CLouds · CLimatE · Aerosols · Radiation

Science Applications for Higher-level Aerosol Property Retrievals based on Machine Learning Models Applied to EarthCARE ATLID observations

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UK EarthCARE workshop, Reading – June 6, 2025

Importance & challenge of observing CCN and ABS vertical distribution

REVIEW ARTICLE
10.1002/2013RG000441

Global observations of aerosol-cloud-precipitation-climate interactions

Key Points:
- Quantifying aerosol-cloud-climate interactions is a major challenge
- The science of existing and emerging new observational methods is reviewed
- A roadmap for in situ and remote sensing energy closure experiments is provided

Daniel Rosenfeld[1], Meinrat O. Andreae[2], Ari Asmi[3], Mian Chin[4], Gerrit de Leeuw[3,5], David P. Donovan[6], Ralph Kahn[4], Stefan Kinne[7], Niku Kivekäs[5,8], Markku Kulmala[3], William Lau[4], K. Sebastian Schmidt[9], Tanja Suni[3], Thomas Wagner[10], Martin Wild[11], and Johannes Quaas[12]

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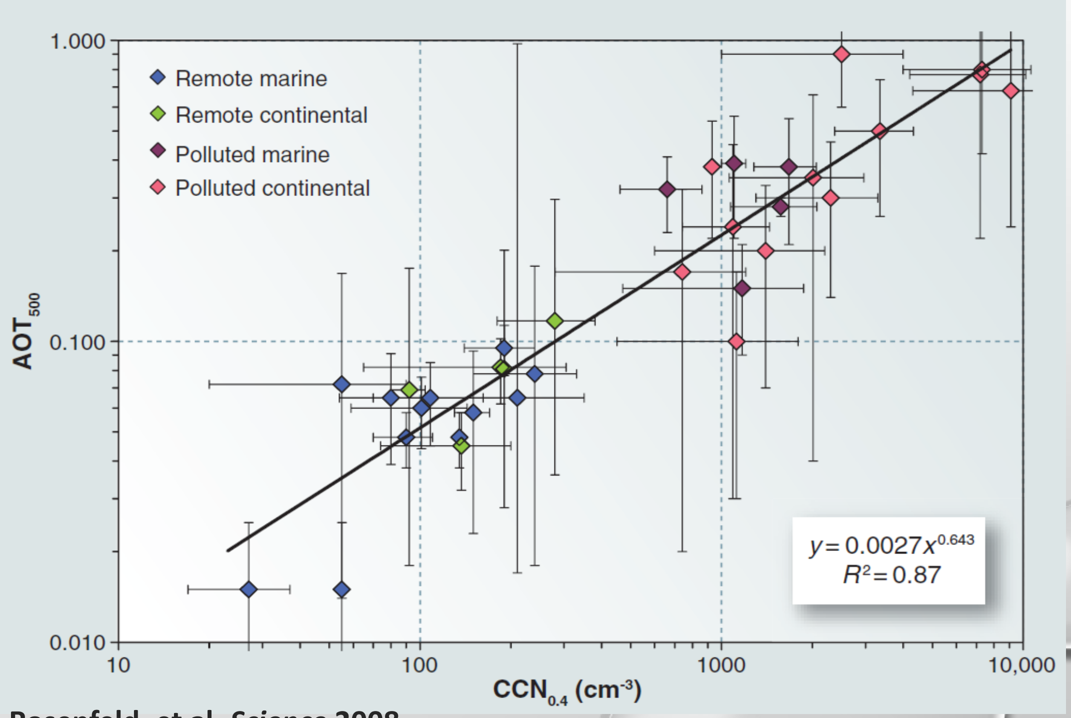
- **Column-effective aerosol quantities may not be relevant to aerosol-cloud interaction.**
- **The uncertainty of CCN-AOD parameterization is large, depending on:**
  - **Aerosol Type**
  - **Vertical distribution**
  - **Humidity response of light scattering**
  - **Spatiotemporal variability**
- “An urgent need for global observations of CCN(S) by remote sensing follows from these considerations. “
- **Limitations on many physics-based remote sensing retrievals of CCN**
  - **Heavy dependence on *a priori* information (aerosol size distribution and chemical composition)**
  - **Computationally very expensive.**



