



EarthCARE 2026 Science and Validation workshop

8–12 June 2026 | Rhodes House | Oxford, UK

Machine Learning Retrieval of Near-Real-Time 3D EarthCARE Scenes from
MTG-FCI Observations

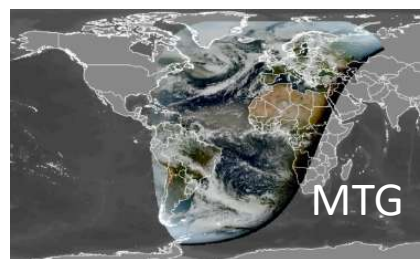
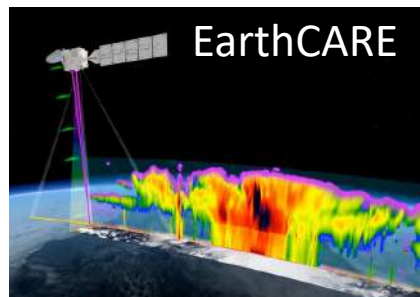
Stella Girtsou, Dimitra Karkani, Aggelos Georgakis, Giorgos Giannopoulos, Charalambos Kontoes, Alexandra Tsekeri
National Observatory of Athens



Obs3Rve Overview



Input

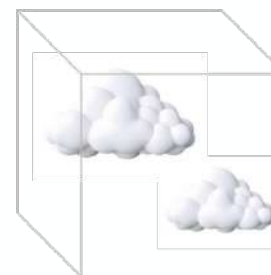
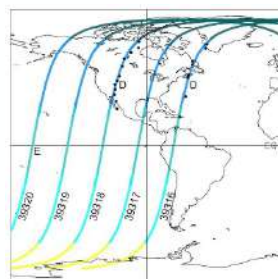


MACHINE
LEARNING

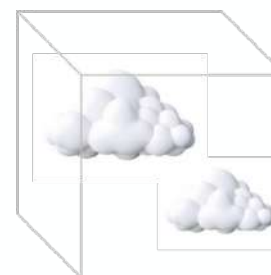
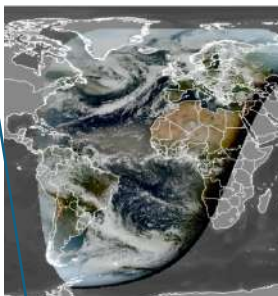


Products

EarthCARE 3D product

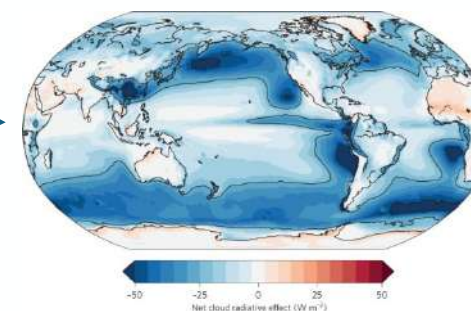


MTG 3D product

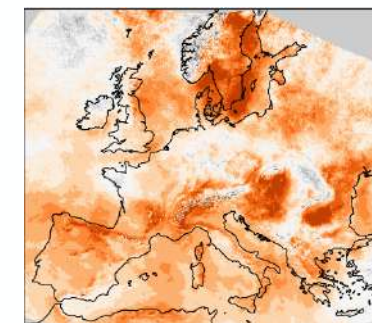


Scientific impact

Cloud radiative effect



Solar radiation/energy



Synergy
with
ESA/EC
projects



Validation



b) cloud types
height / km



Enhance the 3D RT capabilities of **EarthCARE** using **machine learning** and **MTG** data with the construction of realistic **3D** scenes

Real-time Cloud Maps at Europe and the Atlantic Ocean.

Input: FCI/MTG radiances

Output: 3D maps of **cloud types** and cloud **microphysical properties** (i.e. liquid water content, ice water content, effective radius)

