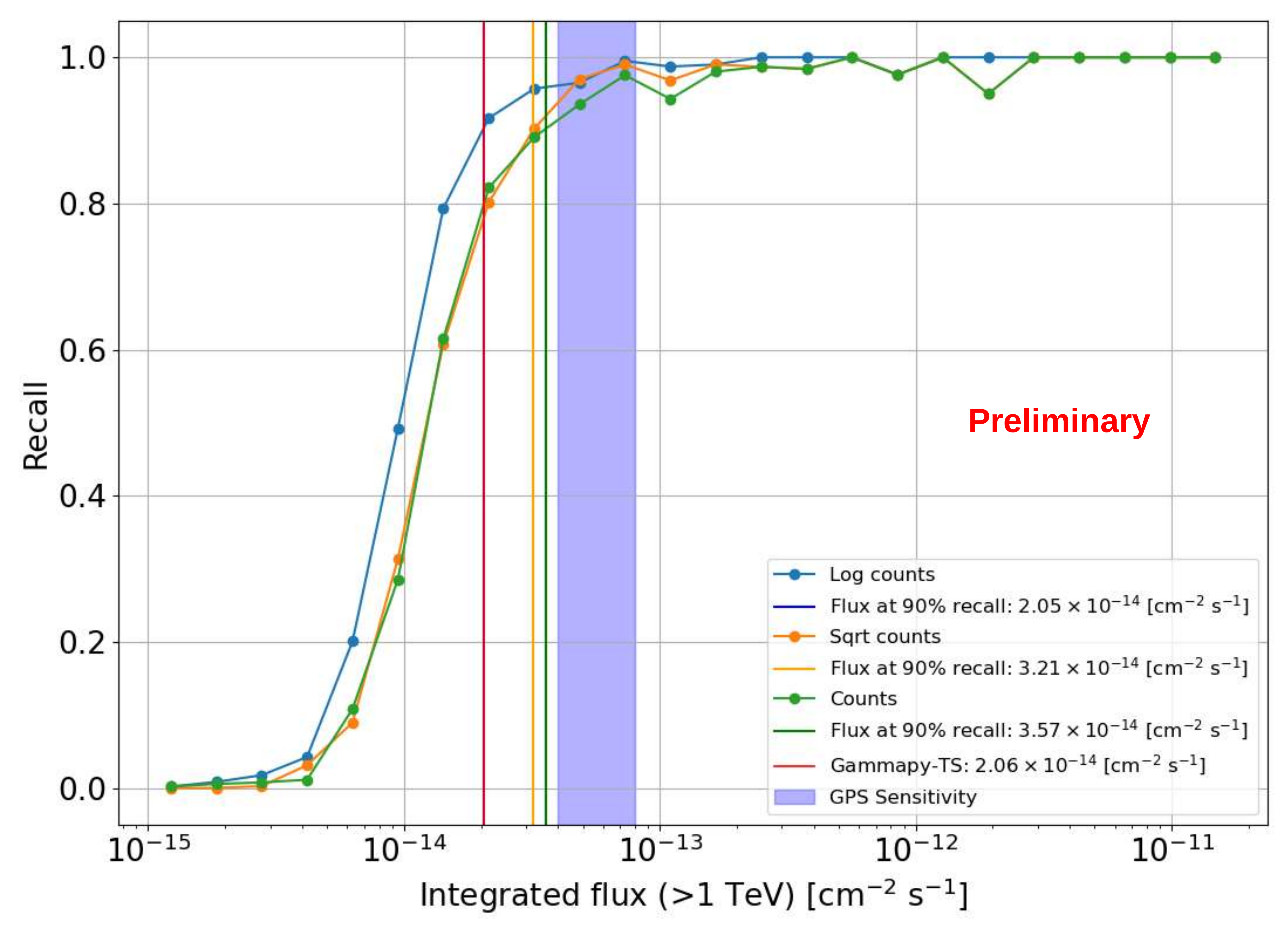
- Integrated flux of TPs
- Log slightly better at recovering fainter sources

Results - counts scaling comparison

Model trained on log scaled counts achieves 1.7x lower flux threshold than model trained on just counts



How to compare ML recall to traditional likelihood-based approach



Traditional - Maximum likelihood method:

$$TS = -2\ln\left(\frac{\mathcal{L}(\mu_b)}{\mathcal{L}(\mu_s + \mu_b)}\right)$$

TS=25 → 5σ

source

background

- Not a simple comparison task; U-Nets do not provide statistical significance
- **Suggested Approach**: According to the ASID paper, the flux level where both precision and recall reach 90% might be roughly comparable to traditional detection sensitivity, though this comparison is not rigorous!

