Studying the cloud layer detection from EarthCARE CPR to improve MSI cloud properties

Gregor Walter, Anja Hünerbein, Sebastian Bley, Andreas Macke

Leibniz Institute for Tropospheric Research, Leipzig, Germany

contact: walter@tropos.de

Introduction

Simplifications in cloud properties retrievals: 1D vs. 3D perspective

- The **Multi-spectral Imager (MSI)** retrieves **Level 2 cloud properties**, such as cloud optical thickness (COT) and cloud effective radius (CER), from captured radiances and brightness temperatures (BTs)
- **Passive sensor retrievals** assume clouds as **plane-parallel** and **homogeneous** and treat pixels **independently**, therefore neglecting vertical variability of clouds
- Complex cloud formations e.g multilayer systems can cause significant inaccuracies in imager-based cloud property retrievals (Fig. 1)
- By **combining MSI** with EarthCARE's active instruments (**CPR, ATLID**), nadir pixels can be linked to vertical atmospheric profiles
- Objectives:
  - **Reconstruction** of the **vertical cloud profile** using EarthCARE capabilities and **Deep neural networks** to develop an advanced **image generation algorithm**
  - **Maximize information** obtained from MSI and **improve accuracy** of retrievals

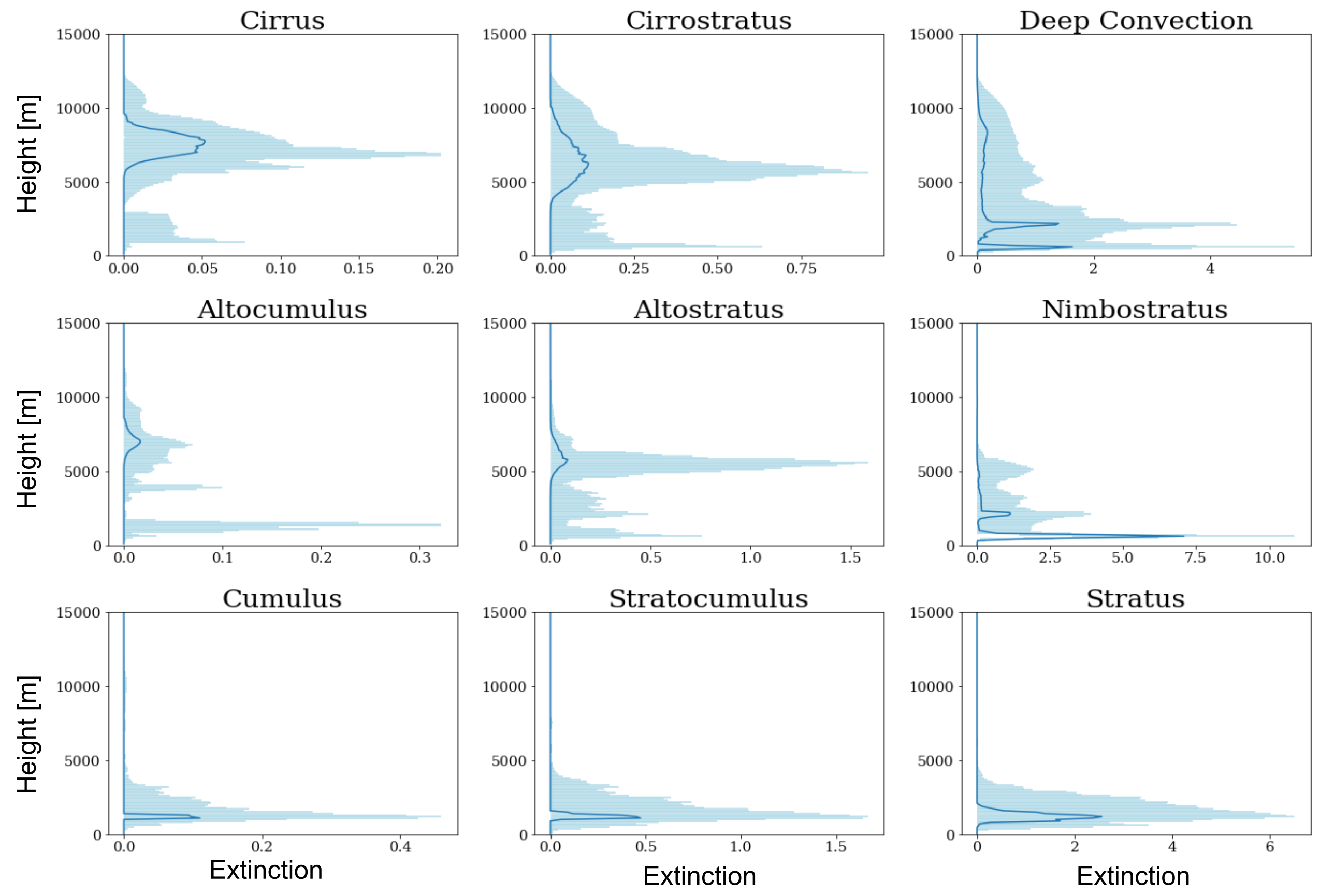

Fig. 1: Extinction profiles from Halifax scene, assigned to cloud types retrieved from MSI L2a algorithm (provided by Julian Bischay)

Method

Data: Leveraging MSI and CPR synergy

- MSI: Level 1 **reflectances** of **four solar channels** + **BTs** of **three thermal channels** with **0.5 km** spatial resolution
- CPR: Level 2 **corrected radar reflectivities** on joint standard grid (JSG) with **1.0 km along track resolution**

