



Above Cloud Aerosol Detection and Retrieval from Multi-Angular Polarimetric Satellite Measurements in a Neural Network Ensemble Approach

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Abstract. This paper describes an algorithm for above-cloud aerosol (ACA) retrievals from PARASOL (Polarisation and Anisotropy of Reflectances for Atmospheric Science coupled with Observations from a Lidar) Multi-Angle Polarimetric measurements. The algorithm, based on neural networks (NNs), has been trained on synthetic measurements and has been applied to the processing of one-year PARASOL data. The algorithm makes use of three subsequent NNs: 1) for the detection of liquid clouds, 2) for the retrieval of aerosol properties for ACA cases, and 3) an NN forward model to evaluate the goodness-of-fit of the retrieval. The NN's theoretical capability of retrieval is investigated by several synthetic data studies. It is shown that the NN is able to retrieve ACAOT (above cloud aerosol optical depth), AE (Angstrom exponent), and SSA (single scattering albedo) yielding an RMSE (root mean squared error) of ~ 0.1 on ACAOT, ~ 0.4 on AE and ~ 0.04 on SSA in synthetic experiments. Finally, comparison between the NN retrievals and adjacent PARASOL-RemoTAP clear sky retrieval in 2008 shows good agreement within the range that is expected from the synthetic study.

1 Introduction

Knowledge about above-cloud aerosol (ACA) is important for understanding aerosol's impact on Earth's energy balance and climate dynamics (Li et al., 2022). From a perspective of aerosol-radiation interaction, it leads to large regional variations in the aerosol direct radiative effect (DRE; Lacagnina et al. (2017); de Graaf et al. (2020); Wilcox (2012)). The sign of the above cloud aerosol direct radiative effect may differ from that of a clear-sky situation (de Graaf et al., 2023), which depends on a number of factors including the cloud albedo, the aerosol type and its level of absorption (Lenoble et al., 1982; Keil and Haywood, 2003; Peers et al., 2015; Kacenelenbogen et al., 2019). Furthermore, when absorbing aerosols are located above stratocumulus clouds, warming of the layers above the clouds stabilizes the boundary layer, reducing entrainment rates and fostering a moister boundary layer. This may ultimately result in an increased liquid water content and the preservation of cloud cover (Johnson et al., 2004; Brioude et al., 2009). However, uncertainties arise when aerosol and cloud properties are not adequately known, impacting ACA's DRE estimation (de Graaf et al., 2020) and our understanding of aerosol-cloud interaction



(Arola et al., 2022). Therefore, obtaining better-retrieved properties for aerosols and clouds in ACA scenarios is important for a comprehensive understanding of the ACA's effect on both radiation and clouds.

Satellite-based remote sensing plays a crucial role in quantifying the aerosol direct effect (Myhre et al., 2009; Lacagnina et al., 2015, 2017; Chen et al., 2022) and indirect effect (Gryspeerdt et al., 2017; Hasekamp et al., 2019b; Quaas et al., 2020; Gryspeerdt et al., 2023; Rosenfeld et al., 2024). For passive sensors, the largest information content on aerosols is available from multi-angle, multiwavelength measurements of both radiance and polarization (Mishchenko and Travis, 1997; Hasekamp and Landgraf, 2007; Dubovik et al., 2019). This type of instrument is referred to as a Multi-Angle Polarimeter (MAP) in this study. Three versions of the POLarization and Directionality of Earth Reflectances (POLDER) instrument have flown since 1995. Only POLDER-3 on PARASOL has provided a multi-year data set between 2004 to 2013. The instrument 3MI (Fougnie et al., 2018), which is an improved version of POLDER, is scheduled to launch in 2025 on the Metop SG-A satellite. The NASA PACE mission (Werdell et al., 2019), which launched in February 2024, significantly improves aerosol and cloud retrieval capabilities through advanced MAP measurements, in terms of accuracy as well as spectral and angular sampling. PACE includes two polarimeters: SPEXone (Hasekamp et al., 2019a; Fu et al., 2025), providing hyperspectral measurements at five viewing angles, and HARP-2, providing hyper-angular measurements at four discrete spectral bands. PACE is the first mission in over a decade to deliver advanced MAP data products for aerosols and clouds.

Currently, measurements from satellite-borne MAP instruments can be used to retrieve above cloud aerosol properties, as the above cloud aerosol can significantly affect the reflected polarized radiance at a certain range of scattering angles (Knobelspiesse et al., 2015). Waquet et al. (2009) presented an algorithm for above cloud aerosol property retrieval from PARASOL and evaluated it for biomass-burning aerosols transported over stratocumulus clouds. In Waquet et al. (2013), it was further updated to allow retrieving also the properties of mineral dust particles above clouds. Apart from the discrepancies in polarization, the different wavelength dependency in the mechanism between light scattering by aerosols and clouds also provides information in separating above cloud aerosol from clouds. Based on this, another algorithm, the "color ratio" method, uses the ratio between the measurements at a shorter (470 nm) and a longer (860 nm) wavelength to derive aerosol optical thickness (AOT) and COT, and has been applied on single-viewing radiance measurements of OMI (Torres et al., 2012) and MODIS (Jethva et al., 2013).

The use of Neural Networks (NNs) provides a promising alternative for physics-based and look-up table (LUT) retrievals because of the efficiency in computation and the possibility to take into account the effect on the measured signal of different parameters (e.g., surface reflection) without explicitly retrieving them (e.g., Yuan et al. (2024)). NNs have been used successfully in polarimetric remote sensing of aerosols by e.g. Di Noia et al. (2017), Gao et al. (2021a), Segal-Rozenhaimer et al. (2018), and Gao et al. (2021b), as well as for polarimetric remote sensing of cloud microphysical properties by Di Noia et al. (2019). This work aims at developing an above cloud aerosol detection and retrieval scheme for MAP instruments, and focuses on the POLDER-3/PARASOL instrument (hereafter simply referred to as PARASOL) because it is the only MAP with a long-term data set.

The paper is organized as follows: Section 2 introduces the data used in the study, Section 3 describes the Neural Network configurations and the datasets used for the training, Section 4 investigates the performance of the Neural Network on different



synthetic datasets, Section 5 shows the data processing of one year (2008) PARASOL measurements and comparison with adjacent PARASOL-RemoTAP clear-sky aerosol retrievals. Finally, Section 6 summarizes and concludes this paper.

2 Data description

2.1 PARASOL

PARASOL (Fougnie et al., 2007) provided multi-angle observations (up to 16 viewing angles per ground pixel) in 9 spectral bands (443, 490, 565, 670, 763, 765, 865, 910, 1020 nm) for intensity and 3 spectral bands for Stokes parameters Q and U (490, 670, 865 nm). The mission was operational in the period 2004-2013 (until 2009 as part of the NASA A-Train satellite constellation). The level 1 data are provide on a common sinusoidally grid of approximately with ground pixels of approxi-
65 mately $6 \times 6 \text{ km}^2$. This study uses PARASOL measurements from 6 spectral bands (443, 490, 565, 670, 865, 1020 nm) within latitude ranges from 60° S to 60° N and with at least 14 available viewing angles.