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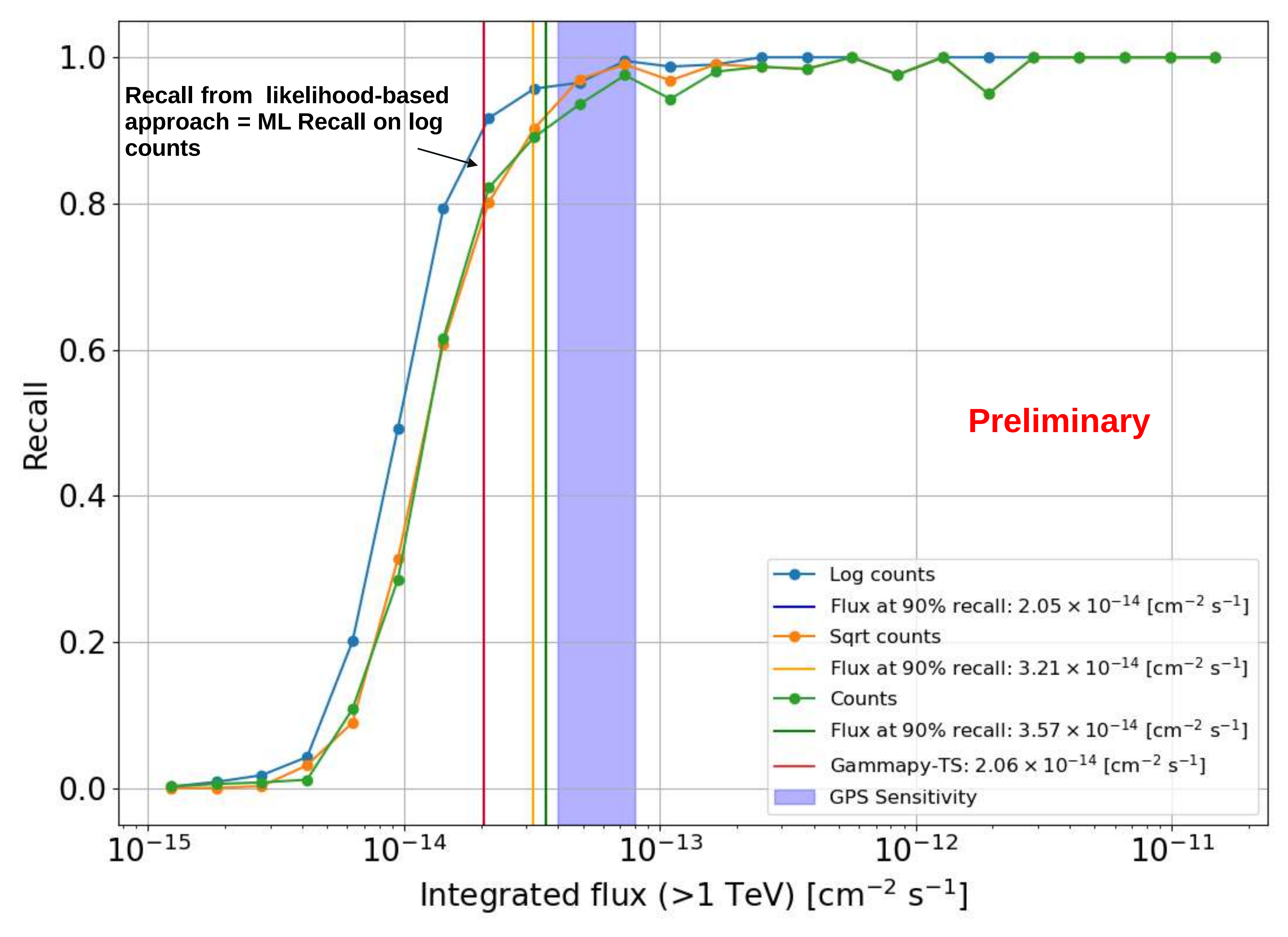

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- Not a simple comparison task; U-Nets do not provide statistical significance
- **Suggested Approach**: According to the ASID paper, the flux level where both precision and recall reach 90% might be roughly comparable to traditional detection sensitivity, though this comparison is not rigorous!
- Use traditional method on our test data and calculate recall – **we achieve a comparable flux threshold to our ML model trained on log counts!**

Conclusions and future prospects

- ML is proving to be a promising tool for gamma-ray analysis, though its potential still must be explored

We find that:

    - Data scaling methods affect model performance, with logarithmic scaling showing the most promise for detecting faint sources.
    - ML demonstrated comparable sensitivity to traditional methods, with potential improvements

- Future work will include a binary classifier to reduce false positives and expanding methods to detect extended sources
- Consider testing background-subtracted data to improve signal-to-noise ratio

Thank you!

