AI-derived 3D cloud tomography from geostationary 2D satellite data

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Abstract. Satellite instruments provide high-temporal-resolution data on a global scale, but extracting 3D information from current instruments remains a challenge. Most observational data is 2D, offering either cloud top information or vertical profiles. We trained a neural network (Res-UNet) to merge high-resolution satellite images from MSG SEVIRI with 2D CloudSat radar reflectivities to generate 3D cloud structures. The Res-UNet extrapolates the 2D reflectivities across the full disk of MSG SEVIRI, enabling a reconstruction of the cloud intensity, height, and shape in 3D. The imbalance between cloudy and clear-sky CloudSat profiles results in an overestimation of cloud-free pixels. Our RMSE accounts for 2.99 dBZ. This corresponds to 6.6 % error on a reflectivity scale between -25 and 20 dBZ. While the model aligns well with CloudSat data, it simplifies multi-level and mesoscale clouds, in particular. Despite these limitations, the results can bridge data gaps and support research in climate science such as the analysis of deep convection over time and space.

1 Introduction

Clouds and their interdependent feedback mechanisms have been a source of uncertainty in Earth system models for decades. As they influence different spheres of the environment, their accurate representation is needed for an improved understanding

~~of interconnected dynamics (Norris et al., 2016; Stevens and Bony, 2013; Vial et al., 2013). Although their connection~~ Their influence to atmospheric gases and general circulation patterns is evident ~~, further quantification is required~~ (Rasp et al., 2018; Shepherd, 2014; Bony et al., 2015). ~~The pressing need to adapt society to climate changeemphasizes the need for reliable data~~ In a world affected by climate change, we require an accurate representation of cloud dynamics today more than ever ~~(Dubovik et al., 2021)~~(Norris et al., 2016; Stevens and Bony, 2013; Vial et al., 2013).

In recent years, observational data from remote sensing instruments ~~have been proven reliable in investigating~~ has been used to investigate cloud properties on multiple scales (Jeppesen et al., 2019). ~~Although these approaches drove research forward~~Nevertheless, techniques to detect three-dimensional (3D) cloud structures ~~still need to be developed (Bocquet et al., 2015). While passive sensors like geostationary satellites~~ on a large-scale are not yet established (Bocquet et al., 2015). Observations from passive sensors on geostationary satellites have a high spatio-temporal coverage, but they are limited to monitor the upper-most atmospheric layer ~~from space with a two-dimensional~~ in two-dimensions (2D) ~~output (Noh et al., 2022)~~(Noh et al., 2022).

By using the satellite's specificity at different wavelengths (Thies and Bendix, 2011), and subjective labeling or fixed thresholds (Platnick et al., 2017), we can estimate cloud physical properties like the cloud optical thickness (Henken et al., 2011) or the effective radius (Chen et al., 2020). In contrast, active radar penetrates the cloud top and delivers ~~detailed~~ information on the subjacent reflectivity distribution (Barker et al., 2011). The ~~latter provides a thorough but spatially and temporally limited perspective (Wang et al., 2023). An approximation of cloud physical properties like the cloud optical thickness, the effective radius, or the cloud water path is obtainable using the satellite's specificity at different wavelengths (Thies and Bendix, 2011; Platnick et al., . While this analysis often rests upon subjective labeling or fixed thresholds, it is under the risk of bias (Stubenrauch et al., 2013). Besides, passive sensors lack the inherent sensitivity to detect information from deep within cloud layers to accurately differentiate cloud types (Noh et al., 2022). At this point, combining~~ radar receives detailed information on the cloud column along a 2D cross section with a high ground resolution and constant sun illumination. Due to its sun-synchronous orbit, it observes the same spot at the same local time. Compared to geostationary satellites, the active radar does not provide a continuous spatial and temporal coverage (Wang et al., 2023). Passive sensors can be used to deliver an approximation of the cloud vertical column, but their information density is reduced compared to active sensors (Noh et al., 2022). Combining data sources can ~~substantially leverage the quality of analysis (Amato et al., 2020; Steiner et al., 1995). A joined~~ fill current data gaps (Amato et al., 2020; Steiner et al., 1995). The combined use of different instruments ~~to derive comprehensive 3D structures~~ has been investigated before~~either by~~. This research comprises the usage of statistical algorithms (Miller et al., 2014; Seiz and Davies, 2006; Noh et al., 2022), the integration of radiative transfer approaches (Forster et al., 2021; Zhang et al., 2012), or the derivation of the multi-angle geometry of neighboring clouds (Barker et al., 2011; Ham et al., 2015) ~~. The large-scale generability of these methods is expandable since their 3D results are limited to the cloud's spatial vicinity (Leinonen et al., 2019). To this day, no interpolation of~~ to reconstruct the cloud vertical column~~to a large-scale, supra-regional perspective exists (Wang et al., 2023; Dubovik et al., 2021)~~.

Emerging facilitators of data availability, like open-data policies and improved technological standards, ~~open up unforeseen possibilities (Jeppesen et al., 2019; Liu et al., 2016; Reichstein et al., 2019). These developments promote~~ enable effective processing of memory-consuming data (Irrgang et al., 2021; Rasp et al., 2018). This development promotes a further integration of com-

puter science methods in climate science (Jeppesen et al., 2019; Liu et al., 2016). Ever-growing quantities of data surpass the capability of the human mind to extract explainable information efficiently (Lee et al., 2021; Karpatne et al., 2019). Here, the usage of artificial intelligence (AI) has been assigned a primary role (Runge et al., 2019). Cloud properties have been analyzed before by Machine Learning (ML) algorithms (Reichstein et al., 2019; Marais et al., 2020). The recent technological advances enable unprecedented operations (Amato et al., 2020). Deep-Learning (DL) based networks are suitable to identify spatial, spectral, and temporal patterns and their adaptation on big data (Jeppesen et al., 2019; Hilburn et al., 2020). In contrast to traditional ML frameworks, they do not require manual feature engineering (Le Goff et al., 2017). Adapting DL frameworks to applications in climate science offer new perspectives for a gain in knowledge (Rolnick et al., 2022; Jones, 2017).

So far, cloud properties have been investigated by DL algorithms in various applications. These comprise the detection (Drönner et al., 2018) and segmentation of cloud fields (Jeppesen et al., 2019; Lee et al., 2021; Le Goff et al., 2017; Tarrio et al., 2020), or the classification of distinct cloud types from meteorological satellites and aerial imagery (Marais et al., 2020; Wang et al., 2023). Zantedeschi et al. (2022) used a neural network to bring together information from an active radar and high resoluted satellite image data to reconstruct cloud labels. Regressive models were used to predict rain rates (Han et al., 2022) or convective onset (Pan et al., 2021) for an improved weather forecast. These studies are often limited to reflect horizontal processes within the cloud field. Current studies by Hilburn et al. (2020) and Leinonen et al. (2019) use AI techniques such as convolutional neural networks (CNN) and conditional generative adversarial networks (CGAN) to address this issue. They reconstruct the 1D cloud column (Hilburn et al., 2020) or the 2D cross section of the input data (Wang et al., 2023). To our best knowledge, no extrapolation of 2D radar data to a large-scale 3D perspective was conducted before (Wang et al., 2023; Dubovik et al., 2021). Clouds move within a 3D space. This limits the prediction of multi-layer and mesoscale events by a 1D or 2D pixel-wise reconstruction (Hilburn et al., 2020). Models that do not consider the spatial coherence between pixels fail to reconstruct comprehensive cloud structures (Hu et al., 2021). Image segmentation approaches like the UNet (Ronneberger et al., 2015; Jiao et al., 2020; Wieland et al., 2019) may reconstruct the ground truth data more adequately. They can be used to provide the indicators for predicting clouds in 3D with

its adjacent boundaries, shadow locations, and geometries ~~. Defining each cloud as a connected entity~~ (Wang et al., 2023).

95 This can lead to a more realistic representation of the ~~actual distribution of clouds and their interactions around the globe (Jiao et al., 2020; Hu et al., 2021; Wang et al., 2023)~~predicted clouds (Jiao et al., 2020).

~~This study combines the benefits of active and passive instruments by~~ In this study, we employ a modified Res-UNet (Diakogiannis et al., 2020; Hu et al., 2021) to ~~reconstruct the~~ integrate 2D data from active (polar orbiting satellite, radar) and passive (geostationary satellite, spectrometer) instruments to reconstruct a 3D ~~vertical cloud column of volumetric radar data~~

100 ~~from 2D geostationary satellite~~data. ~~In contrast to former studies focusing on the pixel-based perspective along the radar track, the spatial connectivity between individual pixels is preserved~~ cloud field. Previous studies focused on reconstructing the 1D cloud column or 2D cross section. In contrast, our approach utilizes a DL framework to predict the ~~results for the spatial extent of the input image and infer them to a large-scale area on the~~ radar reflectivity not only along the radar cross section but across the entire satellite full disk (FD). We use the radar height levels to extend 2D satellite channels into a 3D perspective.

105 The goal is to ~~derive~~ establish a spatio-temporal consistent cloud tomography ~~based exclusively on real-world data. This information can be used to improve the availability and quality~~ solely based on observational data. Predicted reflectivities can enhance the availability of 3D resolved cloud structures, ~~especially in data-sparse regions , and their further investigation in a hydro-climatological context~~particularly in regions with limited data.

2 Methods

110 ### 2.1 Data overview

Our approach uses observational data from two different remote sensing sensors to predict a 3D cloud tomography. The input data for the ~~network originates~~ neural network originates from a geostationary satellite. We use data from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Spinning Enhanced Visible and InfraRed Imager (SEVIRI) instrument on the Meteosat Second Generation (MSG) satellite (EUMETSAT Data Services, 2023). This sensor

115 observes the Earth ~~surface from space providing~~ from a height of 36000 km and provides 2D image data in a high spatial and temporal resolution. The ground truth of the study is derived from an active radar ~~orbiting the globe on a sinusoidal track (CloudSat Data Processing Center, 2023). It receives~~ on board the CloudSat satellite which moves on a sun-synchronous orbit (CloudSat Data Processing Center, 2023). The 2D profiles along the track contain information on the cloud reflectivity~~during this flight, point by point, which are combined into vertical profiles. Here~~. In our study, we feed the ~~satellite data into the~~

120 ~~model to delineate the relationships needed to accurately reconstruct these profiles~~MSG SEVIRI data into a neural network to reconstruct the CloudSat radar reflectivity and extrapolate the 2D profiles to a 3D perspective.

2.1.1 ~~Satellite~~ Geostationary satellite data

~~Data from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Spinning Enhanced Visible and InfraRed Imager (SEVIRI) instrument on the Meteosat Second Generation (MSG) satellite~~ Image data from

Table 1. Overview of MSG SEVIRI channels (Schmetz et al., 2002).