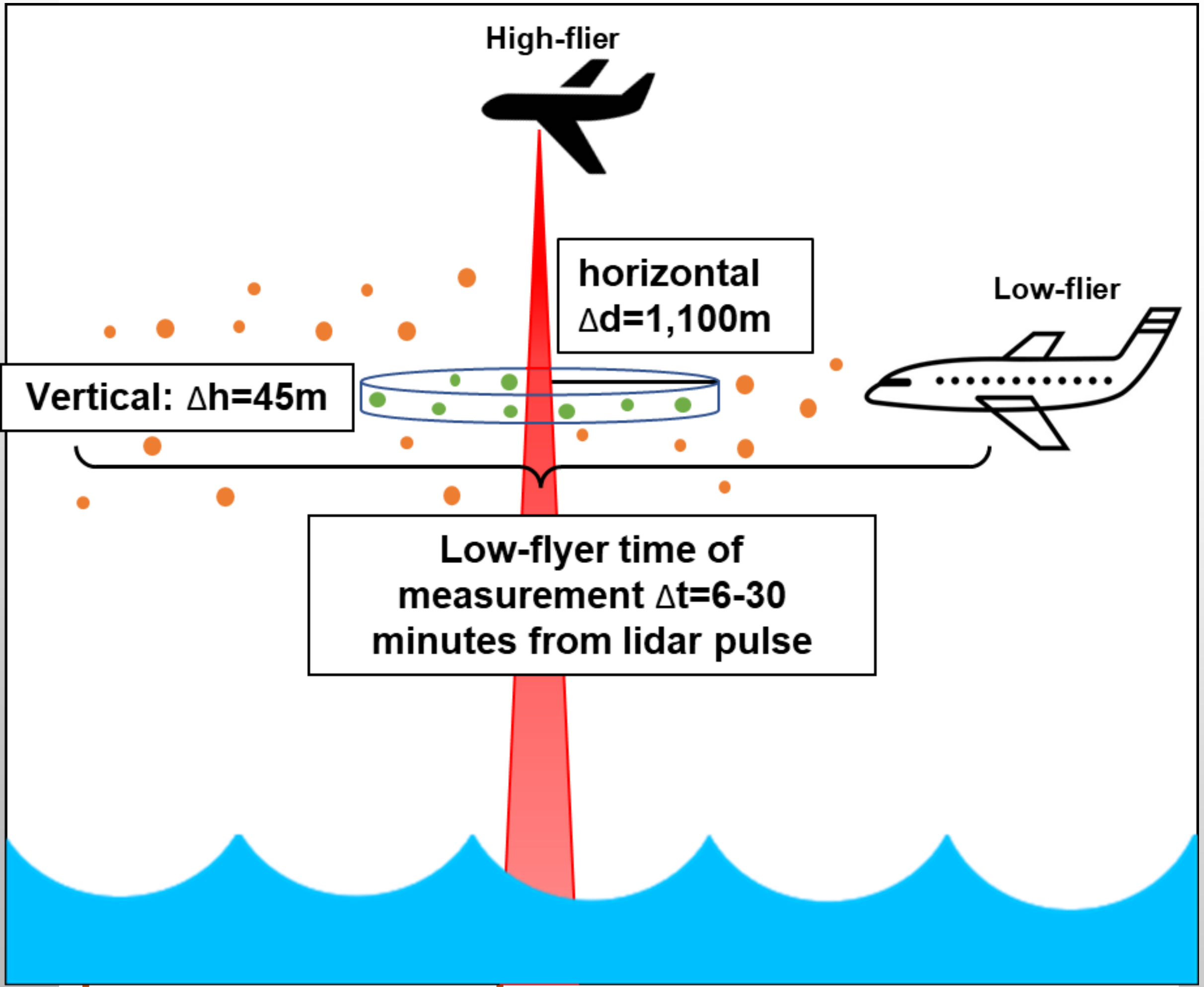
Rosenfeld, et al. *Science* 2008

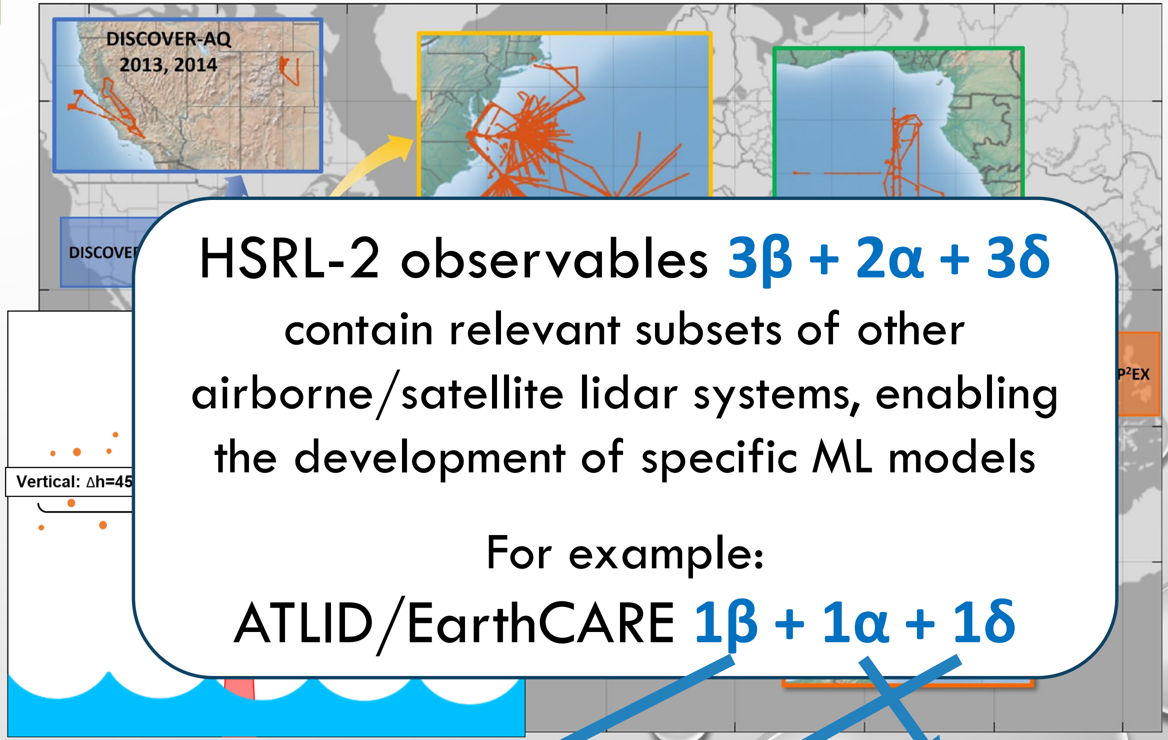
Stier, 2016: “…71 % of the area of the globe shows correlation coefficients between $CCN_{0.2\,\%}$ at cloud base and aerosol optical depth (AOD) below 0.5.

