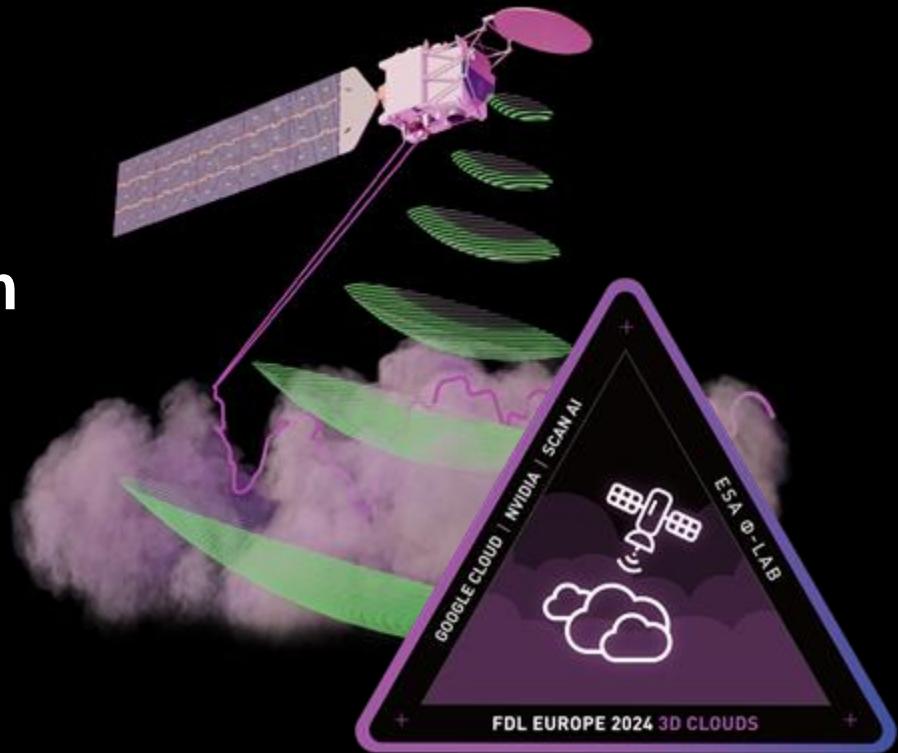


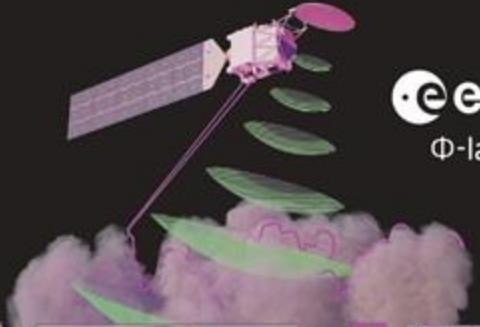
Deriving 3D Cloud Maps from 2D Satellite Imagery using Machine Learning

Anna Jungbluth & William Jones

17 October 2024



3D CLOUDS USING MULTI-SENSING - 2024



•esa
Φ-lab

FDL 2024
EUROPE

EARTH
SYSTEMS
LAB



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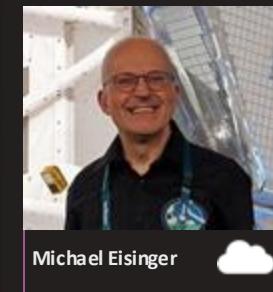
FACULTY