Channel	Center (μm)	Range (μm)	Solar (reflectance)
VIS0.6	0.635	0.56-0.71	yes
VIS0.8	0.81	0.74-0.88	yes
NIR1.6	1.6	1.5-1.78	yes
IR3.9	3.92	3.48-4.36	daytime
WV6.2	6.25	5.35-7.15	no
WV7.3	7.35	6.85-7.85	no
IR8.7	8.70	8.30-9.10	no
IR9.7	9.66	9.38-9.94	no
IR10.8	10.8	9.80-11.80	no
IR12.0	12.0	11.00-13.00	no
IR 13.4	13.4	12.40-14.40	no
HRV	n/a	0.5-0.9	yes

125 the MSG SEVIRI instrument displays the input for the network (later referred to as "satellite data") (Schmetz et al., 2002). Observing the Earth's surface in intervals of 15 min and with a spatial resolution of 3 km at nadir, ~~it~~ MSG SEVIRI provides information in ~~11~~ 12 channels centered within wavelengths from 0.6–132 μm (Benas et al., 2017). ~~While the first three~~ Depending on the wavelength and daytime of retrieval, the channels are sensitive to reflected solar radiation ~~, the others measure~~

~~surface emissions within the near to thermal infrared spectrum. These channels~~ or surface emissions (Table 1). They can be

130 applied to approximate cloud physical properties (Sieglaff et al., 2013). ~~Regions close to the poles are discarded due to reduced sensor accuracy at the satellite's outer~~ Our approach uses 11 channels. The HRV channel is excluded due to its different resolution and uncertain added value. Three of the channels are sensitive to solar radiation, which restricts us to using only daytime data. We reformat all satellite images onto a spatial grid with geographic coordinates, employing the global reference system WGS84 (Drönner et al., 2018). Each pixel has a resolution of 0.03 ° in both width (W) and height (H). To account for

135 diminishing accuracy from the equator to the poles, we exclude the areas near the sensor boundaries (Bedka et al., 2010). The ~~final~~ designated area of interest (AOI) ~~comprises an extent between~~ extends 60 ° in all directions ~~and represents~~, marking the boundaries of the new FD. ~~All satellite images are resampled to a geographic grid using the global reference system WGS84 (Drönner et al., 2018).~~

2.1.2   Radar data

140 Within the CloudSat (CS) GEOPROF-2B product, a nadir-looking 94 GHz ~~active radar~~ cloud profiling radar (CPR) delivers information on the cloud reflectivity in logarithmic dBZ scale (later referred to as "radar data") (Stephens et al., 2008). The radar ~~scenes reflect the predominant cloud structure at the given transect~~ receives a 2D cross section of the cloud column with a

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horizontal resolution of 1.1 km. The vertical dimension (Z) comprises 125 height levels with a bin size of 240 m (Guillaume et al., 2018). From the ground surface to the lower stratosphere, the vertical extent covers 30 km. We use the reflectivity transects as the ground truth to train and evaluate the model. In the subsequent steps, we adjust the height levels of the radar. The lower altitudes, specifically those between 0 and 3 km, are influenced by the topography and a radar signal weakening due to attenuation (Marchand et al., 2008). To enhance the model performance, we omit the lowest 10 height levels. Since we notice a significant imbalance between clear-sky and cloudy pixels, we exclude the predominantly cloud-free areas within the upper 25 height levels (Stephens et al., 2008). The final Z-dimension encompasses 90 height levels ranging from 2.4 km to 24 km. We note that due to the sun-synchronous orbit of CloudSat, it has a reduced ability to account for diurnal variations within specific regions of the AOI (Stephens et al., 2008).

2.1.3 Matching scheme

We obtain training data for our study by aligning MSG SEVIRI scenes with CloudSat radar data as shown in Figure 1 (a). To match the datasets, we compare their timestamps and locations. If the radar coordinates fall within the AOI of the satellite, we determine the flight direction to identify whether CloudSat circles the Earth in ascending or descending orbit. We then extract images of 128 x 128 [H x W] pixels from each MSG SEVIRI channel along the radar coordinates using a moving-window approach with a 50 % overlap between image-profile pairs (Denby, 2020; Jeppesen et al., 2019).

We prepare the matched image-profile pairs for further processing. To do this, we combine the 11 MSG SEVIRI channels into a single 3D array with dimensions 11 x 128 x 128 [C x H x W] pixels. CloudSat flies across a horizontal transect within the satellite scene. It has a higher native resolution than MSG SEVIRI. To align the datasets, we downsample the radar pixels by aggregating them based on the local maximum reflectivity. This adjusts the CloudSat pixels to the MSG SEVIRI resolution of 0.03 ° but leads to some loss of sharp contrast in radar pixels (Jordahl et al., 2020). We standardize the data shape by transforming the 2D cross section into a sparse 3D array of 125 x 128 x 128 [Z x H x W] pixels, representing reflectivities along the cross section. After downsampling, the transect becomes one-pixel wide. We label pixels outside the
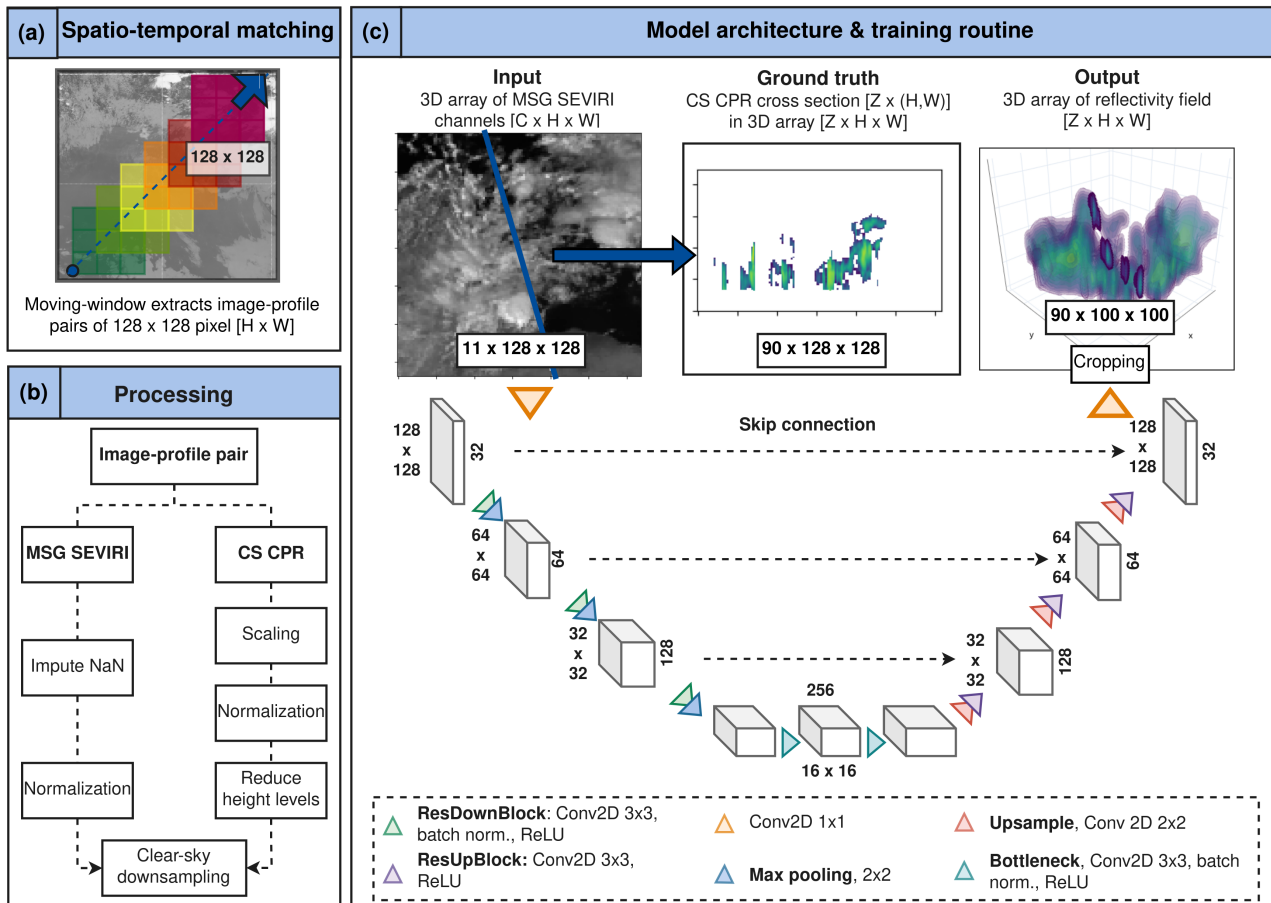
Figure 1. Workflow of the study. Part ~~(1)~~ (a) points out the moving-window approach used for matching the radar and the satellite data. Steps needed for the processing of both datasets ~~is~~ are depicted in ~~(2)~~(b). In ~~(3)~~(c), the architecture of the proposed Res-UNet is ~~pictured alongside~~ illustrated. The upper row visualizes an example for the input data, ground truth (with reduced 90 height levels and full transparency for values <= -25 dBZ), and ~~predicted~~ output respectively. ~~In the output sample, the~~ The location of the radar transect within the 3D output image is pictured with full opacity. ~~Each numbered box refers~~ The numbers alongside the boxes in the architecture sketch refer to the feature channels (right) and image sizes (left) at the given model depth.

transect as missing values to maintain the CloudSat data's location during training. We use these pixel indices to compute the loss between the CloudSat data and the predicted cross section and to evaluate the model performance.

2.1.4 ~~Processing~~Data processing

180 ~~Extracted satellite samples display the physical predictors fed into the network to reconstruct the vertical cloud distribution.~~ ~~Using a whole~~ Before training the model, we process the extracted image-profile pairs. We utilize a full year of data (2017) ~~integrates~~ to incorporate seasonal variations into the modeling ~~routine, leading to 30.000 samples. From these,~~ process. We split the 30000 matched image-profile pairs, with 75 % ~~went into training the model~~ (January to September) used for training and 25 % ~~into its evaluation. Since the radar data distribution is highly skewed towards clear-sky samples, reducing the percentage~~

185 ~~of cloud-free ground truth in the final dataset to 10 % tackles this imbalance (Jeppesen et al., 2019). This threshold accounts for the classification of whole samples, not the proportion within single images. Nevertheless, a cloudy scene can still consist of a big proportion of background pixels (Fig. 1). Data~~ (October to December) for validation. Our test set is derived from data in May 2016, from which the matching algorithm extracts 1500 image-profile pairs. We impute missing data in the 3D MSG SEVIRI array by an interpolation of neighbouring pixels (Troyanskaya et al., 2001). Afterwards, data from each satellite

190 channel x was normalized between [~~-1~~0,1] by

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

using the arithmetic mean μ and standard deviation σ of the training data (Leinonen et al., 2019). ~~The technical limitations of the sensor require rescaling all radar tracks between 20 dBZ and -25 dBZ. Reducing the data to 90 height levels between 2.4 and 24 km minimizes the influence of the topography and higher atmosphere. Otherwise, the high attenuation degrades~~

195 ~~the quality flag of the CloudSat radar in high and low altitudes. Smoothing the CloudSat values by its internal quality flag diminishes noise within the samples (Marchand et al., 2008). Here, pixels~~ As described in Section 2.1.2, we reduce the height levels of the CloudSat profile from 125 to 90 (Fig. 1, b). We use the CloudSat quality index to identify noisy pixels. Pixels with a quality index lower than six were ~~classified as missing values and~~ set to a background value of -25 dBZ ~~. After the quality assessment, all~~ to reduce noise (Marchand et al., 2008). All radar reflectivity values Z_{dB} were normalized ~~to~~ between [-1,1] as

200 follows

$$Z'_{dB} = 2\frac{Z_{dB} + 35dB}{55dB} \underset{\sim}{\pm} 1 \tag{2}$$

by the maximum and minimum reflectivity between [-35, 20] ~~of the value range (Stephens et al., 2008; Leinonen et al., 2019)~~ ~~.~~ (Stephens et al., 2008; Leinonen et al., 2019). The CloudSat data is highly skewed towards clear-sky samples. We limit the percentage of cloud-free profiles to 10 % to tackle this imbalance (Jeppesen et al., 2019).