2.2 PARASOL RemoTAP aerosol retrievals

In this study, PARASOL RemoTAP (Remote Sensing of Trace Gas and Aerosol Products) aerosol retrievals provide some of the aerosol and surface properties in the training set and are also used for evaluation of the NN ACA retrievals on real PARASOL
70 measurements. The RemoTAP PARASOL retrievals herein (Hasekamp et al., 2024) are based on a parametric 3-mode aerosol description characterized by three log-normal size distribution modes ($N_{\text{modes}} = 3$): one fine mode and two coarse modes (dust and soluble). A detailed overview of RemoTAP can be found in Hasekamp et al. (2024) and Lu et al. (2022).

2.3 Cloud phase from MODIS-Aqua cloud product

The MODIS cloud phase product used in this work is generated at 1-km (at nadir) spatial resolutions from MODIS-Aqua
75 L2 data product (MYD06_L2, Platnick et al. (2015)). Five different cloud flags are categorized in the product: liquid cloud, ice cloud, mixed cloud, uncertain and clear. Here in this work, a pixel is marked as liquid phase only when the fraction of liquid-cloud-flagged 1-km-resolution MODIS pixels within a $6\text{km} \times 6\text{km}$ PARASOL grid cell is larger than 80%.

3 Methodology

3.1 General settings of the forward simulation

80 The neural network (NN) training in this study utilizes the synthetic measurements of top-of-atmosphere intensity vector $\mathbf{I}$ consisting Stokes parameters I , Q , U , as a function of wavelength and viewing-solar geometries. The synthetic measurements are generated by the RemoTAP forward model (Hasekamp and Landgraf, 2002, 2005; Schepers et al., 2014), which is a linearized radiative transfer model employed in the RemoTAP retrieval algorithm (Hasekamp et al., 2011; Fu and Hasekamp, 2018; Fu et al., 2020; Lu et al., 2022; Fu et al., 2025). In the calculation of the synthetic measurements, liquid clouds are



85 represented by spherical particles with a Gamma size distribution, and the refractive index of water is taken from Hess et al. (1998). For ice clouds, hexagonal crystals with varying aspect ratios and surface distortions are used as proxies for variable-complex-shaped ice crystals (van Dienenhoven et al., 2020). The aerosol size distribution follows three log-normal modes, as described in Lu et al. (2022), where each mode is described by the effective radius, effective variance, complex refractive index (dependent on wavelength), aerosol optical thickness (AOT) at 550 nm, fraction of spherical particles and aerosol layer
90 height. Here we should note that the forward simulation of ACA scenes includes only fine and dust mode aerosols, while the simulation of clear sky scenes considers also a soluble coarse mode. The spectrally dependent refractive index $m(\lambda)$ per mode is parameterized by

$$m(\lambda) = \sum_{k=1}^{n_\alpha} \alpha_k m^k(\lambda), \quad (1)$$

where $m^k(\lambda)$ are prescribed functions of wavelength, for which we use standard refractive index spectra for different aerosol
95 components, i.e., dust (Torres et al., 2007), inorganics and black carbon (d’Almeida et al., 1991), and organic carbon (Kirchstetter et al., 2004). The Mie- and T-matrix-improved geometrical optics database (Dubovik et al., 2006) are used in the computation from aerosol microphysical properties to optical properties. The spheroid aspect ratio distribution proposed in the database is utilized to calculate optical properties for the spheroid-sphere mixture. The ocean reflection properties are parameterized based on wind speed as described in Cox and Munk (1954), and chlorophyll-a concentration as outlined in Fan
100 et al. (2019). For land surface simulations, the bidirectional reflectance distribution function (BRDF) is parameterized using the Ross-Li model (Wanner et al., 1995), while the bidirectional polarization distribution function (BPDF) is parameterized as in Maignan et al. (2009).

The surface (land and ocean) properties are from randomly picked pixels of RemoTAP global retrieval for the year 2008. The cloud properties are generated randomly. The aerosol properties are randomly generated values or randomly picked from
105 RemoTAP global retrieval in 2008, depending on the task of different neural networks. The geometry combination (solar zenith angle, SZA, viewing zenith angle, VZA and relative azimuth angle, RAA) are from randomly picked real PARASOL solar-viewing geometries in 2008. Only the measurements with a minimum of 14 angles are considered for the NN training, in order to evade from a variable-sized input vector to the NN or, as an alternative, an input vector with missing data.

3.2 Neural Network training

110 This work focuses on retrieving the properties of aerosols which are located above a liquid cloud layer, and the retrieval process is depicted in Figure 1. Three NNs are used in the process: 1) NN cloud mask, to select pixels covered by a liquid cloud, 2) NN for aerosol retrieval and 3) NN surrogate radiative transfer model (hereafter referred to as NN forward model). The NN forward model is implemented because we wish to have a computational inexpensive goodness-of-fit mask to screen out retrievals that do not match with the MAP measurement used as input. Additionally, MODIS cloud phase flags are used to mask cases with
115 thin cirrus above liquid cloud.

The first NN (liquid cloud mask) takes intensity, degree of linear polarization (DoLP), and viewing geometries (SZA, VZA, RAA and scattering angle) as input and outputs liquid cloud fraction and ice cloud fraction separately. The independent pixel

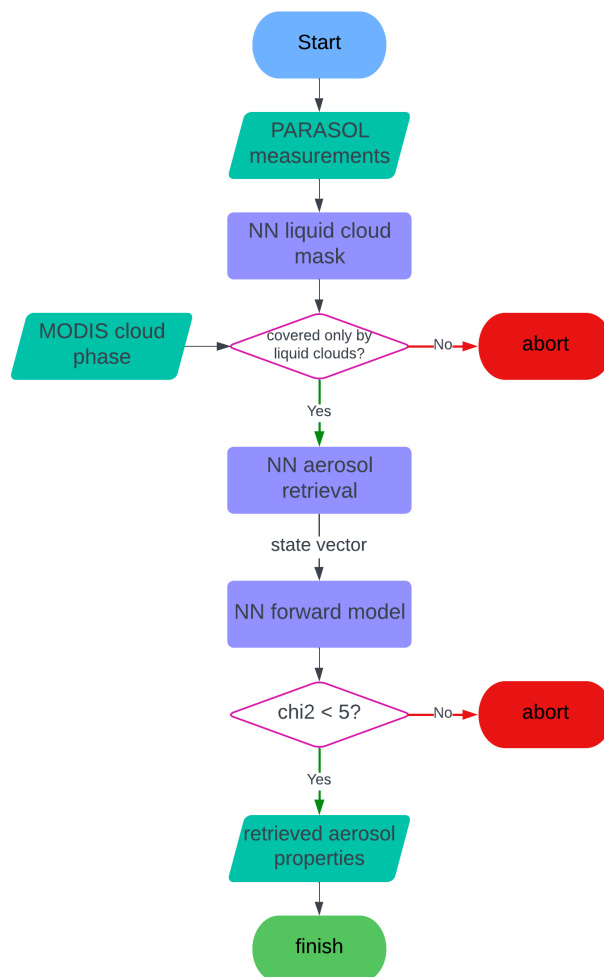


Figure 1. A flowchart of the NN ACA retrieval process. Three NNs (in the purple rectangles) are used in the process: NN for cloud mask, NN for ACA retrievals and NN forward model. MODIS cloud phase data are used to screen out the residual thin cirrus above liquid clouds. The aerosol retrieval will be discarded if any of the following situations happen: 1) NN liquid cloud fraction < 0.8, 2) NN ice cloud fraction > 0.2, 3) MODIS suggests the cloud phase is not liquid, or 4) the goodness-of-fit (χ^2) > 5.