Global Cloud Maps

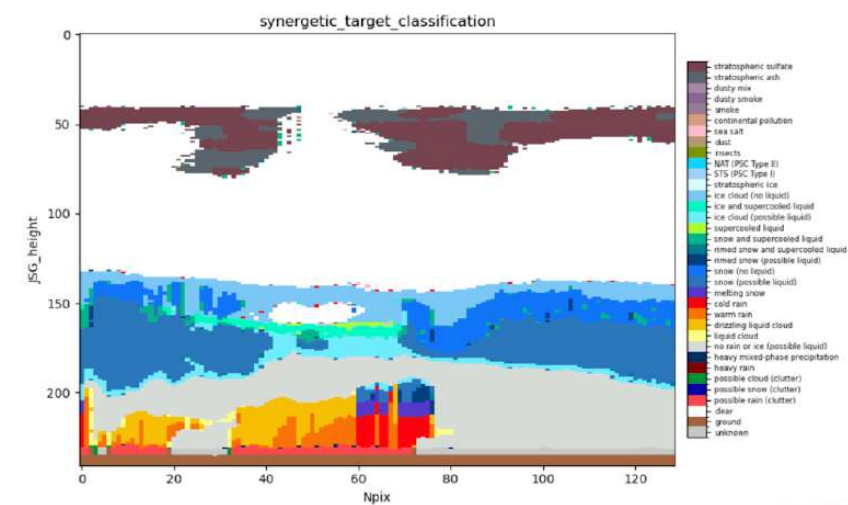
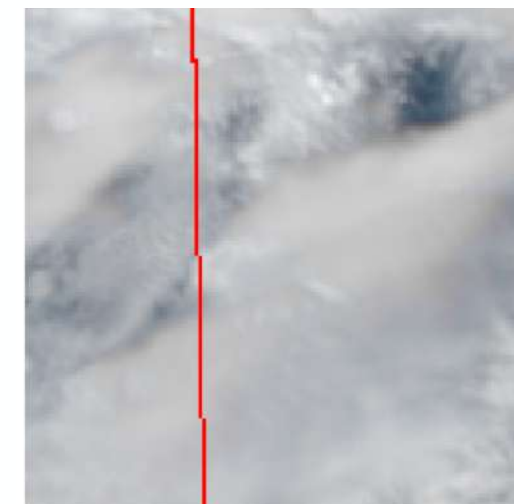
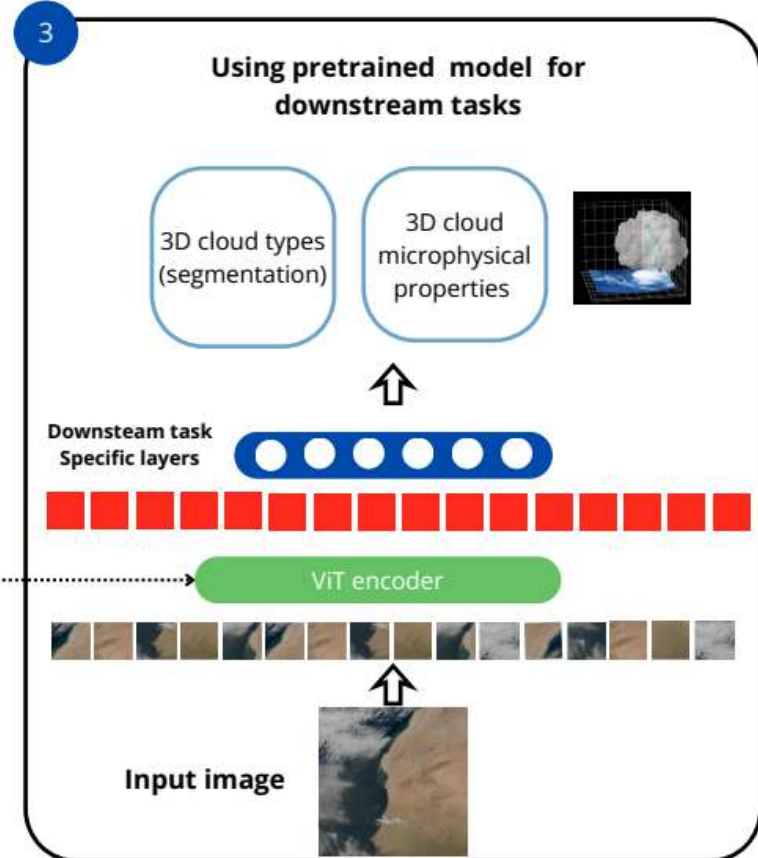
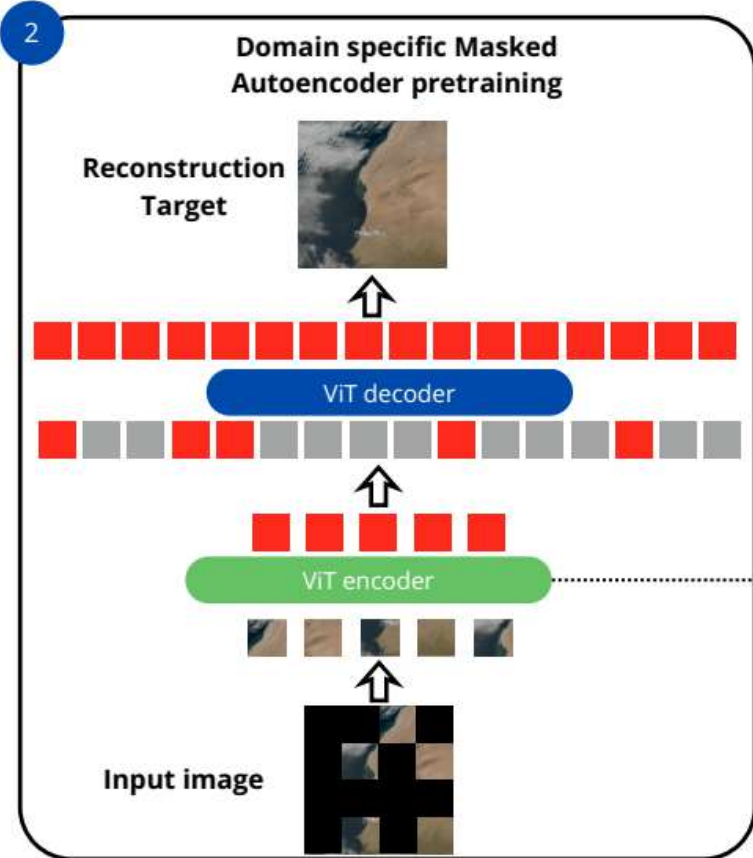
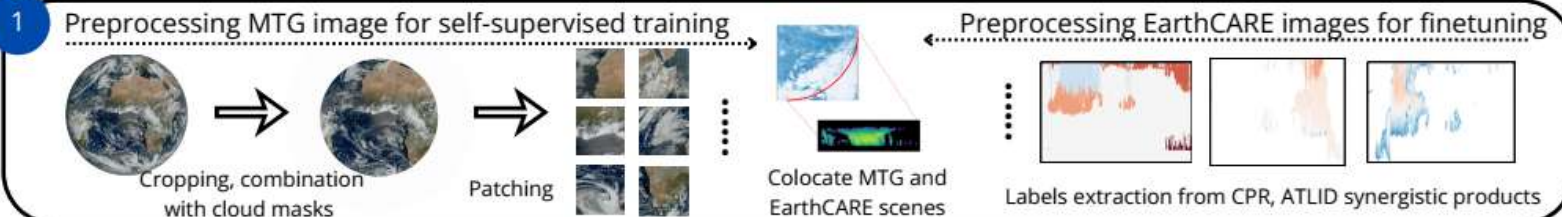
Input: EarthCARE MSI radiances, CPR reflectivity profiles, ATLID backscatter profiles

Output: 3D maps of **cloud types** and cloud **microphysical properties** (i.e. liquid water content, ice water content, effective radius)