William Jones



Anna Jungbluth



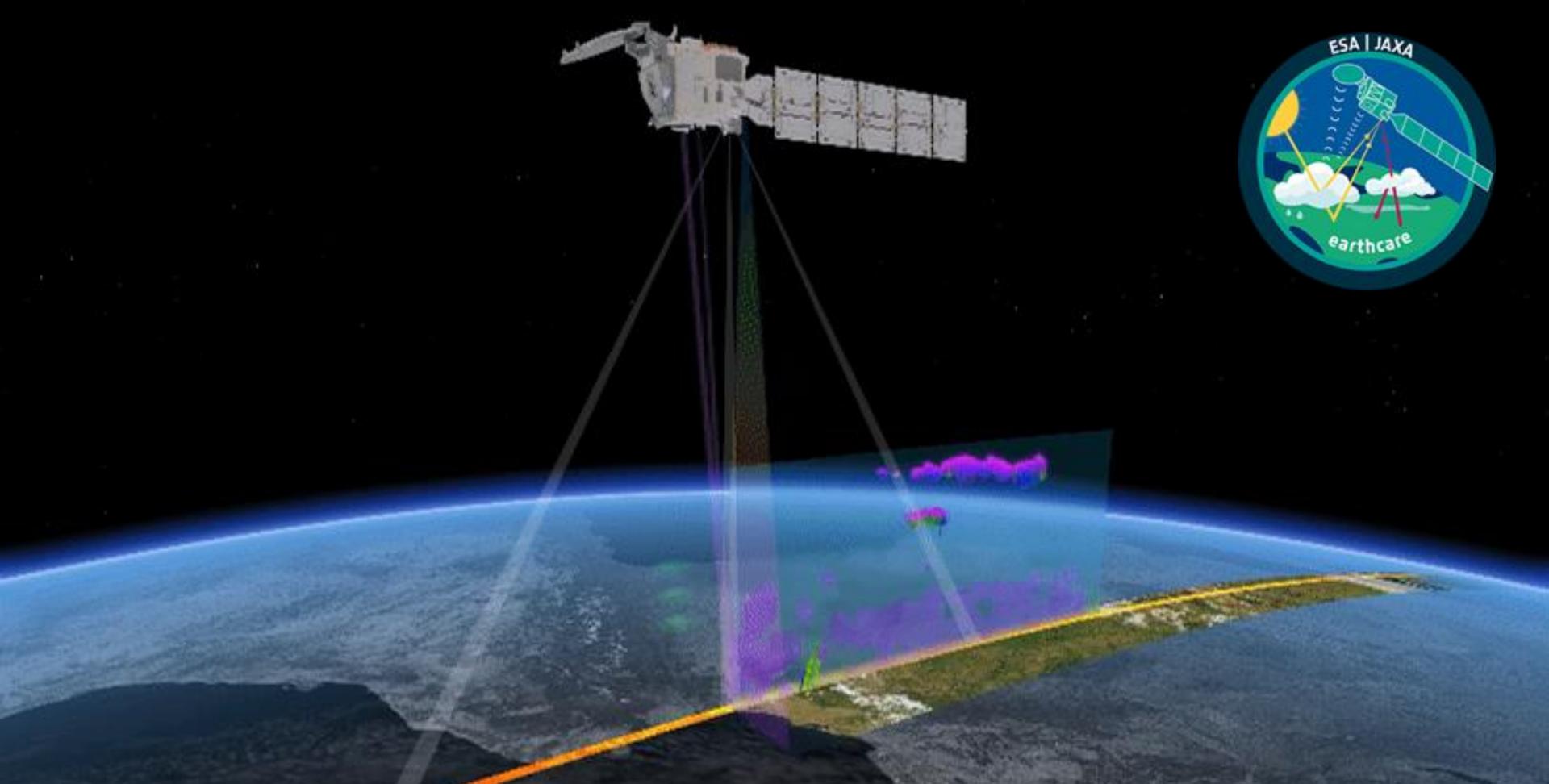
Michael Eisinger





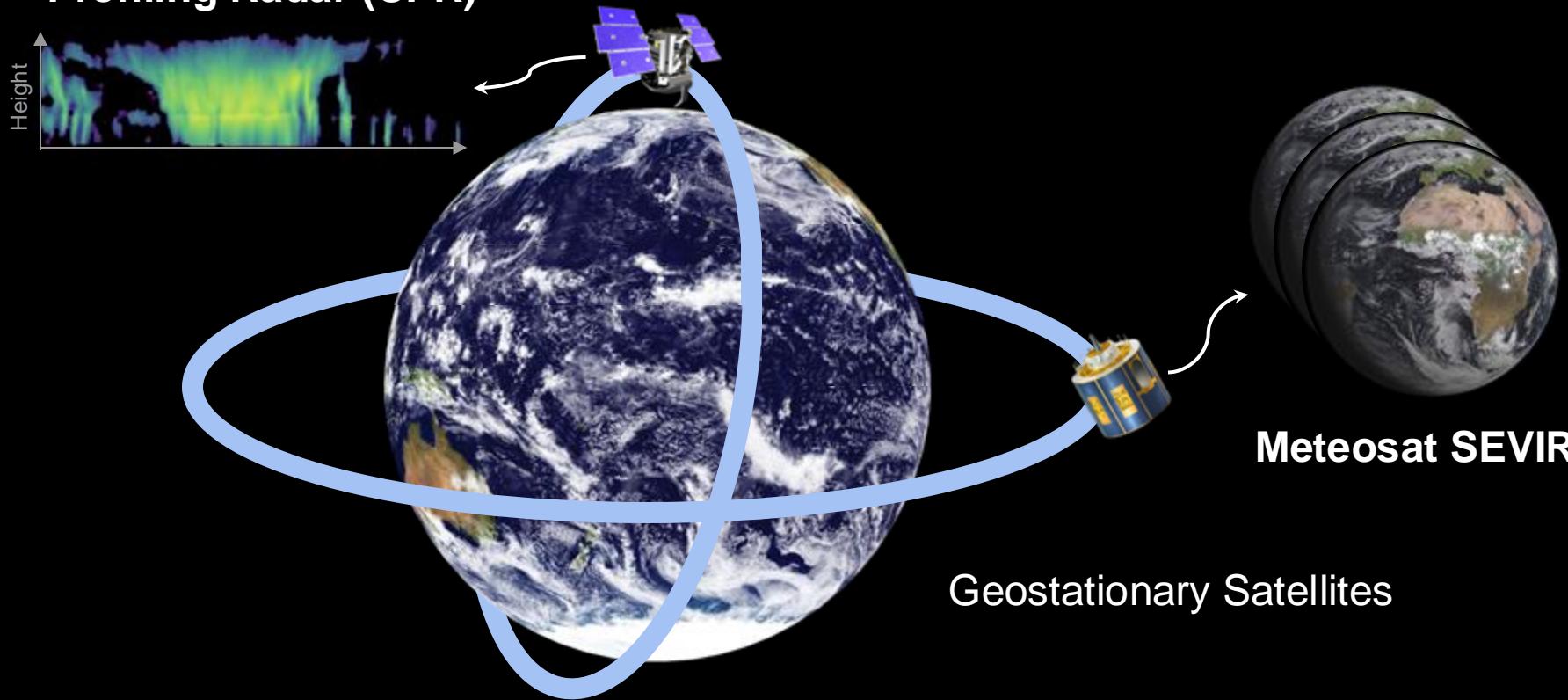
Change is “a distant problem that requires sacrifices
How to avoid **uncertain losses far in the future**”

- Daniel Kahneman

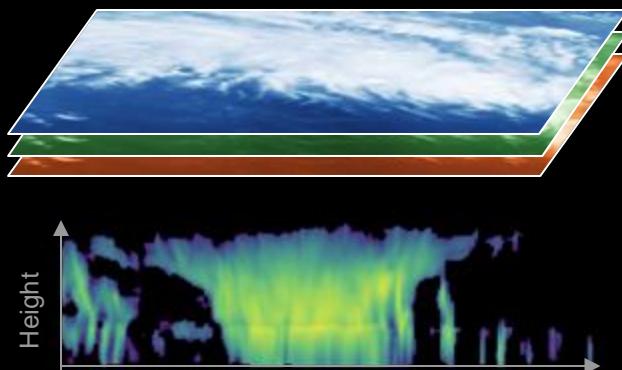


Cloudsat Cloud Profiling Radar (CPR)

