GLOBAL 3D RECONSTRUCTIONS:
CLOUDS & TROPICAL CYCLONES

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1. PREDICTING HURRICANE INTENSIFICATION

Motivation: Numerical weather predictions struggle to accurately predict which cyclones will intensify and underperform on rapid intensification. Predicting tropical cyclone (TC) intensity is difficult for many reasons, including...

Poorly resolved — Possible role of microphysics — Sparse direct observations

Data: Currently, satellites capture cyclones from atop (geostationary imagery) and with thin profiles (e.g. CloudSat & EarthCARE) with global coverage every 16 days.

Proposition: Continuous/global modeling of 3D microphysical properties to help better understand TC intensification and improve early warnings.

2. DATASETS FOR CLOUDS & TROPICAL CYCLONES

Input data: Geostationary weather satellites (GOES-16, MSG, Himawari-8) provide visible and IR imagery (11-16 channels) at moderate resolution (2-3 km) with high temporal frequency (10-15 minutes). CloudSat provides vertical profiles of cloud properties using W-band (94 Ghz) radar. The international best track archive for climate stewardship (IBTrACS) provides trajectories of historical tropical cyclones.

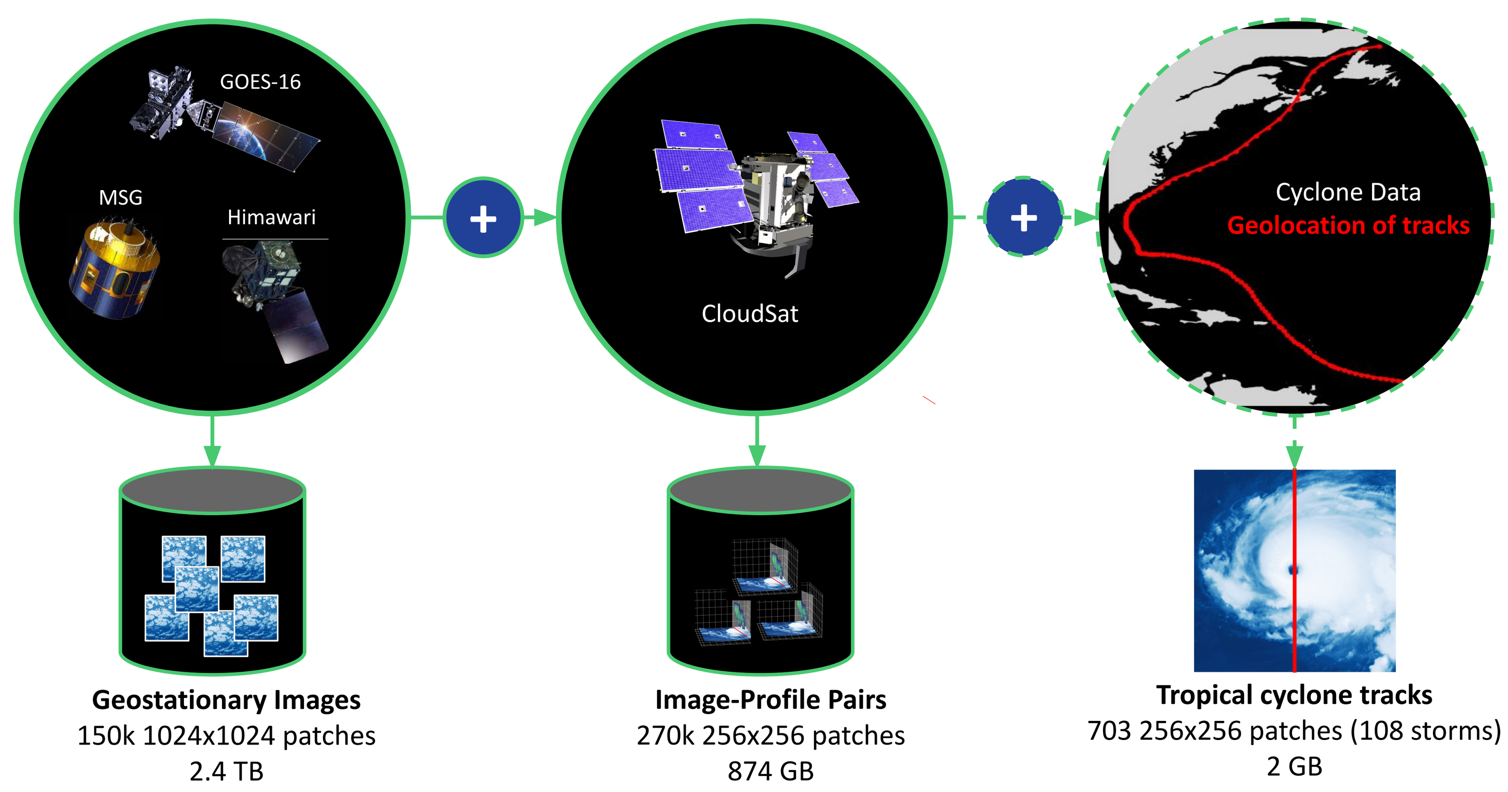

Fig. 1: Training set components. (a) Pre-training: Geostationary satellite images of 1024×1024 pixels, randomly cropped to 256×256 during training. (b) Fine-tuning: Aligned pairs of geostationary imagery and CloudSat profiles of cloud properties. (c) Evaluation dataset for tropical cyclones: Aligned geostationary image/CloudSat profile pairs that pass within 256 km of the centre of an active tropical cyclone.