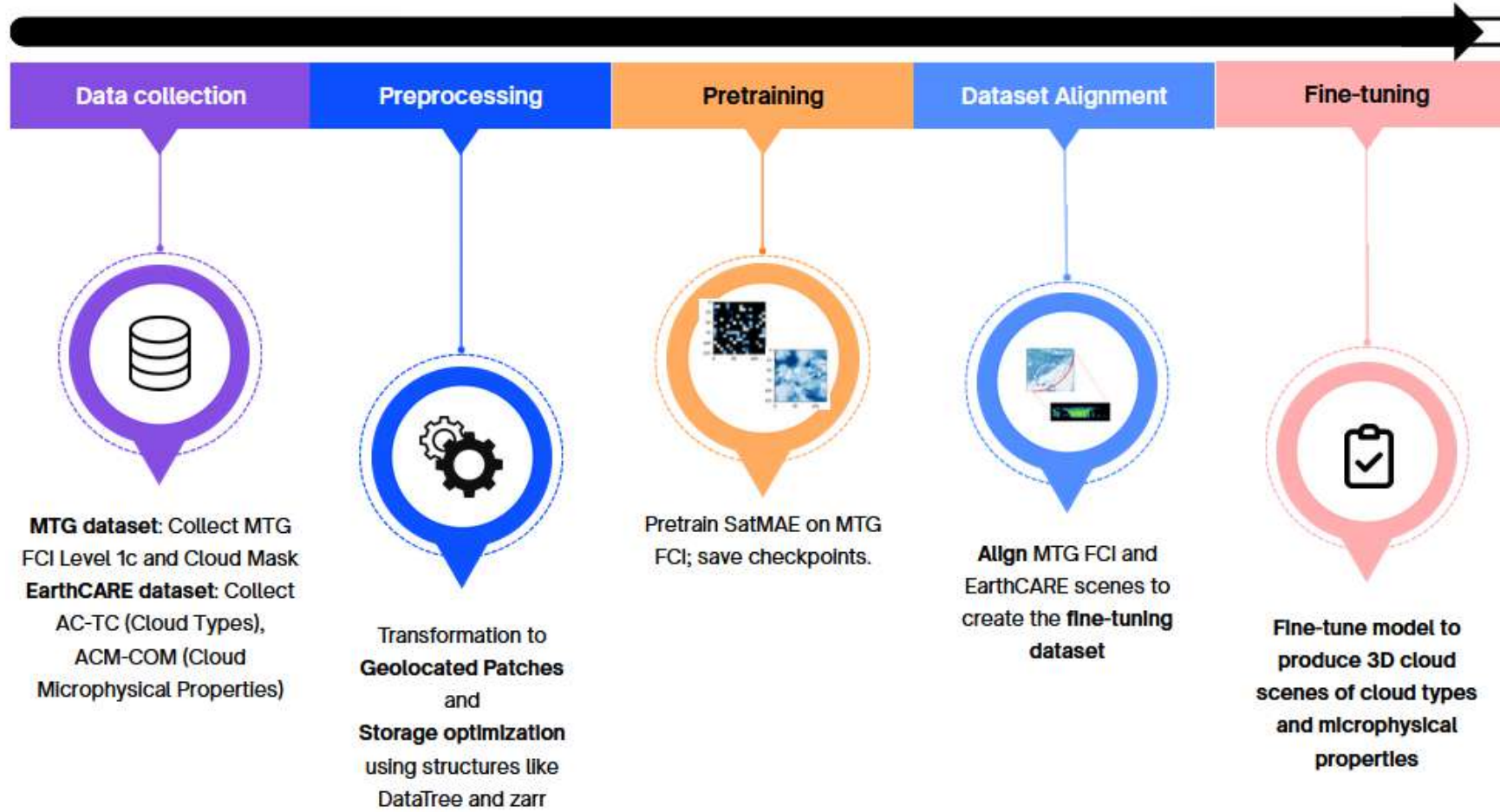
Based on the FDL work

[3D Cloud reconstruction through geospatially-aware Masked Autoencoders](#), Stella Girtsou, Emiliano Diaz Salas-Porras, Lilli Freischem, Joppe Massant, Kyriaki-Margarita Bintsi, Guiseppe Castiglione, William Jones, Michael Eisinger, Emmanuel Johnson, Anna Jungbluth

ML methodology



Pipeline

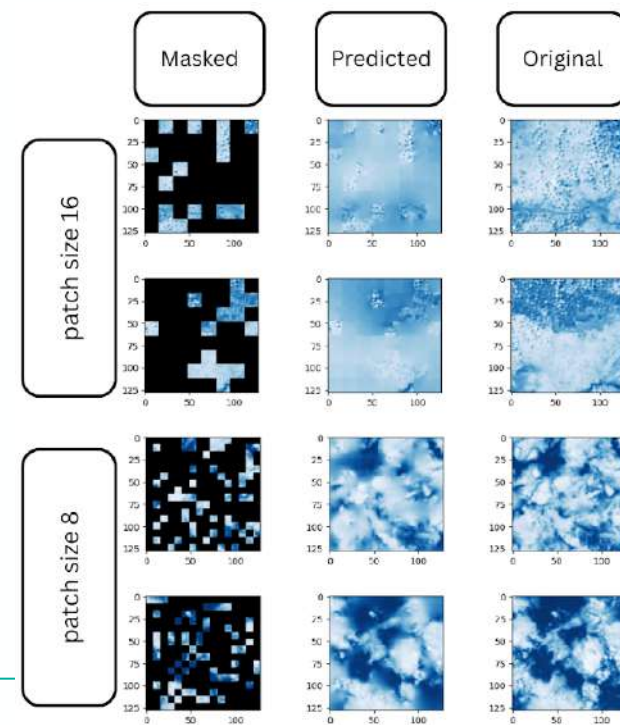
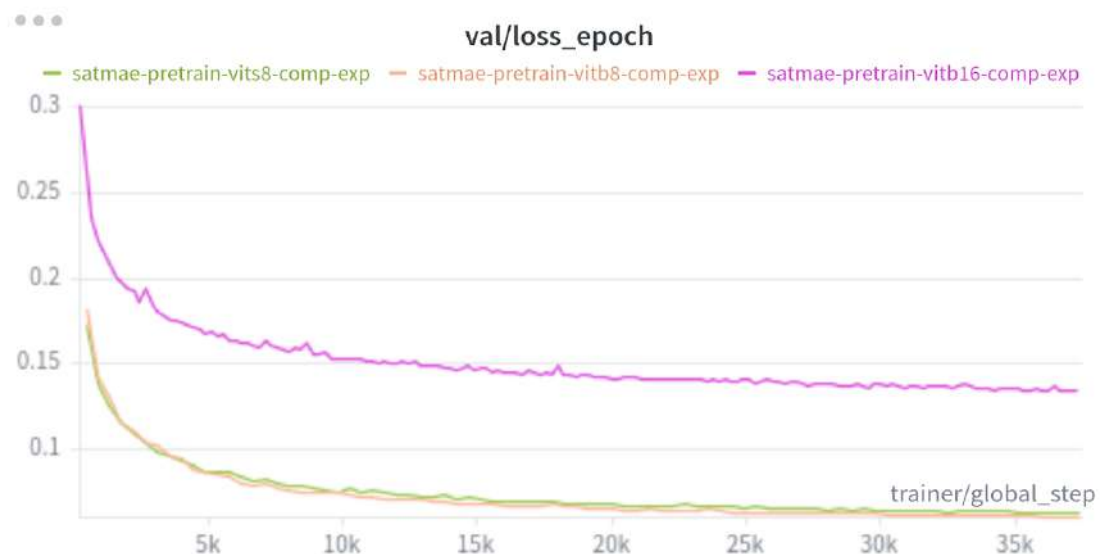


Pretraining



Experiments	Architecture	Patch size
1	ViT Base	16
2	ViT Base	8
3	ViT Small	8

Epochs: 200
Learning Rate: $1.5e-4$
Masking Ratio: 0.75
Image size: 128
Time encoding



Classes grouping: EarthCARE AC-TC target classifications gives 35 classes - not all relevant to clouds

- Tried 3 different groupings created based on classes imbalance and no precipitation distinction