The Machine Learning augmentation…
to physics-based aerosol retrievals

Redemann and Gao, Nature Communications, 2024

Machine Learning models to estimate CCN and ABS from multispectral lidar and reanalysis data as predictors





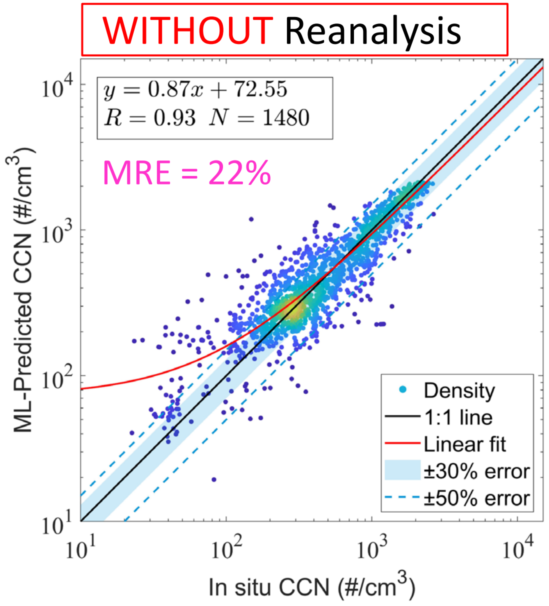
HSRL-2 observables **3β + 2α + 3δ** contain relevant subsets of other airborne/satellite lidar systems, enabling the development of specific ML models

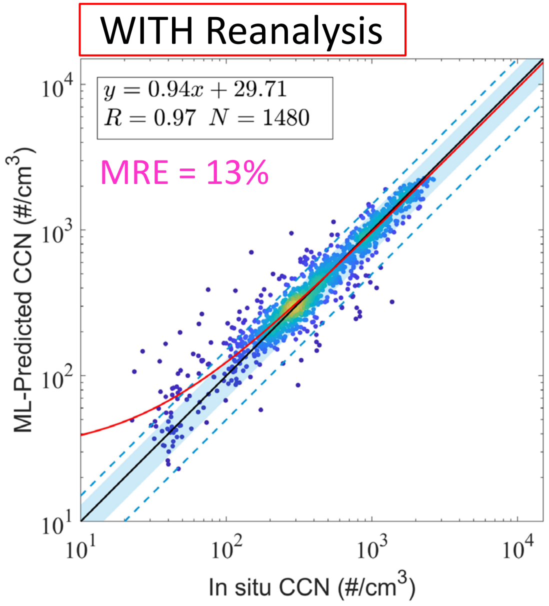
For example:
ATLID/EarthCARE **1β + 1α + 1δ**

Lidar observables	BSC_{355}, BSC_{532}, BSC_{1064}, EXT_{355}, EXT_{532}, $DEPO_{355}$, $DEPO_{532}$, $DEPO_{1064}$
Reanalysis	Relative humidity (RH), Temperature (T)
In situ	CCN concentration at 0.4% SS (~9,900) Absorption, ABS (~2,700)

Simulation of ML retrievals: CCN/ABS for full set of HSRL-2 observables (3β + 2α + 3δ)