approximation (IPA) is used to generate partly cloudy cases in the training set, as described in Yuan et al. (2024). The training set consists of 8 million samples including 20% cloud-free pixels, 10% fully covered by liquid cloud, 10% fully covered by ice cloud, and the other 60% partly covered by a mix of liquid cloud and ice cloud. The total cloud fraction is uniformly distributed in a square space (probability density function: $f(x) = x^2$) with more cloud fractions close to 1 in order to acquire better sensitivity at almost fully cloudy cases. The radiative contribution of aerosol and surface properties is also taken into account, as described by Yuan et al. (2024). In the training set, 20% of the samples represent the situation where the aerosol layer is located above the cloud top, in order to improve NN's ability to produce liquid and ice cloud fractions in areas of interest for this study. A pixel will be further processed, if this NN outputs a liquid cloud fraction > 0.8 and an ice cloud fraction < 0.2 , and the MODIS cloud flag also indicate this pixel is covered by liquid cloud. Here, the MODIS cloud flag is used to screen out cases where a thin cirrus is above liquid clouds, which are challenging to be identified by PARASOL measurements alone.

The aerosol retrieval NN takes the input of MAP measurements (i.e., radiance and DoLP), together with the observation geometry. It produces both fine mode and dust mode aerosol properties and underlying liquid cloud properties. Here we use a bi-modal aerosol description, where the size distribution is characterized by two log-normal modes, comprising one fine mode and one coarse mode representing dust. The state vector of the fine mode includes the effective radius (r_{eff}), effective variance (v_{eff}), spherical fraction (f_{sph}), aerosol column number (N_{aer}), spherical fraction (f_{sph}), and refractive index coefficients (c_k), which correspond to the standard refractive index spectra of inorganic aerosol (real part), black carbon (imaginary part), organic carbon (imaginary part), and water. The state vector of the dust mode (consisting of non-spherical dust) includes r_{eff} , v_{eff} , N_{aer} and a coefficient for the imaginary part of the dust refractive index. The parameter f_{sph} is fixed to 0 and c_k of the dust refractive index real part is fixed to 1. The liquid cloud properties included in the state vector are cloud optical thickness (COT), cloud layer height (CLH), and the liquid droplet effective radius (v_{eff}) and effective variance (v_{eff}). To better represent the real situations, the fine-mode fraction (fraction of fine mode AOT over the total AOT) is randomly taken from PARASOL-RemoTAP clear-sky retrievals, while the total ACAOT is randomly generated by a log-uniform distribution between 0 and 2. It should be noted that the coarse soluble mode is not considered in this step as it is usually low in the atmosphere and hence below the cloud layer. An overview of the distribution for the different state vector elements for the training set are given in Table A2. The intensity and DoLP, as a function of wavelength and viewing angle, are compressed using a principal component analysis (PCA) before the training. A total of 25 principal components are retained for radiance and 33 for DoLP.

The NN for forward calculation is designed to reproduce the MAP measurements from the viewing geometries and the retrieved properties, including aerosol properties of both fine mode and coarse mode and the liquid cloud properties. To make the forward model flexible in viewing geometries, it is trained separately per viewing direction and with the uniformly random-generated SZA, VZA and RAA. For each aerosol retrieval, the NN should be applied 14 times to simulate a MAP measurement at 14 viewing angles. The goodness-of-fit criterion is calculated as:

$$\chi^2 = \frac{1}{n} \sum_i^n \frac{(y_i - \mathbf{F}_i)^2}{\sigma_i^2}, \quad (2)$$



where n is the total channel of measurements, and y_i , F_i respectively stands for the satellite measurements and the NN reproduced measurements at the i -th channel. For the PARASOL measurements in this study, a total of 126 channels are used including 6 wavelengths for intensity and 3 wavelengths for DoLP with 14 viewing angles per wavelength. The noise σ_i is the estimated absolute noise of each channel. Here we use a relative noise of 0.02 for the intensity and an absolute noise of 0.012 for DoLP.

It should be noted that the NN forward model is not a complete forward model. It only works for pixels fully covered by a liquid cloud without any radiative contribution from the surface and is designed only for the purpose of goodness-of-fit assessment for above cloud aerosol retrievals.

To increase numerical efficiency and reduce memory usage during the training process, we choose the "neural network ensemble" approach (Hansen and Salamon, 1990), where the whole training set is equally and randomly divided into several parts, and an individual NN is trained on each part of the training set. The final output is the average of the outputs from all the ensembles. Here, three ensembles are used for liquid cloud mask NN, 16 ensembles for the aerosol retrieval NN, and six ensembles for the NN forward model.

For the cloud mask and retrieval NN, we add measurement noise to the training set as a form of regularization (Bishop, 1995). The measurement noise is modeled as a Gaussian random number with a zero mean and a standard deviation of 1 %–3 % relative noise for intensity and 0.012 absolute noise for DoLP.

In this study, Pytorch (version 1.11.0, <https://pytorch.org/>, last accessed: 11 October 2021) is used to implement the NNs, which are structured as multi-layer perceptrons (MLPs). The training process employs the backpropagation (BP) algorithm (Rumelhart et al., 1986) and batch training with a batch size of 12,000. The Adam optimizer (Kingma and Ba, 2014) is used to minimize the mean root square error (RMSE) loss function. The architecture of the neural network used in this work consists of three hidden layers. The liquid cloud mask NN has 64 neurons in each layer, the aerosol retrieval NN has 128 neurons and the NN forward model has 192 neurons. The detailed statistical distribution of the training sets can be found in the appendix A1, A2 and A3.

4 Synthetic experiments

Before applying the NNs to the real measurements, we perform synthetic experiments to investigate the theoretical capability of PARASOL measurements to provide ACA retrievals and to investigate the sensitivity of the retrieval to different aspects.

