

Identification of Second Trip and Weak echoes with Deep Learning techniques

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Introduction

- **MAIN CONCERN:** Cloud Profiling Radar observations can be contaminated by second-trip echoes. These are typically associated with mirror images or long multiple scattering tails, which are physically observed as ghost clouds at high altitudes and can leak into the actual reflectivity signals at cloud tops [1].
- **SOLUTION APPROACH:** By exploiting the **ATLID-CPR synergy** [2] and incorporating it into a **Deep Learning pipeline**, we are able to properly identify and flag second-trip features (**GhostFinder**) and reconstruct weak echoes from optically thin clouds previously detected only by ATLID (**ThinCloudsFinder**).

Methodology

- The core of the pipeline is a Deep Learning approach utilizing a **U-Net convolutional neural network**.
- The absolute reference (**Ground Truth**) is generated synergistically by combining the CPR and ATLID masks, exploiting the complementary observational strengths of both instruments.
- The U-Net is trained to map CPR input profiles to this combined Ground Truth, learning the complex mappings required to filter out contamination or extract low-reflectivity features.

DATASET DEFINITION & PARTITION

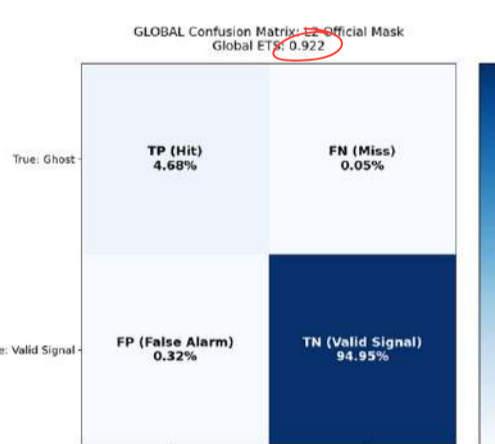
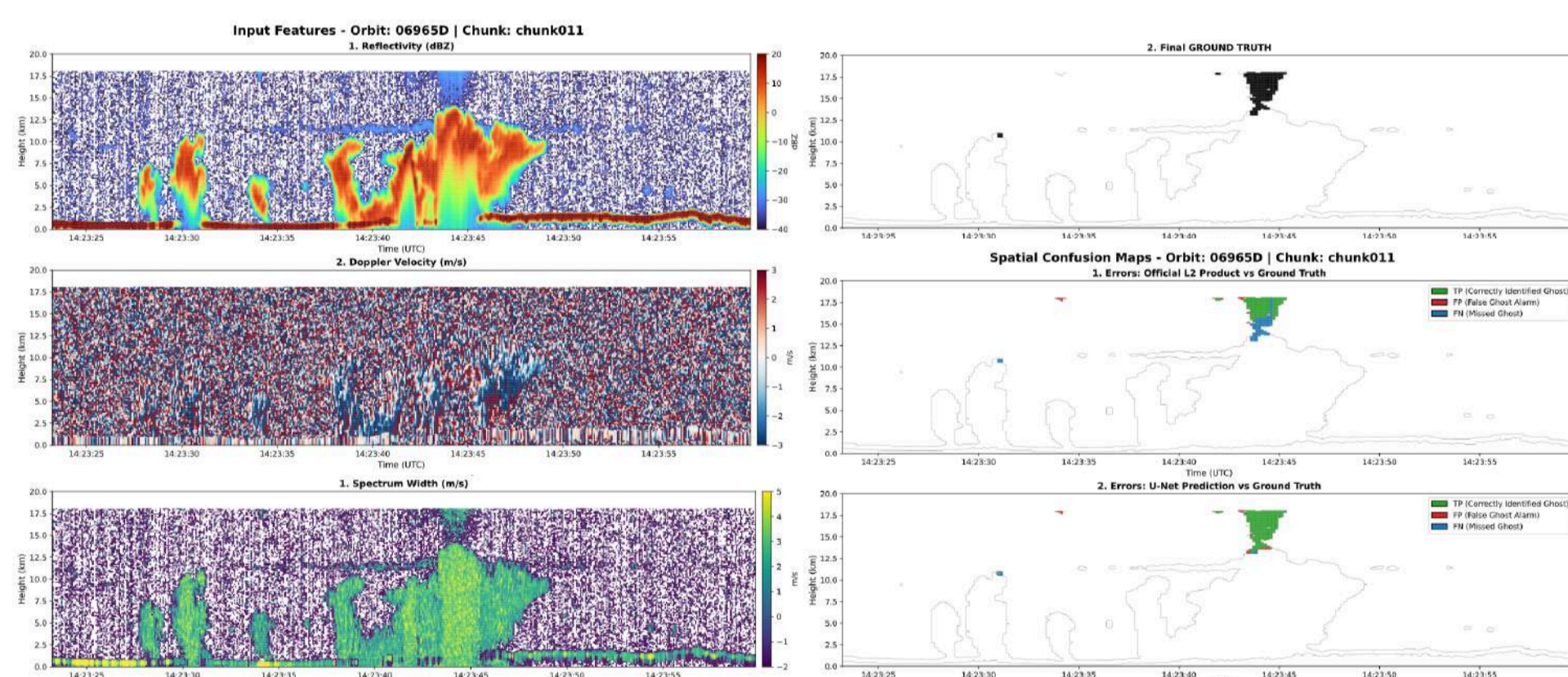
- **Dataset:** EarthCARE acquisitions from March to October 2025, utilizing products from **CNOM** to **AC_TC** files.
- **Data Partitioning:** The full dataset is subdivided into independent Training, Validation and Testing subsets to ensure unbiased model evaluation and prevent overfitting.