205 ## 2.2 Model architecture and training

~~The backbone of the study rests upon the Res-UNet architecture (LeCun et al., 2015; Ronneberger et al., 2015). While the UNet is well established for tasks from vision computing, evaluating its feasibility for environmental data is still in progress~~

(Dixit et al., 2021) Neural networks can capture highly complex relationships between input and output data (Lee et al., 2021). The Res-UNet used in this study displays a modified framework designed for the use-case of remote sensing data , By adding

210 (Dixit et al., 2021). Additional residual connections and continuous pooling operations , aim to reduce the dependence of the network on the input's location is reduced (Diakogiannis et al., 2020). Former studies dealing using the Res-UNet dealt with the classification of tree species (Cao and Zhang, 2020) , the segmentation of buildings (Dixit et al., 2021), or the delineation of precipitation intensity (Zhang et al., 2023)emphasize or the potential prediction of precipitation (Zhang et al., 2023). Obtained results emphasize the ability of the Res-UNet to adequately address the importance of the spatial coherence in a dynamic

215 environment environmental research (Marais et al., 2020). In this study, the regression derives we derive the cloud reflectivities in dBZ for each pixel in a three-dimensional image field (Hilburn et al., 2020; Leinonen et al., 2019; Zhang et al., 2023) . By seeking non-linear approximations of between the input and the output data, the neural network can detect complex relationships between the variables (Lee et al., 2021)from the satellite channels by a regression task (Hilburn et al., 2020; Zhang et al., 2023 .

220 As introduced by Ronneberger et al. (2015), the UNet and its modifications provide an almost symmetrical architecture. Figure 1 illustrates the network architecture whereas each convolution is expanded by the structure of a residual block as described by Diakogiannis et al. (2020). Following a sequence of down-sampling layers on the encoder side, the original spatial extent of 128 x 128 pixels is reconstructed by continuous up-sampling layers in The network architecture of the decoder side (Lee et al., 2021). To maintain the spatial coherence in the last down-sampling layer, the model depth is restricted to 4

225 subsequent convolutions. Each residual block consists of a convolution with a kernel size of Res-UNet is shown in Figure 1 (c). The parameters of the network are listed in Table A1 in Appendix A. Each box represents the layer sizes on the encoder and decoder side. On the right side of each box, the filter size is given. The respective height and width are given on the left side.

The Res-UNet consists of six residual blocks, each including two 2D convolutions (3 x 3 and shortcut connections used to

230 avoid model degradation (Diakogiannis et al., 2020). A batch normalizationlayer and an activation layer with a rectified linear unit (ReLU)follow the convolution of the input layer for improved robustness and to avoid extreme values (Le Goff et al., 2017; Li et al., 20 . A maximum pooling of size 2 kernel, stride 1) and ReLU activation (Diakogiannis et al., 2020). On the encoder side, we add batch normalization. The output is merged with a skip connection that consists of one 2D convolution (3 x 3 kernel, stride 1), and a batch normalization. Adding the skip connection and the convolutional layer represents the output of a residual block.

235 We increase the channel dimension of the initial satellite image from 11 x 2 reduces the initial spatial extent from 128 x 128 pixels with a 1 x 1 2D convolution to a feature map of size 32 x 128 x 128. In the encoder branch, we then employ a sequence of three residual blocks with doubling filter sizes, each followed by a 2 x 2 max pooling layer (Lee et al., 2021). We subsequently reduce the feature map size to 64 x 64 pixels (Lee et al., 2021). Repeating this routine of operations for every layer in the encoder , we halve the image size every time while doubling the number of feature channels leading to a final size

240 of 256 x 8 x 8 pixels (Ronneberger et al., 2015). After the last pooling layer16 x 16 pixels in the bottleneck layer. Here, we apply a sequence of repeated convolutions two 2D convolution layers followed by batch normalization and a ReLU activation.

~~On the decoder side , a likewise sequence of upsampling blocks accompanied by features originating skip connections expands the low-resolution image to its original extent but with a modified representation (Li et al., 2018). In this case, these are the 3D radar reflectivities. The upsampling displays the inversion of the pooling on the encoder side, doubling the spatial~~

245 ~~extent to fit the size of the~~ The decoder side features three residual blocks, each with an upsampling layer (2D convolution, 2 x 2 kernel, stride 2) and a corresponding skip connection ~~. In each step, the upsampling is followed by~~ from the encoder. After upsampling, we apply a residual block with ~~a convolution and a ReLU activationlayer ((Lee et al., 2021)). After the last upsampling block, a convolution with a kernel size of~~ 2D convolution (3 x 3 kernel, stride 1) and ReLU activation, doubling the spatial extent to match the skip connection while halving the channel dimension (Li et al., 2018). The final 1 x 1 convolution

250 maps the output to ~~a size of~~ 90 x 128 x 128 pixels~~. A subsequent removal of the outermost pixels leads to a final size~~, representing the 90 height levels of the radar cross-section (Jeppesen et al., 2019). We remove the border pixels of the output, resulting in a final radar reflectivity output of 90 x 100 x 100 pixels ~~(Jeppesen et al., 2019)~~[C x W x H]. Predicted reflectivities are scaled between -35 and 20 dBZ, with values below -25 dBZ considered as cloud-free (Leinonen et al., 2019).

~~Choosing~~ We conducted the training for 50 epochs with a batch size of 4 and a weight decay of 0.00001 (see Table A1

255 in Appendix A). We have 1893328 total trainable parameters. The estimated total size of the model is 194.27 MB (see Table B1 in Appendix B). We use the Adaptive Moment Estimation (ADAM) method ~~ensures~~ for model optimization due to its fast convergence rate (Kingma and Ba, 2014). ~~As flipped images are perceived as new samples, we~~ The learning rate is initially set to 0.001 (see Table A1 in Appendix A). It is reduced by a learning rate scheduler during the training process when reaching a plateau. To enhance the amount of training data~~by giving all samples~~, we give all input data a chance of 25 % to be

260 ~~either vertically or horizontally rotated (Jeppesen et al., 2019). Predicted reflectivities are matched to the CloudSat value range with a lower limit of -25 dBZ to differentiate a cloud signal from background noise (Leinonen et al., 2019)~~rotated by 90 ° (Jeppesen et al., 2019). These flipped images are perceived as new samples. The goal is to increase the model invariance to the orientation of the radar cross section.

2.3 Evaluation

265 ### 2.3.1 ~~Model~~ **Analyzing and comparing the model** performance

The model performance is ~~evaluated by~~ quantified during training (loss function) and evaluated afterwards by calculating the root-mean-square error (RMSE) ~~, which equally penalizes~~ (see Table A1 in Appendix A). The RMSE is equally able to penalize misses and false alarms (Lee et al., 2021). ~~Since ground truth is limited to the radar overpass, only~~ As described in Section 2.1.3, we preserve the pixel indices of the CloudSat cross section within each image-profile pair during training. We use the

270 location of these pixels to filter the observed and predicted transect. The RMSE is calculated along the filtered cross sections. Since it is only evaluated on a small subset of 10 ~~% of the pixels are used for the error calculation (Wang et al., 2020). The loss is calculated according to:~~

$$RMSE = \sqrt{\sum_{i=1}^{D}(x_i - y_i)^2}.$$

~~The results of the DL network are compared against two pixel-based methods to examine its performance along the radar~~ ~~track. Training data for these approaches is extracted from the previously created dataset. For each image, the horizontal~~ ~~diagonal of the radar overpass is divided into pixel-wise training samples along the XY–axis. The final input consists of an array~~ ~~of 11 satellite channels. Each ground truth sample displays an array of 90 height bins along the Z–axis (Fig. 1). Preserving~~ ~~the index of the pixel along the diagonal during the training routine allows a reconstruction of the radar track. Both models~~ ~~utilize the normalized satellite data to reconstruct the radar reflectivity (Sect. 2.1.4). The RMSE is calculated after rescaling~~ ~~the output back to the dBZ scale~~% of all pixels, we have a sparse regression task (Wang et al., 2020). We cannot quantify the model performance on the full 3D prediction of the cloud field.

The results of the Res-UNet are compared against two competitive methods (Drönner et al., 2018). First, ~~this study applies~~ we predict the radar reflectivity by an ordinary least squares model with multiple regression output (OLS)~~as a baseline model~~ ~~(Miller et al., 2014). In this case, all~~. The 11 satellite channels were used as independent predictor variables~~to estimate~~ ~~the radar reflectivity for each pixel along the~~. The output is a 1D cloud column. Second, a Random-Forest (RF) regression is applied ~~(Wang et al., 2021). As~~ (Breiman, 2001). The RF is a supervised ML algorithm ~~, the RF pictures a robust~~ ~~method~~ suitable when working with ~~large~~ environmental datasets in the natural sciences (Boulesteix et al., 2012). ~~In the~~ ~~past, numerous studies investigated its~~Its feasibility for complex meteorological data was investigated before, e.g., ~~detecting~~ ~~clouds(McCandless and Jiménez, 2020) or delineating rain rates (Kühnlein et al., 2014). This study tested a minimal~~McCandless and Jimén used a RF regression to detect clouds. Our study uses a setup with 100 trees, each choosing a random subset of ~~predictors~~ ~~(McCandless and Jiménez, 2020). Both models~~ satellite channels to predict the reflectivity along a 1D cloud column. We use the same ~~data split as~~ training, validation and test split as for the Res-UNet~~(Sect. 2.1.4). After training,the original radar track is~~ ~~restored to enable a track-wise comparison~~. For each image-profile pair, we filter the 3D array to locate the radar cross section. This transect is separated into 1D cloud columns. For every pixel along the cross section, we receive a ground truth in the shape of 90 x 1 [Z x (H,W)]. The 3D array containing the satellite channels was filtered by the radar profile location and divided into images of the size 11 x 1 [C, (H,W)]. The OLS and RF map the satellite image to an output size of 90 x 1 pixels [Z x (H,W)]. We calculate the RMSE between the observed and predicted cloud column and scale the output between -35–20 dBZ. We reconstruct the 2D transect by the preserved index of each pixel of the cross section. These profiles are compared to the output of the Res-UNet.

2.3.2 ~~Comprehensive predictions~~Merging 3D reflectivities on the FD

~~A~~ We predict the radar reflectivity for each MSG SEVIRI file in the test dataset (May 2016) using the trained Res-UNet. The result is a contiguous 3D cloud tomography ~~can be achieved by dividing the satellite FD into~~ for every 15 minute time step. The MSG SEVIRI FD covers an extent of 2400 x 2400 pixels. For the FD prediction, we divide the FD into overlapping

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subsets of 128 x 128 ~~pixel subsets. These images are individually~~ pixels. These subsets are processed and fed into the network.

305 ~~Combining their outputs of~~ The output is a 3D reflectivity image of 90 x 100 x 100 pixels ~~into a joined 3D prediction of 2400 x 2400 pixels enables a whole satellite gridcoverage. This comprehensive cloud tomography is derived for every time step of the satellite dataset and is used~~ [Z x H x W], which equals 2.5 ° on the MSG SEVIRI grid. We merge the tiles to cover the whole satellite AOI. Between the tiles, there is no overlap. The goal is to evaluate the network's ability to ~~create a smooth interpolation of~~ extrapolate a large-scale cloud ~~fields~~field from single tiles.