4.1 Performance over fine mode aerosol dominated dataset and dust mode aerosol dominated dataset

To test the compatibility of the algorithm for different aerosol conditions, we apply the NN to three datasets: 1) based on a uniform distribution of the fine-mode fraction between 0 and 1, as a baseline, 2) fine mode dominated cases only (fine-mode fraction > 0.7), and 3) dust mode dominated cases only (fine-mode fraction < 0.3). Details on the statistical distribution of the datasets can be found at Appendix B1. Figure 2 shows the scatter plot of ACAOT, Angstrom Exponent (AE), and SSA on the three datasets. The AE is calculated using ACAOT (τ) at 440nm and 670nm.

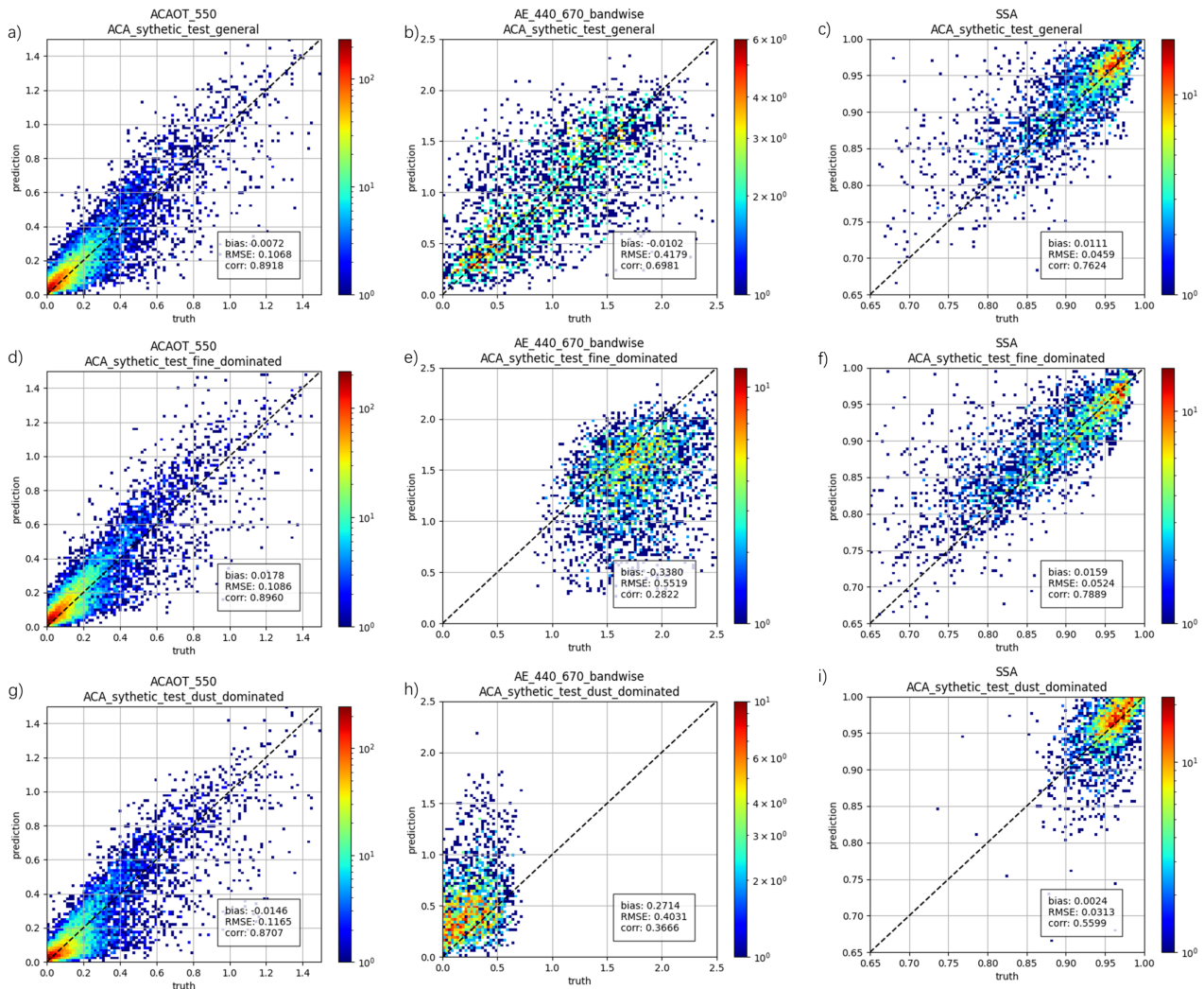


Figure 2. Scatter plots of ACAOT (a, d, g), AE (b, e, h), and SSA (c, f, i) on three synthetic datasets, where one contains both fine-mode-aerosol-dominated cases and dust-mode-aerosol-dominated cases (a, b, c) while others contain only fine-mode-aerosol-dominated cases (d, e, f) or dust-mode-aerosol-dominated cases (g, h, i). The x-axis is the truth of the property and the y-axis is the NN retrieval. The color of each scatter point stands for the number of retrievals (density) on the point.

The retrievals are filtered by a retrieved liquid cloud fraction > 0.8 , ice cloud fraction < 0.2 , and the goodness-of-fit χ^2 of the retrieval < 5 , all of which can be obtained from the NN for cloud mask and the NN forward model. For AE and SSA, an additional mask of retrieved ACAOT > 0.2 is applied. The RMSE is 0.11 for ACAOT, 0.42 for AE, and 0.05 for SSA in the mixed dataset. In the fine-dominated dataset, it is 0.11 for ACAOT, 0.55 for AE, and 0.05 for SSA. For the dust-dominated dataset, the RMSE is 0.12 for ACAOT, 0.40 for AE, and 0.03 for SSA.



4.2 Sensitivity analysis of the underlying cloud optical thickness

Retrieval simulations have been performed on five fully liquid-cloud-covered datasets to investigate the retrieval sensitivity of the optical thickness of the underlying liquid cloud. The datasets have the same aerosol, cloud, and surface properties but liquid cloud optical thickness are varied between 3 and 40. Each dataset has a total of 10000 samples for both land and ocean. Details on the statistical distribution of the datasets can be found at Appendix B2.

Figure 3 shows the RMSE, and number of remaining pixels as a function of the liquid COT. The retrievals are always masked by a retrieved liquid cloud fraction larger than 0.8, an ice cloud fraction smaller than 0.2 and a goodness-of-fit mask from the NN forward model. The AE and SSA retrievals are additionally masked by $ACAOT > 0.2$. For samples with $COT < 5$, 80% ocean pixels and almost all land pixels are screened by the cloud mask and goodness-of-fit mask. When the COT is larger than 10 over ocean and 20 over land, the percentage of the good retrievals (that can pass the cloud mask and goodness-of-fit mask) is larger than 80%. For retrievals over land, we see that the RMSE decreases with increasing COT when $COT < 20$ and then stays constant. This behavior can be explained by the fact that for $COT < 20$ the measurement is still affected to some extend by the underlying surface which causes a large RMSE. Over ocean, we see an opposite effect (except for very small COT), because the contribution from the ocean is relatively small and a smaller COT would even enhance the relative contribution of the aerosol signal compared to the cloud signal.