Polar Orbiting Satellites



SEVIRI
multi-channel imagery

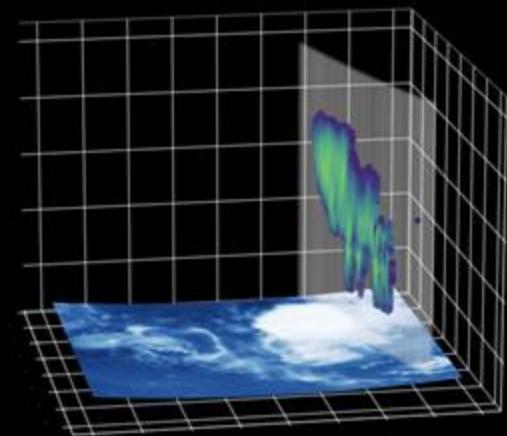


CPR radar profiles

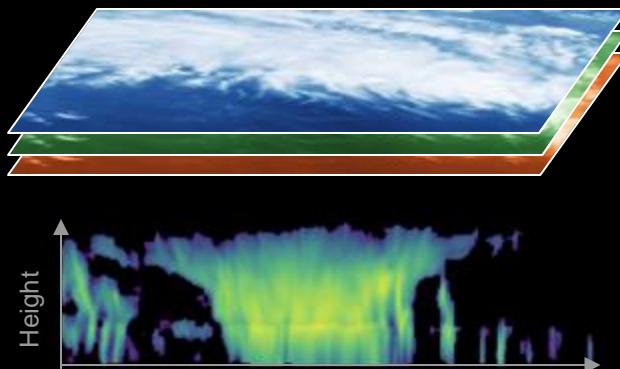
Align in space
and time



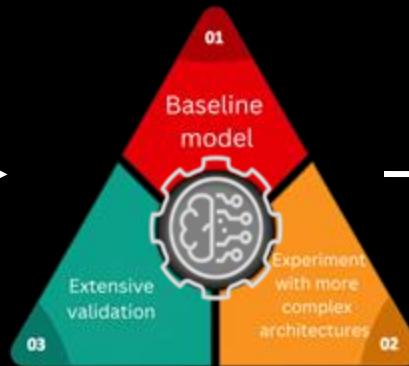
Transform to
3D cube



Paired observations



3D cloud maps

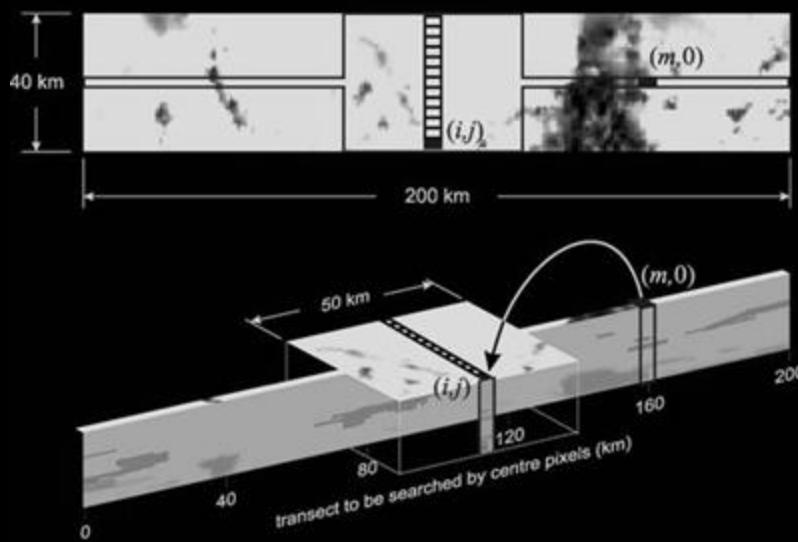


State-of-the-art approaches

EarthCARE across-track reconstruction

Pattern matching

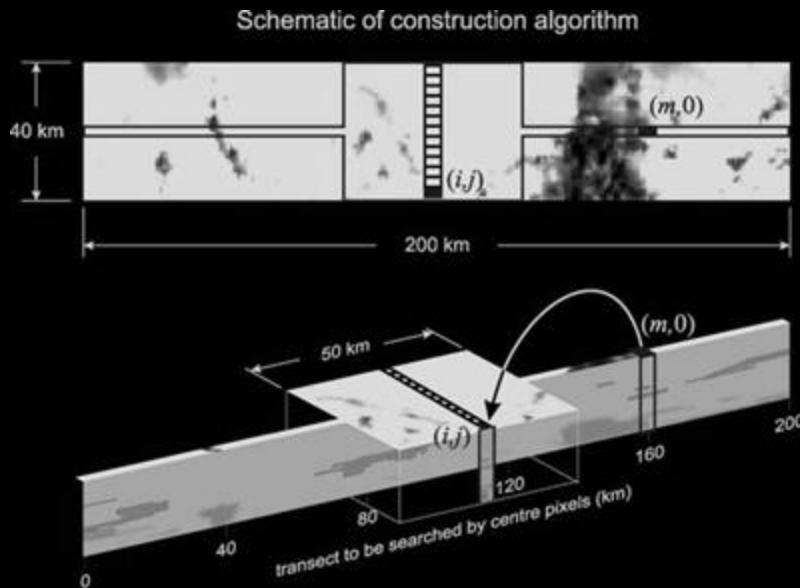
Schematic of construction algorithm



Barker et al., "A 3D cloud-construction algorithm for the EarthCARE satellite mission", QJRMS 2011

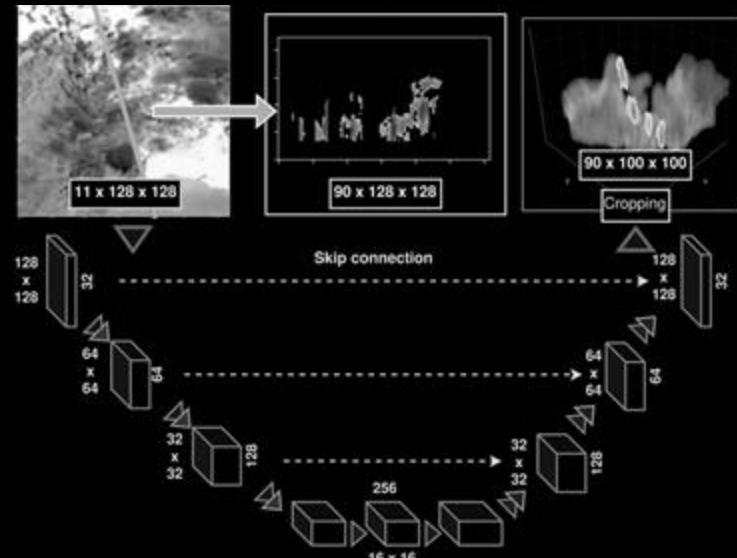
State-of-the-art approaches

EarthCARE across-track reconstruction *Pattern matching*

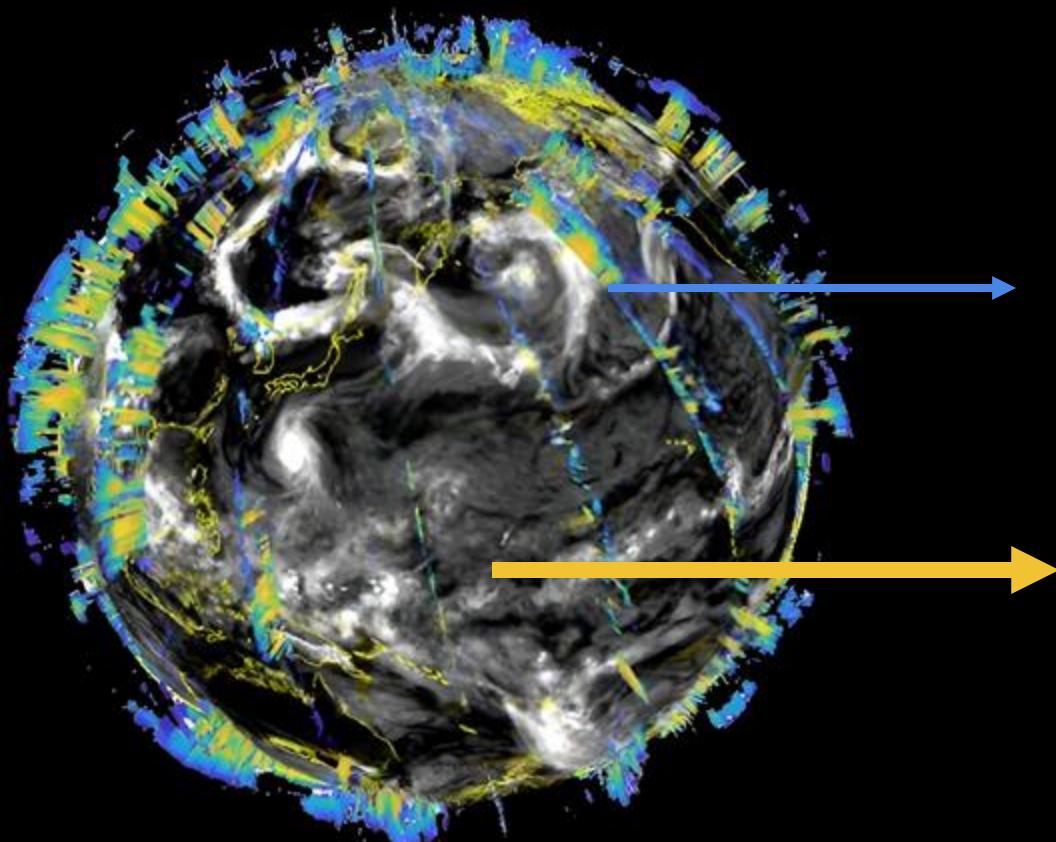


Barker et al., "A 3D cloud-construction algorithm for the EarthCARE satellite mission", *QJRMS* 2011

U-Net 3D reconstruction *Image-to-image translation*



Brüning et al., "Artificial intelligence (AI)-derived 3D cloud tomography from geostationary 2D satellite data", *AMT* 2024.