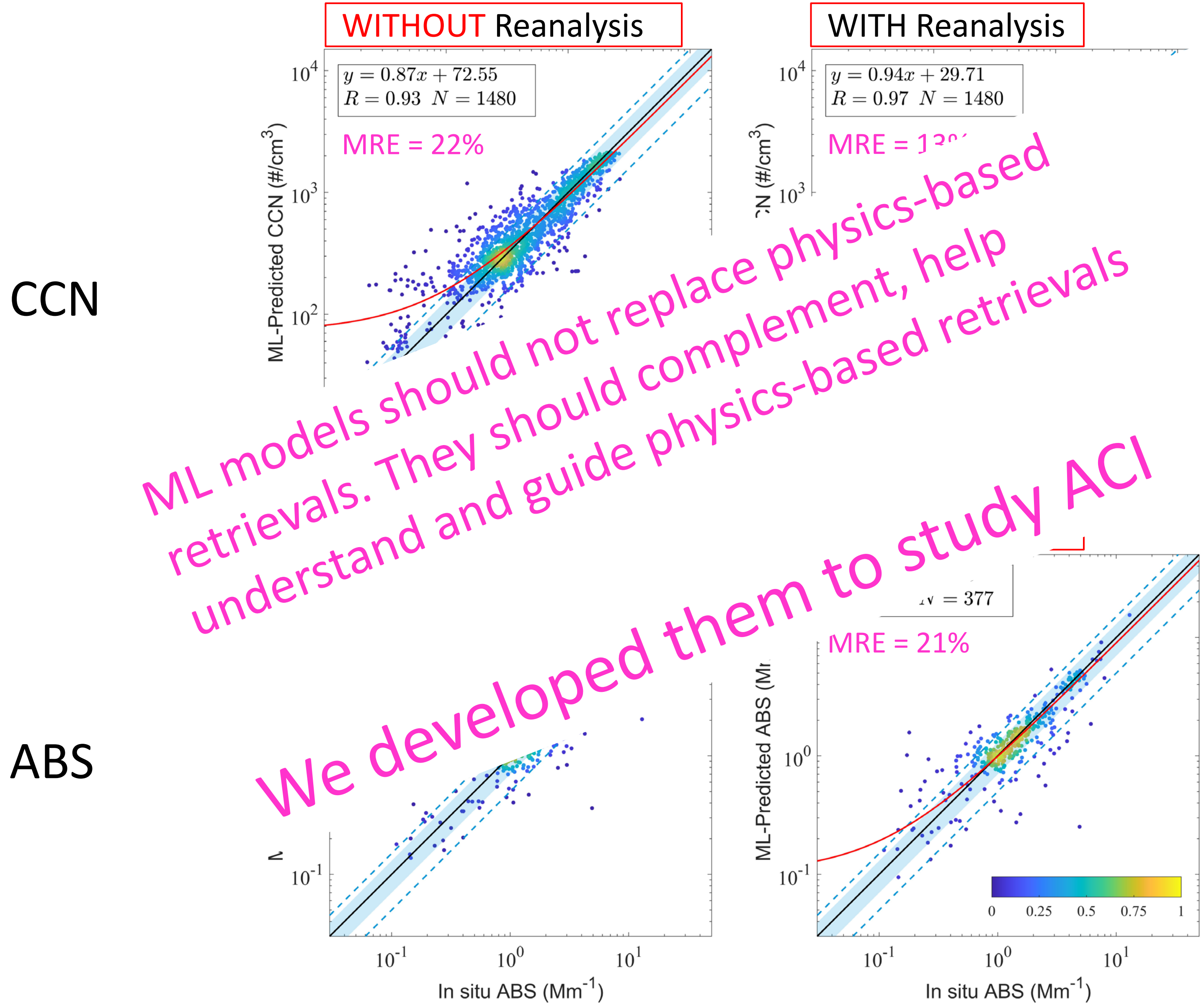
CCN





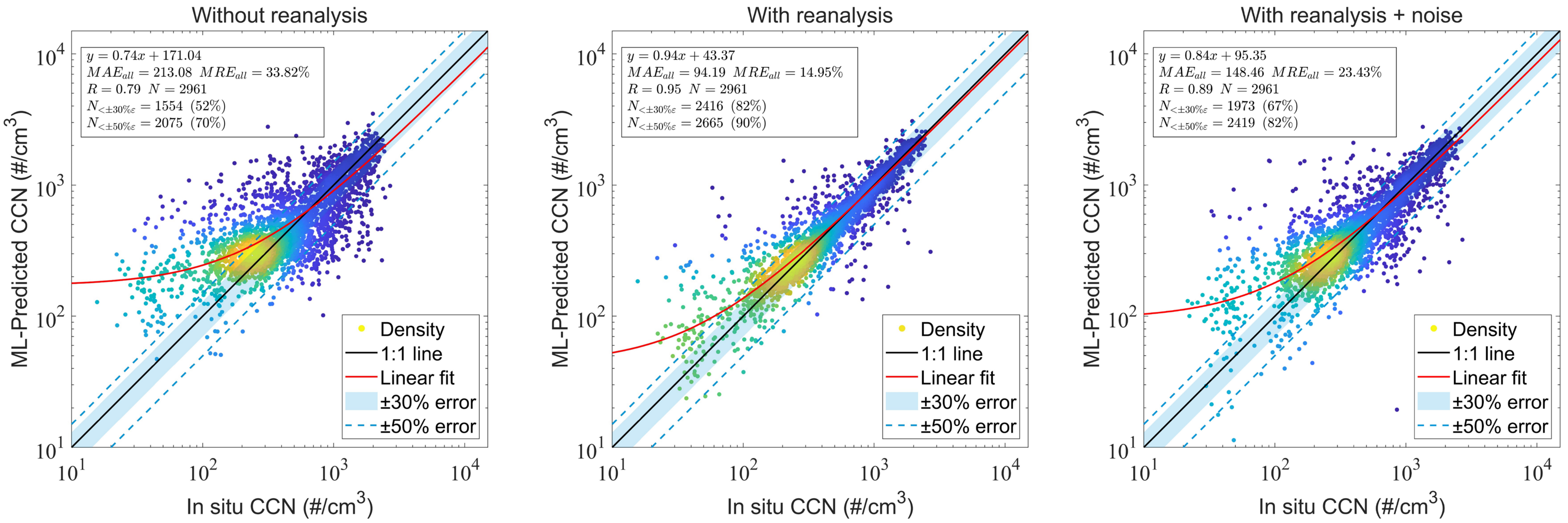
Error characteristics and information content of HSRL allow ML models to assess non-linear and multi-variate correlations between lidar observables and CCN/ABS