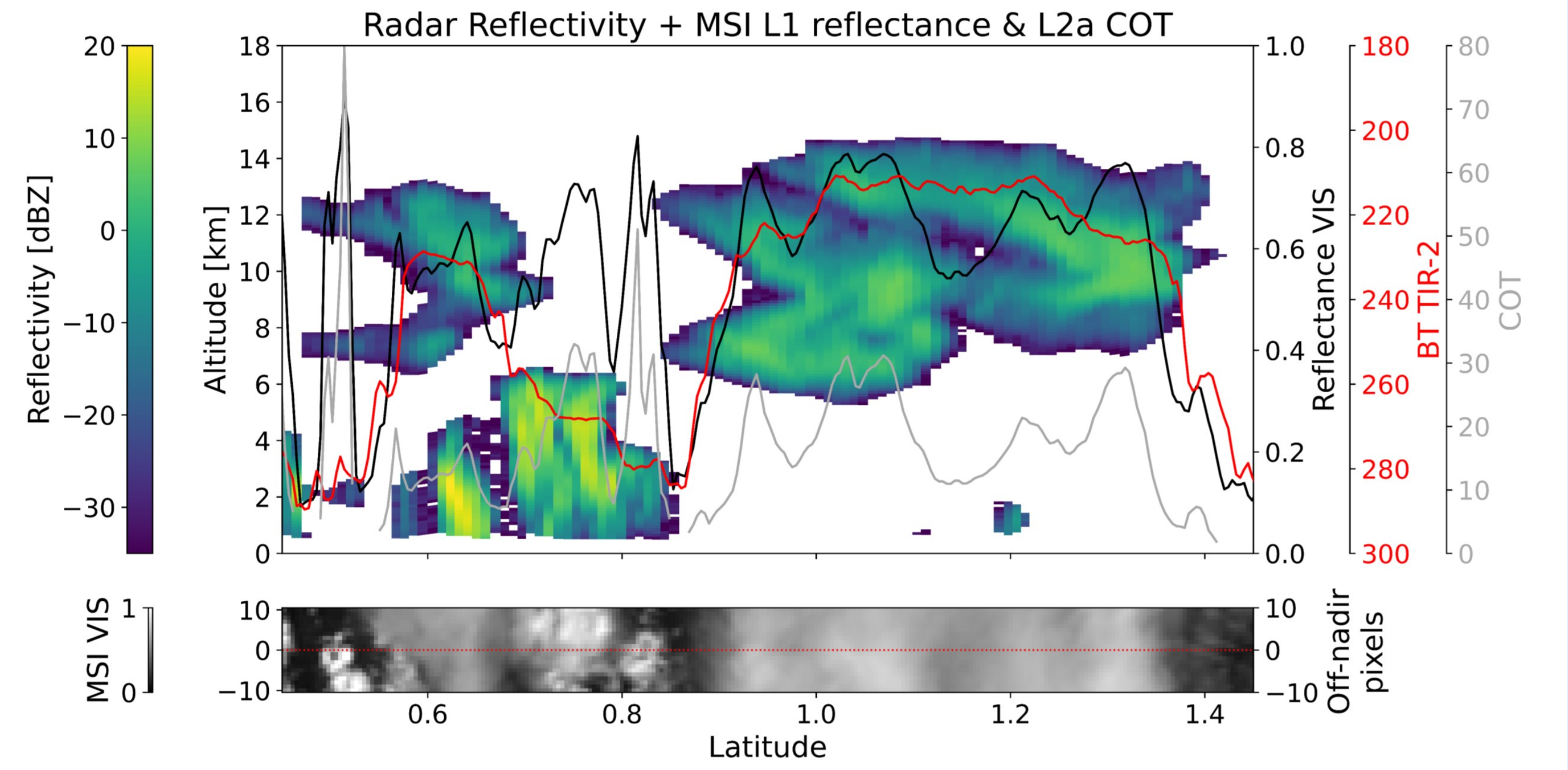

Fig. 2: Radar reflectivity (Kollias et al.) with corresponding nadir MSI reflectance (VIS), BT (TIR-2) and COT of Level 2a (Hünerbein et al.) from 01.01.2025 (03381E)

Data processing:

- Selection of usable cases: Ensure **high data quality** for **MSI** and **CPR** + select only **ocean** pixels and avoid **sunglint**
- Image processing:
  - Align MSI pixels to JSG to generate radar-imager pairs
  - Create **128x128 pixel images** of **radar reflectivity**
  - **Normalization** of input

Train the model:

- General concept:

  Train the model using **MSI** and **CPR** data to **reconstruct cloud profiles** for the full **MSI swath**
- Algorithm development:

