This presentation participates in OSPP

Outstanding Student & PhD candidate Presentation contest

DEEP LEARNING-BASED GENERATION OF 3D CLOUD STRUCTURES FROM GEOSTATIONARY SATELLITE DATA

Sarah Brüning[1](sbruenin@uni-mainz.de), Stefan Niebler[2] & Holger Tost[1]
EGU 2023, Session ITS1.14/CL5.8
Institute for Atmospheric Physics[1], Institute of Computer Science[2], Johannes Gutenberg-University Mainz, Germany

1 Introduction

As changes in the environment are already noticeable and clouds are known to significantly influence the earth's energy budget and hydrological balance [1], deriving connected dynamics is today more important than ever [2]. That said, clouds can be characterized as one of the **most important yet most minor well-understood** climate feedback [3]. This study aims to **bring together spatial information** from different remote sensing sources needed for a gain in knowledge [4] to **improve the quality of information** in data-sparse regions and, finally, the further advance of climate science.

2 Methods

With the help of a **Deep-Learning** approach, a high-resolution **3-D cloud tomography** is inferred for the area of interest (AOI) comprising a domain between 60° in all directions (NSEW) [5]. For that purpose, a spatio-temporal matching scheme is used to generate training samples. Those are fed into the network to reconstruct (1) the vertical distribution of volumetric radar data along the pixel-based cloud column and (2) infer those cloud structures to the image extent (Fig. 1). The study is based on **two sources**: input data from **Eumetsat's MSG SEVIRI** geostationary satellite and ground truth from **CloudSat's CloudProfilingRadar (CS CPR)**.