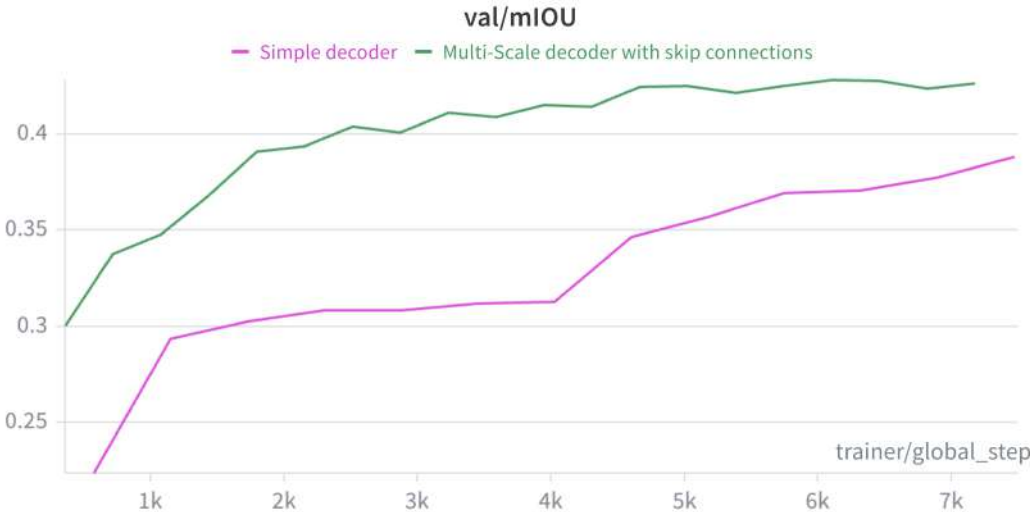
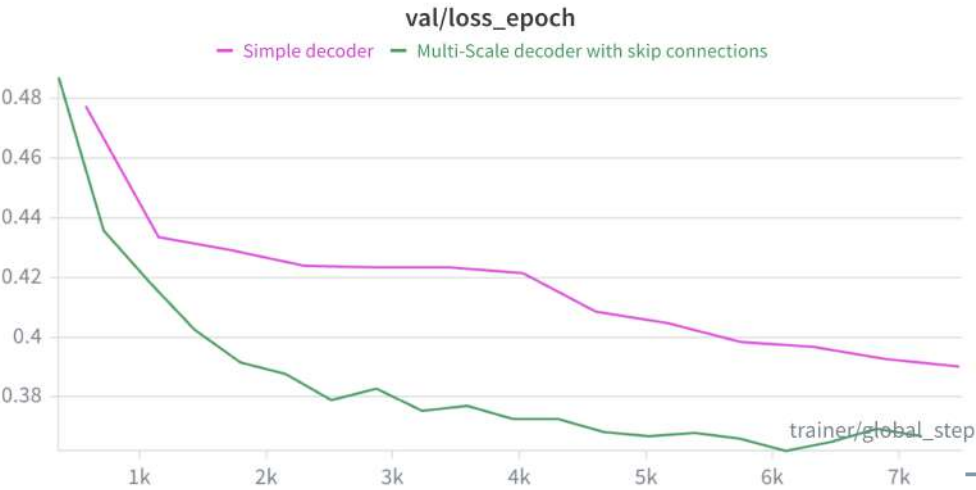
Architectures: 2 different finetuning architectures, one with only 2 layers and one with more layers and skip connections

Class weights: Major class imbalance on certain cloud types addressed with various class weights

Loss functions: 10 different ways to train our network and make it learn the difficult patterns

- Cross-Entropy Loss: compares predicted **probabilities** with the true class labels.
- Dice Loss: optimizes **overlap** between prediction and ground truth
- Tversky Loss: weights false positives and false negatives differently, making it useful for **imbalanced segmentation** tasks.
- Focal Loss: Focuses training on **hard-to-classify examples** helping improve performance on minority or **difficult classes**.

Validation

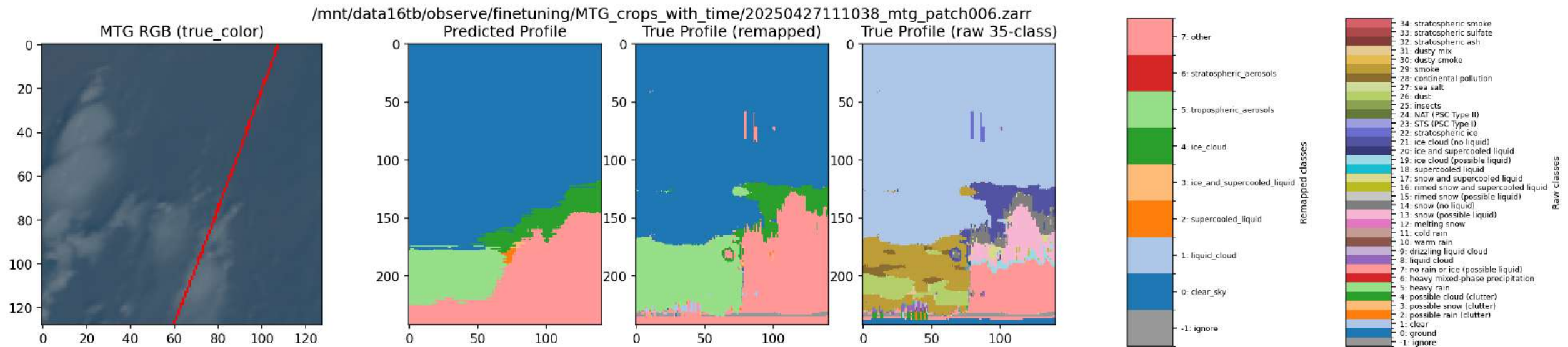


Test

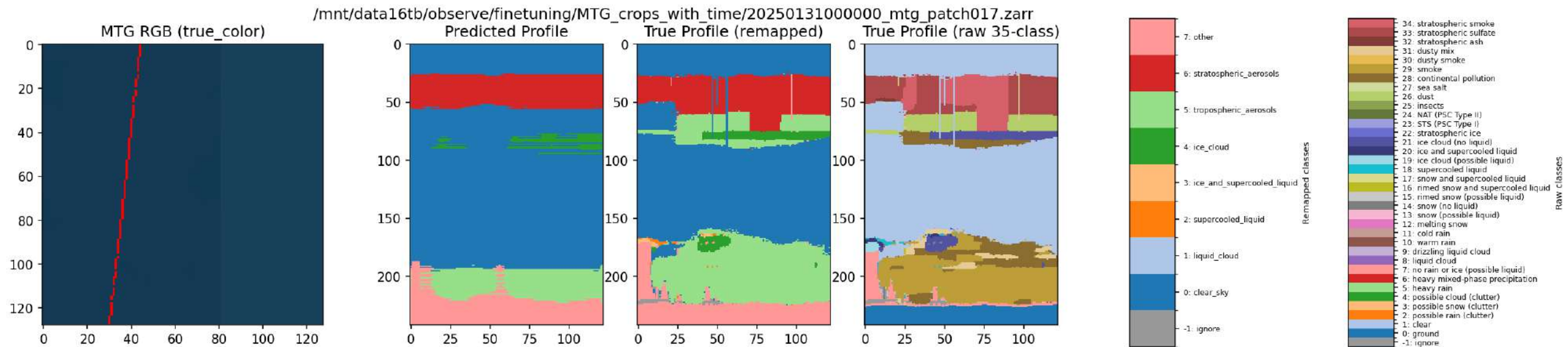
F1		
Class	Simple	Multi-Scale
0 — clear sky	0.928	0.926
1 — liquid cloud	0.241	0.261
2 — supercooled liquid	0.182	0.187
3 — ice + supercooled	0.180	0.205
4 — ice cloud	0.545	0.520
5 — tropospheric aerosols	0.728	0.715
6 — stratospheric aerosols	0.672	0.656
7 — other	0.851	0.852