Simulation of ML retrievals: CCN/ABS for full set of HSRL-2 observables (3β + 2α + 3δ)



Error characteristics and information content of HSRL allow ML models to assess non-linear and multi-variate correlations between lidar observables and CCN/ABS

Simulation of ML retrievals: CCN for EarthCARE/ATLID observables (1β + 1α + 1δ)

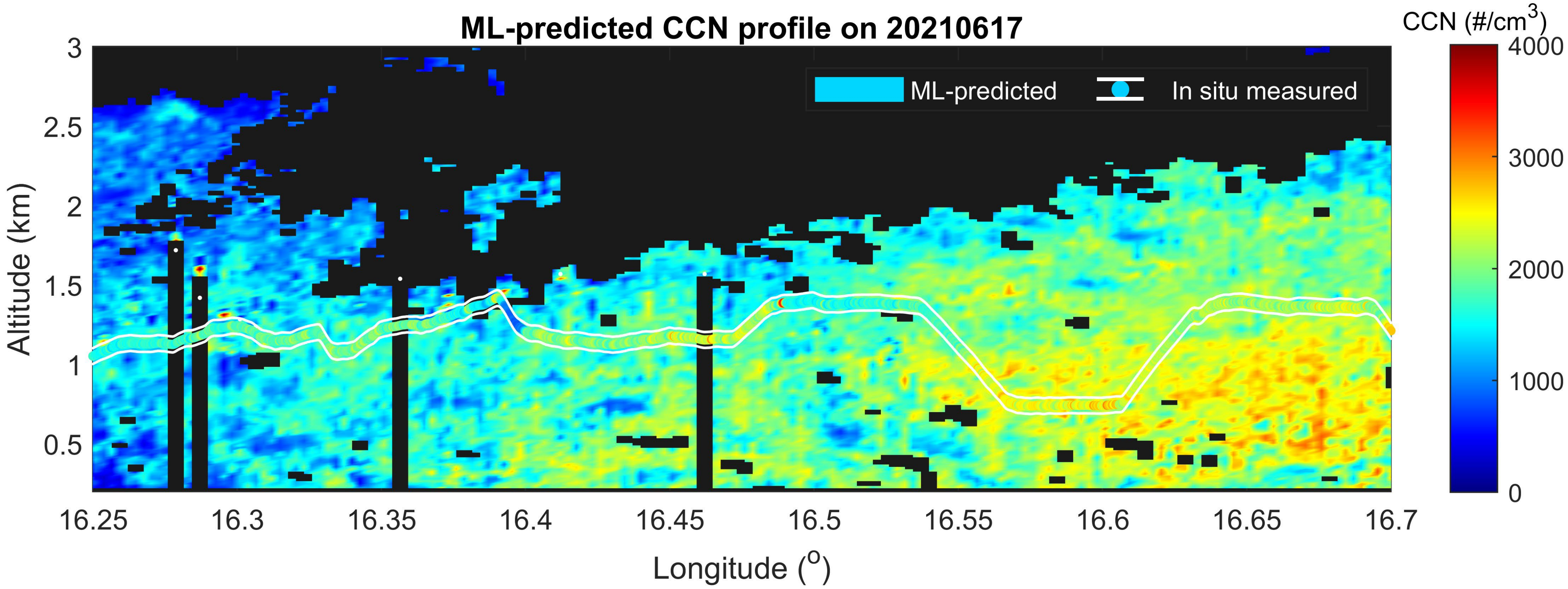


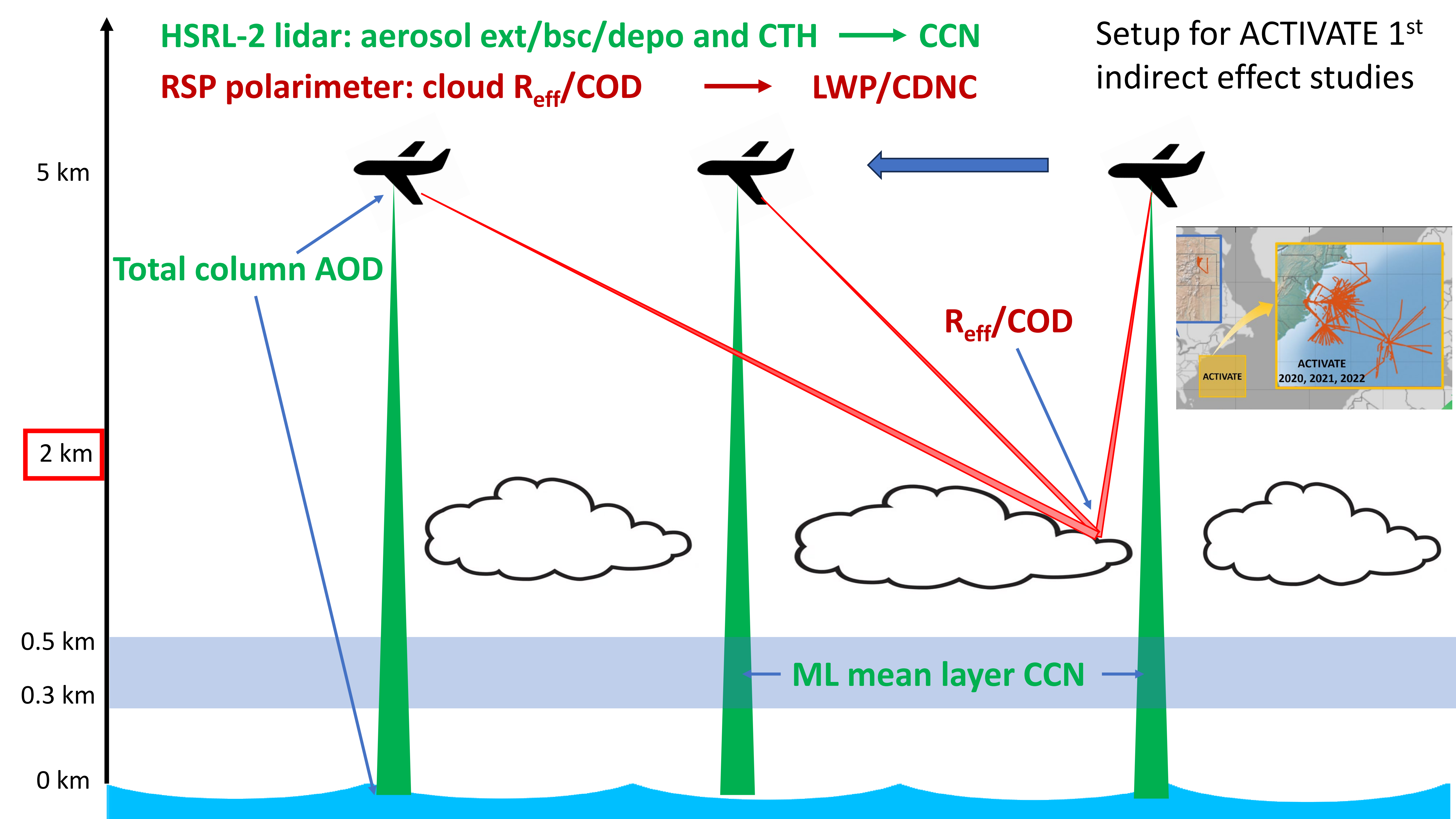
Adding reanalysis RH, T

Adding simulated noise

Potentially deliverable product – ACTIVATE curtain example

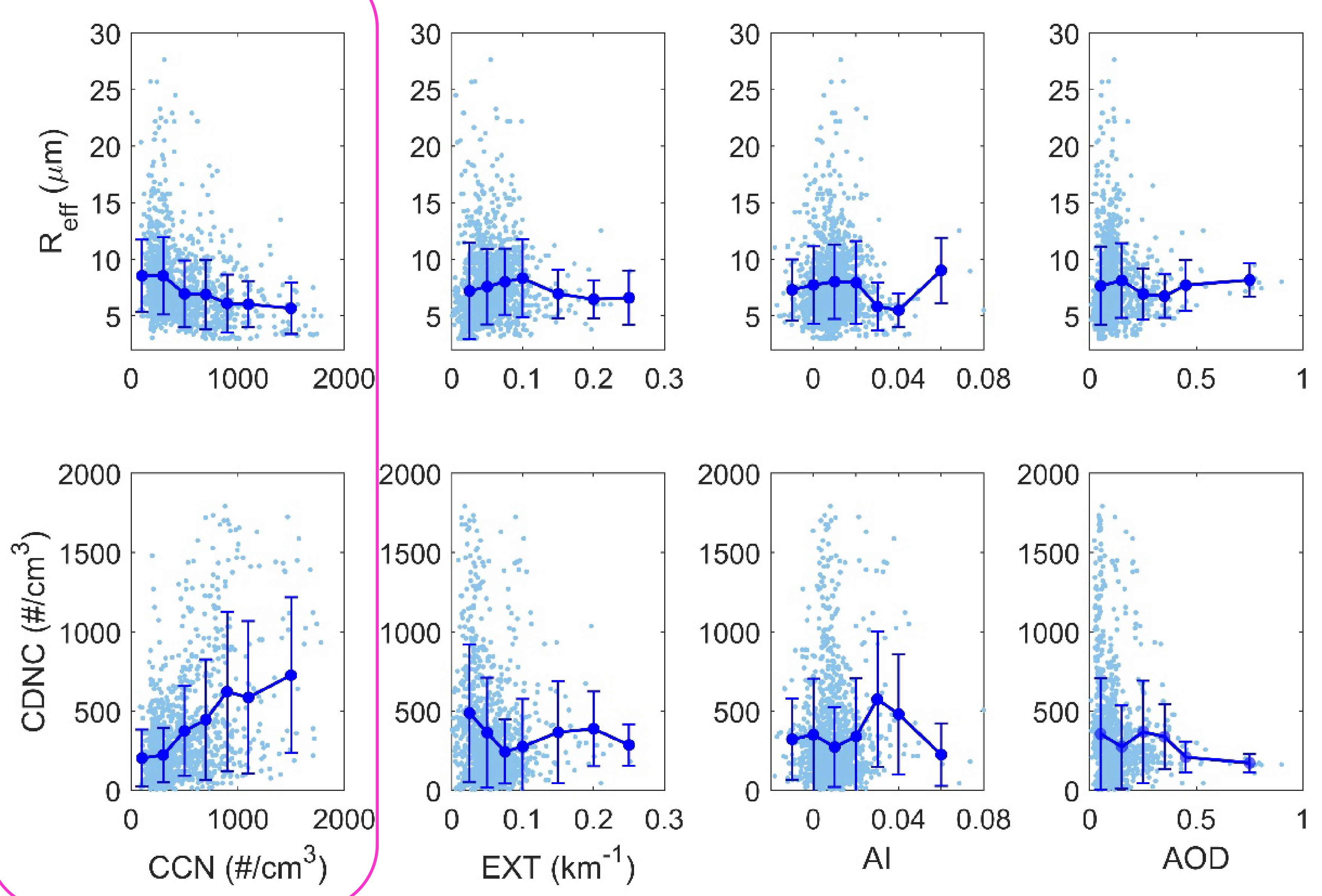
- CCN profile at lidar product grid when lidar observables are available.





HSRL-2 lidar: aerosol ext/bsc/depo and CTH → CCN
RSP polarimeter: cloud R_{eff}/COD → LWP/CDNC
Setup for ACTIVATE 1st indirect effect studies
5 km
2 km
0.5 km
0.3 km
0 km
Total column AOD
R_{eff}/COD
ML mean layer CCN
ACTIVATE
ACTIVATE 2020, 2021, 2022

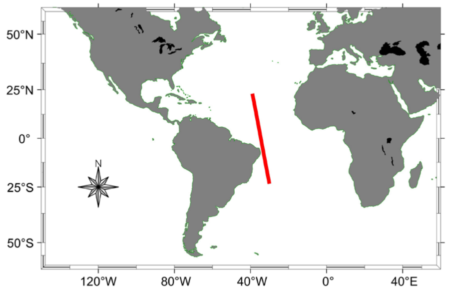
Strength of using below cloud CCN to study aerosol-cloud interaction