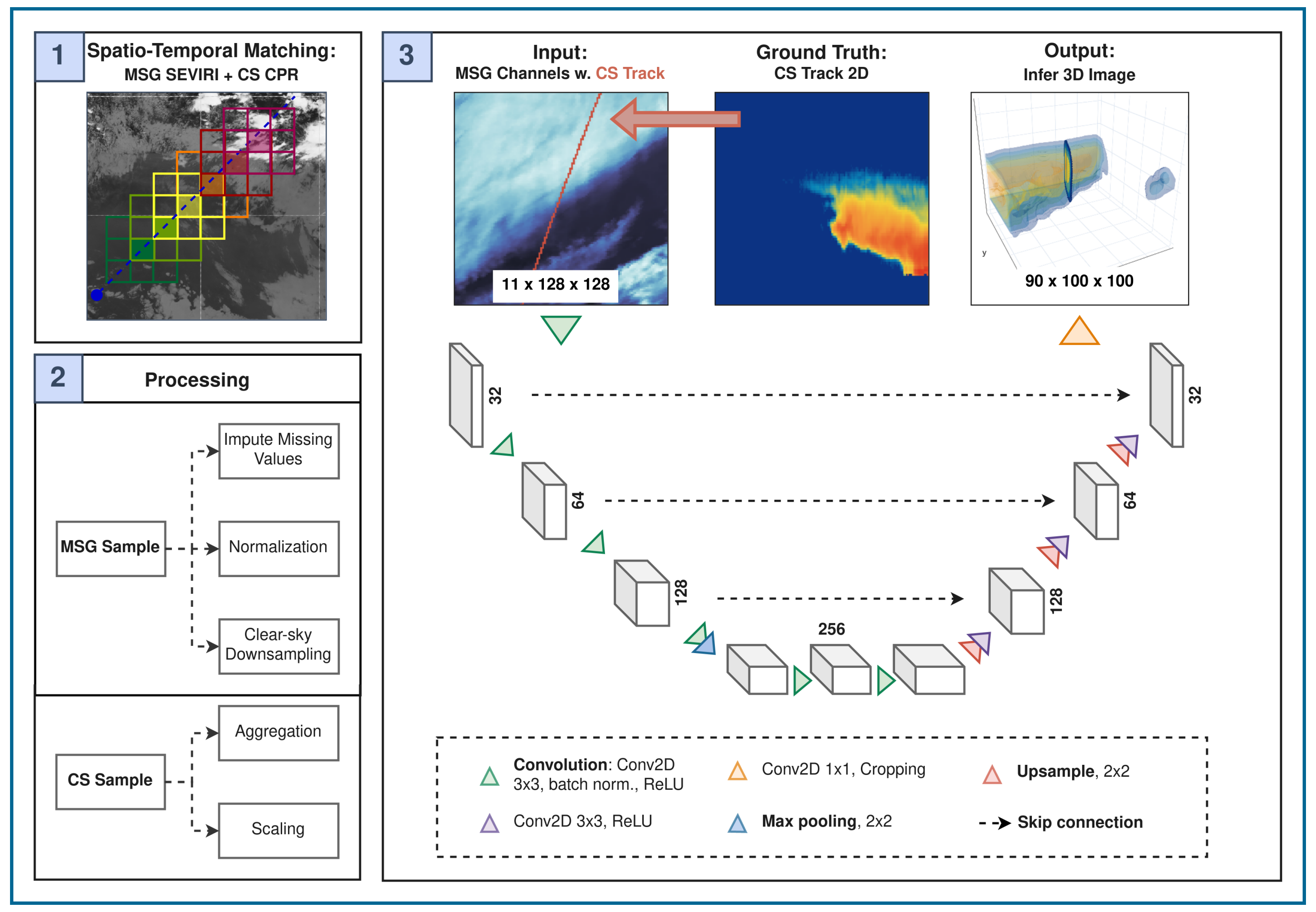

Fig. 1: Workflow scheme of the data processing and the modeling routine using a Res-UNet.