5 Application on PARASOL data

5.1 Comparison between PARASOL-NN above cloud aerosol retrievals and adjacent RemoTAP clear-sky aerosol retrievals

The ACA retrievals are evaluated with nearby RemoTAP clear-sky aerosol retrievals in 2008 (Hasekamp et al., 2024) within the same $1^\circ \times 1^\circ$ grid cell. If a grid cell contains at least 3 above cloud retrievals and at least 3 clear-sky retrievals, then the comparisons are made by taking the average of the retrieved aerosol properties for both above-cloud and clear-sky retrievals, respectively. The comparison between the ACA retrievals and the matching clear-sky retrievals is shown in Figure 4. For AOT, there is a root-mean-square difference (RMSD) between the above-cloud and clear-sky retrievals of 0.155. This is larger than the RMSE for the synthetic experiment (~ 0.10) but we should keep in mind that the clear-sky RemoTAP retrievals do not provide an exact reference. In the first place, the retrieval error in the RemoTAP clear-sky retrievals (based on AERONET validation) is ~ 0.10 over land and ~ 0.05 over ocean (Hasekamp et al., 2024). Second, we will in general expect a lower above-cloud AOT than the adjacent clear-sky AOT, because part of the aerosol may be located below the cloud, which explains the negative bias in the above-cloud AOT. However, we also find cases where the above-cloud AOT is higher than the adjacent clear-sky AOT, which suggests the above-cloud retrievals may still be contaminated by cirrus, despite the NN cloud mask and the MODIS cloud phase mask. For AE, the RMSE (0.429) in Figure 4 is similar to the RMSE found in the synthetic experiment (Figure 2), despite the fact that the AE error on the clear-sky retrievals is ~ 0.37 over land and ~ 0.25 over ocean (Hasekamp et al., 2024). For SSA, the RMSD (0.0586) is somewhat larger than in the synthetic experiment, but the results suggest that

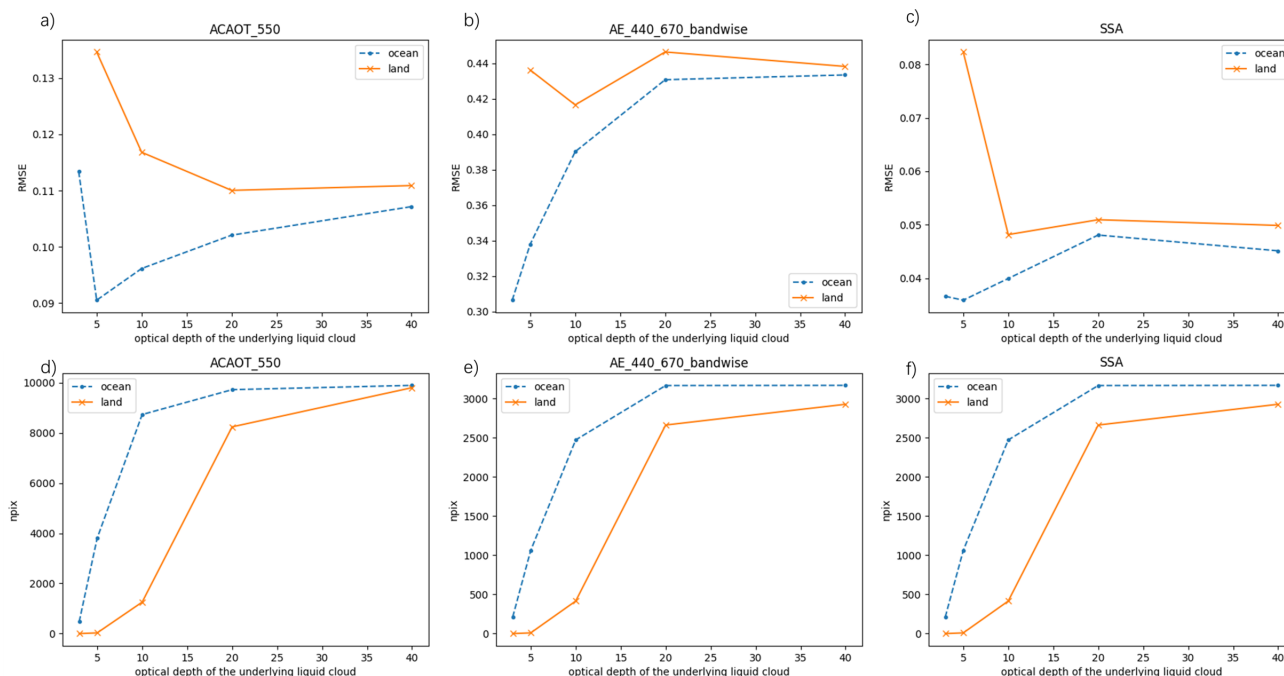


Figure 3. RMSE (a, b, c) and number of remaining pixels (d, e, f) as a function of the liquid COT for ACAOT (a, d), AE (b, e) and SSA (c, f). The dashed lines are the result of pixels over ocean and the solid lines are over land. The result are both screened by the cloud mask and the goodness-of-fit $\chi^2 < 5$ mask.

the intrinsic aerosol properties (AE and SSA) are more comparable for above-cloud and adjacent clear-sky retrievals than the AOT.

5.2 Distribution of the ACA events' frequency and the ACA properties in 2008

Figure 5 shows the global seasonal average of ACAOT and the number of ACA events in spring (Mar–May), summer (Jun–Aug), autumn (Sep–Nov) and winter (Dec, Jan and Feb) on the $1^\circ \times 1^\circ$ grid. The average of ACAOT is calculated only when at least 25 valid PARASOL retrievals are found in the grid cell. The number of ACA events in a cell is defined as the total number of "good" retrievals where ACAOT is larger than 0.1.

The results in Figure 5 agree well with the major ACA regions from previous studies (Waquet et al., 2013; Jethva et al., 2018), which include: 1) Tropical Southeast Atlantic, primarily consisting of biomass burning aerosols. 2) North Pacific, mainly containing industrial pollutants. 3) "Dust Belt" ($5\text{--}40^\circ\text{N}$), where mineral dust particles are commonly detected above clouds in this latitudinal band.