PERFORMANCE EVALUATION & BASELINE

- **Primary Metric:** The Equitable Threat Score (**ETS**) is utilized to quantify the model's predictive skill and spatial accuracy.
- **GhostFinder Baseline:** To benchmark the performance and validate the added value of the AI approach, the network's outputs are directly compared against the standard **L2b CPR 2nd trip echoes detection mask**.

Results

GhostFinder Model



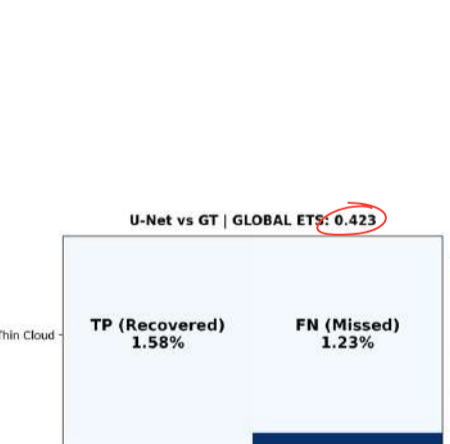
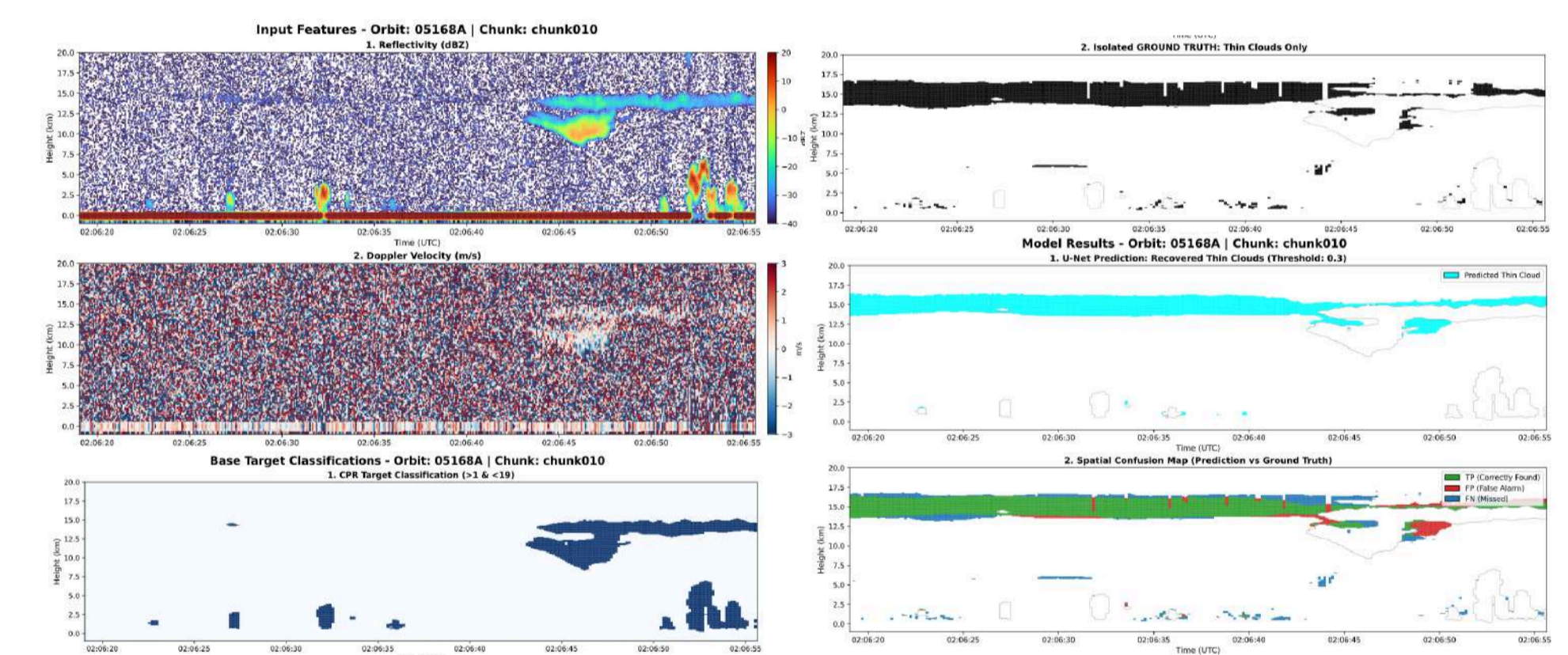
- **Input Features:** CPR Reflectivity, Doppler Velocity, Spectrum Width, PRF, Land/Water Flag.
- **Ground Truth Definition:** **2nd trip echo mask** → CPR detects a signal above **cloud top** defined by ATLID.

PERFORMANCE: U-Net vs L2b Official Mask

- **Global ETS:** 0.948 (U-Net) vs 0.922 (L2b).
- **False Alarms (FP):** Halved by U-Net (0.15% vs 0.32%).
- **Hit Rate (TP):** Highly stable (4.64% vs 4.68%).

→ U-Net visibly eliminates False Positive clusters at physical cloud edges compared to the L2 baseline.

ThinCloudsFinder Model



- **Input Features:** Echo Power Received, Doppler Velocity.