3 Results

3.1 Model Performance

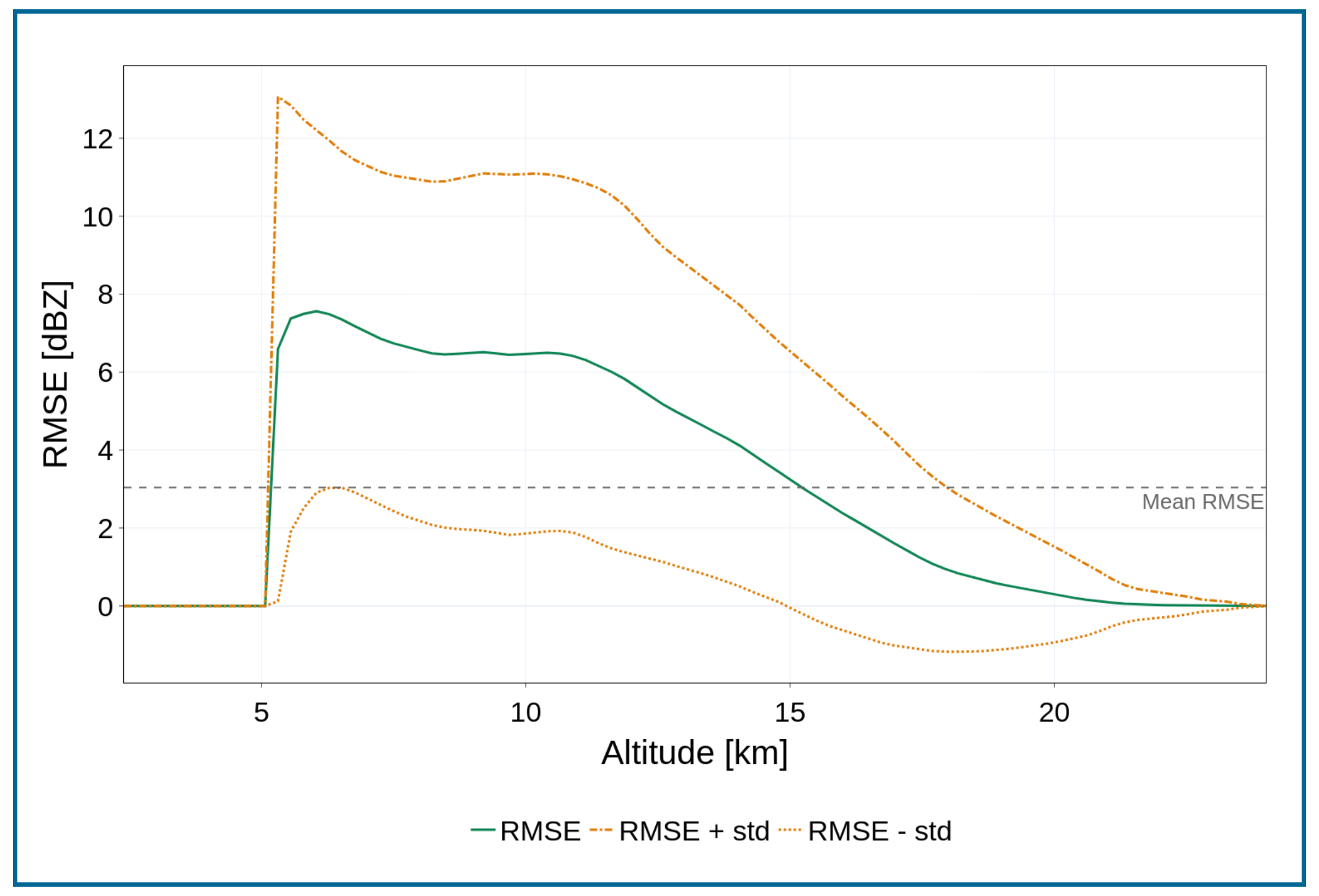

Fig. 2: Computed RMSE for the validation dataset on all altitudes between 2.4 and 24 km (Mean RMSE: 2.99 dBZ).