ML training

Binary cross-entropy loss function:

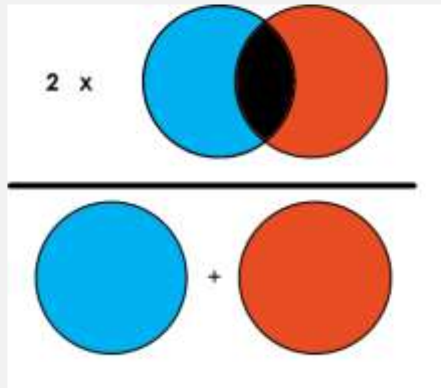
add arrow

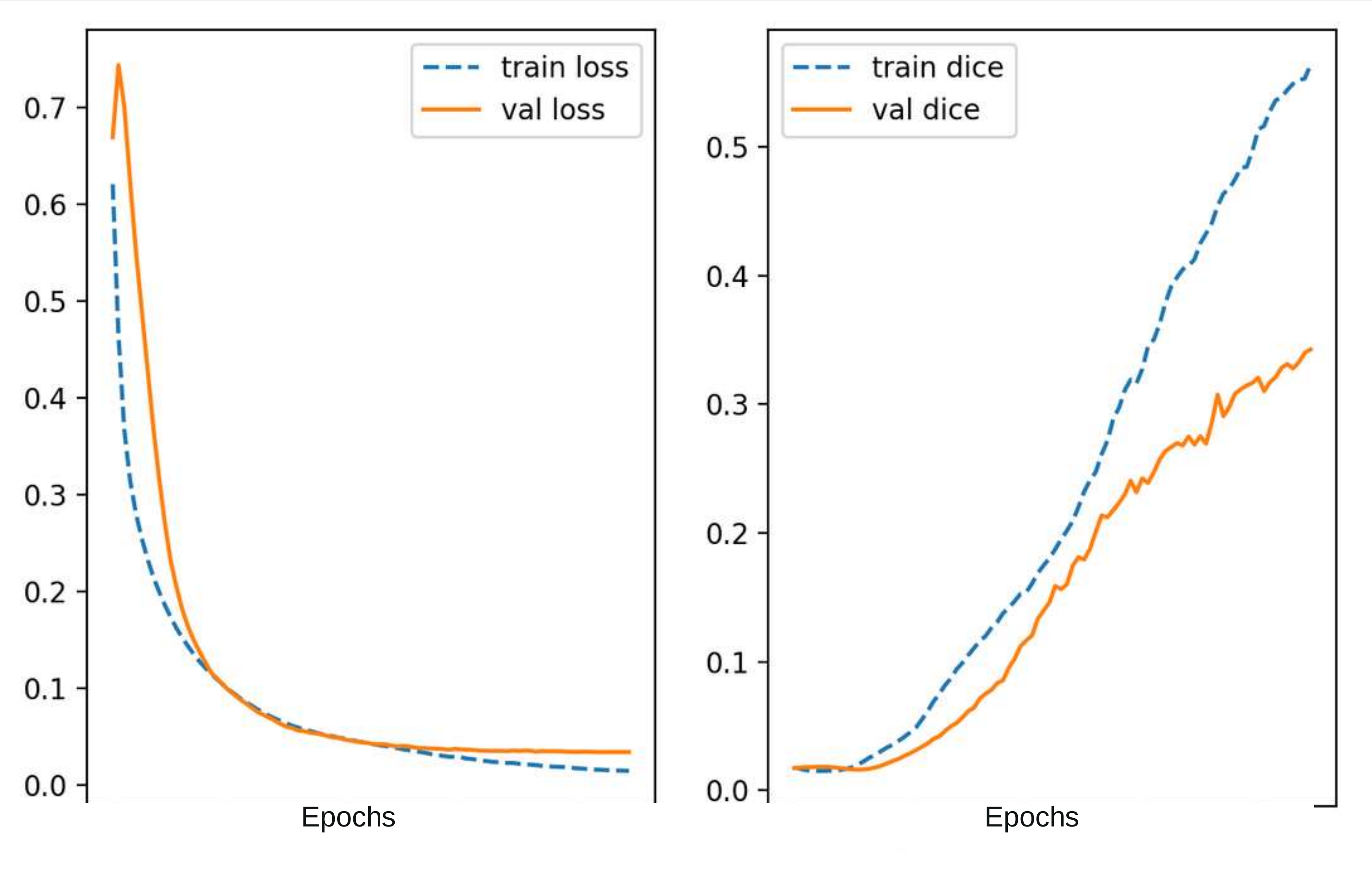