The spatial occurrence of ACA events varies largely among each season. In the western coast of mid-Africa, the ACA events occur more in summer and autumn, while in spring and winter, not many events are observed. In the western coast of North America, although the events are detected for all the seasons, fewer events occurred in autumn and winter compared with the

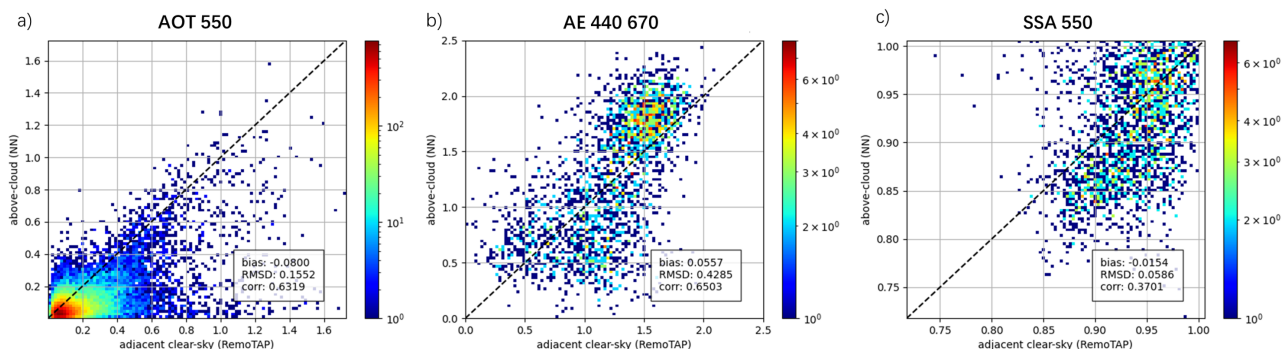


Figure 4. Comparisons of above cloud aerosol retrievals and clear-sky retrievals in the same $1^\circ \times 1^\circ$ grid. RMSD of AOT (a) is 0.155, AE (b) is 0.429 and SSA (c) is 0.0586. Generally we see a lower above-cloud AOT than the adjacent clear-sky AOT, as part of aerosols are below the cloud. In some cases there is the above-cloud AOT larger than that in clear-sky, and this may be due to contamination of cirrus. The intrinsic aerosol properties (AE and SSA) are more comparable than the AOT.

other seasons. The events in southeastern China can also be observed for almost all the seasons with somewhat less events in summer and autumn.

When looking into the global seasonal average of ACAOT, we can find two regions with significantly heavy above-cloud aerosol load: the western coast of mid-Africa (mainly summer and autumn, $ACAOT > 0.5$), western coast of Morocco in north Africa (during summer, $ACAOT > 0.5$) and northeastern China (during spring, $ACAOT \sim 0.2$), and these regions are also observed to have a large number of ACA events. In contrast, for some regions with frequent ACA events, such as the western coast of North America, the seasonal average ACAOT is relatively low ($ACAOT \sim 0.1$). This agrees well with the analyses by Waquet et al. (2013) in the same year 2008.

We also investigated the annual average of AE and SSA, as is shown in Figure 6. The AE and SSA are calculated where $ACAOT > 0.2$. Compared with ACA events in other areas, events around the western coast of mid-Africa exhibit a different characteristic: aerosols have a high AE (indicating smaller particles) and a low SSA (indicating more absorbing components). The high AE and low SSA is an expected feature of the smoke in mid-Africa. We have to remark that our AE in regions between $45^\circ - 60^\circ N$ and $45^\circ - 60^\circ S$ is ~ 0.8 , which differs largely from ~ 1.8 in Waquet et al. (2013), despite the good agreement of our above cloud AE with the adjacent clear-sky AE in these latitudes.

6 Conclusion

This paper presents an NN-based approach to detect and retrieve properties of aerosol located above a uniform liquid cloud layer from multi-angle, multi-wavelength polarimetric measurements. The proposed approach is based on a cascade of three neural networks trained on synthetic measurements. Separate NNs have been trained for the subtasks of liquid cloud detection,

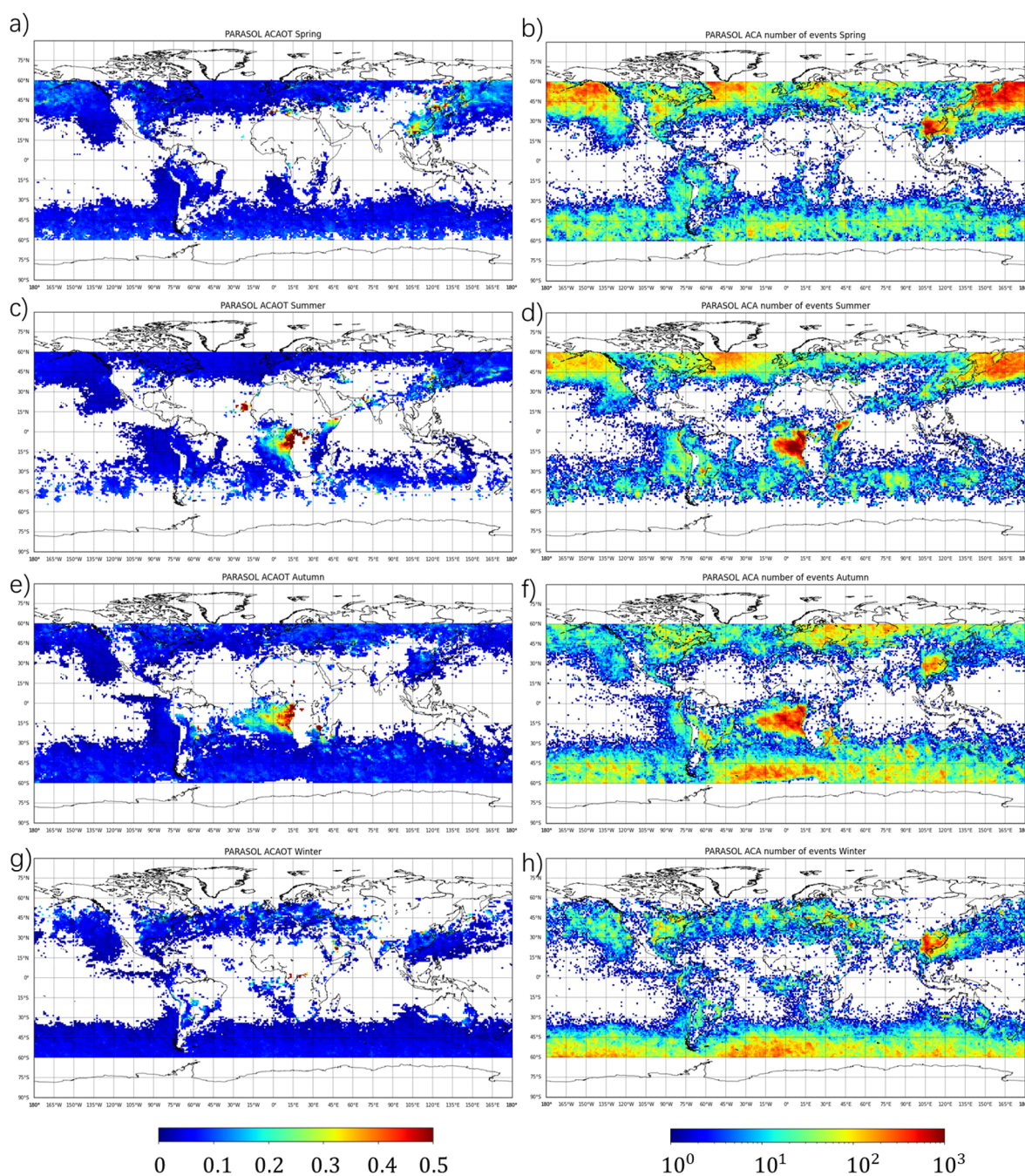


Figure 5. Seasonal ACAOT average (a, c, e, g) on each $1^\circ \times 1^\circ$ grid and the total number of ACA events (b, d, f, h) on each grid in 2008. From the top to the bottom row, spring (Mar–May), summer (Jun–Aug), autumn (Sep–Nov) and winter (Dec, Jan and Feb). An ACA event is defined when a PARASOL retrieval has passed the cloud mask and goodness-of-fit mask and produces an ACAOT larger than 0.1.