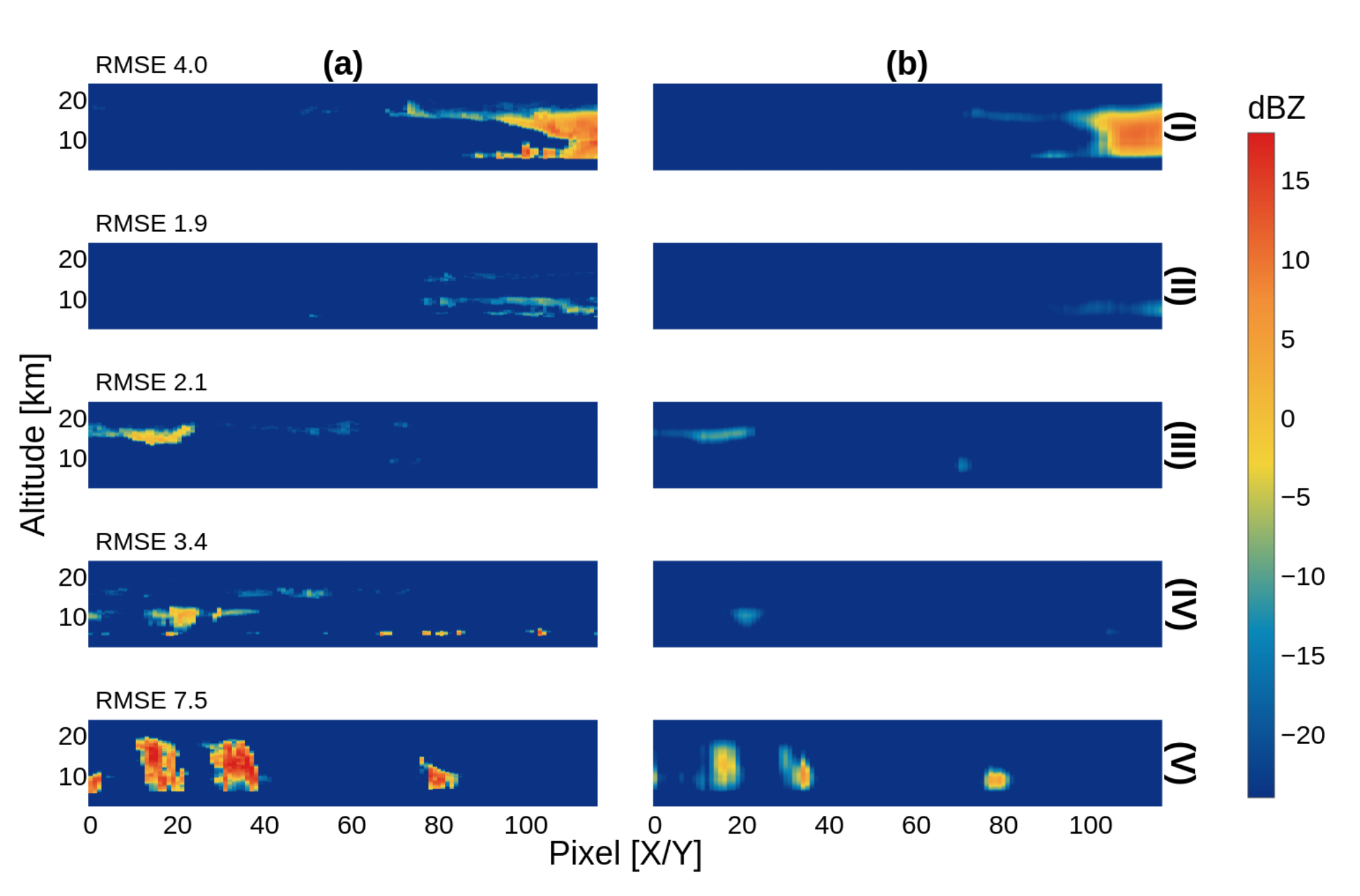

Fig. 3: Vertical reconstruction of the diagonal radar track for observed **(a)** and predicted **(b)** samples **(I)** - **(V)**.