3. MODEL & TRAINING

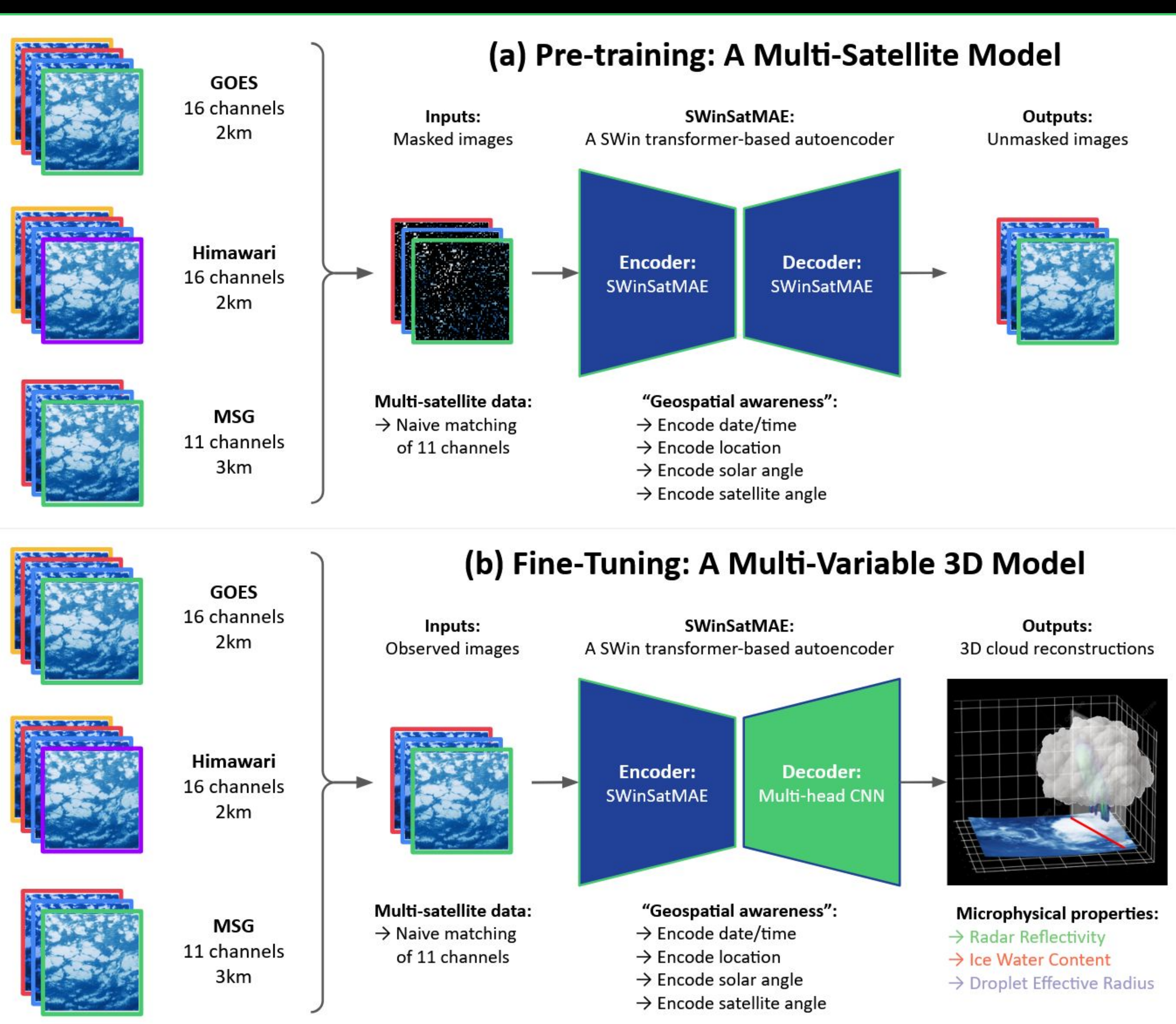

Fig. 2: SWinSatMAE. To create a consistent model input, the 11-closest channels from different sensors are matched. (a) Pre-training: Learn cloud structures by re-covering masked images. (b) Fine-tuning: Train a decoder to infer 3D microphysical properties – radar reflectivity, ice water content, droplet effective radius.