Gigabytes of
Image-Profile
Pairs



Terabytes of
Unpaired
Images

Our Approach

Step 1:

Learn from terabytes of unpaired images

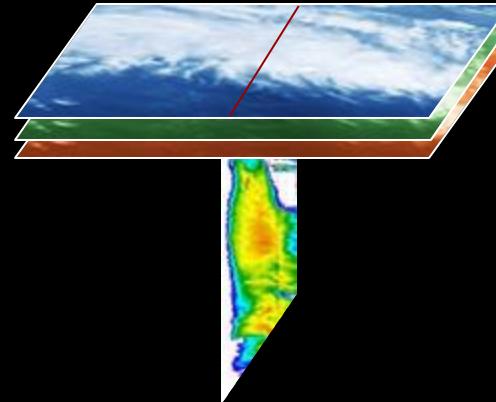
Via **Self-Supervised Learning**



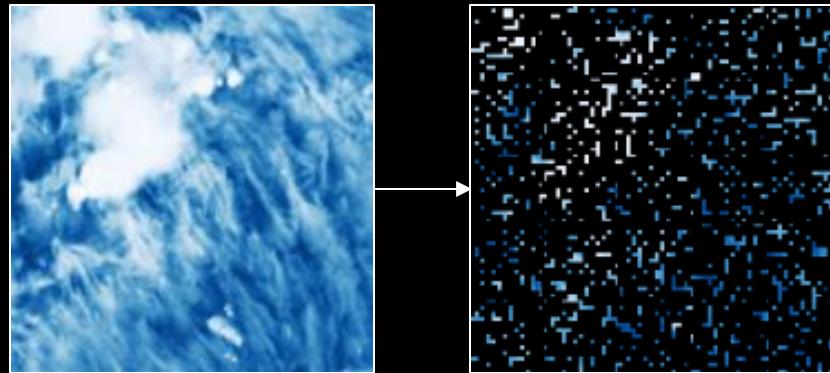
Step 2:

Specialize to predict 3D from image-profile pairs

Via **Supervised Learning**



Step 1: Learn from TBs of unpaired images via self-supervised learning

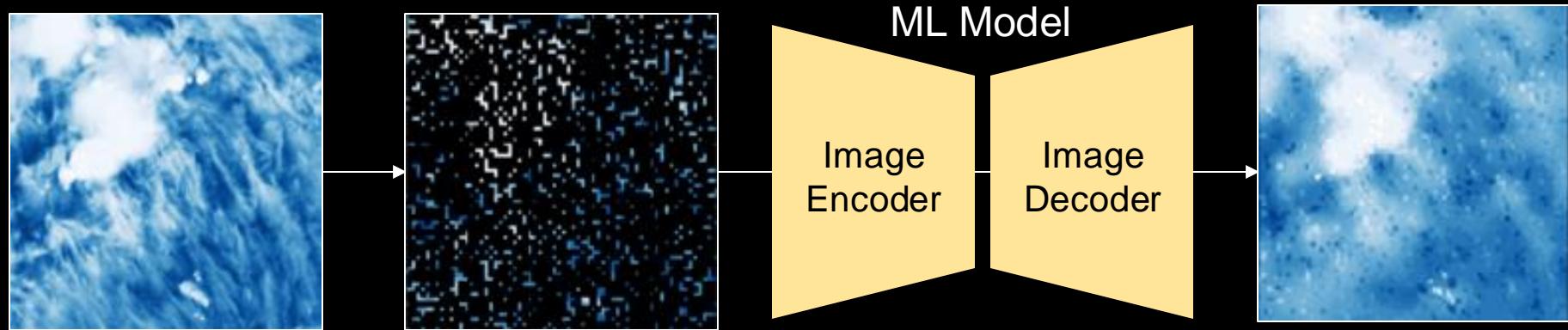


Goal:
Learn underlying features
in satellite data!

Masked Autoencoders (MAEs)

Credit: He et al. Masked Autoencoders Are Scalable Vision Learners, arXiv:2111.06377

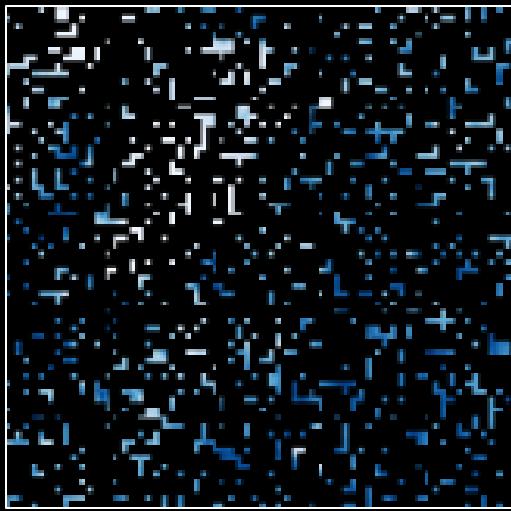
Step 1: Learn from TBs of unpaired images via self-supervised learning



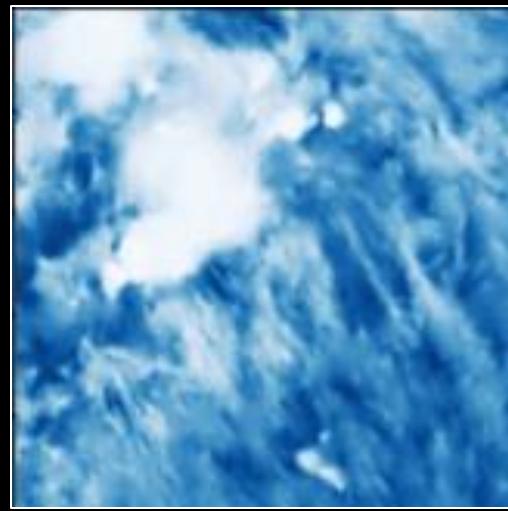
Masked Autoencoders (MAEs)

Credit: He et al. Masked Autoencoders Are Scalable Vision Learners, arXiv:2111.06377

Masked



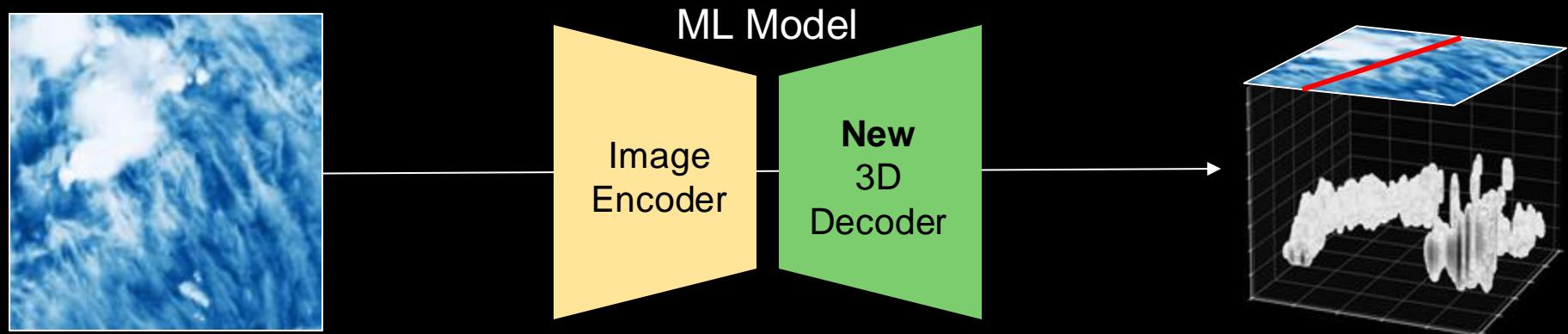
Reconstructed



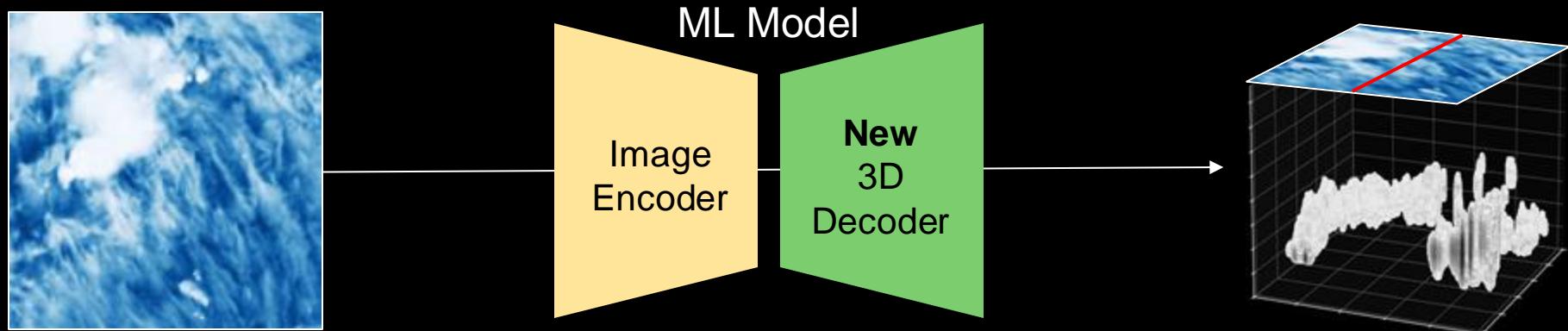
Original



Step 2: Specialize to predict 3D from image-profile pairs via supervised learning