IOU		
Class	Simple	Multi-Scale
0 — clear sky	0.866	0.863
1 — liquid cloud	0.137	0.150
2 — supercooled liquid	0.100	0.103
3 — ice + supercooled	0.099	0.114
4 — ice cloud	0.374	0.352
5 — tropospheric aerosols	0.573	0.556
6 — stratospheric aerosols	0.506	0.488
7 — other	0.741	0.742

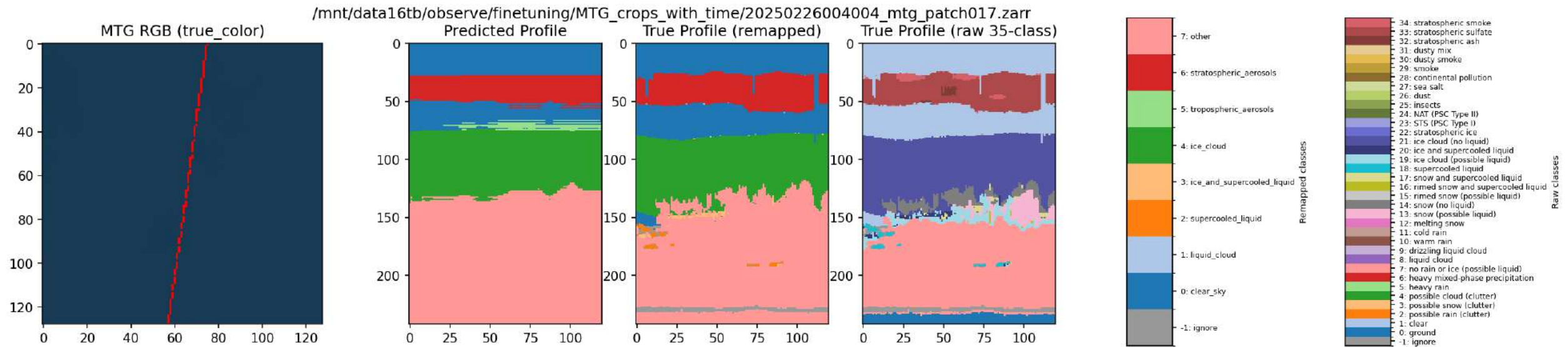
Results



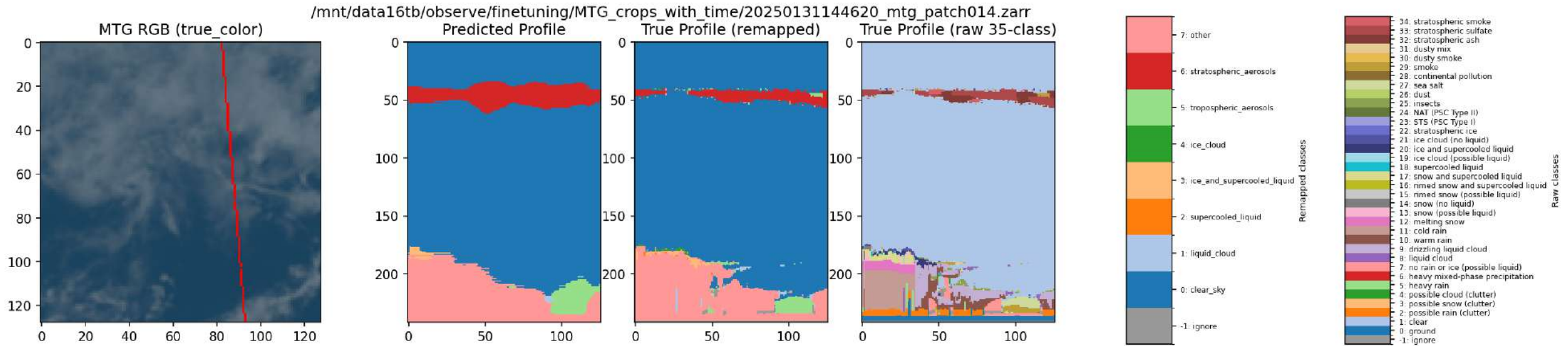
Results



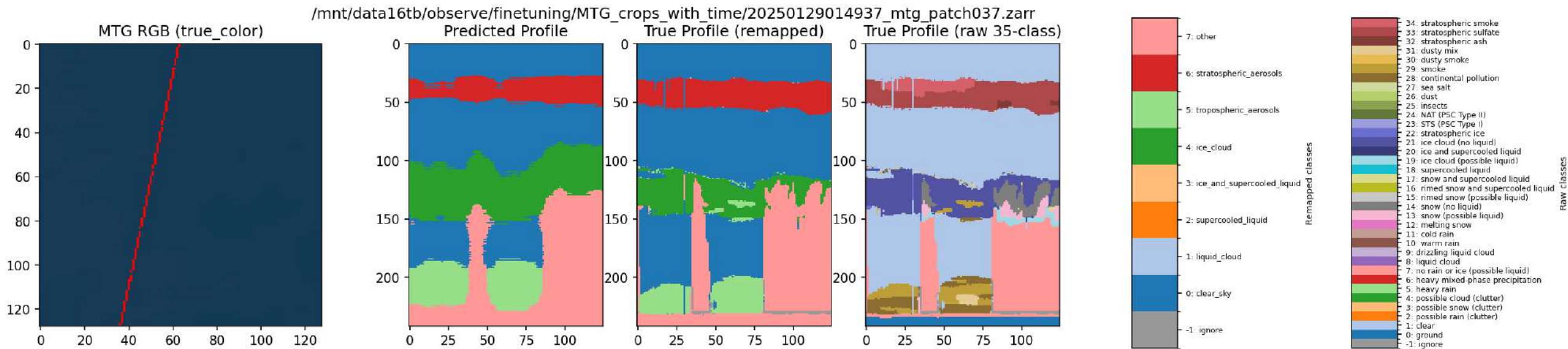
Results



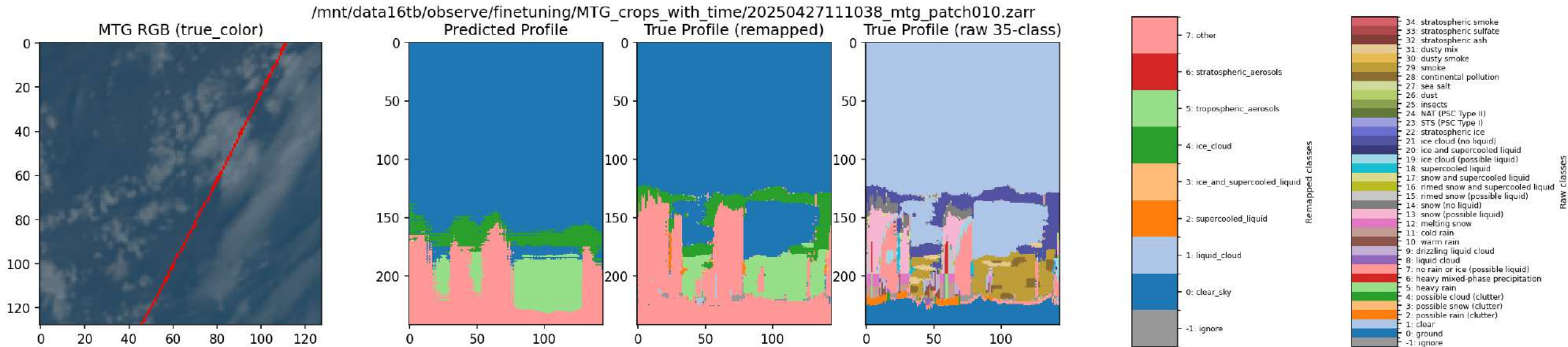
Results



Results



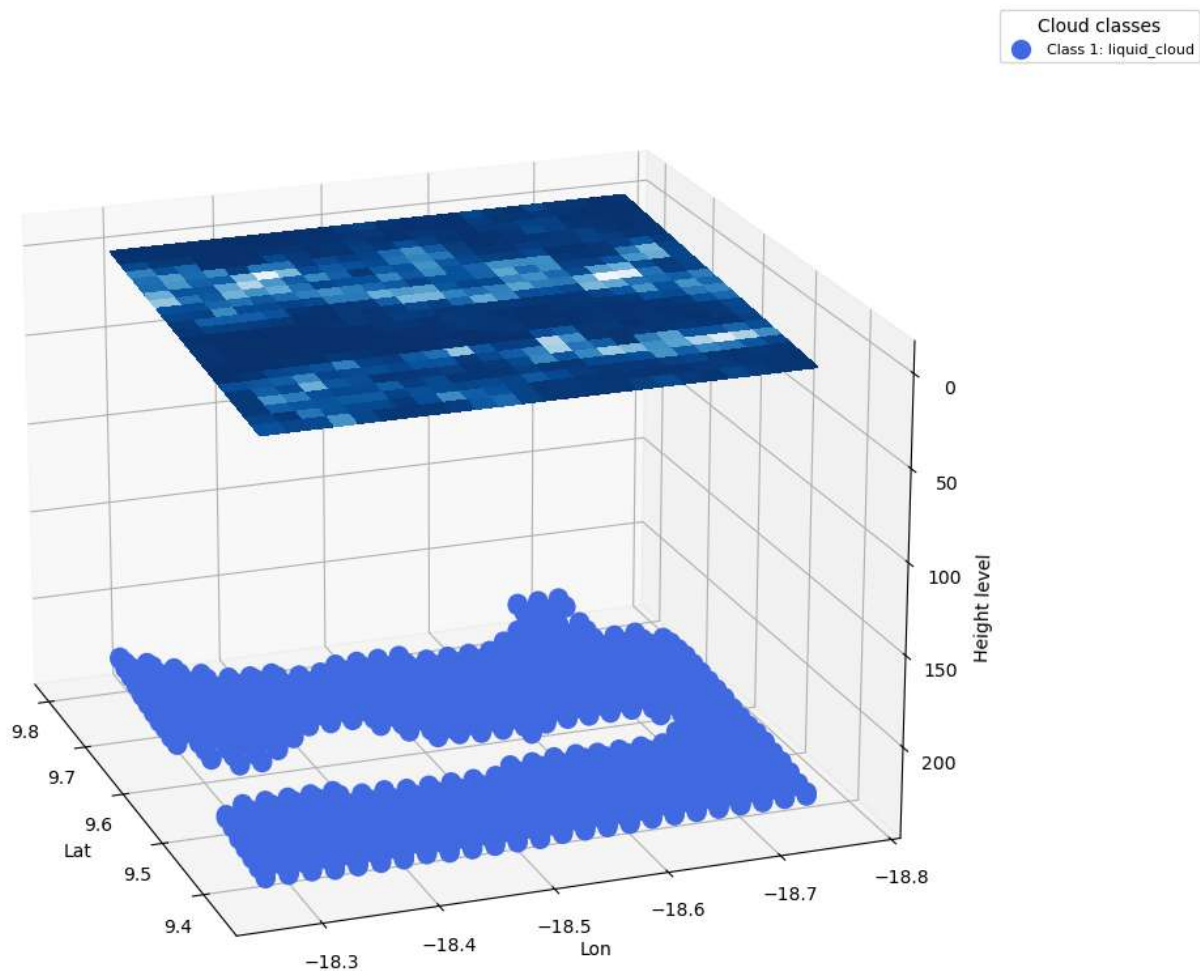
Results



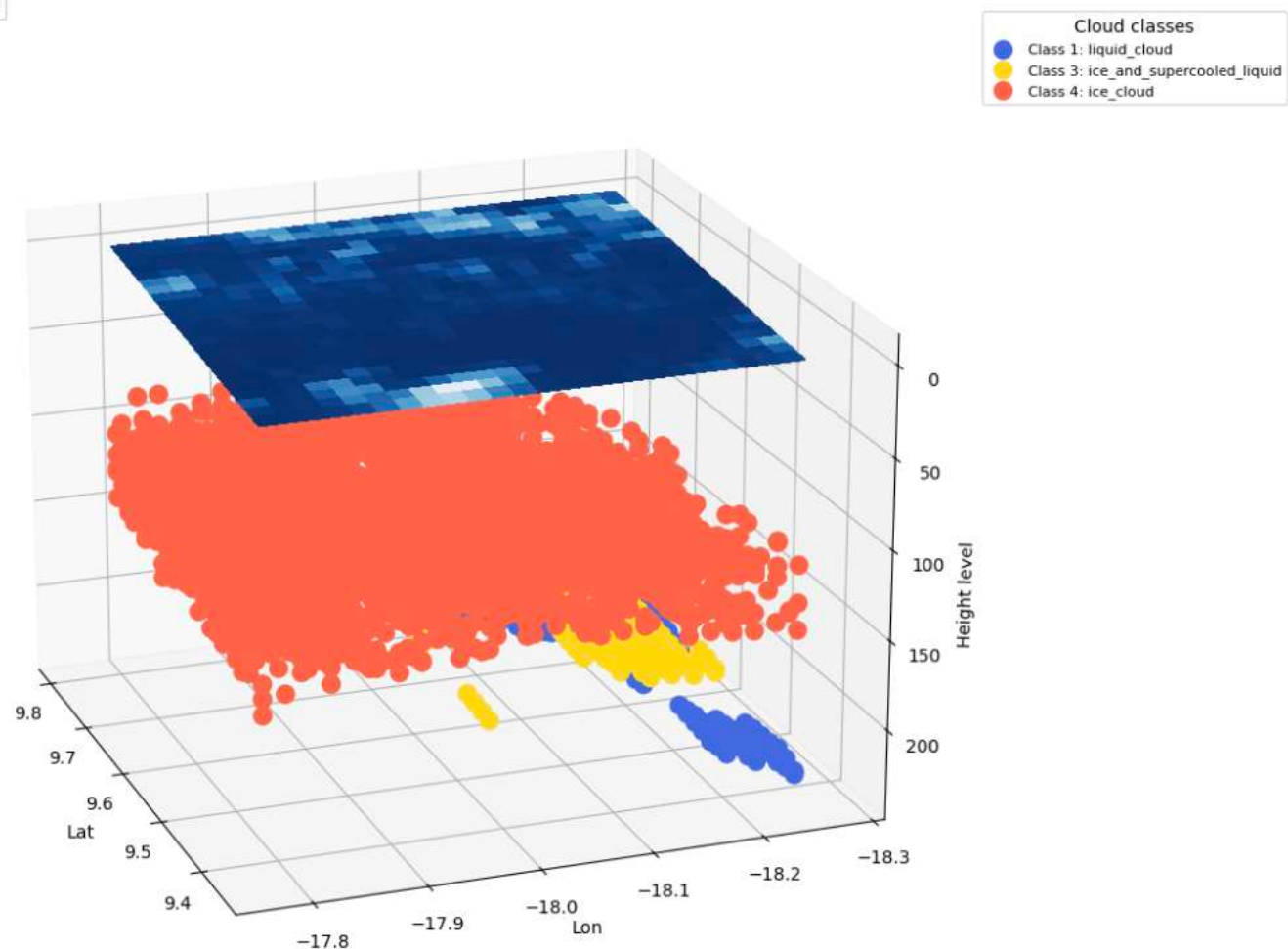
Results - 3D



Segmentation — cloud classes 1-4



Segmentation — cloud classes 1-4



Remarkable results given the input (only MTG)

Strong detection of ice clouds, as well as tropospheric and stratospheric aerosols