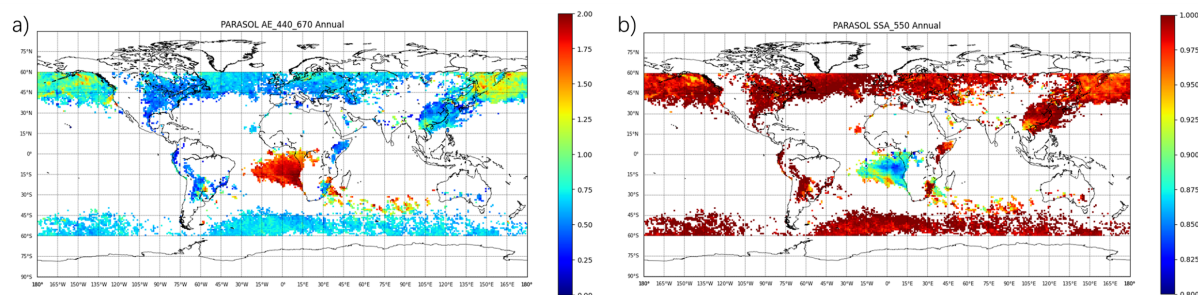


Figure 6. Annual AE (a) and SSA (b) average on each $1^\circ \times 1^\circ$ grid in 2008. The AE and SSA are calculated where $ACAOT > 0.2$. The ACA events in the western coast of mid-Africa have a distinctive feature than others, that the aerosols have a large AE (smaller particles) and a smaller SSA (more absorbing).

above cloud aerosol retrieval, and forward modeling for goodness-of-fit calculation. The aerosol retrievals are only performed on fully liquid cloud-covered pixels.

We evaluated the approach on different synthetic datasets. The experiment on three datasets (containing both fine- and dust-mode-dominated aerosol, only fine-mode-dominated aerosol and only dust-mode-dominated aerosol) indicates the NNs have the ability to retrieve AOT, AE and SSA from both fine- and dust-mode-dominated aerosol, as well as mixed scenes with an RMSE between 0.10-0.12 for AOT, 0.40-0.55 for AE, and 0.03-0.05 for SSA. The experiments on synthetic data sets with different liquid cloud optical depths analyze the theoretical sensitivity of the ACA retrieval. Over land, RMSE decreases as COT increases up to 20, then remains constant, likely due to surface influence at lower COT. Over ocean, RMSE shows the opposite trend (except at very low COT), as the relatively small contribution of the ocean surface makes aerosol signals more prominent compared to cloud signals.

The NN-based approach has been applied to a year of PARASOL data. The retrieved aerosol properties (AOT, AE, and SSA) are compared with adjacent clear-sky RemoTAP-PARASOL aerosol retrievals in the same $1^\circ \times 1^\circ$ grid with an RMSD of 0.155 for AOT, 0.429 for AE and 0.0586 for SSA. The seasonal global average of the retrieved ACAOT and the number of ACA events are also analyzed, and the results show frequent ACA events and a larger mean ACAOT in mid-Africa and North Africa on the western coast in summer and autumn months, while frequent events in other regions are also observed (e.g., southeastern China in autumn) with a relatively small averaged ACAOT, which agrees well with the analyses by Waquet et al. (2013) in the same year 2008. We also observed a distinctively larger AE and a smaller SSA on the western coast of mid-Africa, as a result of the smoke there. However, it has to be noted that our AE in regions between $45^\circ - 60^\circ N$ and $45^\circ - 60^\circ S$ is smaller than that from the previous research (Waquet et al., 2013), although the AE of the above cloud aerosol in these regions agrees well with the AE of the adjacent clear-sky aerosol AE.

Based on the experiments above, it can be concluded that NNs with input of measurements from satellite-borne multi-angular polarimetric instruments are able to retrieve above-cloud aerosol information, and the NN-based surrogate forward model, just like the full-physical model, can provide goodness-of-fit mask to filter unphysical retrievals, which may due to imperfect



275 cloud mask or some challenging aerosol/cloud/surface combination. The proposed approach could be applied for analyzing
data from newly developed multi-angle polarimeters. By modifying instrument-specific parameters, such as the number of
viewing angles, spectral channels, and noise configurations during neural network training, it can be tailored for existing on-
orbit instruments like SPEXone (Hasekamp et al., 2019a; Fu et al., 2025) and HARP2 aboard NASA's PACE satellite (Werdell
et al., 2019). It can also be adapted for future instruments, e.g., the 3MI (Fougnie et al., 2018) on the ESA/EUMETSAT Metop
280 SG-A satellite and the Multi-Angle Polarimeter (MAP) on the Copernicus CO2M mission (Spilling and Thales, 2021), both
scheduled for launch in the coming years.

6.0.1 Data availability

The MODIS MYD_06 is from https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/61/MYD06_L2/ (Platnick et al., 2015).
The PARASOL level-1 data can be downloaded from <http://www.icare.univ-lille1.fr/parasol/products> (CNES/ICARE, 2018).
285 The RemoTAP aerosol retrieval results used in the article can be found at [https://public.spider.surfsara.nl/project/spexone/](https://public.spider.surfsara.nl/project/spexone/POLDER/GRIDDED/)
POLDER/GRIDDED/ (Hasekamp et al., 2024).

6.0.2 Competing interests

Some authors are members of the editorial board of journal Atmospheric Measurement Techniques. The authors have also no
other competing interests to declare.

290 6.0.3 Author contributions

ZY performed the experiments designed by OPH and ZY. GF performed RemoTAP clear-sky aerosol retrievals. ZY wrote the
first draft, which was further revised by OPH and GF. HXL and JWE provided comments on the manuscript and advice on the
research strategy.