4. RETRIEVAL OF MICROPHYSICAL PROPERTIES

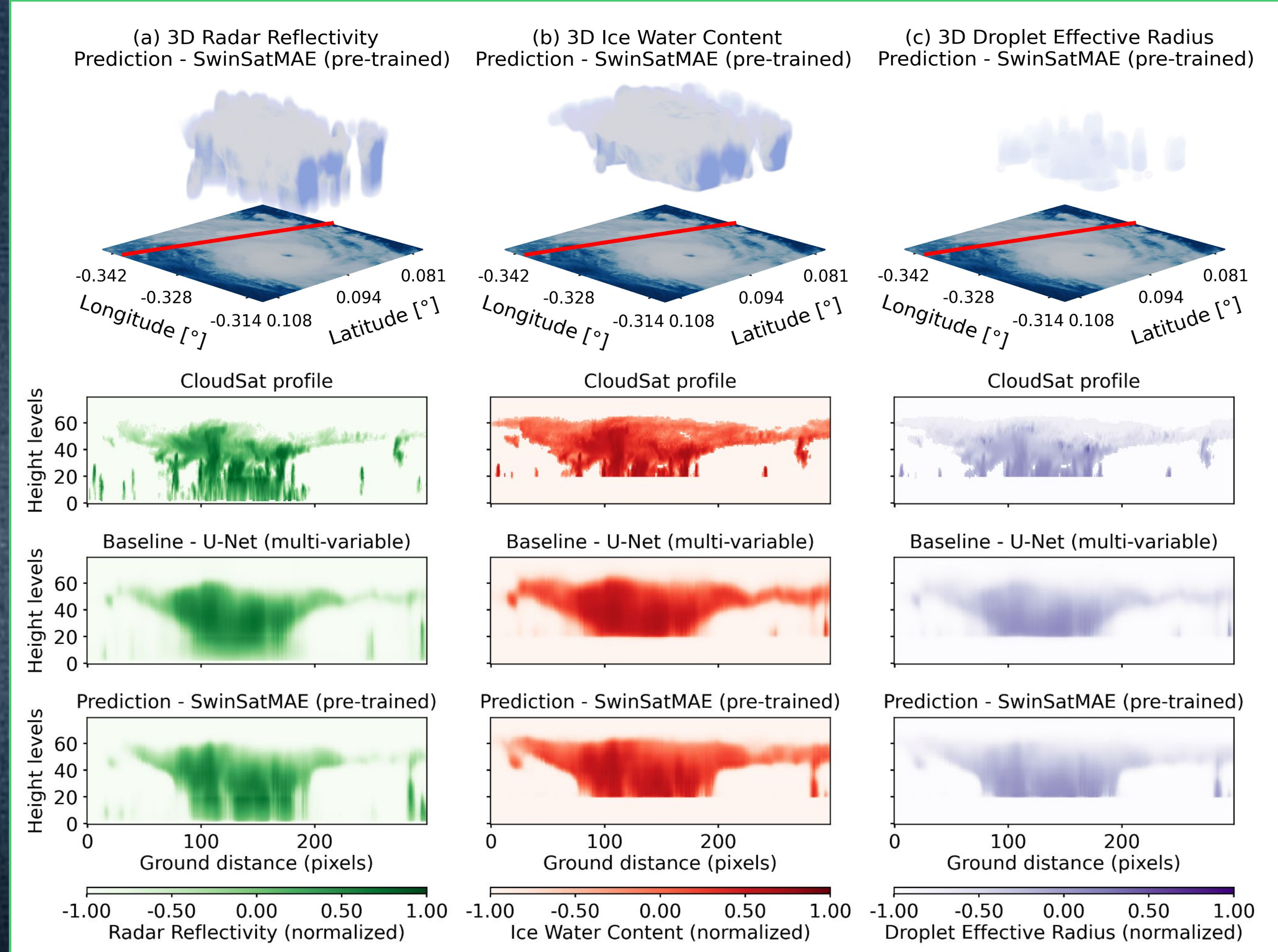

Fig. 3: 3D reconstructions of (a) radar reflectivity, (b) ice water content, (c) droplet effective radius by the SWinSatMAE model for TC Dorian. The geostationary image from GOES channel 7 is shown under each 3D render, with the location of the CloudSat track marked in red. Below it are the associated ClouSat