2.3.3 ~~Cloud~~ Computing the cloud top properties

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~~Since neither simulations nor observational-based models deliver comparable data, the predictions are interpreted~~ To our best knowledge, there exist no comparable datasets to the 3D cloud tomography in this study. Instead of a quantitative evaluation of the reflectivity, we evaluate the predictions based on their ~~applicability for deriving cloud-top properties (Wang et al., 2023). At first, CloudSat data and track-wise predictions are used to compute~~ performance to derive the cloud top height (CTH)
315 ~~for the validation data~~(Wang et al., 2023). We use the FD predictions for the test dataset (May 2016) for the computation. The CTH is defined as the distance between the ground surface and the uppermost cloud layer for every 1D vertical column (Huo et al., 2020). This calculation requires converting the ~~CloudSat height bins~~ height levels into a kilometer scale. ~~Values with a reflectivity higher than~~ We use a fixed threshold of -15 dBZ ~~display a cloudy signal, whereas lower values are classified as the background class~~ to differentiate a cloudy from a clear-sky pixel (Marchand et al., 2008). The ~~final output displays an~~
320 ~~aggregation on a monthly scale. Afterward, the CTH~~ result is a binary classification for each pixel in the 3D cloud field. On this dataset, we extract the CTH as the top cloud signal on each 1d cloud column of the FD~~3D reflectivities is compared~~. We aggregate the results on a monthly scale and compare the predicted CTH to the operational product CLAAS-V002E1 (CLoud property dAtAset using SEVIRI, Edition 2) (Finkensieper et al., 2020). ~~Based~~ It is based on the MSG SEVIRI channels and additional model data ~~, CLAAS-V002E1~~ and provides information on the macrophysical and microphysical cloud properties.
325 ~~It is available as~~ We use a monthly aggregate with a resolution of 0.05 ° on the MSG SEVIRI FD. ~~The goal is to rate the predicted CTH compared to CLAAS-V002E1 by pointing out the overall agreement and regional differences.~~

3 Results

3.1 Evaluating the ~~model performance~~reflectivity distribution

~~Comparison of the height dependent RMSE for every height bin between 5–24 km and the mean error for all models calculated on the validation dataset.~~

~~Joint plot of the normalized difference between the observed and predicted reflectivity. The deviation on each height bin between 5–24 km is compared for the Res-UNet (a), the ordinary least squares model (OLS) (b), and the Random-Forest regression (RF) (c).~~

~~Three models were trained to compare the performance of the different approaches (Sect. 2.3.1). Due to the applied CloudSat quality flag, predictions below 5 km are influenced by the high amount of background values at -25 dBZ~~ We analyze the ability of the three models (Res-UNet, OLS, and RF) to reconstruct the cloud vertical distribution for the test dataset in May, 2016 (Sect. ~~2.1.4). As a consequence, the following evaluation refers to the predicted reflectivity above~~ 2.3.1). The OLS and RF predict a 1D column whereas the output of the Res-UNet comprises a 3D image of the cloud field. We filter all outputs by the preserved location of the radar cross sections to derive the original 2D transect. At first, we compute the height dependent reflectivity distribution of the CloudSat data and the three models. Due to the applied quality flag (Sect. 2.1.4), we have few observations below 5 ~~km. The results illustrate a substantial improvement when applying a DL framework compared to the OLS and RF. Figure 2 illustrates the variance of the error between 5–24 km. The mean RMSE varies between 3.41 dBZ for the Res-UNet and 4.91 dBZ (RF) or 5.27 dBZ (OLS). This difference depicts a reduction of the total error from 11.7 % (OLS)or 10.9 % (RF)to 7.5 % for the DL network. The overall RMSE and the difference between the models reach their maximum in low altitudes~~ km height (Fig. 2, a). This leads to a shift in low height levels. The models overestimate cloud-free values below -25 dBZ. The CloudSat reflectivities have a peak at 0–10 dBZ between 5–7 km~~height. In higher altitudes with more uniform clouds, the performance of all models improves. Nevertheless, the DL network outperforms the other approaches at every height level~~ . A second, weaker peak is observed between 12–15 km for reflectivities < 0 dBZ. All predictions underestimate the first peak > 0 dBZ. Instead, they overestimate the occurrence of reflectivities < -20 dBZ (Fig. 2~~) .~~, b–d). The OLS shows an especially high shift towards low reflectivities. The Res-UNet predicts low reflectivities < -20 dBZ along all height levels between 5–15 km whereas we observe a distinct peak at 5 km for the RF.

~~To evaluate the accuracy of the models on different height levels , the normalized~~ We analyze the difference between the observed and predicted reflectivities ~~is analyzed~~ by a two-dimensional joint distribution plot. For this purpose, we calculate the density distribution of the reflectivity between 2.4–24 km. Here, we use a bin size of 1 dbZ and 240 m height, respectively (Steiner et al., 1995). All ~~models deviate~~ distributions are calculated on the test dataset and normalized by the distribution size (n = 1500). Predictions differ from the original radar data, especially for values > 0 dBZ and in low altitudes (Fig. 3). ~~The differences get smaller in higher parts of the troposphere and tropopause. A diagonal of high agreement with the observed data from high altitudes with low reflectivities to lower altitudes with higher reflectivities can be observed with the steepest diversion for the OLS. Appearing~~ In the joint plot, the highest agreement appears in the shape of ~~two contrasting parts, the direction differs between the Res-UNet and the other models. That said, the DL network indicates an underestimation~~ a

curved line between low reflectivities > 15 km to high reflectivities at 7 km. The results indicate an overestimation of high reflectivities and an ~~overestimation~~ underestimation of low reflectivities, especially for low-level clouds. ~~Predictions in higher altitudes represent a~~ ~~smaller deviation from the ground truth. The other models show an overestimation of high reflectivities and an underestimation of low values in both, low- and mid-altitude. In terms of total deviation from the ground truth,~~ Since we observe few clouds in high altitudes (Fig. 2, a), the distribution differences get smaller above 15 km. The joint plot shows a similar distribution for the Res-UNet and the ~~Res-UNet performs best out of~~ RF, whereas the error of the ~~three proposed models~~Res-UNet is slightly lower for reflectivities between -15–0 dBZ (Fig. 3, a, c). We observe few predictions > 0 dBZ and a strong overestimation of reflectivities < -20 dBZ for the OLS (Fig. 3, b).

3.2 ~~Analysis of cloud vertical properties~~

~~Figure 4 depicts the model predictions and the observed CloudSat reflectivities along the radar track for four samples. All models~~ ~~detect the horizontal location of different clouds along the XY–axis. A detailed view of the individual radar tracks illustrates the transferability of the proposed DL method. In contrast to the RF and OLS, the~~

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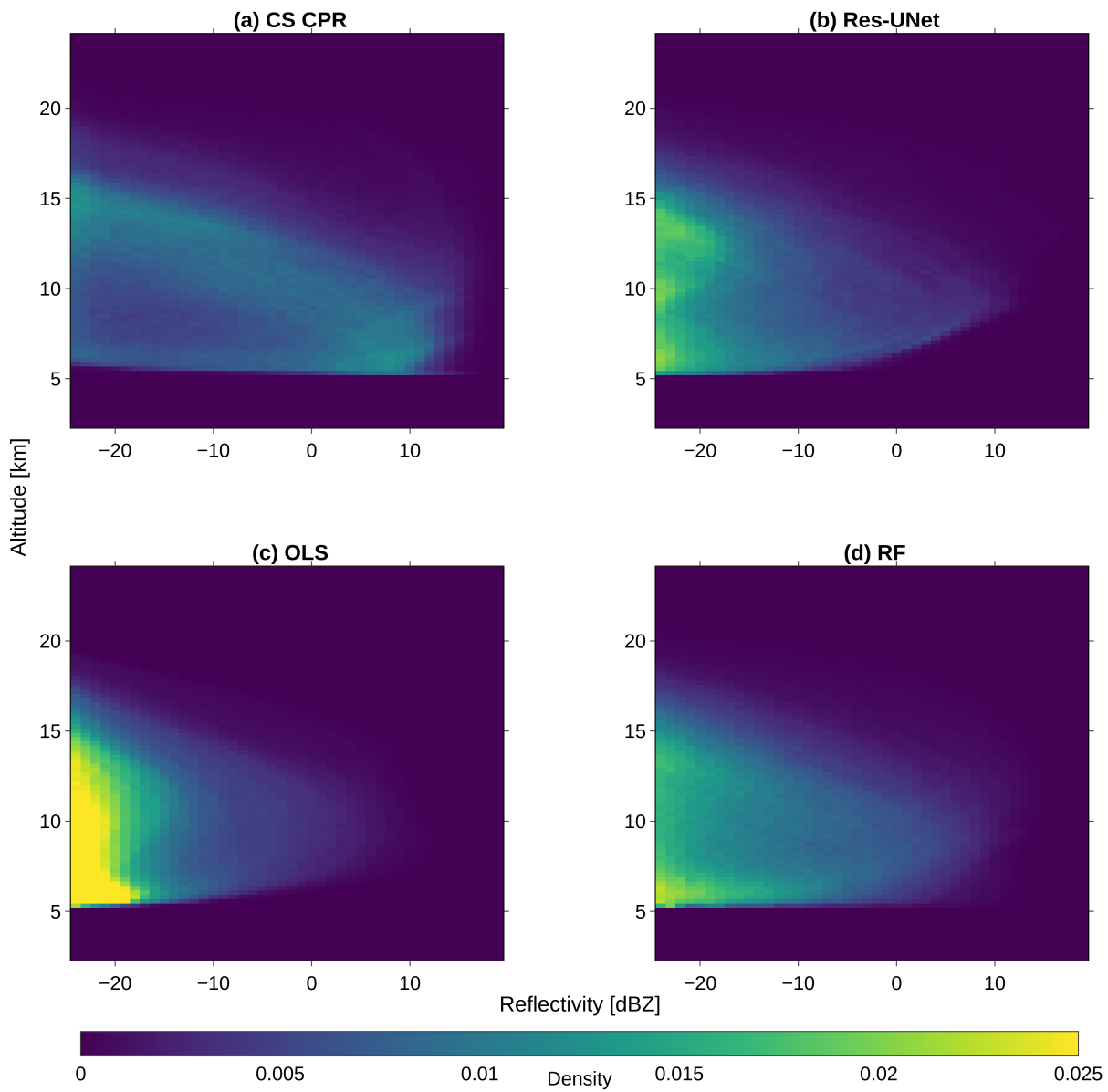
Figure 2. Height dependent reflectivity distribution for every height bin between 2.4–24 km for the CloudSat data (CS CPR) **(a)**, the Res-UNet **(b)**, the ordinary least squares model (OLS), **(c)**, and the Random-Forest regression (RF) **(d)** (n = 1500).
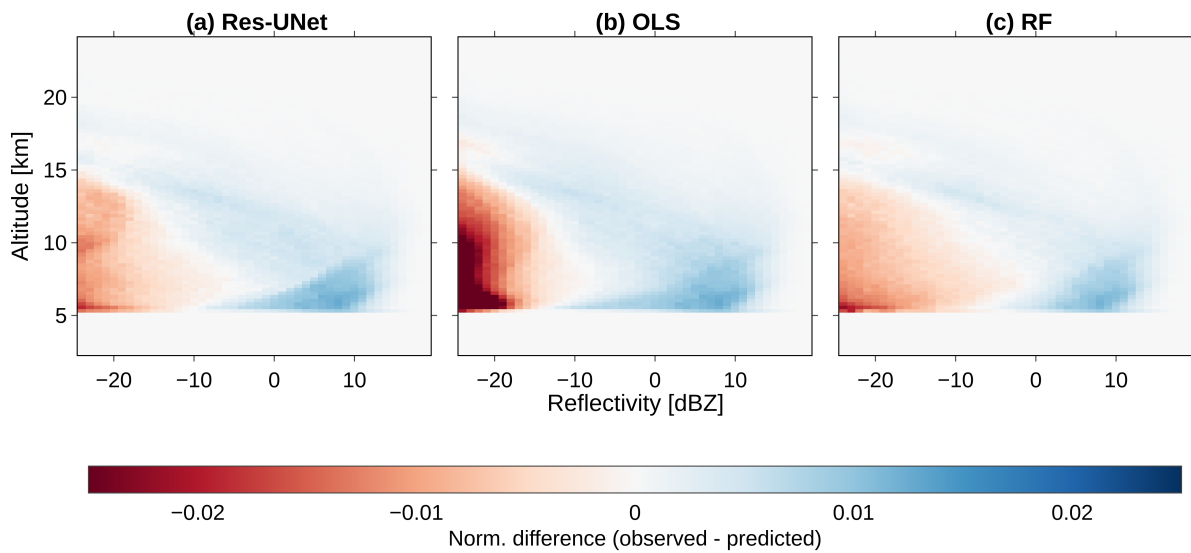
Figure 3. Joint plot of the normalized difference between the observed and predicted reflectivity on the test dataset (n = 1500). For each height bin between 2.4–24 km, we compare the CloudSat density distribution (CS CPR) to the distribution of the Res-UNet **(a)**, the ordinary least squares model (OLS) **(b)**, and the Random-Forest regression (RF) **(c)**.