3.2 Multiscale Predictions

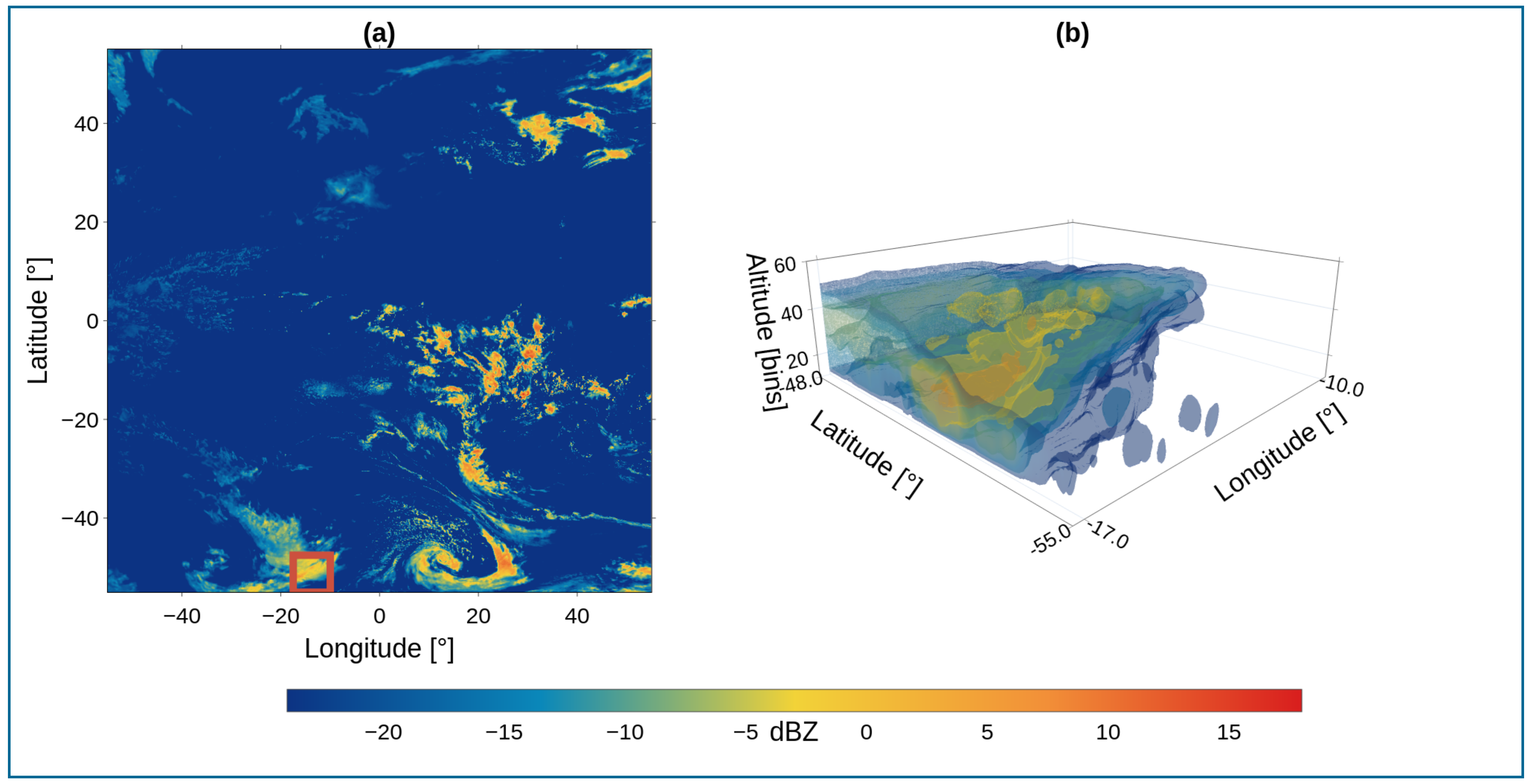

Fig. 4: Prediction of three-dimensional cloud structures on the MSG SEVIRI AOI (01.05.2016, 12 UTC). Scene **(a)** shows a top-view on the maximum cloud column reflectivity per pixel. Zooming in the red square with an extent of 150 x 150 pixels **(b)** demonstrates the absence of subset boundaries.