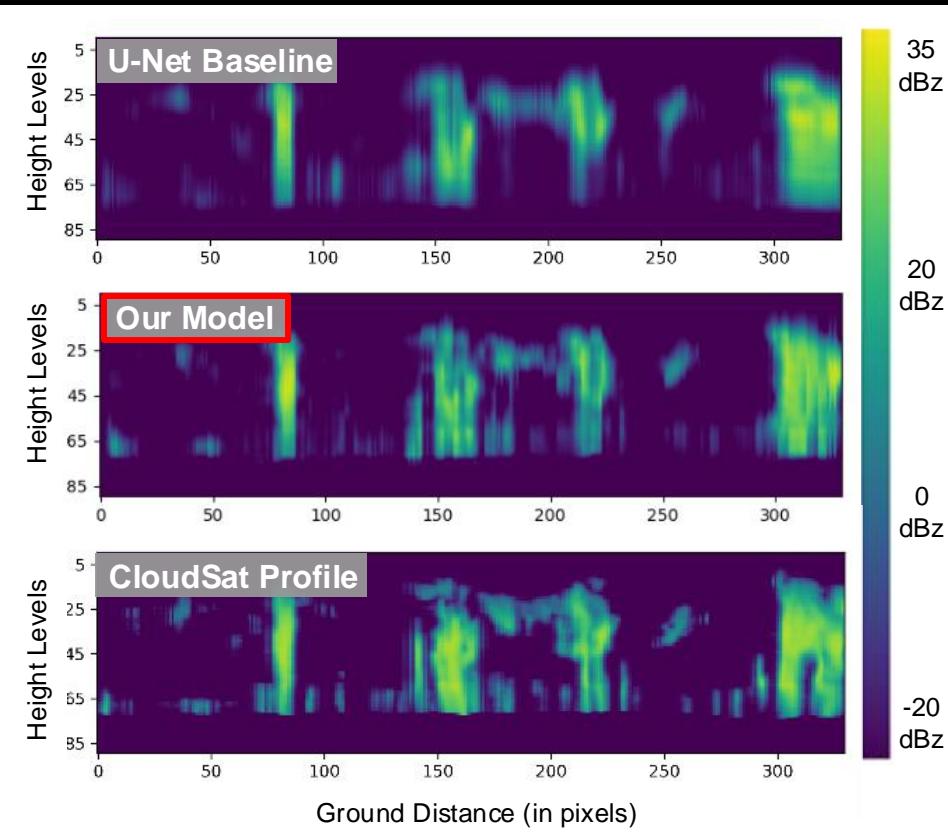
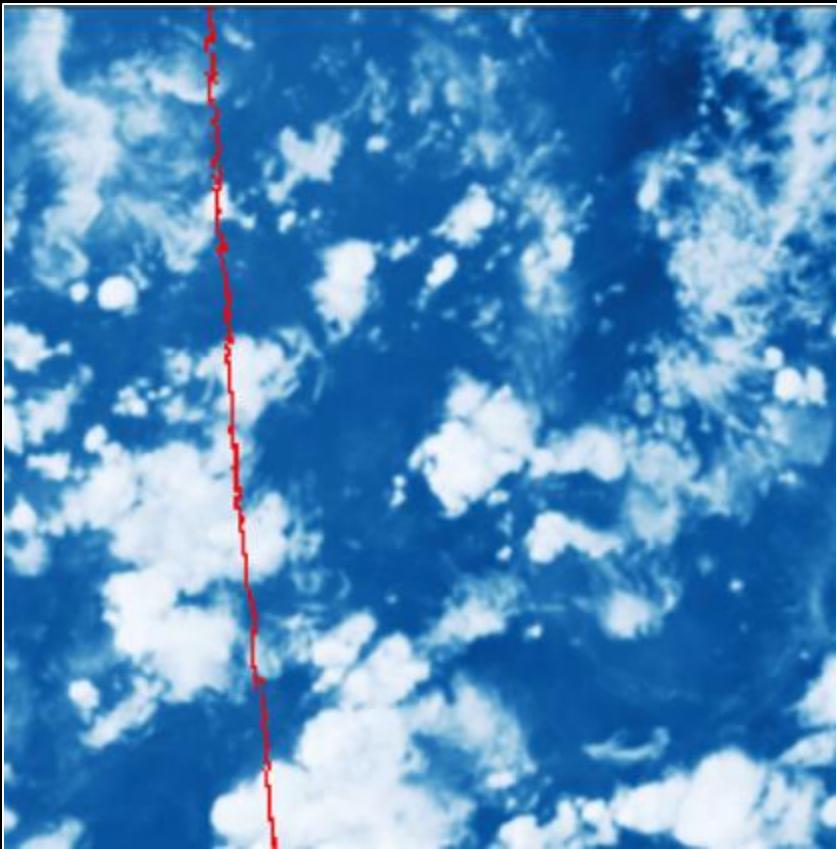


Step 2: Specialize to predict 3D from image-profile pairs via supervised learning