3.2 Height-dependent model performance

We analyze the model error (RMSE) along the vertical cloud column. For all models, we calculate the mean RMSE on the test dataset between 2.4–24 km. The results point out an overall lower RMSE for the Res-UNet than for the OLS and RF (Fig. 4). The mean RMSE varies between 2.99 dBZ for the Res-UNet, 4.1 dBZ (RF), or 4.58 dBZ (OLS). On a dBZ scale between -25–20 dBZ, this is equivalent to an error of 10.1 % (OLS), 9.1 % (RF), or 6.6 % (Res-UNet). Between 2.4–5 km, the RMSE is 0. This is due to the lack of CloudSat observations after filtering noisy pixels (Fig. 2, a). Between 5–7 km, the RMSE increases to up to 8 dBZ for the Res-UNet, 10 dBZ for the RF, and 12 dBZ for the OLS (Fig. 4). In higher altitudes, the performance of all models improves. The RMSE decreases to 4 dBZ (5.7 dBZ, 6 dBZ) for the Res-UNet (RF, OLS) at 15 km and reaches its minimum at 22 km (24 km for OLS and RF). Above 15 km, we have few CloudSat observations > 15 dBZ (Fig. 2, a). We observe a lower model error (Fig. 4) and reduced difference between the distributions (Fig. 3) in these height levels for all three models. The improved performance can be led back to the superior number of background reflectivities or the presence of more uniform clouds, like extended tropical cirrus. Over all height levels, the Res-UNet has the lowest RMSE of the three models. Compared to the OLS (RF), the mean RMSE of the Res-UNet is reduced by 34,8 % (27,1 %).

Figure 5 shows the predicted and observed reflectivity along the radar transect for four randomly chosen samples. For all models, the reconstructed cloud signal is predicted at the right horizontal location along the cross section. Clear-sky situations of -25 dBZ are recognized without noise. The cross sections in Figure 5 (a) are created using processed CloudSat reflectivities with a resolution of 0.03 °. Although the radar pixels lose some sharp contrasts after the downsampling, we observe a higher blurriness for the predictions. The edges of individual clouds smear out for all three models. Even though all transects were labelled as cloudy, we see a high percentage of background pixels.

For the Res-UNet, we observe a RMSE between 3.3 and 8.2 dBZ. The overall shape and increased intensification towards the cloud's core follow the radar, even though edges are blurred, and peak reflectivities remain underestimated (Fig. 5, b).

Legend: Res-UNet (Mean RMSE: 2.99) — RF (Mean RMSE: 4.1) — OLS (Mean RMSE: 4.58)
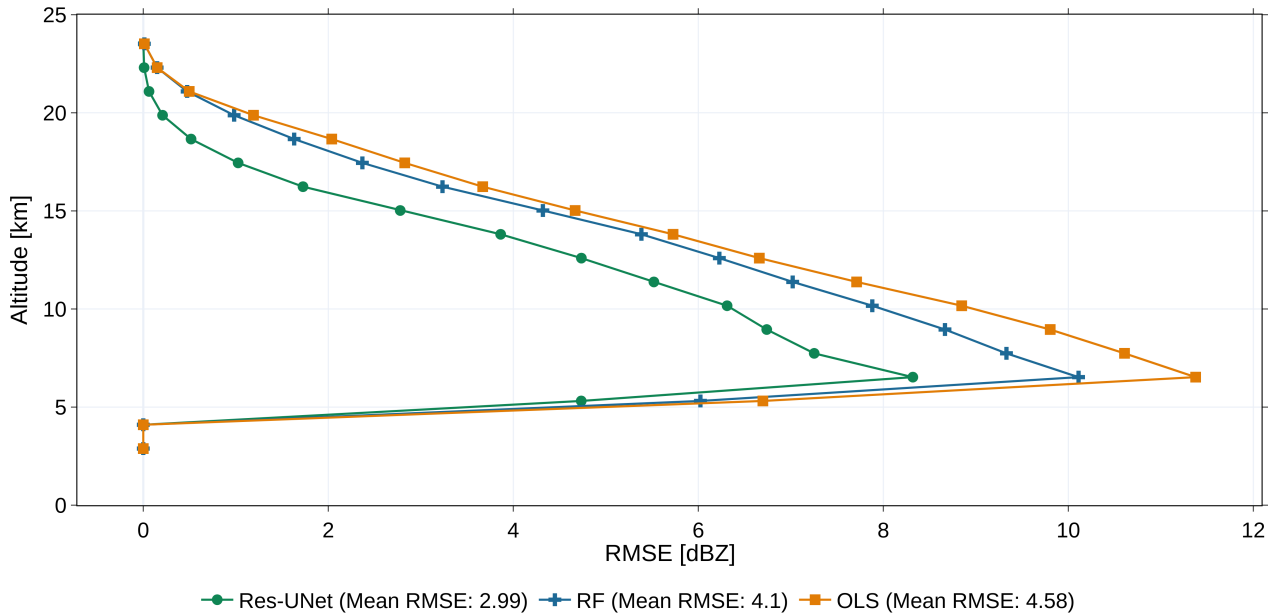
~~Reconstructing the vertical radar track along the horizontal diagonal XY–axis. Values lower than -25 dBZ are displayed transparent. For each sample (I)–(IV) the reflectivity is compared between the processed CloudSat CPR track and the predictions of the Res-UNet, the OLS, and the RF.~~

Figure 4. Height dependent RMSE for every height bin and the mean RMSE for all models calculated on the test dataset (n = 1500).

This issue is reflected within the reflectivity distribution of the DL model (Fig. 2, b). While the Res-UNet accurately identifies single-layer clouds, it misses sharp edges of multi-layer clouds, especially in mid-altitudes. Clouds over multiple height levels are blurry and show a reduced small-scale accuracy in the vertical dimension (Fig. 5, III). The lower height levels of multi-layer clouds are only partly represented (Fig. 5, II, IV). Instead, we observe a simplification of these cloud layers.

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For the OLS and the RF, the underestimation of the cloud core reflectivities resembles the Res-UNet (Fig. 5, II, III). All four examples show a higher RMSE for the OLS and RF than for the Res-UNet (Fig. 5, c, d). The difference varies between 0.1 (I) and 2.7 (IV) dBZ. While the error is predominantly similar for all three models, the shape of the predicted clouds differs (I, III). The OLS (RF) fails to accurately reconstruct the vertical extent in all transects. Instead, the reflectivity is uniform along the cloud column. We see a continuous cloud signal between 5–15 km (Fig. 5, c). Contrasting, the Res-UNet predicts

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the vertical variability more precisely (Fig. 5, b). While the 2D profiles of the Res-UNet are smooth, the RF and OLS lead to a fragmented structure with a high value variability between the single pixels of the transect (I, IV). The examples show an inaccurate reconstruction of shallow clouds and multi-layer clouds for the OLS and RF.
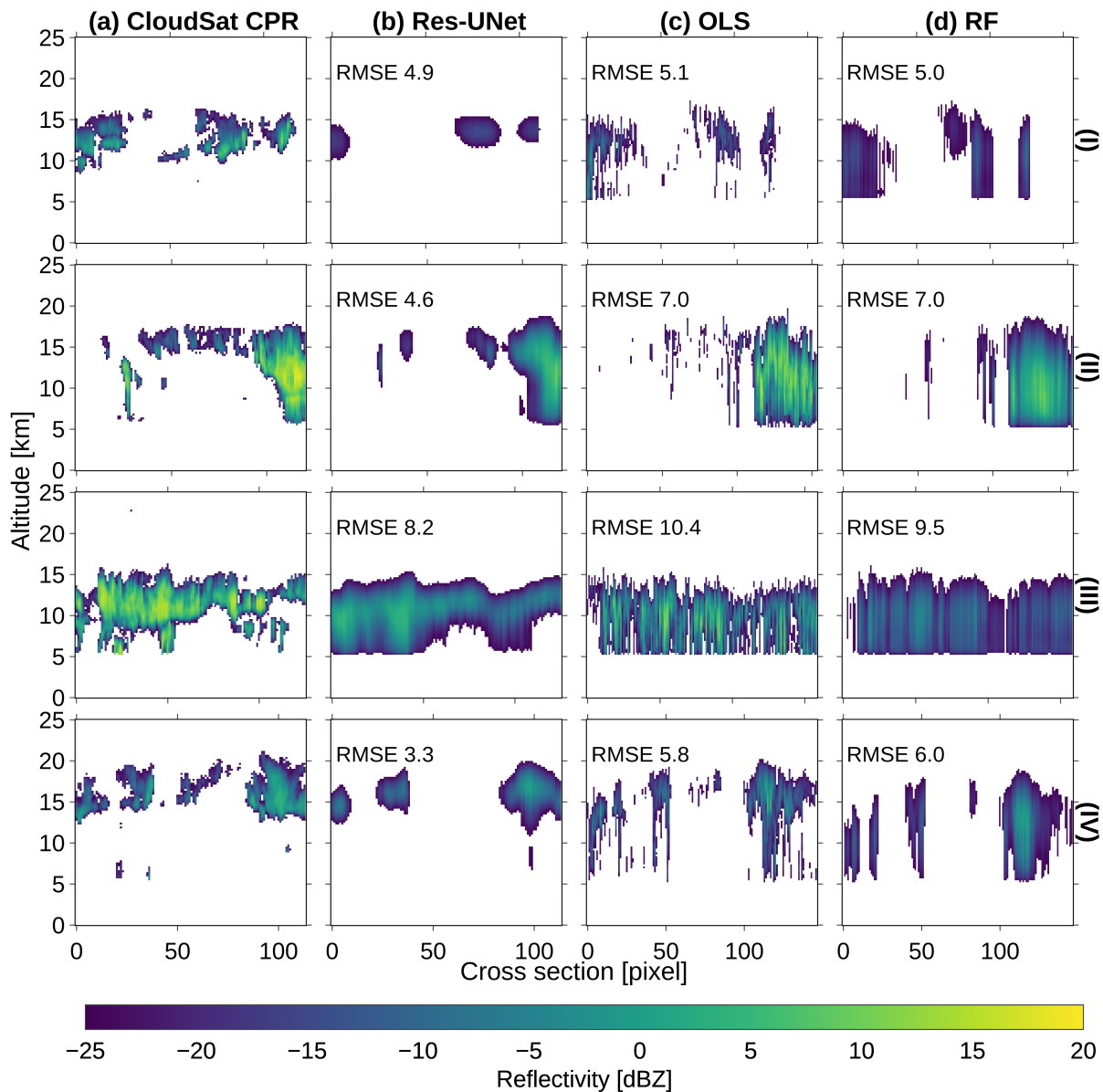
Figure 5. Reconstructing the radar cross section for four random examples of the test dataset (n = 1500). Values <= -25 dBZ are displayed transparent. We compare the reflectivity between the processed CloudSat cross sections **(a)** and the predictions of the Res-UNet **(b)**, the OLS **(c)**, and the RF **(d)** for each transect **(I)**–**(IV)**. The RMSE describes the error between the CloudSat data and the predicted profile.