Predicted probability

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

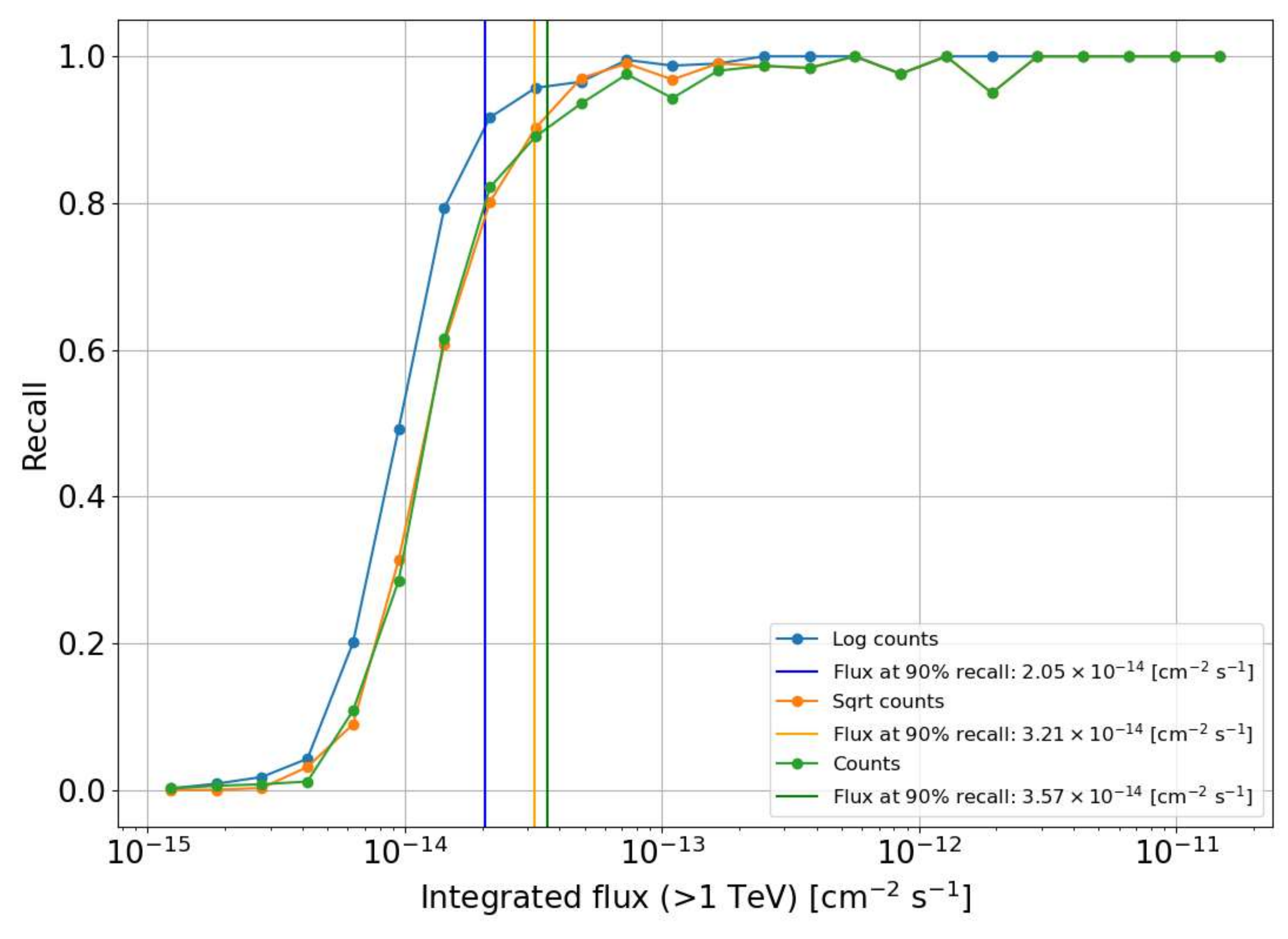
True label (0: background, 1: source)