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Appendix A: Statistical distributions of the training data sets for the different NNs



Table A1. Details of the statistical distributions of the aerosol and cloud parameters used to generate the training datasets for cloud mask NN. Distribution of "RemoTAP" means properties are randomly taken from 2008 PARASOL-RemoTAP L2 database.

parameter	min	max	mean	distribution
wind speed (m/s)	0.1	87	7.52	RemoTAP
chl- α concentration	0.001	10	1.92	RemoTAP
Li-sparse	0	0.35	0.14	RemoTAP
Ross-thick	0	1.4	0.41	RemoTAP
Maignan bpdf	0.2	10	3.02	RemoTAP
brdf scaling coefficient (443nm)	0	0.40	0.06	RemoTAP
brdf scaling coefficient (490nm)	0	0.45	0.10	RemoTAP
brdf scaling coefficient (565nm)	0	0.50	0.17	RemoTAP
brdf scaling coefficient (670nm)	0	0.65	0.23	RemoTAP
brdf scaling coefficient (865nm)	0	0.80	0.33	RemoTAP
brdf scaling coefficient (1020nm)	0	0.90	0.37	RemoTAP
effective radius of liquid cloud (μm)	3	25	14	uniform
effective variance of liquid cloud	0.03	0.35	0.19	uniform
cloud optical thickness of liquid cloud	1	40	10.6	log-uniform
cloud layer height of liquid cloud (km)	1	8	5.5	uniform
effective radius of ice cloud (μm)	10	60	30	uniform
cloud optical thickness of ice cloud	1	100	21.5	log-uniform
cloud layer height of ice cloud (km)	8	17	9.5	uniform
aspect ratio of ice cloud crystals	0.179	5.592	1.57	log-uniform
distortion of ice cloud crystals	0.1	0.7	0.4	uniform
aerosol effective radius of fine mode	0.02	0.57	0.14	RemoTAP
aerosol effective variance of fine mode	0.01	0.8	0.20	RemoTAP
aerosol optical thickness of fine mode	0	4.58	0.67	log-uniform
aerosol effective radius of dust mode	0.7	6.12	1.89	RemoTAP
aerosol effective variance of dust mode	0.01	0.8	0.58	RemoTAP
aerosol optical thickness of dust mode	0	3.95	0.60	log-uniform
aerosol effective radius of soluble mode	0.7	6.12	3.24	RemoTAP
aerosol effective variance of soluble mode	0.01	0.8	0.59	RemoTAP
aerosol optical thickness of soluble mode	0	3.95	0.60	log-uniform



Table A2. Details of the statistical distributions of the aerosol and cloud parameters used to generate the training datasets for NN ACA retrieval. Distribution of "RemoTAP" means properties are randomly taken from 2008 PARASOL-RemoTAP L2 database.

parameter	min	max	mean	distribution
effective radius of liquid cloud (μm)	3	25	14	uniform
effective variance of liquid cloud	0.03	0.35	0.19	uniform
cloud optical thickness of liquid cloud	3	40	14.3	log-uniform
cloud layer height of liquid cloud (km)	0.4	4	2.2	uniform
aerosol effective radius of fine mode	0.02	0.57	0.14	RemoTAP
aerosol effective variance of fine mode	0.01	0.8	0.20	RemoTAP
above cloud aerosol optical thickness of fine mode	0	2	0.26	log-uniform
aerosol effective radius of dust mode	0.7	6.12	1.89	RemoTAP
aerosol effective variance of dust mode	0.01	0.8	0.58	RemoTAP
above cloud aerosol optical thickness of dust mode	0	2	0.26	log-uniform

Table A3. Details of the statistical distributions of the aerosol and cloud parameters used to generate the training datasets for NN forward model. The range of aerosol effective radius and effective variance for both fine mode and dust mode is smaller than that for the retrieval, because here it takes no extreme cases into account, which is relatively rare.

parameter	min	max	mean	distribution
effective radius of liquid cloud (μm)	3	25	14	uniform
effective variance of liquid cloud	0.03	0.35	0.19	uniform
cloud optical thickness of liquid cloud	3	40	14.3	log-uniform
cloud layer height of liquid cloud (km)	0.4	4	2.2	uniform
aerosol effective radius of fine mode	0.03	0.3	0.15	uniform
aerosol effective variance of fine mode	0.1	0.3	0.20	uniform
above cloud aerosol optical thickness of fine mode	0	2	0.26	log-uniform
aerosol effective radius of dust mode	0.8	3.0	1.9	uniform
aerosol effective variance of dust mode	0.4	0.8	0.6	uniform
above cloud aerosol optical thickness of dust mode	0	2	0.26	log-uniform



Appendix B: Statistical distributions of the synthetic datasets for testing

Table B1. Details of the statistical distributions of the aerosol and cloud parameters used to generate the datasets for experiment of fine mode, dust mode separate and together. Distribution of "RemoTAP" means properties are randomly taken from 2008 PARASOL-RemoTAP L2 database.

parameter	min	max	mean	distribution
effective radius of liquid cloud (μm)	3	25	14	uniform
effective variance of liquid cloud	0.03	0.35	0.19	uniform
cloud optical thickness of liquid cloud	3	40	14.3	log-uniform
cloud layer height of liquid cloud (km)	0.4	4	2.2	uniform
aerosol effective radius of fine mode	0.02	0.57	0.14	RemoTAP
aerosol effective variance of fine mode	0.01	0.8	0.20	RemoTAP
above cloud aerosol optical thickness of fine mode (if exists)	0	2	0.26	log-uniform
aerosol effective radius of dust mode	0.7	6.12	1.89	RemoTAP
aerosol effective variance of dust mode	0.01	0.8	0.58	RemoTAP
above cloud aerosol optical thickness of dust mode (if exists)	0	2	0.26	log-uniform



Table B2. Details of the statistical distributions of the aerosol and cloud parameters used to generate the datasets for sensitivity analysis of underlying liquid cloud optical depth. Distribution of "RemoTAP" means properties are randomly taken from 2008 PARASOL-RemoTAP L2 database. COT of liquid cloud (distribution "special") is constant in each experiment for sensitivity tests.

parameter	min	max	mean	distribution
wind speed (m/s)	0.1	87	7.52	RemoTAP
chl- α concentration	0.001	10	1.92	RemoTAP
Li-sparse	0	0.35	0.14	RemoTAP
Ross-thick	0	1.4	0.41	RemoTAP
Maignan bpdf	0.2	10	3.02	RemoTAP
brdf scaling coefficient (443nm)	0	0.40	0.06	RemoTAP
brdf scaling coefficient (490nm)	0	0.45	0.10	RemoTAP
brdf scaling coefficient (565nm)	0	0.50	0.17	RemoTAP
brdf scaling coefficient (670nm)	0	0.65	0.23	RemoTAP
brdf scaling coefficient (865nm)	0	0.80	0.33	RemoTAP
brdf scaling coefficient (1020nm)	0	0.90	0.37	RemoTAP
effective radius of liquid cloud (μm)	3	25	14	uniform
effective variance of liquid cloud	0.03	0.35	0.19	uniform
cloud optical thickness of liquid cloud	3	40	N/A	special
cloud layer height of liquid cloud (km)	0.4	4	2.2	uniform
aerosol effective radius of fine mode	0.02	0.57	0.14	RemoTAP
aerosol effective variance of fine mode	0.01	0.8	0.20	RemoTAP
above cloud aerosol optical thickness of fine mode	0	2	0.26	log-uniform
aerosol effective radius of dust mode	0.7	6.12	1.89	RemoTAP
aerosol effective variance of dust mode	0.01	0.8	0.58	RemoTAP
above cloud aerosol optical thickness of dust mode	0	2	0.26	log-uniform