3.3 Geographic analysis of the 3D cloud tomography

With the trained Res-UNet, we predict clouds on the MSG SEVIRI AOI. Since the network was trained using VIS channels, we cannot provide an accurate representation of the nocturnal cloud field. An exemplary 3D cloud tomography is predicted for 06 May 2016, 13:00 UTC. For that purpose, the satellite scene was divided into small subsets of overlapping 128 x 128 pixel images as described in Section 2.3.2. After feeding each subset into the network, the output tiles of 90 x 100 x 100 pixels were merged into a FD scene of 90 x 2400 x 2400 pixels for the whole AOI (Fig. 6, a).

The results contain a 3D cloud field along 90 height bins between 2.4–24 km. As shown in Figure 6 (a), the top-view on the maximum reflectivity per cloud column demonstrates the absence of hard borders between single prediction tiles. Even though CloudSat data is only available at the radar transects, we can extrapolate smooth cloud structures on the FD. The example tiles (b)–(d) point out a fluent transition between the edges of single prediction tiles (Fig. 6). Each example spans a horizontal extent of > 2.5 ° (100 x 100 pixels) to demonstrate the absence of artifacts between the tiles. High reaching convective complexes (b) and large-scale structures (c, d) are extrapolated at the FD scale regardless their location. Even though the overall reflectivity is underestimated, low-level and multi-layer clouds are displayed as contiguous entities.

We visualize the mean RMSE between 60 °N and 60 °S to investigate zonal variations for the test dataset. The geographic analysis is used to evaluate the reliability of the 3D cloud tomography. The RMSE shows a high latitudinal variability. At 30–50 °N, we observe the highest RMSE of 6–7 dBZ (Fig. 7, a). The RMSE at mid-latitudes on the southern hemisphere is lower than at the norther hemisphere. Nevertheless, the lowest RMSE is achieved in the tropics between 20 °N–20 °S. We analyze the RMSE in relation to the number of image-profile pairs originating the matching scheme in Section 2.1.3. Most image-profile pairs are located around the equator and the mid-latitudes (Fig. 7, b). Few pairs are matched around 10 °N and 30 °S. Regions in the mid-latitudes have the highest RMSE and the highest number of observations. In the tropics, the RMSE is lower. Here, we obtain a high amount of image-profile pairs from the matching scheme. The predicted cloud field points out a high geographic variability of the RMSE. We observe a higher RMSE for the northern than for the southern hemisphere. Clouds in the subtropics are more accurately represented than clouds in high latitudes. At the same time, we lack observations here. The analysis emphasizes the importance of the geographic location on the model predictions as well as the influence of the CloudSat orbit.
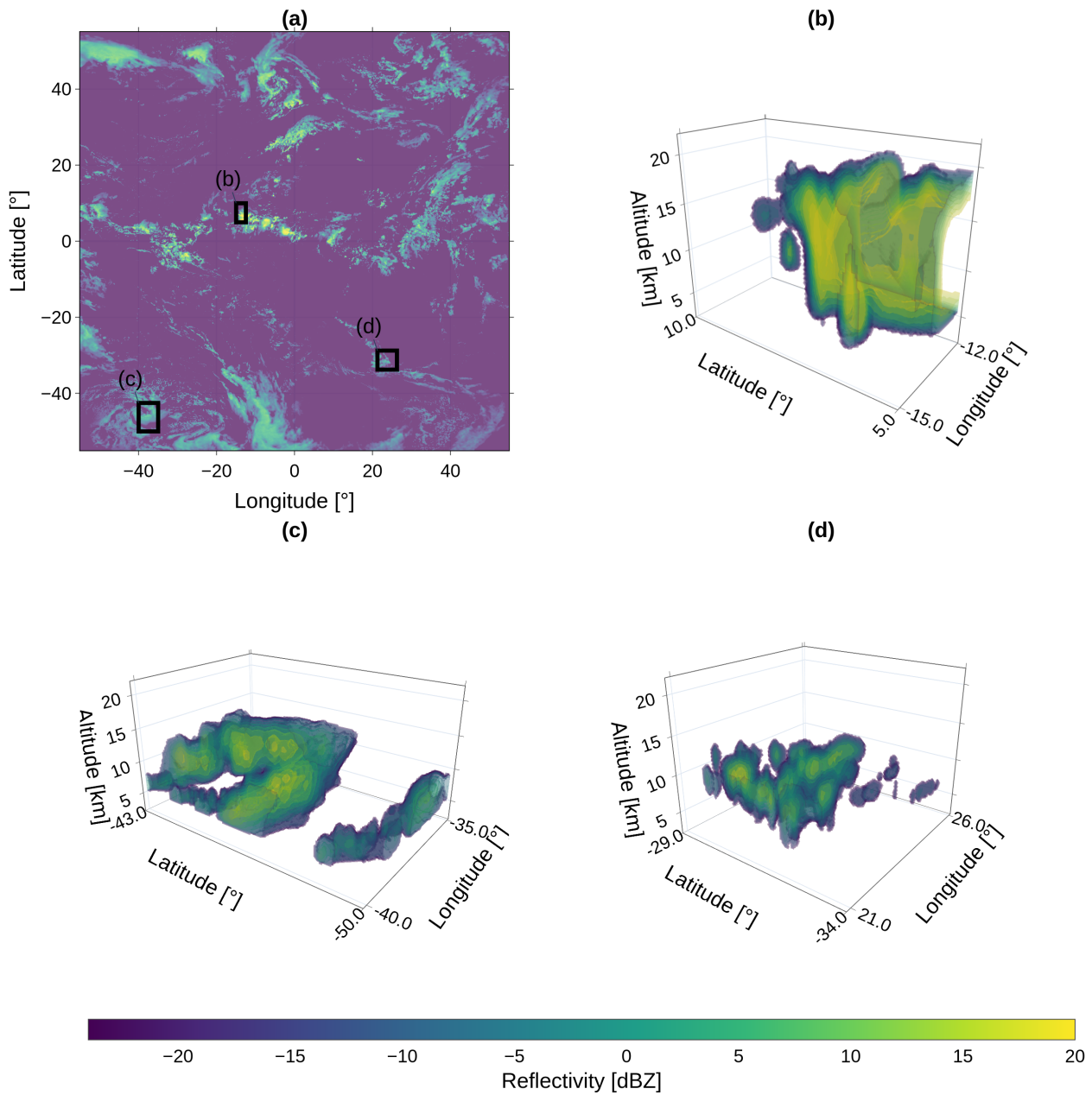
Figure 6. Prediction of 3D cloud structures from the Res-UNet along the FD MSG SEVIRI domain with a a top-view on the maximum cloud column reflectivity for each pixel on 06 May 2016, 13:00 UTC **(a)**. The detailed views in **(b)**, **(c)**, and **(d)** span several tiles of 100 x 100 pixels (2.5 ° on the geographic grid) to point out the absence of artifacts between predictions.
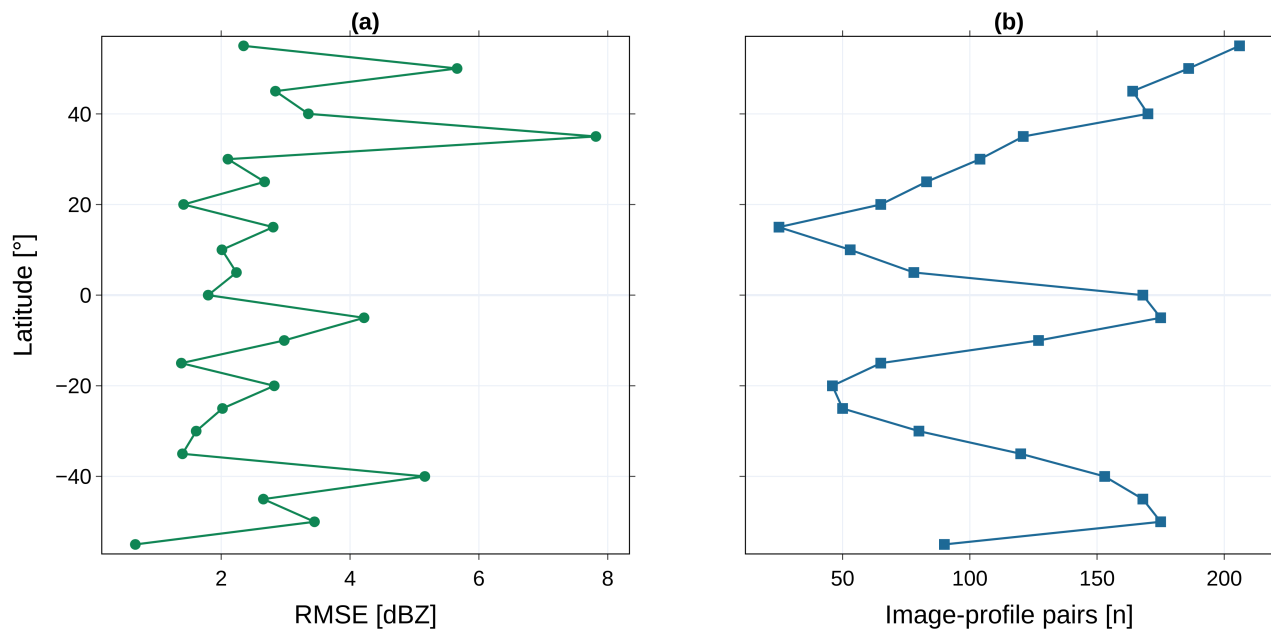
Figure 7. Zonal RMSE of the Res-UNet **(a)** and number of matched image-profile pairs used for model evaluation **(b)** for latitudes between 60 °N and 60 °S (n = 1500).

3.4 Comparison of the predicted CTH

To evaluate the quality of the Res-UNet predictions, we compare the reflectivity distribution between CloudSat and the Res-UNet predictions. In a second step, we calculate the CTH on the test dataset. The reflectivities in Figure 8 (a) are provided in logarithmic scale due to the high proportion of cloud-free pixels around -25 dBZ (Fig. 8 a, c). Values < -15 dBZ are visualized with a grey background. They lie below the threshold used to determine a cloud signal for the calculation of the CTH (Sect. 2.3.3). The distribution of CloudSat and predicted reflectivities is similar for up to -10 dBZ. For higher reflectivities, the distributions diverge. As demonstrated in Figure 2, the network fails to accurately reconstruct high reflectivities. The difference increases for reflectivities > 0 dBZ. Both reflectivity distributions are dominated by cloud-free pixels of -25 dBZ 8 (c). The comparison points out the importance on the background value for the whole distribution. For values > -15 dBZ, the difference between the distributions decreases. The shift of the distribution is reflected in the CTH in Figure 8 (b). Both datasets display a maximum CTH at 7 km height. This first peak is overestimated by the model. A second peak around 12–15 km height is underestimated by the Res-UNet. The difference between the predicted CTH is reflected within Figure 8 (d). The mismatch between the two peaks is about the same size. The underestimated second peak can be led back to the inaccuracy of the predicted reflectivities. The Res-UNet overestimates reflectivities < -15 dBZ at all height levels up to 15 km. It misses high reflectivities responsible for the peak of the CTH at 12–15 km (Fig. 3, b). Instead, we see an overall surplus of background values in the FD prediction.

Calculating the CTH on the FD predictions substantially increases the amount of available data points compared to the CloudSat data. Predicted images surpass the radar observations by a factor of 10000. We use the 3D cloud tomography to derive the FD CTH on the test dataset. For each time step, we calculate the CTH on the FD and aggregate the results to a monthly mean. These values are compared to the CLAAS-V002E1 product with a resolution of 0.05 ° (Finkensieper et al., 2020). The predicted CTH has a resolution of 0.03 °. Due to this mismatch, our predictions show more fragmented structures (Sect. 2.3.3). Although the small-scale accuracy is improvable, the results allow an investigation of regional differences on the large scale. The analysis reveals an overall high agreement. Regional differences arise around the equator and mid- to high-latitudes (Fig. 9). In mid-latitudes, the CTH over water bodies is overestimated in the southern hemisphere and underestimated in the northern hemisphere. These differences can

be led back to an increased RMSE in these regions (Fig. 7). In contrast, a low RMSE in the subtropics increases the accuracy of the predicted CTH. The model is biased toward predicting lower clouds . In the latter regions, they appear too intense, especially over water bodies of the southern than the observational data. Overall, the Res-UNet overestimates the occurrence of clouds in 6-8 km while underestimating high clouds (Fig. 8, b).