- **Ground Truth Definition:** **thin clouds mask** → any cloud feature detected by ATLID but missed by the CPR (sub-visible to radar).

PERFORMANCE: U-Net vs CPR signal detection

- **Global ETS:** 0.423 (Demonstrating solid skill in a highly challenging, low-SNR regime).
- **Recovery Rate (TP):** 1.58% (Successfully reconstructed thin cloud pixels).
- **Errors (FN / FP):** Misses at 1.23% and False Alarms at 0.82%.

→ U-Net successfully extends CPR sensitivity boundaries, reconstructing coherent high-altitude thin cloud layers previously invisible/partially visible to the radar. Currently investigating into the compatibility with an adaptive along-track average.

Conclusions

- **Operational Integration:** Embed AI models into standard EarthCARE Level 2 pipelines to upgrade CPR products (enhanced sensitivity, fewer artifacts).
- **Mission Resilience:** The U-Net acts as a "virtual ATLID". It ensures high-quality cloud masks even during lidar malfunctions, safeguarding the mission's scientific lifespan.

References

- [1] Y. Imura et al., EGU sphere, 2026.
- [2] A. J. Illingworth et al., BAMS, 2015. [
- [3] ESA, EarthCARE AC-TC PDD, v11.6.
- [4] F. Tridon et al., AMT, 2026.
- [5] A. Irbah et al., AMT, 2023.