retrievals along the track and the predictions from the baseline model and the SWinSatMAE model.

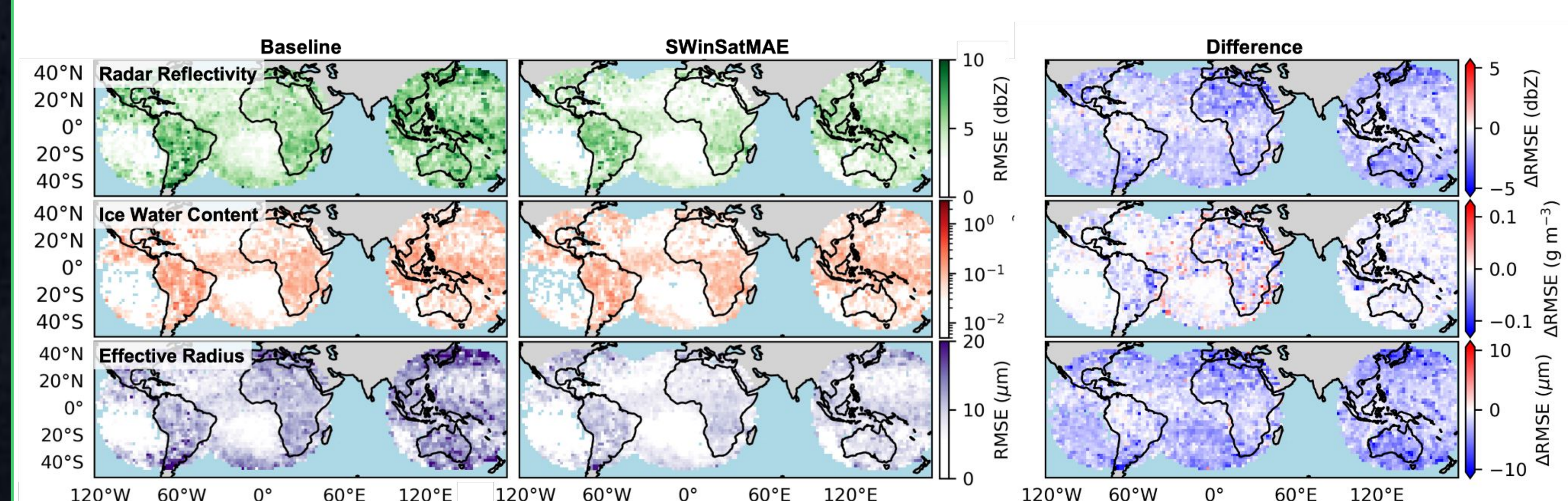

Fig. 4: Spatial distribution of the RMSE for the radar reflectivity (top), ice water content (middle), and droplet effective radius (bottom), as predicted by the baseline model (left) and the SWinSatMAE model (middle), along with their difference (right).