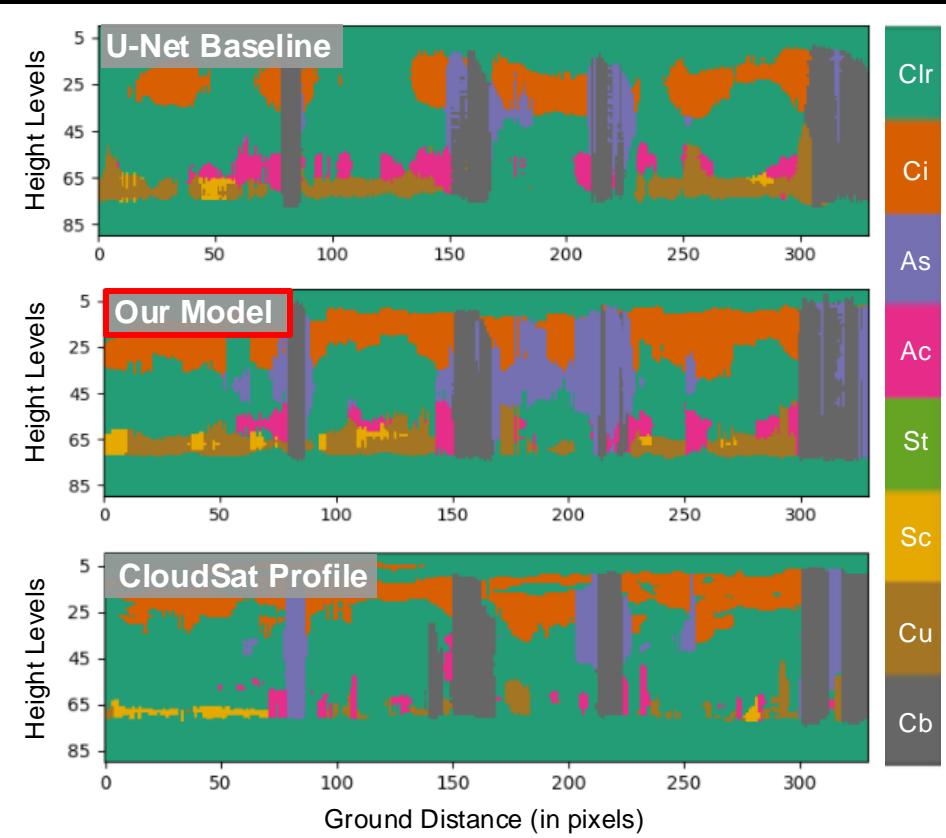
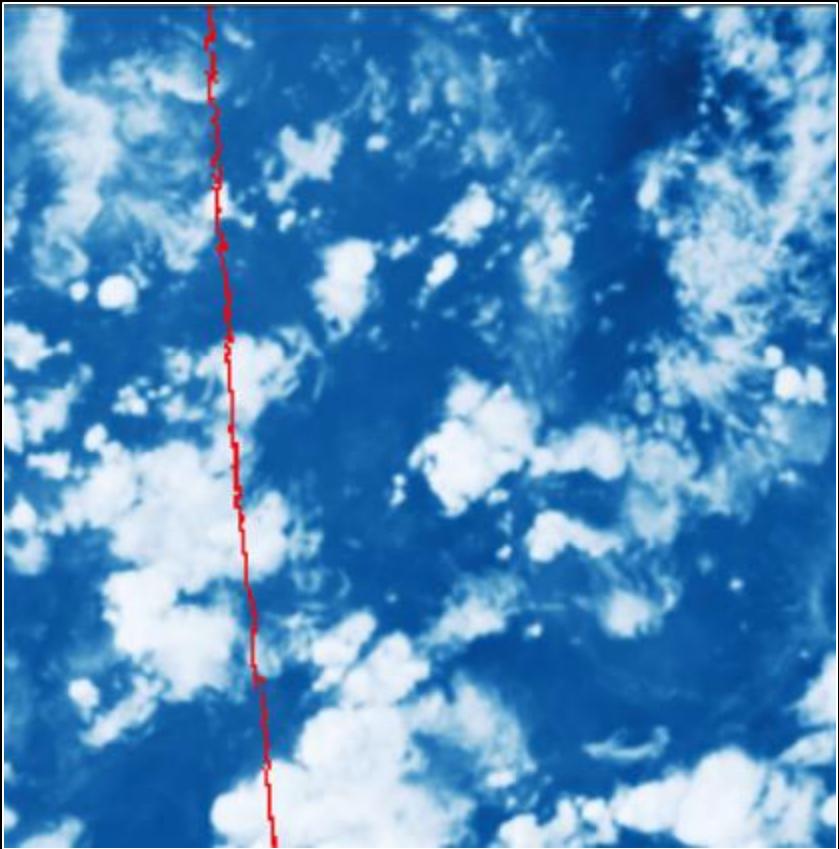


“Geospatially-aware” ML model
→ **Encode time (YYYYMMDD HHMMSS)**
→ **Encode location (Latitude & Longitude)**

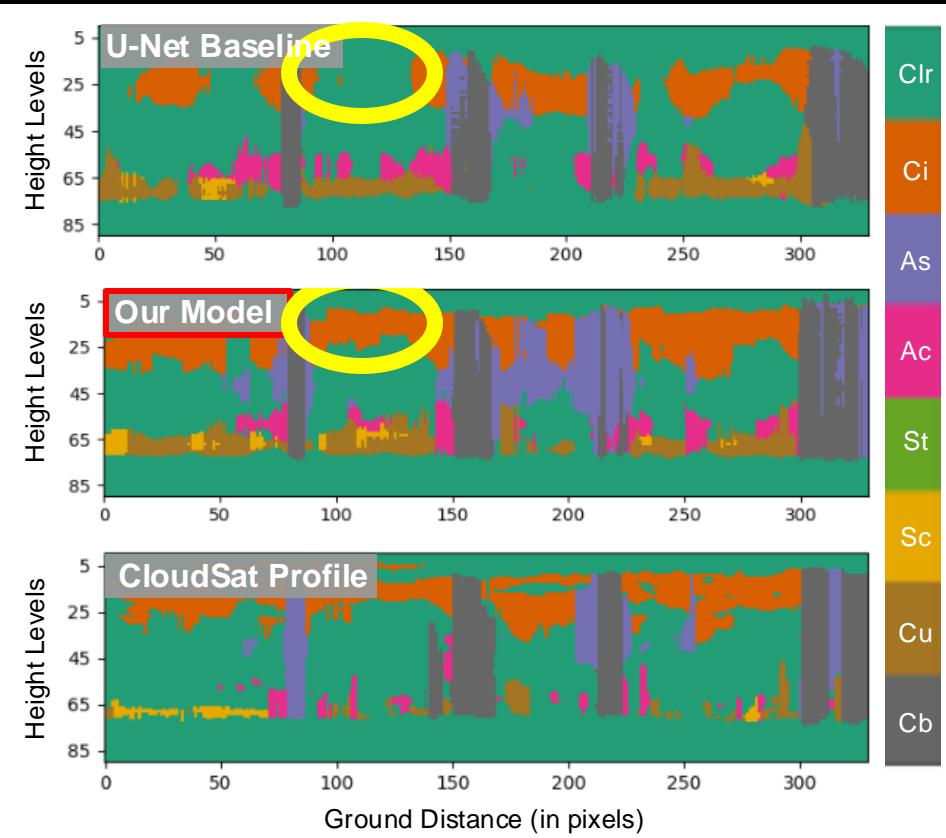
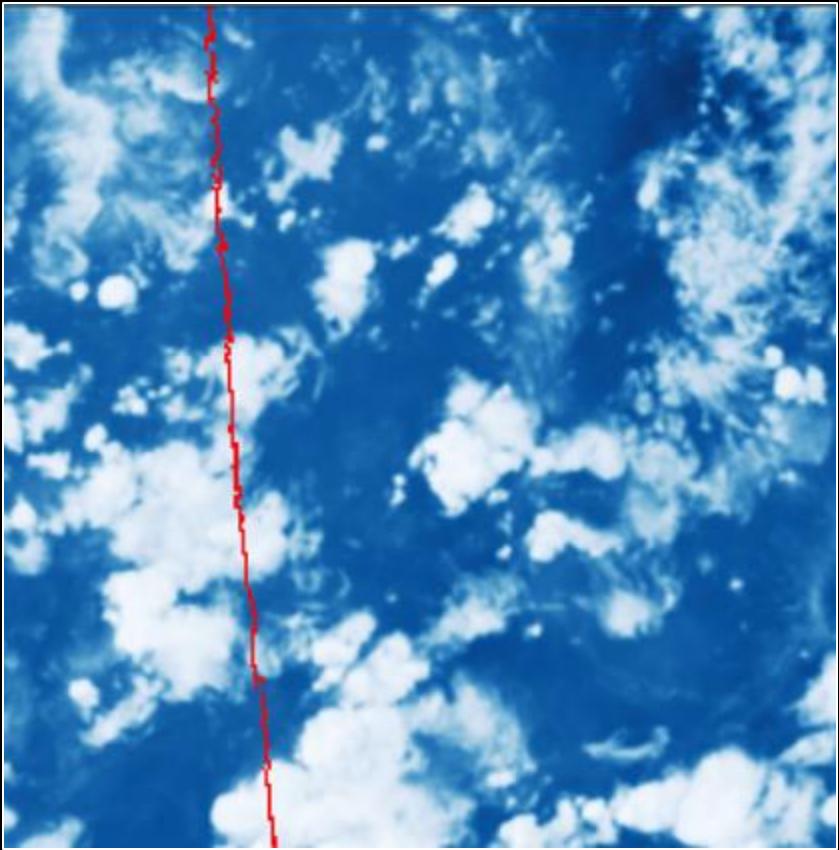
Prediction Results