  Deep learning model with **convolutional layers** to extract **image features**

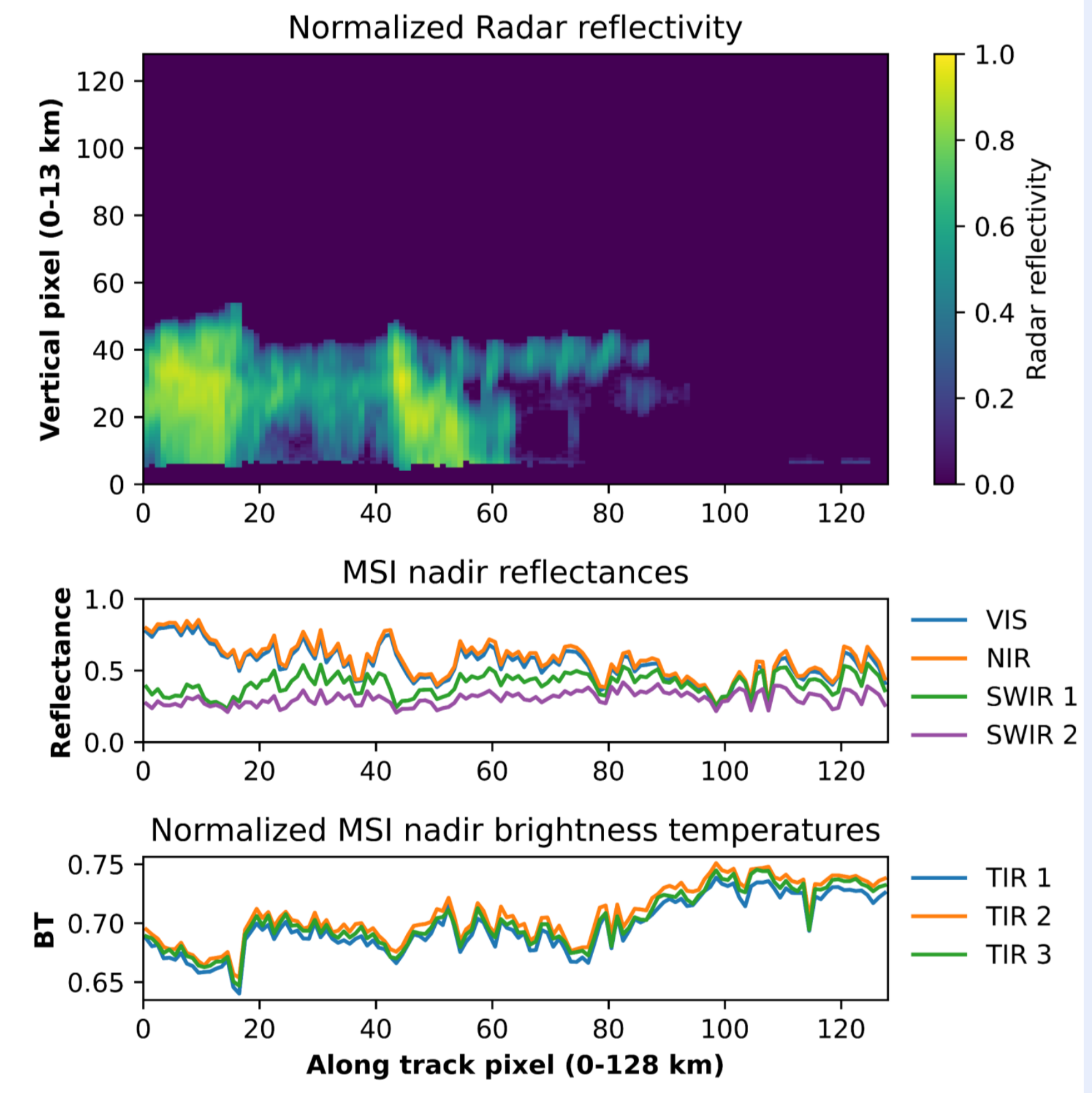

Fig. 3: Example of input data for algorithm training

Challenges:

- Off-nadir pixels: Account for **impact** from **neighbouring pixels**
- Shallow cumulus clouds: Consider **detection limits** by **CPR**
- Cloud Top Height: **Improved accuracy** with **temperature profile**