5. GLOBAL 3D RECONSTRUCTIONS

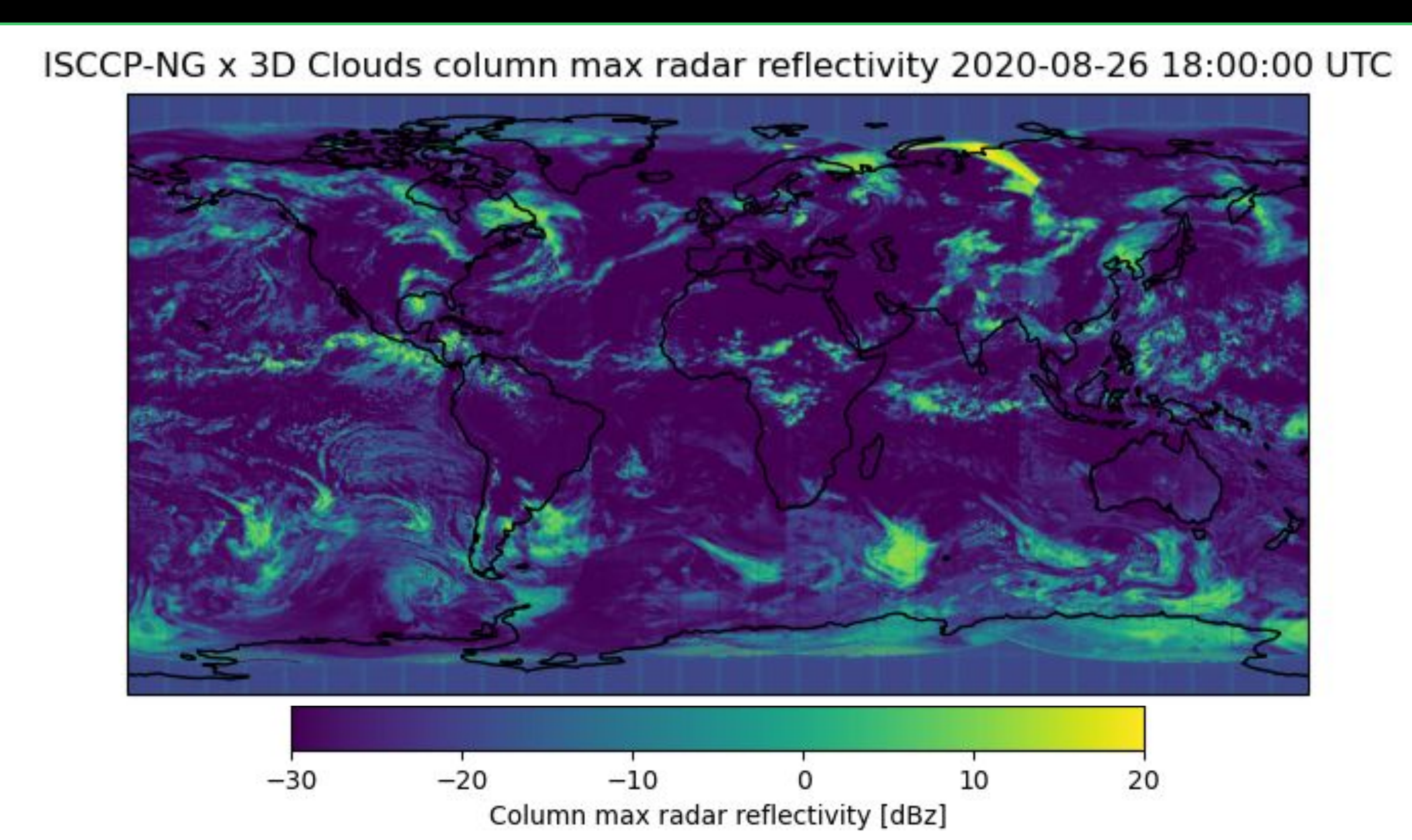

Fig. 5: The ISCCP-NG dataset combines imagery from 5 different geostationary satellites (GOES-16, GOES-17, Meteosat-11, Meteosat-9, Himawari-8) to provide near-global coverage on a 0.05° lat/lon grid. Applying SWinSaeMAE to this dataset enables the production of global, 3D retrievals of cloud properties, such as the column maximum radar reflectivity shown above. The model can also be applied to imagery from each individual satellite and then combined.

6. ACKNOWLEDGEMENTS

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