Dice coeff: captures intersetion over the whole union

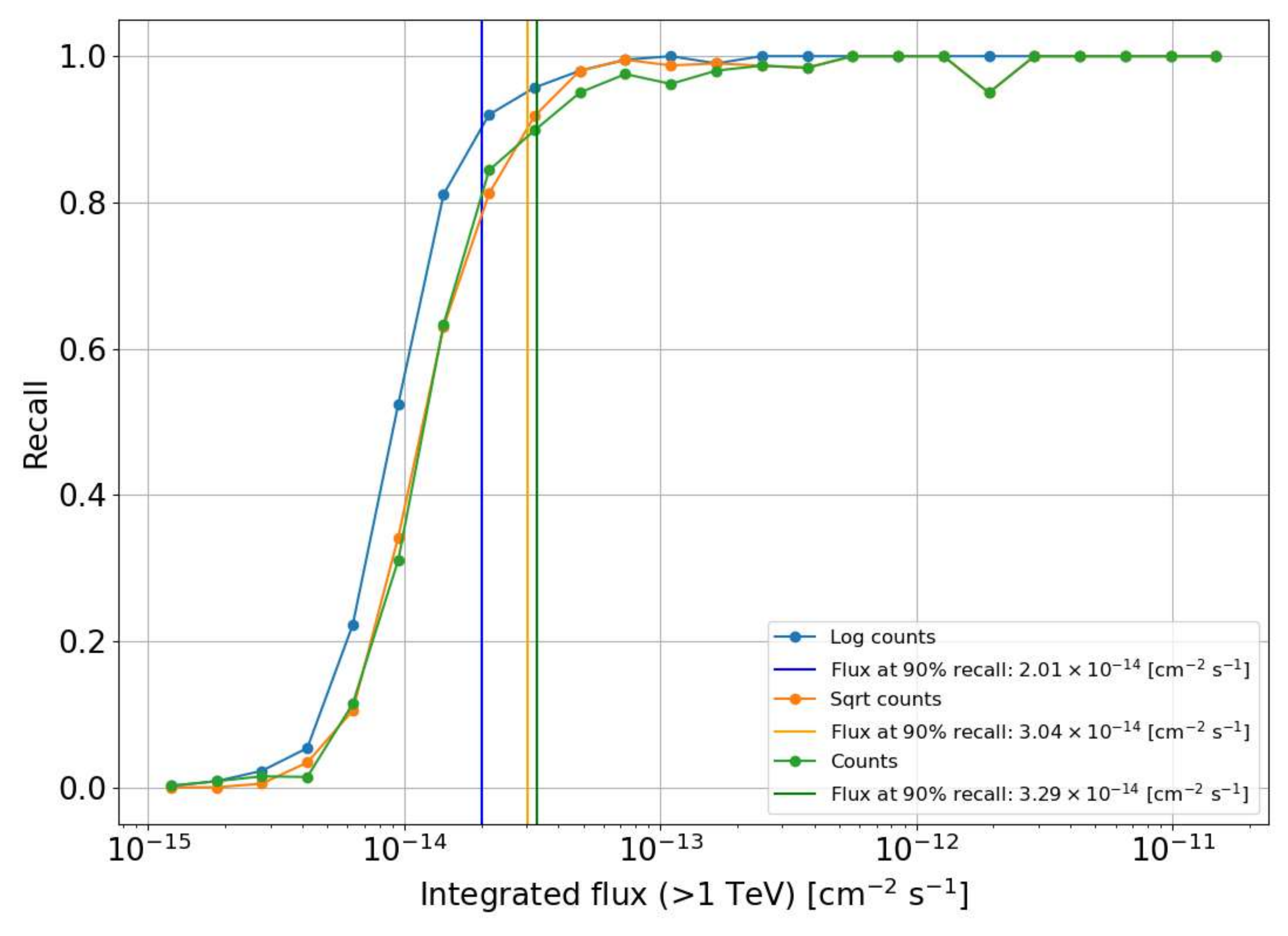




Separation threshold

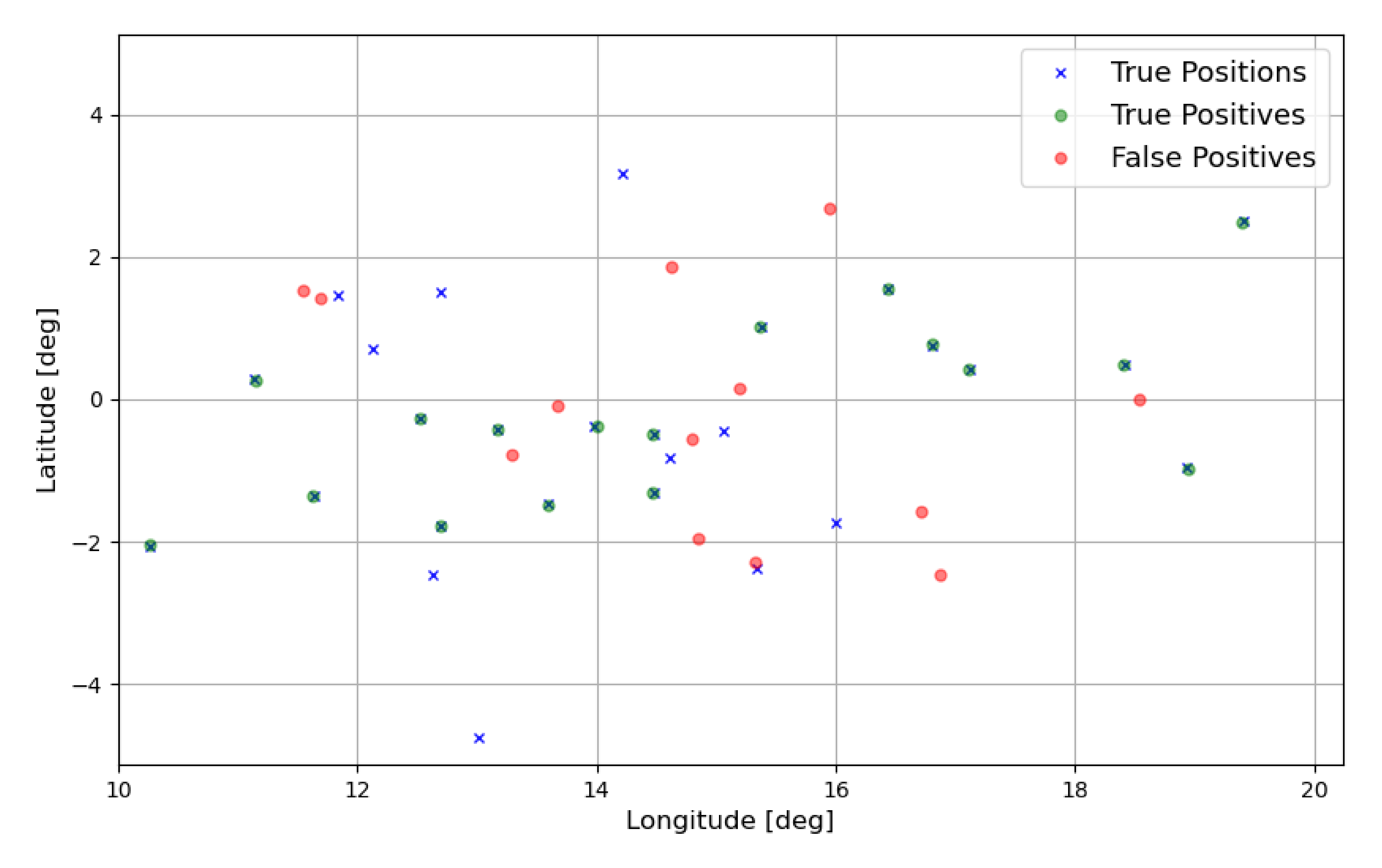


0.03 deg

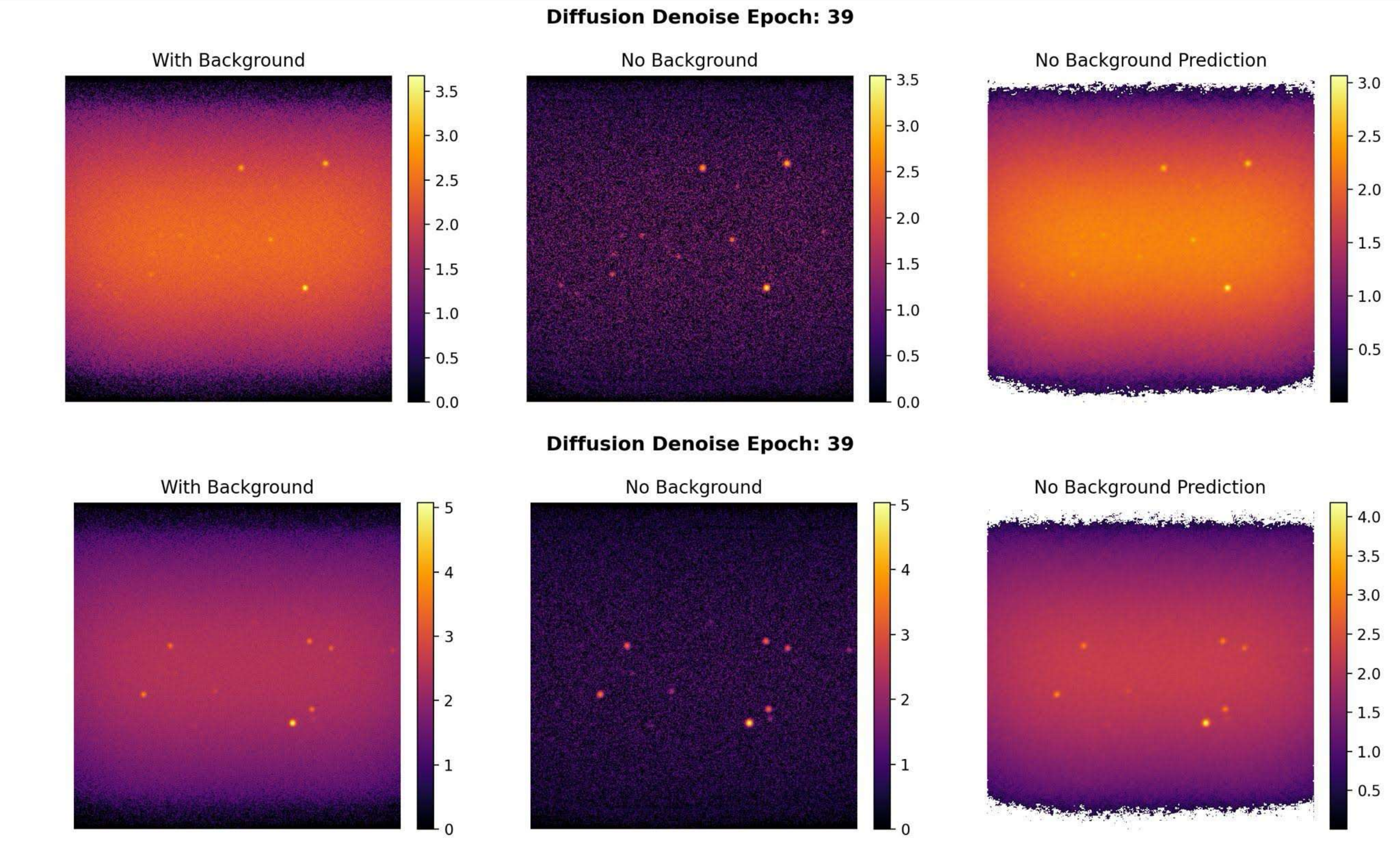