This issue is reflected within Figure 10. Here, we visualize the geographic distribution of the CTH difference (Fig. 10, a). The mean difference over all pixels accounts for 1.28 km. While the data show an overall agreement, the pixel-wise difference rises to a maximum of 10 km. This applies especially to regions in the subtropics. We observe an underestimation of the predicted CTH over land. Above the Atlantic ocean, especially in the tropics, the predictions are too high. The highest difference occurs in subtropics on the northern hemisphere (Fig. 7). Unlike most satellite-based procedures, the CTH is derived without integrating additional data, such as vertical temperature profiles from e. g. , model forecast or re-analysis data. This simplification reduces the workload for users and the co-dependence of corresponding data. Therefore, the approach offers added value in terms of a more efficient investigation of cloud-related processes. 10, b). At 20 °N, the mean difference accounts for 5 km. Around the tropics and mid-latitudes, both datasets are in higher agreement. The distribution of the CTH difference is inversely proportional to the amount of matched image-profile pairs (Fig. 7, b). The CTH difference decreases with an increasing amount of observational data from CloudSat. This applies to predictions over land and sea. Since we lack ground truth in the subtropics, the performance of the predictions decreases. The geographical differences are only partly in accordance to the distribution of the RMSE (Fig. 7, a). While the RMSE is lower in northern subtropics, the error of the predicted CTH reaches its peak (Fig. 10, b). The RMSE alone does not appear to be a suitable measure to define the reliability of the predicted reflectivity on the FD. This is due to influence of the skewed reflectivity distribution on the RMSE and its geographic variability.

Prediction of 3D cloud structures for the FD MSG SEVIRI domain with a a top-view on the maximum cloud column reflectivity for each pixel on 06 May 2016, 13:00 UTC (a). The detailed views in (b), (c), and (d) show the cloud tomography at different locations of the FDEven though the comparison of the CTH points out regional differences, the predictions can be used to represent the CTH pattern on the FD. The CLAAS-V002E1 data is computed using the MSG SEVIRI satellite channels as well as derived products and additional data. Each of them bring their own bias, potentially multiplying their effects on the final CTH. In contrast, our CTH is based only on the predicted reflectivity. In that way, we can minimize the influence of additional data sources.
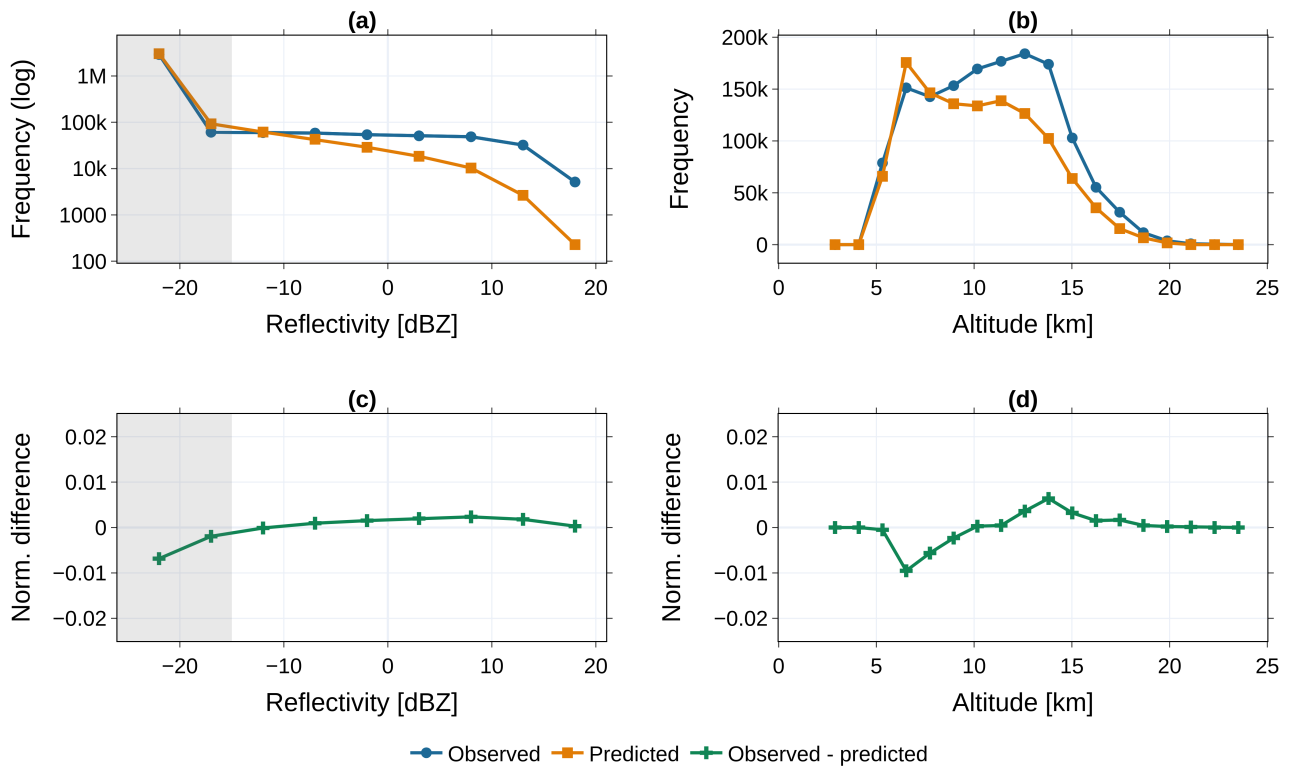
Figure 8. Comparing the ~~FD~~ reflectivity distribution ~~of reflectivities~~ and ~~CTH~~ the derived ~~from~~ CTH for CloudSat and the ~~model~~ Res-UNet predictions. Data is calculated on the test dataset and aggregated ~~for May, 2016.~~ to a monthly mean (n = 1500). The upper row frequencies (**a**) and (**b**) display the dBZ and computed CTH for observed and predicted data. Lower row images (**c**) and ~~their normalized~~ (**d**) show the difference between the observed and predicted data. Grey areas ~~lie~~ on the plots (**a**) and (**c**) contain reflectivities below the threshold of -15 dBZ applied for the CTH analysis.~~Lower row images (c) and (d) picture the frequency of~~
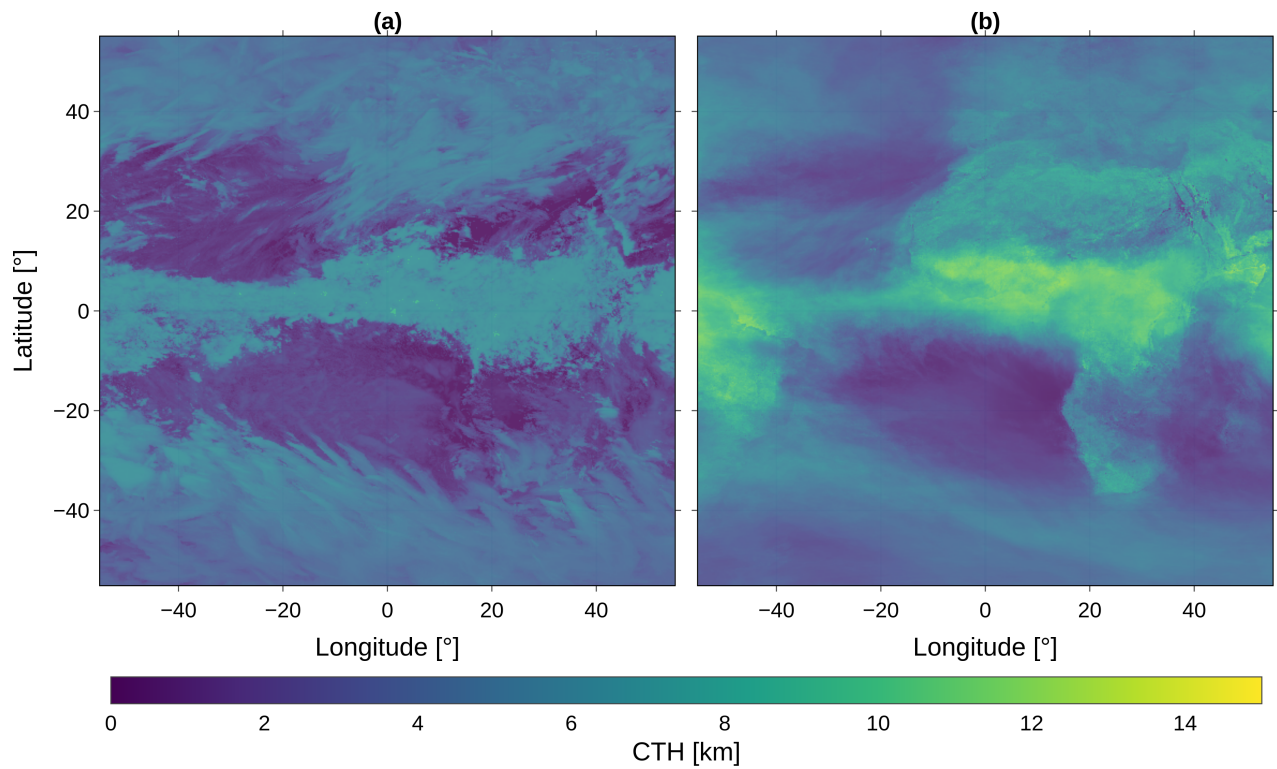
Figure 9. Monthly aggregation for the derived CTH ~~per height level (for~~ ~~observations above -15 dBZ) alongside the normalized difference~~ ~~between 5–24 km height~~May 2016 **(a)** compared to CLAAS-V002E1 CTO **(b)**.
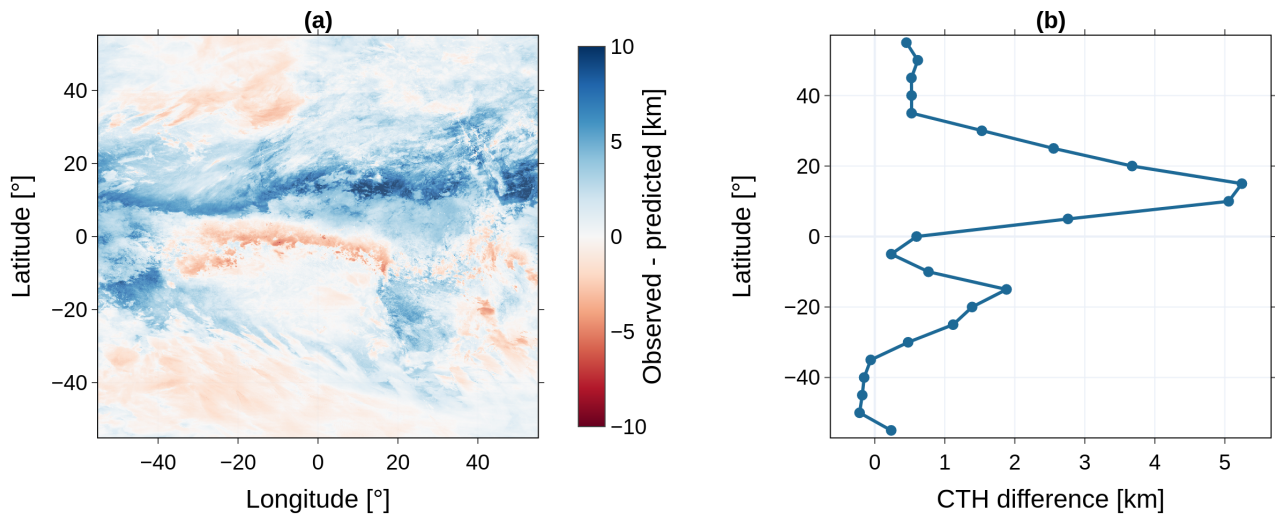
Figure 10. ~~Aggregated CTH derived from the Res-UNet **(a)** and from the~~ Difference between CLAAS-V002E1 CTO ~~product~~ **(b)** and the computed CTH for May ~~,~~ 2016. Plot **(a)** shows the geographic distribution on the FD, **(b)** the zonal error.