Cloud reconstruction

Comparison of Deep Learning techniques

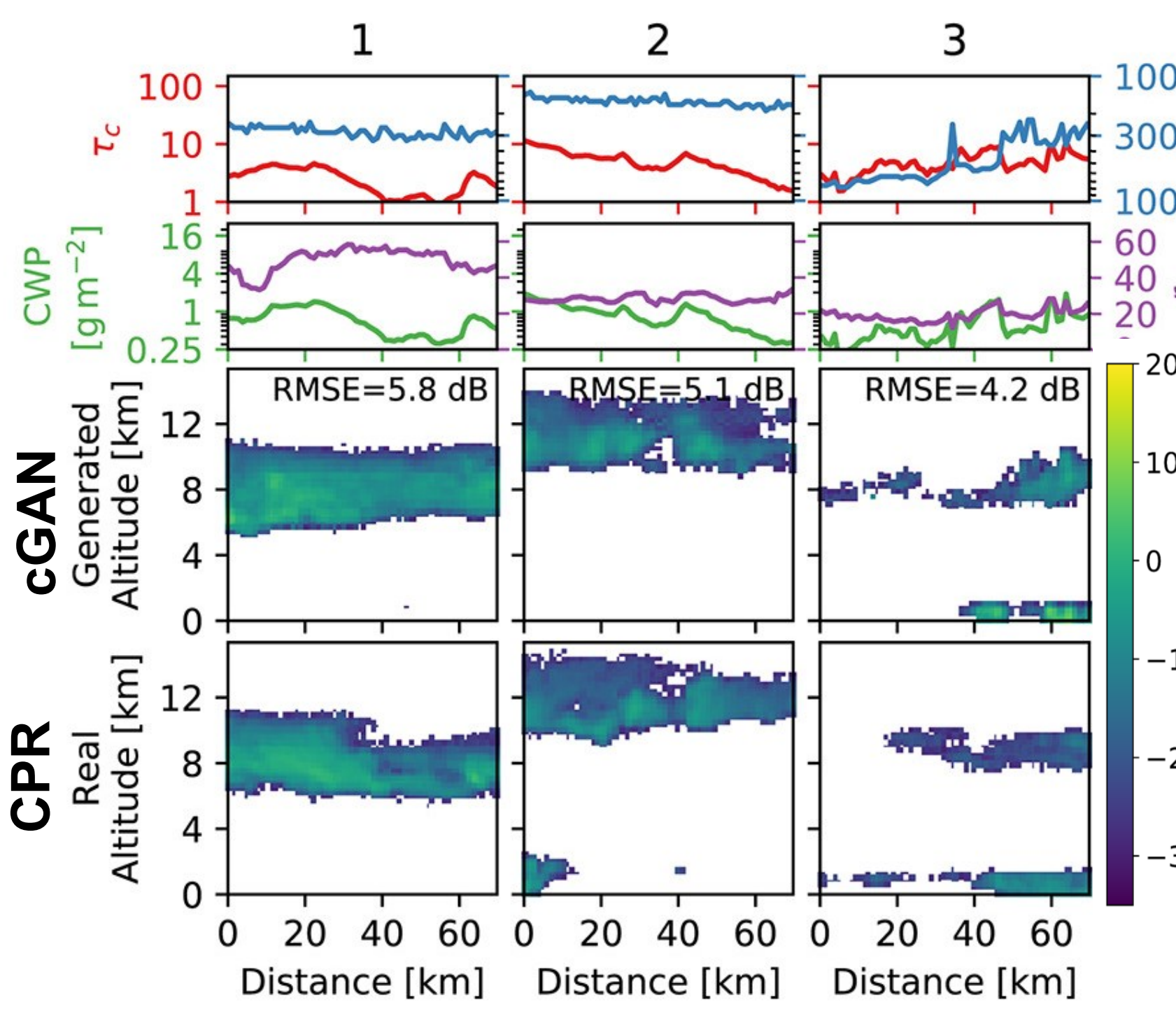

Fig. 4: cGAN cloud reconstruction using MODIS and Cloudsat by Leinonen et al., 2019