Accurate prediction of cloud and aerosol vertical structure

As we continue gathering data from EarthCARE we will explore multimodal schemas

Colocation quality is sensitive to temporal offset: 10 min → poor overlap; 3 min → improved

Minority classes (ice, liquid cloud, supercooled liquid) are underrepresented → standard training fails; addressed via custom metrics, loss functions, and class weights.

Next steps



Work on 3D microphysical properties from 2D **MTG** observations

3D **EarthCARE** products
Having input from MSI, ATLID and CPR will boost the predictions

Evaluate our predictions with how well each scene reproduce the **radiation** in the TOA

Evaluate our predictions with **ground based** cloudnet and aircraft percussion data



Next presentations



Day 3: Wednesday 10 June 2026

T313	11:54	12	Quantifying 3D radiative transfer effects of clouds using ML-generated 3D cloud scenes for EarthCARE, and airborne observations from ORCESTRA/PERCUSION campaign	Dimitra Kouklaki
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Posters

P098	Reconstructing the “unknown” features in AC-TC, utilizing an ML-based approach	Dimitra Karkani
P065	Evaluating EarthCARE Cloud Typing and Microphysics with Cloudnet data (online)	Ioanna Tsikoudi



Thank you!

Stella Girtsou, sgirtsou@noa.gr

Dimitra Karkani, dkarkani@noa.gr

Aggelos Georgakis, ageorgakis@noa.gr

Giorgos Giannopoulos, giannopoulos@noa.gr

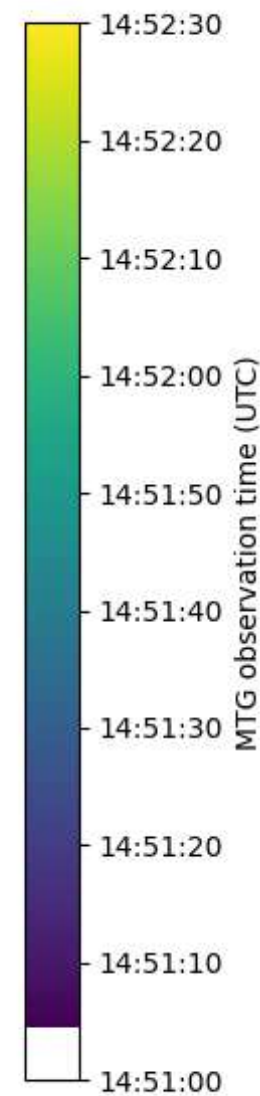
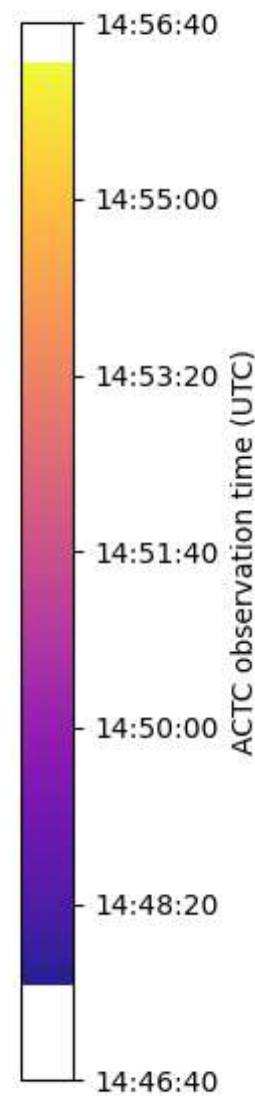
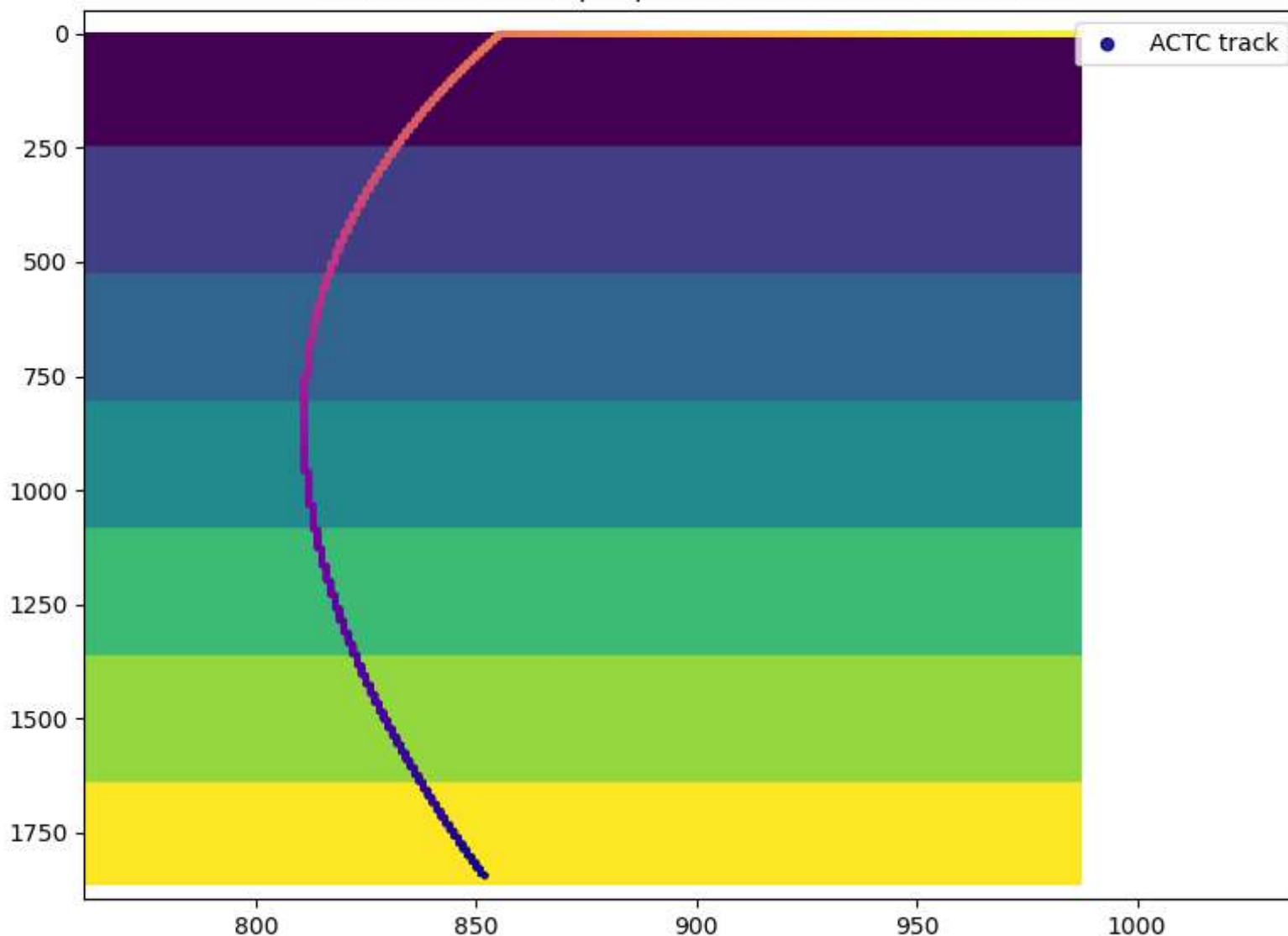
Alexandra Tsekeri, atsekeri@noa.gr