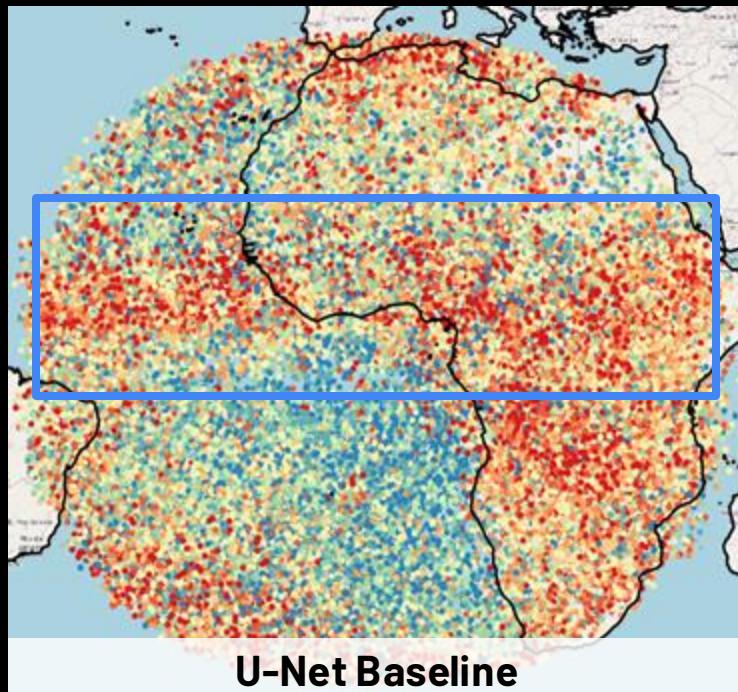
Prediction Results



Prediction Results



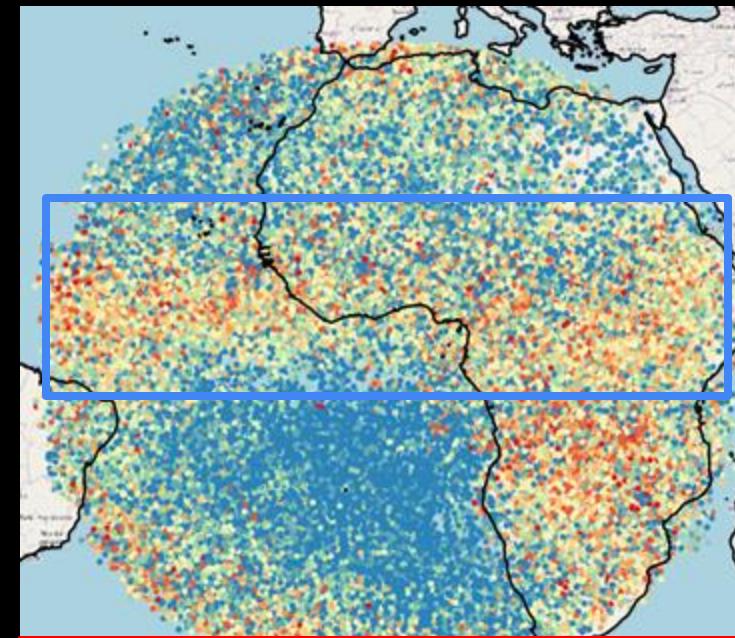
Reduced Regional Bias with Geospatial ML Model