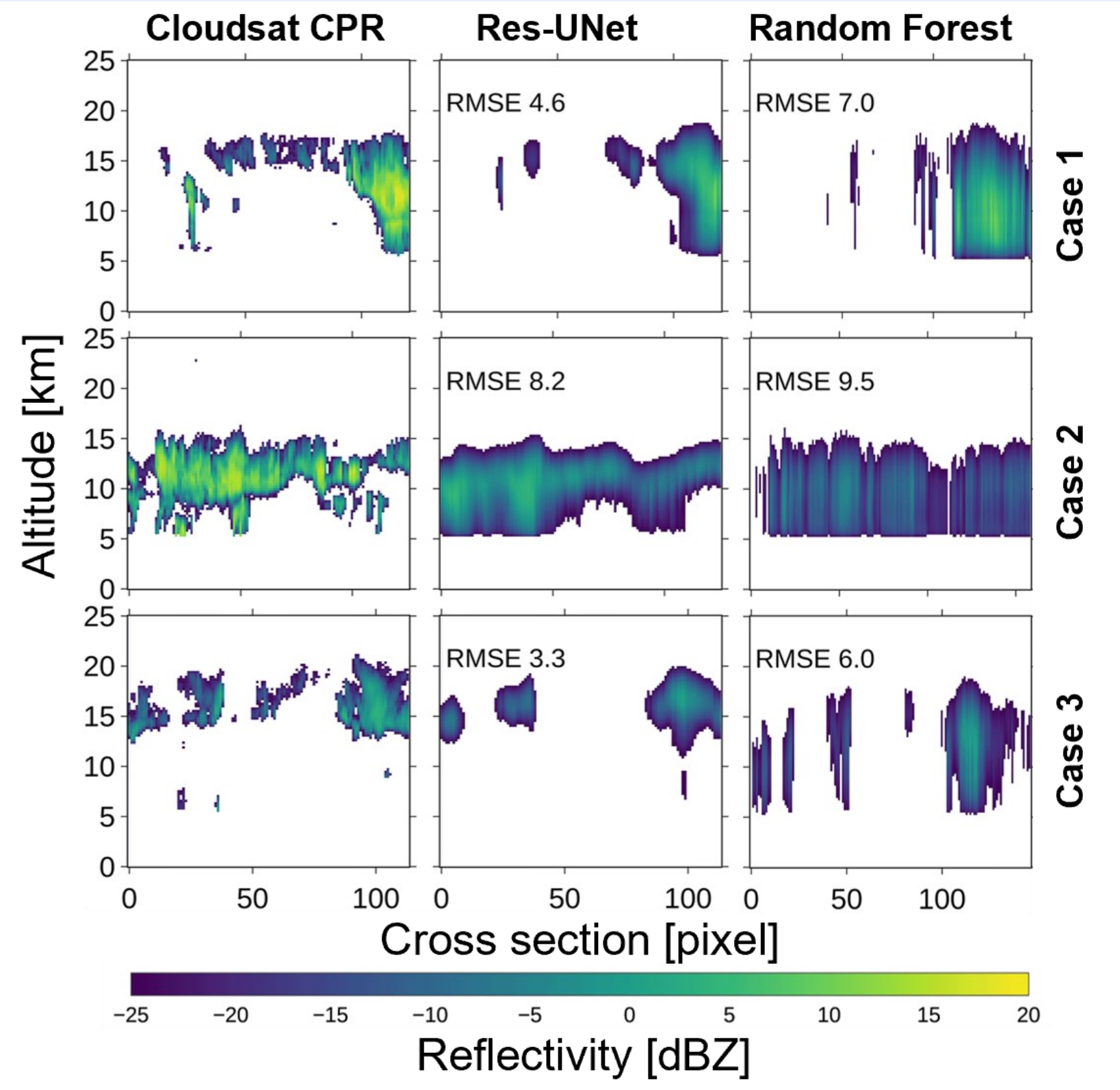

Fig. 5: Res-UNet cloud reconstruction with SEVIRI and Cloudsat by Brüning et al., 2024

Conditional Generative Adversarial Network (cGAN):

- **Generator** creates **fake images**
- **Discriminator** tries to **detect** them
- Training improves the Generator to create realistic images and the discriminator to detect fakes
- Surpassed by new developments

Res-UNet:

- **Encoder**: sequential down-sampling captures features on different levels
- **Decoder**: Reconstruction by up-sampling
- **Residual connections**: Input allowed to skip layers for more effective training
- Brüning et al., 2024 generate 3d cloud profiles with consideration of neighbouring pixels for predictions

➡ Reconstruction of vertical cloud profiles with imagers is feasible

New approaches

- Fast moving field: New machine learning methods have to be considered
- Diffusion models: Add noise to images and learn from the loss of information to generate new images

  Potential improvements over cGANs

Outlook

- **Choice** of **exact training method** is yet to be decided
- **Large amount** of high quality EarthCARE **data** will be required