0.05 deg

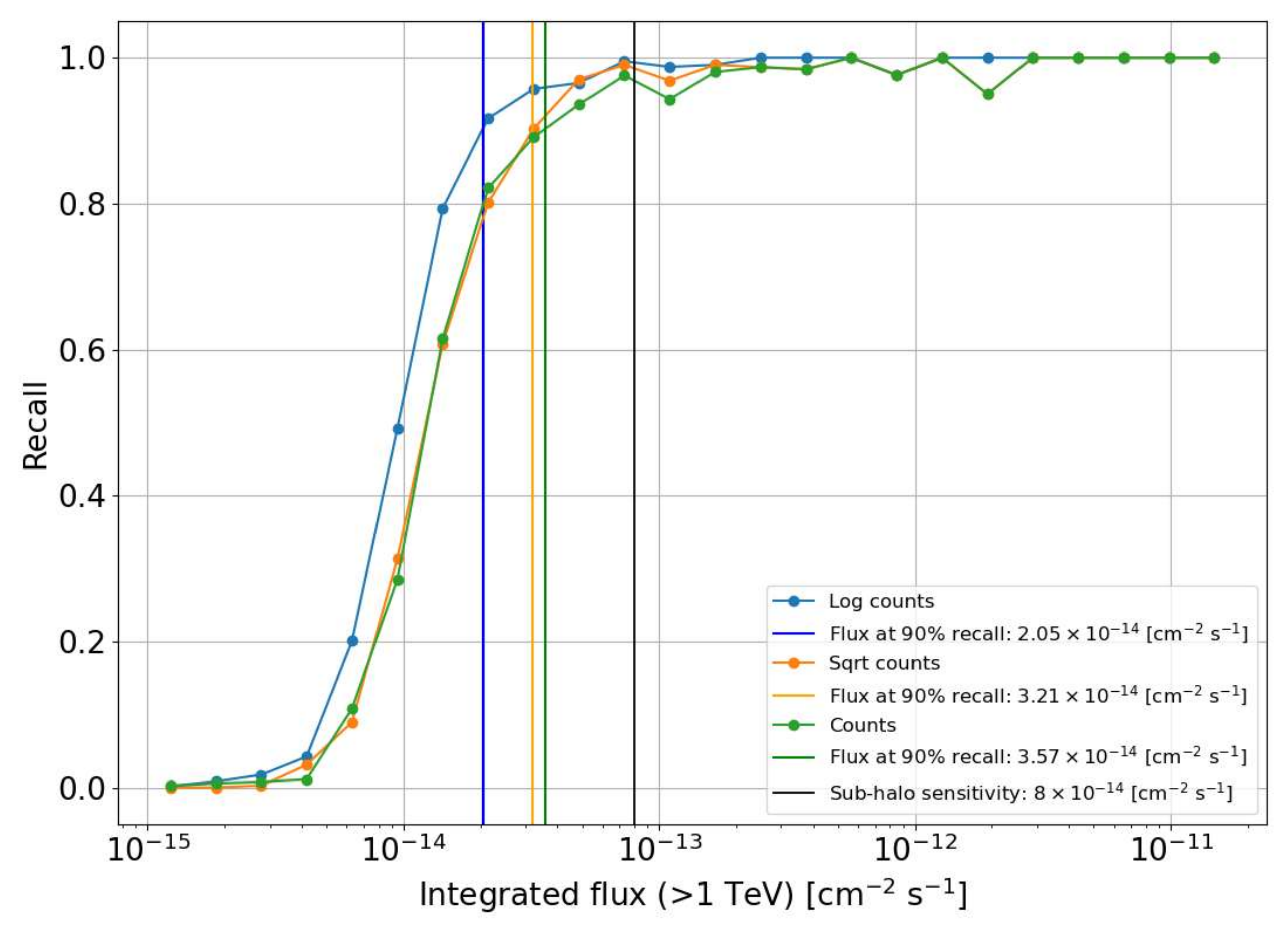
Separation threshold



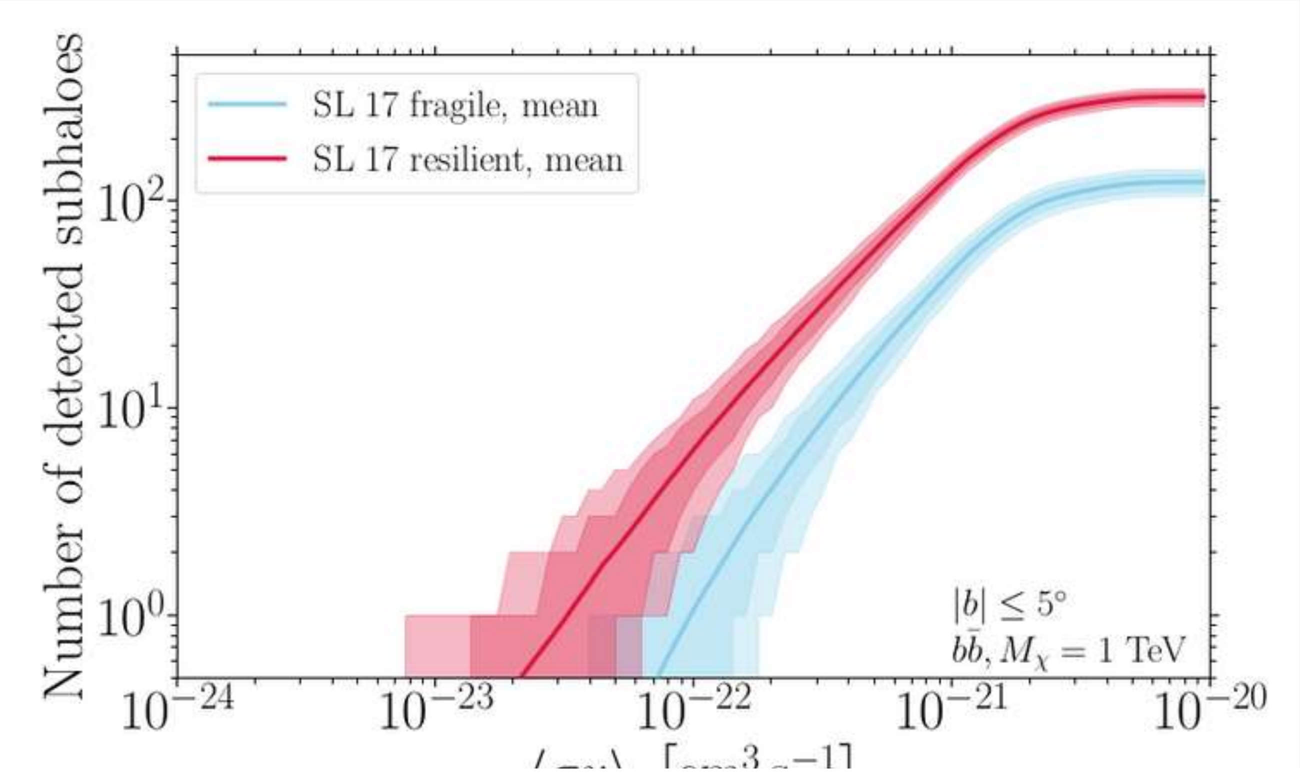
Background removal



Implications on DM sub-halo search



- Gamma-ray flux scales linearly with cross-section
- Potential to have higher flux sensitivity (up to 4x) lower annihilation cross-section by the same factor – not a direct comparison!



Detecting dark matter sub-halos in the Galactic plane with the Cherenkov Telescope Array Observatory

Christopher Eckner,[1, 2, *] Veronika Vodeb,[2, †] Tejas Satheesh,[1, ‡] Francesca Calore,[1, §] Moritz Hütten,[3, ¶] Gabrijela Zaharijas,[2, **] and Pierrick Martin[4, ††]