4 Discussion

~~In contrast to established ML methods like RF which need a cumbersome selection of predictor variables, the network in this study learns directly from the data (Kühnlein et al., 2014; Leinonen et al., 2019). That said, the DL approach reduces the time spent on processing and the user-generated bias (Jeppesen et al., 2019; Jiao et al., 2020). Standard DL models often use~~ The Res-UNet makes predictions based on the satellite channels, preserving the spatial details and global context during training (Wang et al., 2022). The error of the model varies depending on cloud structure within the radar cross-section. Compared to pixel-based approaches like OLS, the Res-UNet better reconstructs the pixel connectivity. The OLS and RF operate on 1D cloud columns. This limits their ability to extrapolate cloud information to a larger scale, resulting in fragmented reconstructions (Fig. 5, c, d). While the RMSE and the reflectivity distribution are similar across all models, only the Res-UNet predicts a contiguous radar cross-section. Choosing a DL framework eliminates the need for prior predictor variable selection (Kühnlein et al., 2014; Leinonen et . This can reduce the user bias in the input data (Jeppesen et al., 2019; Jiao et al., 2020).

The Res-UNet shows a 30 % improvement in the mean RMSE (Fig. 4). We could potentially further enhance the model performance by utilizing a more complex architecture. Our input data differs from typical gray-scale or RGB images ~~(Drönner et al., 2018)~~ ~~. In contrast, the input data in our study consists of multiple satellite channels . That is why~~, as it comprises multiple input channels and results in a 3D output (Drönner et al., 2018). Given the demands of our data and resource constraints, we adapted a standard UNet architecture rather than using a pre-trained model ~~is restrained by expensive modifications (Amato et al., 2020)~~ ~~. To evaluate the feasibility of the approach, we test a minimal architecture for transferring the 2D resolved satellite data to a 3D perspective~~ (Amato et al., 2020). Selecting the RMSE as a loss function can increase the blurriness in the results, particularly as model bias grows (Mathieu et al., 2016). This issue becomes apparent as all models struggle to predict high reflectivities (Fig. 2, b–d). The predictions are influenced by an imbalance within the CloudSat data, with the distribution of all models skewed toward low reflectivities. A resolution mismatch between CloudSat and MSG SEVIRI exacerbates this imbalance, causing peak reflectivities to blur out (Fig. 5, b–d).

~~While Hilburn et al. (2020) were able to reconstruct the radar signal~~ Our study covers a large-scale AOI spanning 60 ° in all directions. In contrast to studies of Leinonen et al. (2019) or Hilburn et al. (2020), we incorporate a diverse landscape into our training. While Hilburn et al. (2020) focused on radar signal reconstruction over the USA ~~, they are limited to a planar representation and leave out cloud development~~ using land-based radar, Leinonen et al. (2019) concentrated on radar cross-section prediction over the sea ~~surface. Contrasting their and others work, our study integrates a heterogeneous landscape into the training routine (Leinonen et al., 2019; Le Goff et al., 2017; Hilburn et al., 2020; Forster et al., 2021). The latitude and topography are highly influential for~~ . In our study, we match image-profile pairs over land and sea to achieve model invariance to the topography. The performance of our Res-UNet is similar to their results. Nevertheless, we observe regional difference, especially for the CTH. We use a geographical analysis to highlight the importance of the topography and land-sea distribution and their impact on cloud microphysics (Wang et al., 2023). ~~Nonetheless, defining those variables as additional predictors has a negligible effect on the model performance. Instead, the network performs equally well over land and ocean bodies capturing the shape of convective and shallow clouds. Predictions at nighttime are limited~~

We emphasize the influence of the geographic location and the CloudSat orbit, particularly in regions farther from the equator, where sensor accuracy diminishes (Fig. 7). Currently, we estimate the model error to be mainly influenced by the data imbalance and chosen loss function. In the future, addressing the cloud parallax shift in high-angle satellite observations could enhance the results by a more accurate image-profile matching (Bieliński, 2020). The most accurate predictions fall between 25 °N and 25 °S (Fig. 7), while mid- and high-latitudes exhibit a higher RMSE. This is likely due to the land-sea distribution and connected cloud patterns. Over ocean bodies, the model overestimates the reflectivity (Fig. 10, a). Using the water vapor channels could lead to this distortion. Improved predictions are evident over the southern hemisphere. Since CloudSat operates on a sun-synchronous orbit, it misses diurnal variations in each region (Sect. 2.1.2). In this study, we only derive daytime predictions. This is due to the influence of solar radiation in ~~the channels located within wavelengths of the visible spectrum (Hilburn et al., 2020; Jeppesen et al., 2019). Leaving out the affected channels~~downgrades the overall performance. While the results imply a high agreement between observations and predictions, distortions are possible. Since the satellite data deliver only information on the uppermost layer~~visible spectrum (VIS) channels (Hilburn et al., 2020; Jeppesen et al., 2019). Additional distortions may arise from VIS channels, ~~the incoming signal could originate from any surface with an enhanced~~ as satellite images only represent the uppermost cloud layer. Depending on the location, they can be highly influenced by the surface albedo (Drönner et al., 2018).

~~The Res-UNet in this study generates its predictions with the influence of the neighboring pixels along the image domain. In contrast to pixel-based DL methods like the CNN or CGAN, the Res-UNet utilizes a larger receptive field preserving the spatial dimensionality and global context information during the training routine (Wang et al., 2022). Thus, it receives a more accurate spatial connectivity between the pixels and following, the clouds within the image. While the OLS and RF solely get information on the reflectivities along a single cloud column, the Res-UNet enables an interpolation towards an FD perspective. While the CGAN was restrictively trained over sea surfaces, the influence of the variability of the topography beneath needs to be included (Wang et al., 2023). The restoration of the original track is~~Training a model without the VIS channels can help to achieve predictions independent of the daytime. Reducing the extent of the AOI can mitigate the geographic performance differences but limits the applicability of the network. Training regional models and adjusting the loss function and model architectures offer potential solutions to improve the results of the 3D cloud tomography.

The reconstructed CloudSat cross sections are comparable to results achieved by Leinonen et al. (2019)~~and Wang et al. (2023). The ~~. For both studies, the RMSE varies between 0–1 dBZ for cloud-free samples, 3–7 dBZ for more uniform clouds, and more than 10 dBZ for multi-layer clouds~~(Leinonen et al., 2019). All networks struggle to depict ~~. A common limitation is accurately representing multi-layer ~~structures accurately ~~clouds. Using the satellite channels to derive these information may be limited (Schmetz et al., 2002; Thies and Bendix, 2011). High reflectivities tend to be underestimated due to noise near the ground (Stephens et al., 2008). ~~Due to the sensor limitations of CloudSat, few signals close to the ground are received (Stephens et al., 2008). In consequence, predictions at low altitudes are error-prone. This issue is reflected within the normalized differences between observed and predicted reflectivities~~ To mitigate this, we exclude affected height levels, but this results in incomplete model predictions between 0—5 km (Fig. 2). ~~Similar results are achieved by Leinonen et al. (2019) where falsely estimated reflectivities appear in similar dBZ regions up to 12 km height. In both cases, an underestimation of high reflectivities~~

Reducing noise is crucial for improving the performance of DL applications in remote sensing (Enitan and Ilesanmi, 2021). Our results are significantly influenced by the resolution difference between CloudSat and MSG SEVIRI, as well as the choice of the loss function (Sect. 2.1.3). The aggregation of CloudSat pixels blurs contrast within individual clouds (Fig. 5, a), which is further reflected in the increased RMSE. In contrast, Leinonen et al. (2019) use data from the MODIS satellite (Zantedeschi et al., 2022). It has a higher spatial resolution than the MSG SEVIRI data allowing for sharper predictions along the radar transect. However, polar-orbiting satellites like MODIS lack the spatio-temporal coverage of geostationary satellites (Dubovik et al., 2021). In their study, Wang et al. (2023) derive 24000 training samples for matching CloudSat and MODIS over six years. By using MSG SEVIRI data, we amplify the volume of training data. We have extracted approximately 30000 training samples from one year of satellite data, which results in a ratio of about 1:7.

Currently, a compromise on the resolution is necessary to obtain predictions for Europe and Africa. However, promising new instruments are emerging. While data from comparable sources like the GOES-R series and the Himawari 8/9 satellites already offer a 1 km resolution, the recently launched Meteosat Third Generation satellite by EUMETSAT allows to close the gap and enables a more precise representation of individual clouds (Holmlund et al., 2021). Although our approach currently focuses on a region centered around 0 $^\circ$ longitude, we can apply the same framework to other geostationary satellites, potentially achieving global 3D cloud coverage throughout the troposphere. The predicted cloud field can be valuable for time series analysis, enabling the tracking of clouds in four dimensions across space and time. Our results facilitate the identification of large-scale cloud patterns. They offer various applications, such as analyzing cloud organizational structures, pinpointing lightning locations, or conducting precipitation onset analyses. While we use CloudSat radar data as our ground truth, this approach can be adapted to other 2D transect data sources, such as aerosol measurements.

5 Conclusions

With the help of a neural network, we demonstrate for the first time the potential to infer comprehensive 3D radar reflectivities from 2D geostationary satellite images. While former studies provides a flexible

~~and landscape-independent~~ were confined to a smaller region or the reconstruction of the 2D radar transect, we provide a

615 framework to model the ~~cloud signal with~~ 3D cloud field in a high spatio-temporal resolution. ~~Since it is independent of external or interconnected data sources, the bias within the data is reduced~~The study is focused over Africa and Europe, but the approach can be used to predict the radar reflectivity on a global scale. Using only the predicted reflectivity, we derive the CTH without external data sources. Overall, the approach ~~leads to an accurate representation of multi-scale dynamics~~ accurately reconstructs cloud structures in varying environmental conditions on the FD. Although the results are affected by

620 sensor-specific and technical limitations, a vast potential for applications in ~~the field of weather and climate~~ atmospheric and climate sciences is apparent. With steadily growing data and the emergence of improved instruments, the results can close the consisting global data gap. We emphasize the benefit to extrapolate a 3D cloud field, especially in ~~secluded regionsand above the sea surface~~remote oceanic regions. Future work will focus on extending the proposed network by data with an enhanced spatial and temporal resolution and investigating 3D cloud processes in proceeding applications.

625 **Appendix A:** **Overview of Res-UNet parameters**

Table A1. Hyperparameters and training parameters of the Res-UNet.

Type	Parameter	Value
Hyperparameters	Depth	4
	Input channels	11
	Output channels	90
	Filter size	3 x 3
	Pooling size	2 x 2
	Dropout	0
	Activation function	ReLU
Training parameters	Number of epochs	50
	Batch size	4
	Input size	128 x 128
	Crop size	100 x 100
	Initial learning rate	0.001
	LR scheduler (factor)	0.1
	Optimizer	ADAM
	Weight decay	0.00001
	Loss function	RMSE
	Augmentation (horizontal flip)	Randomness = 50 %

Appendix B: **Summary of trainable model parameters**

Table B1. Total number of the Res-UNet model parameters.

Total number of trainable parameters	Estimated total size (MB)
1.893.328	194.27

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