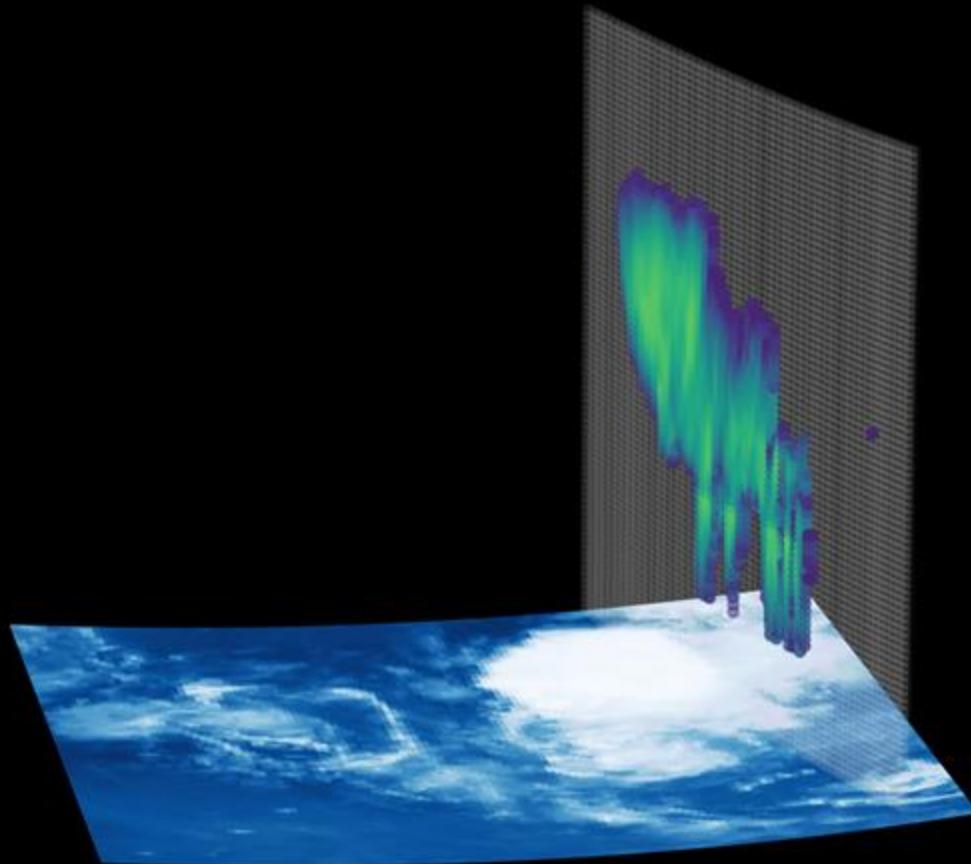
U-Net Baseline

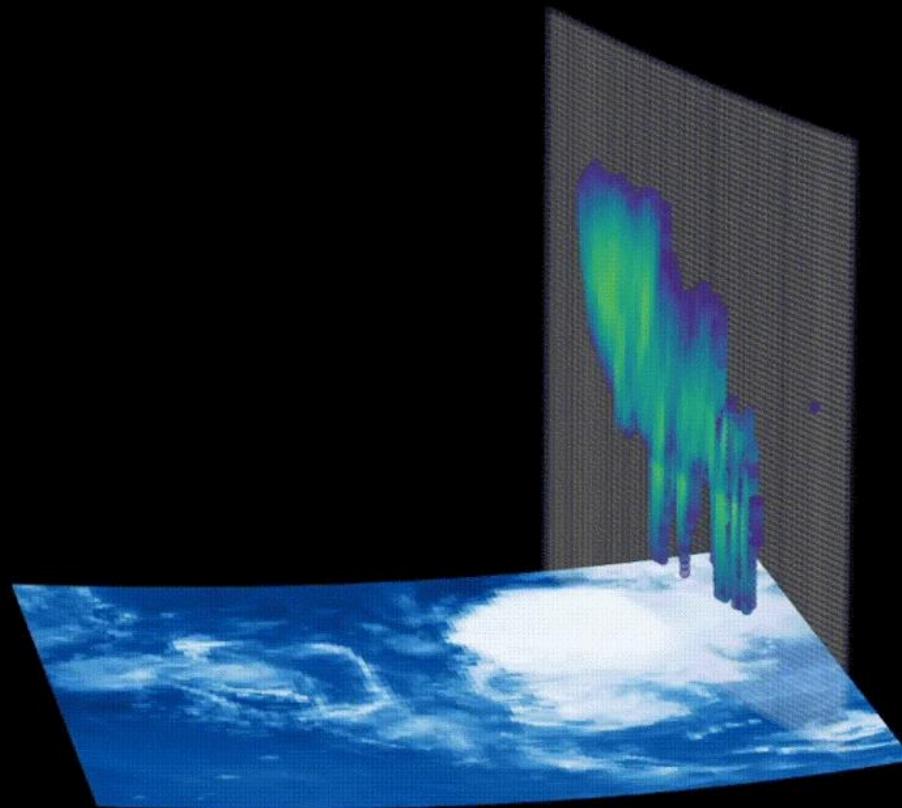
0 1.5 3 4.5 >6.7

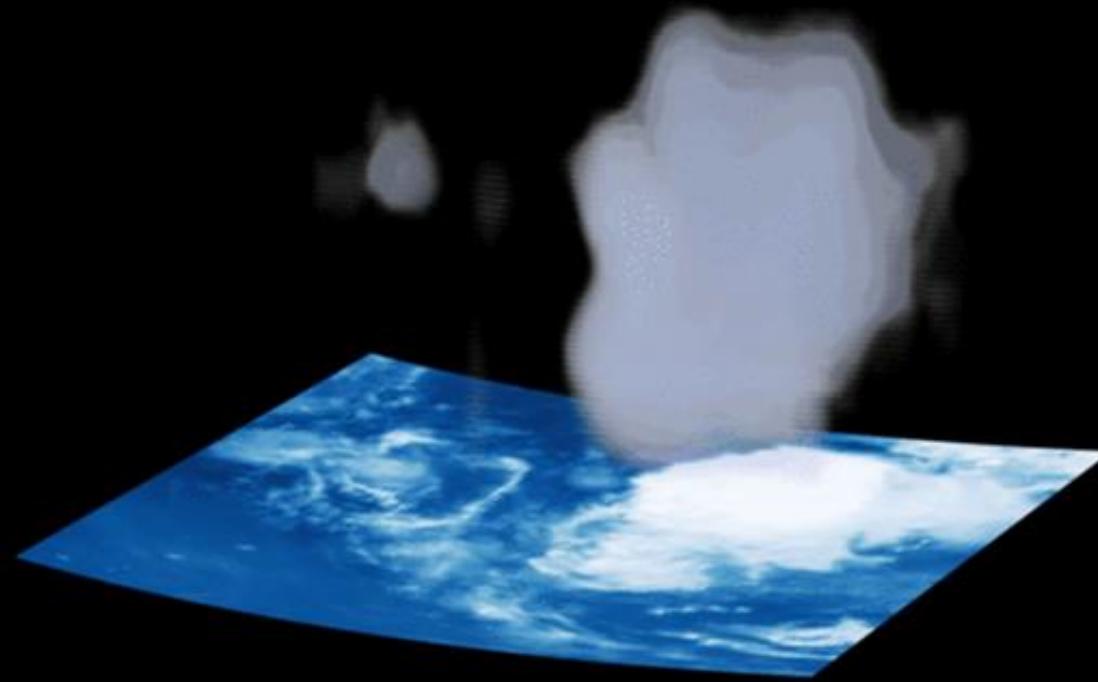
RMSE (dBZ)

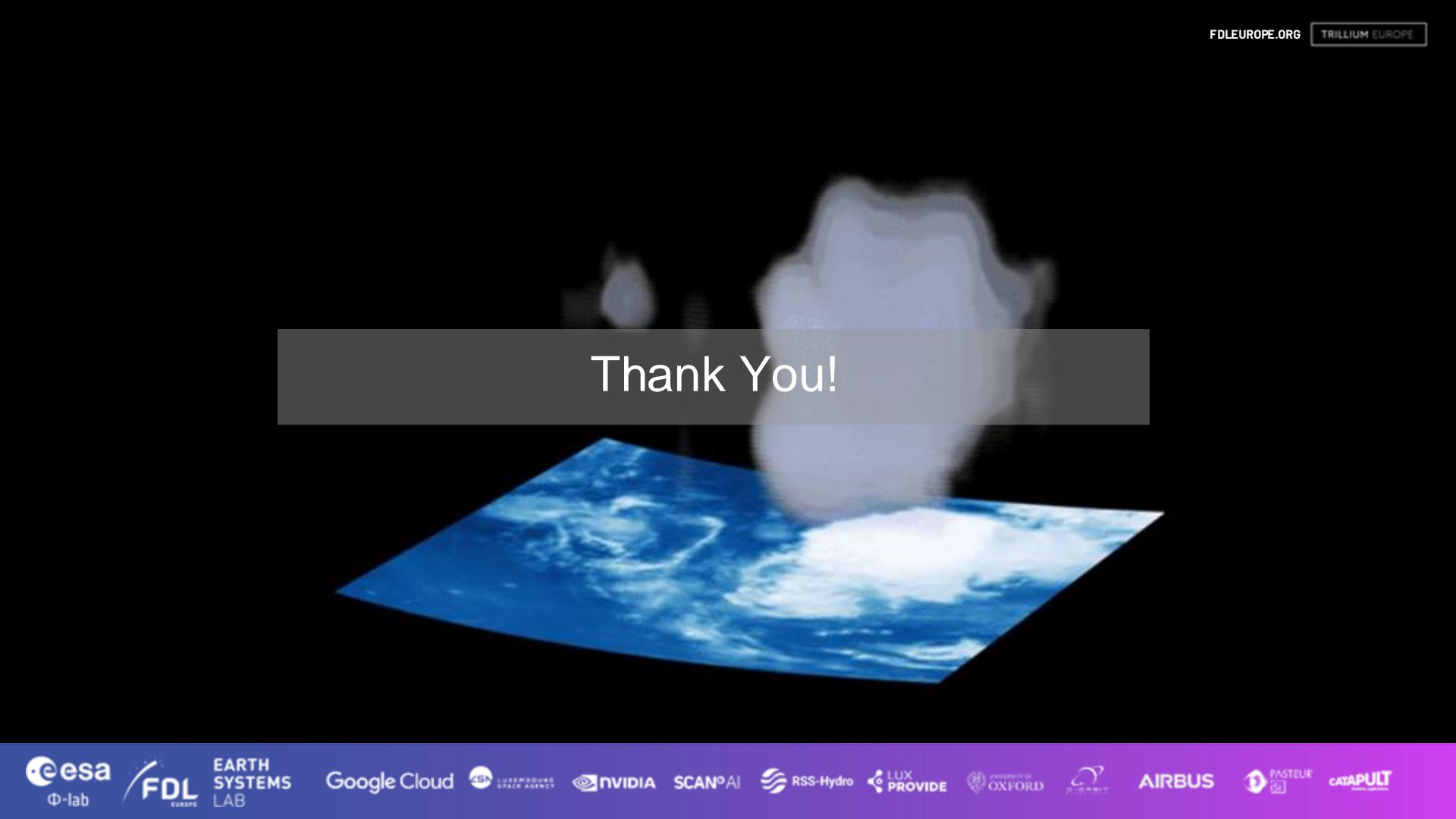


Our Model (incl. time + space)









Thank You!