- **Ice** and **liquid water content** retrieved from **both active instruments** in **ACM-CAP** (Mason et al.) as **input** instead of radar reflectivity

References

Hünerbein, A., Bley, S., Deneke, H., Meirink, J. F., van Zadelhoff, G. J., & Walther, A. (2024). Cloud optical and physical properties retrieval from EarthCARE multi-spectral imager: the M-COP products. Atmospheric Measurement Techniques, 17(1), 261-276. **Kollias, P.**, Puidgomènech Treserras, B., Battaglia, A., Borque, P. C., & Tatarevic, A. (2023). Processing reflectivity and Doppler velocity from EarthCARE's cloud-profiling radar: the C-FMR, C-CD and C-APC products. Atmospheric Measurement Techniques, 16(7), 1901-1914. **Leinonen, J.**, Guillaume, A., & Yuan, T. (2019). Reconstruction of cloud vertical structure with a generative adversarial network. Geophysical Research Letters, 46(12), 7035-7044. **Brüning, S.**, Niebler, S., & Tost, H. (2024). Artificial intelligence (AI)-derived 3D cloud tomography from geostationary 2D satellite data. Atmospheric Measurement Techniques, 17(3), 961-978. **Mason, S. L.**, Hogan, R. J., Bozzo, A., & Pounder, N. L. (2023). A unified synergistic retrieval of clouds, aerosols, and precipitation from EarthCARE: the ACM-CAP product. Atmospheric Measurement Techniques, 16(13), 3459-3486.