3.3 Sample Application: Cloud Top Height (CTH)

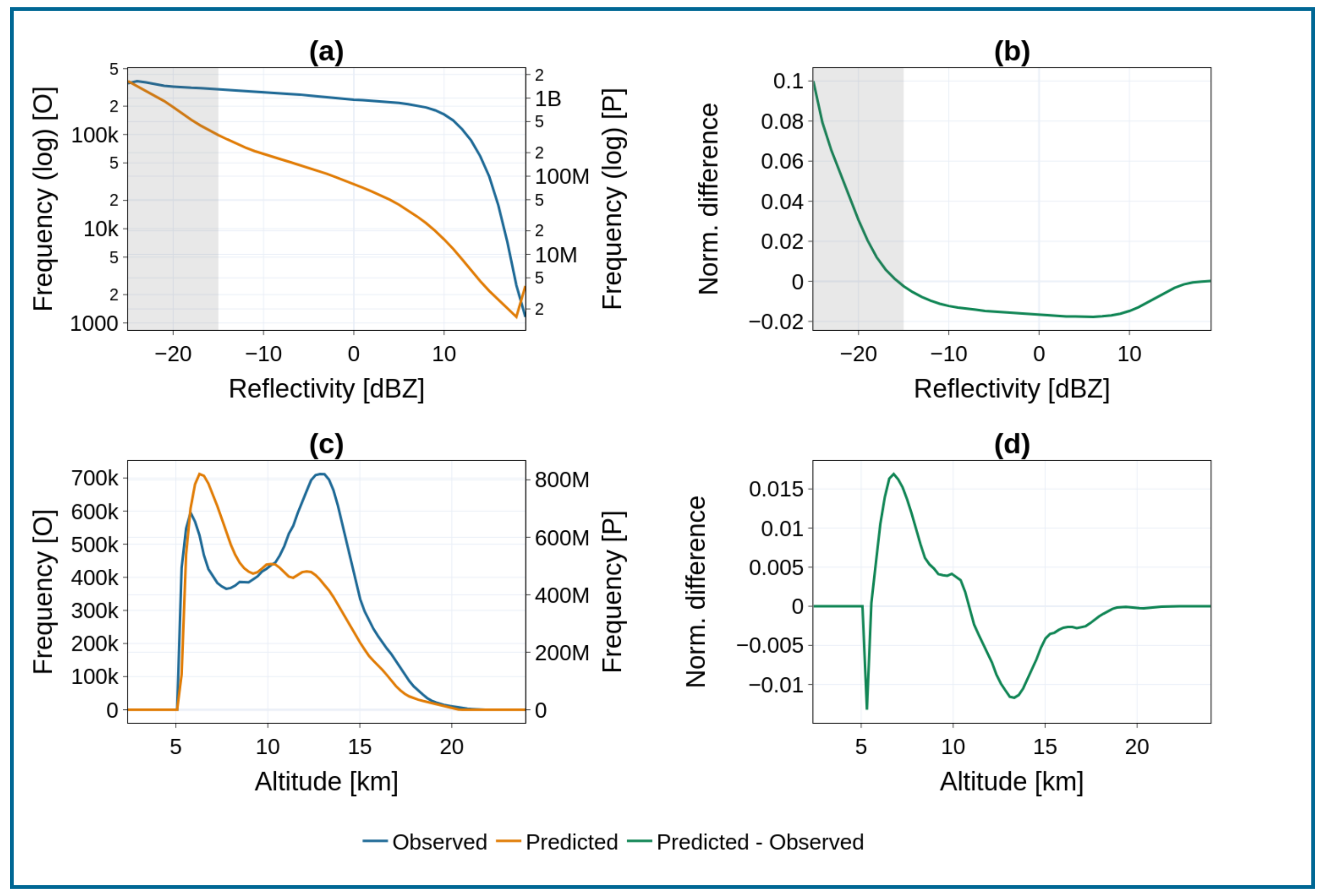

Fig. 5: Frequency distribution from the CS CPR and the model for the reflectivity in dBZ **[(a), (b)]** and the CTH using a threshold of -15 dBZ **[(c), (d)]** for May, 2016. Grey areas are cloudfree.