Colocation



Observation time per pixel — zoomed to ACTC track



Segmentation Task: Highly Imbalanced dataset

```
synergistic_target_classification = {
  -1: "unknown",
  0: "ground",
  1: "clear",
  2: "possible rain (clutter)",
  3: "possible snow (clutter)",
  4: "possible cloud (clutter)",
  5: "heavy rain",
  6: "heavy mixed-phase precipitation",
  7: "no rain or ice (possible liquid)",
  8: "liquid cloud",
  9: "drizzling liquid cloud",
  10: "warm rain",
  11: "cold rain",
  12: "melting snow",
  13: "snow (possible liquid)",
  14: "snow (no liquid)",
  15: "rimed snow (possible liquid)",
  16: "rimed snow and supercooled liquid",
  17: "snow and supercooled liquid",
  18: "supercooled liquid",
  19: "ice cloud (possible liquid)",
  20: "ice and supercooled liquid",
  21: "ice cloud (no liquid)",
  22: "stratospheric ice",
  23: "STS (PSC type I)",
  24: "NAT (PSC type II)",
  25: "insects",
  26: "tropospheric aerosol types",
  27: "tropospheric aerosol types",
  28: "tropospheric aerosol types",
  29: "tropospheric aerosol types",
  30: "tropospheric aerosol types",
  31: "tropospheric aerosol types",
  32: "stratospheric aerosol types",
  33: "stratospheric aerosol types",
  34: "stratospheric aerosol types",
}
```

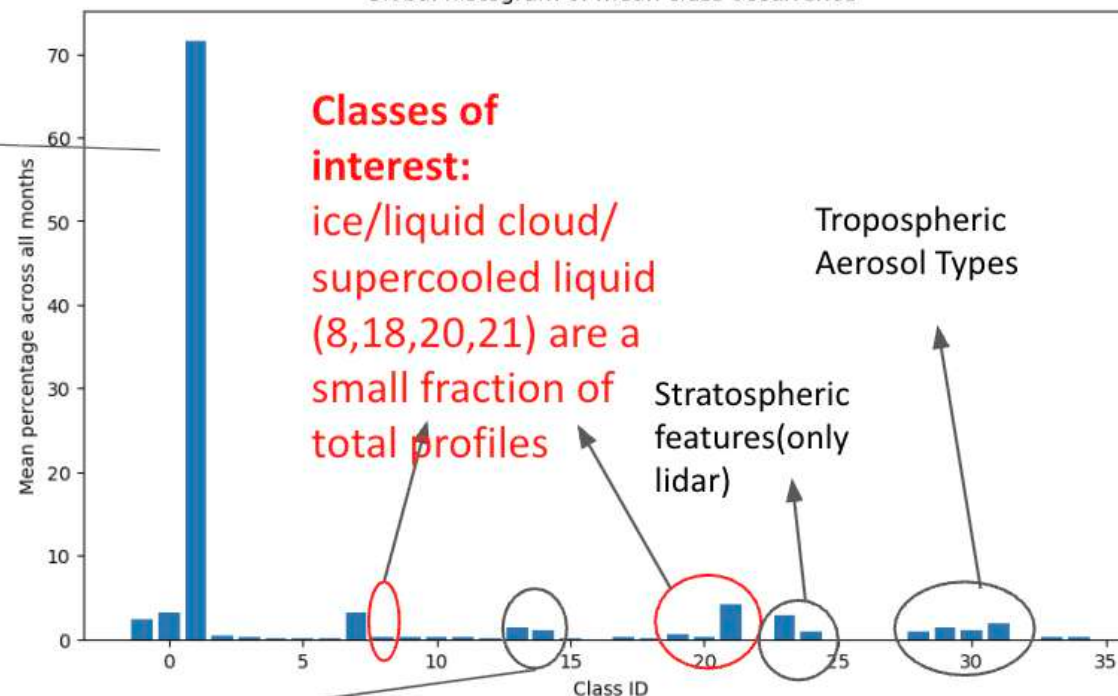
Clear sky pixels dominate:

i.e. When lidar sees clear sky or if the lidar is extinguished and when radar indicates clear sky

Snow, possible liquid/no liquid

i.e. Radar takes over lidar, (missing data or extinguished)/Radar class indicates snow, and lidar does not indicate liquid

Global histogram of mean class occurrence



Classes of interest:
ice/liquid cloud/
supercooled liquid
(8,18,20,21) are a
small fraction of
total profiles

Stratospheric
features (only
lidar)

Tropospheric
Aerosol Types