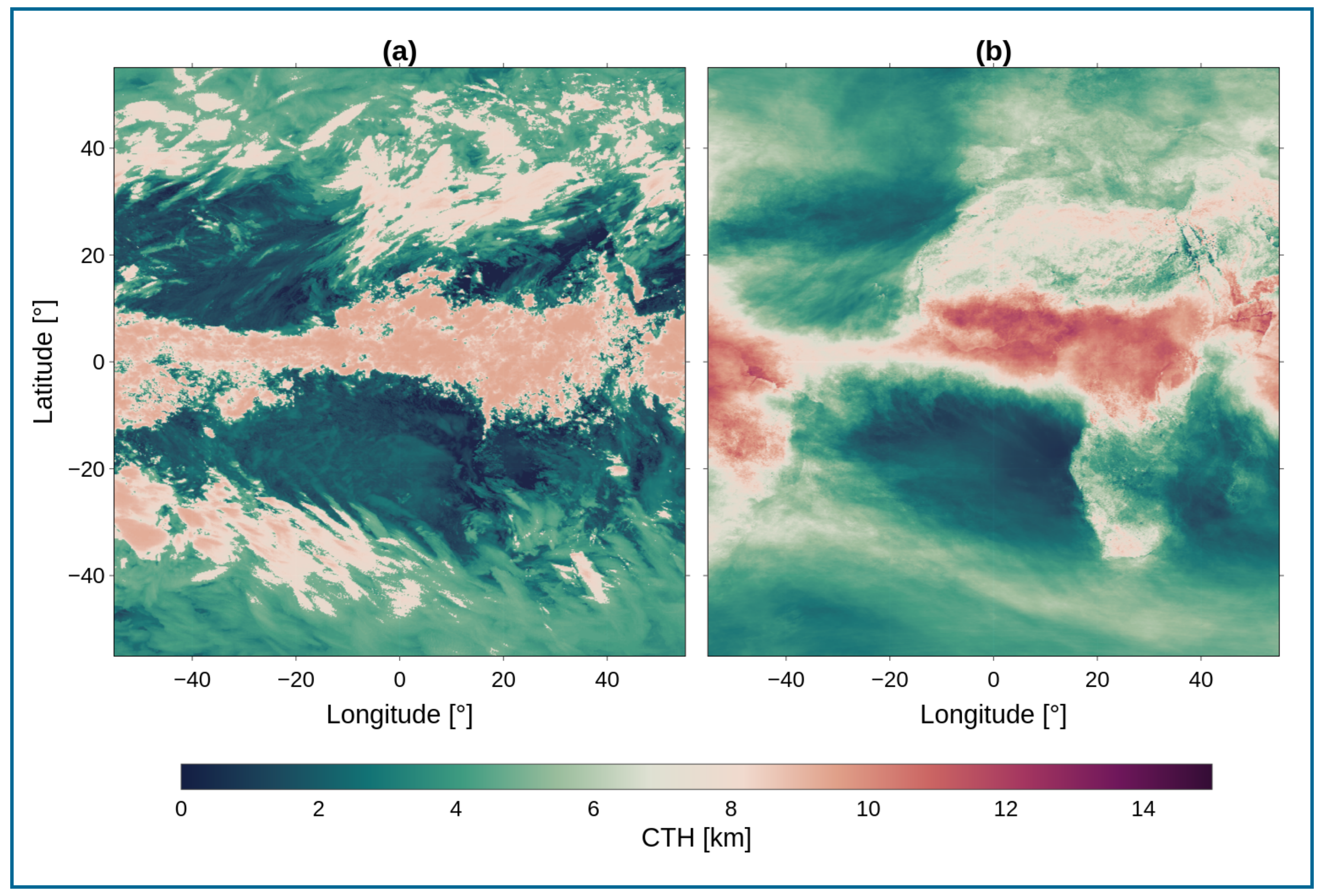

Fig. 6: Comparison between the aggregated model CTH **(a)** and the CLAAS-V003E1 CTO product **(b)** for May, 2016, on the MSG SEVIRI AOI.

4 Outlook

Current results confirm the ability of neural networks to infer **3D clouds from 2D geostationary satellite data** comprehensively. An overall high agreement between observed and predicted data emphasizes the approach's feasibility and potential for use in climate science applications dealing with **multiscale cloud properties** and associated environmental dynamics.
In the next step, the added benefit of the derived data for investigating climate feedback mechanisms will be evaluated in proceeding applications.

References

1. Stevens, B. & Bony, S. What Are Climate Models Missing? *Science* **340,** 1053–1054 (2013).
2. Rasp, S., Pritchard, M. S. & Gentine, P. Deep learning to represent sub-grid processes in climate models. *PNAS* **115,** 9684–9689 (2018).
3. Bony, S. *et al.* Clouds, circulation and climate sensitivity. *Nat. Geosci.* **8,** 261–268 (2015).
4. Reichstein, M. *et al.* Deep learning and process understanding for data-driven Earth system science. *Nature* **566,** 195–204 (2019).
5. Leinonen, J., Guillaume, A. & Yuan, T. Reconstruction of Cloud Vertical Structure With a Generative Adversarial Network. *Geophys. Res. Lett.* **46,** 7035–7044 (2019).

Acknowledgements

The study is supported by the project "Big Data in Atmospheric Physics (BINARY)", funded by the Carl-Zeiss-Stiftung. We acknowledge the infrastructure provided by the Max Planck Graduate Center Mainz. We acknowledge EUMETSAT, the Cooperative Institute for Research in the Atmosphere (CSU) and CM SAF for providing access to imagery data and derived cloud products.

Abstract

Further information on this study's **abstract** can be obtained following this **QR-Code**.