ML-derived CCN yields best estimates of 1st aerosol indirect effect

Gao et al., submitted to Geophysical Research Letters, 2025GL115821

EarthCARE: Data filtering & inputs for ML-CCN prediction

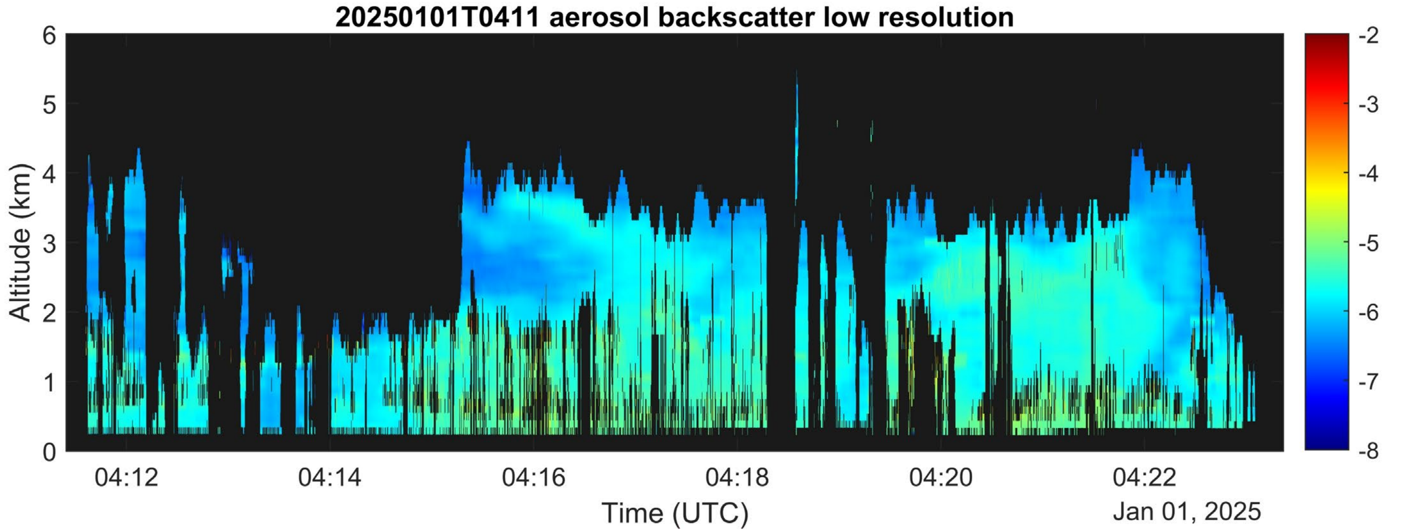


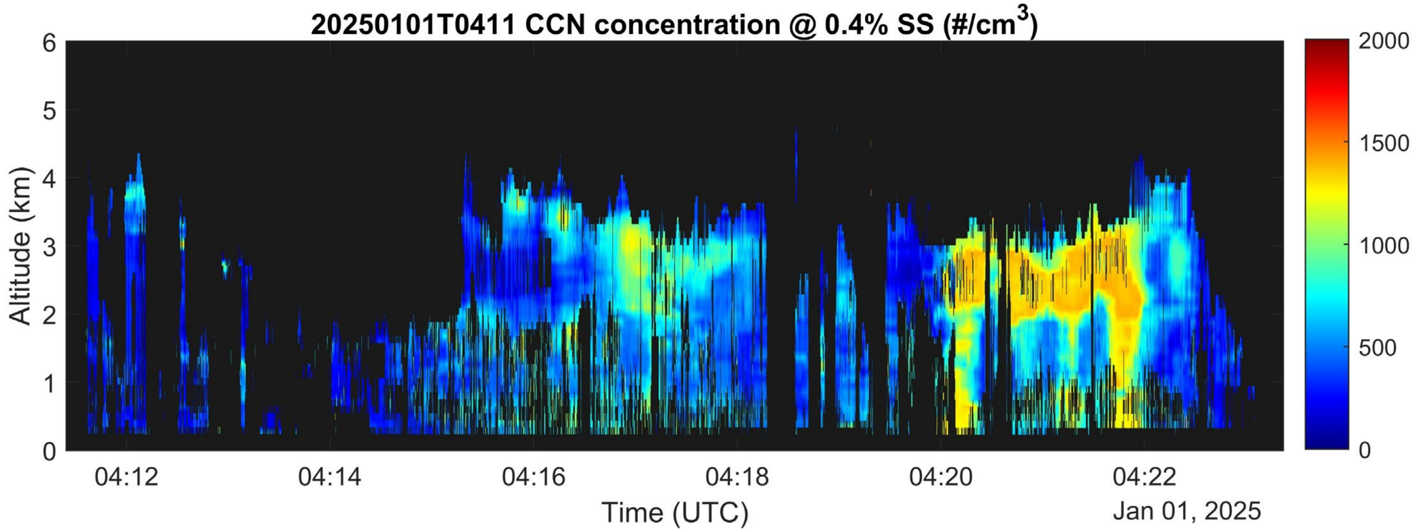
ATLID EBD L2A
E&B&D @355nm

Quality status
Good/likely good

Retain only
aerosol pixels
A-TC classification

ML-CCN algorithm

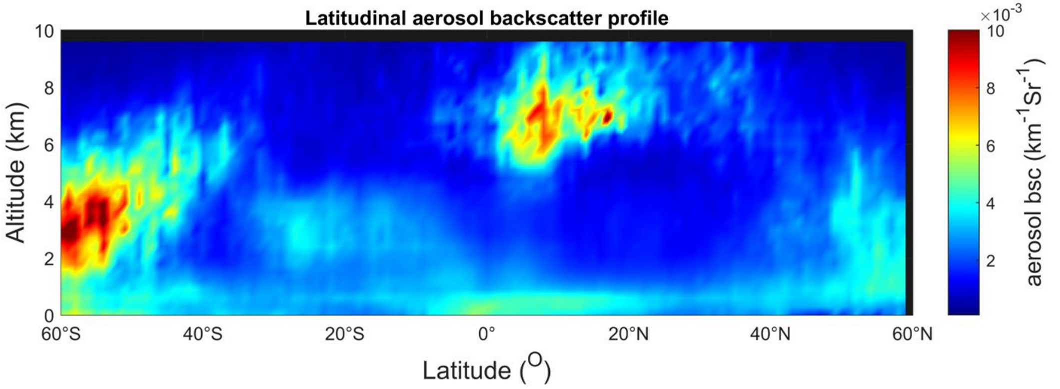


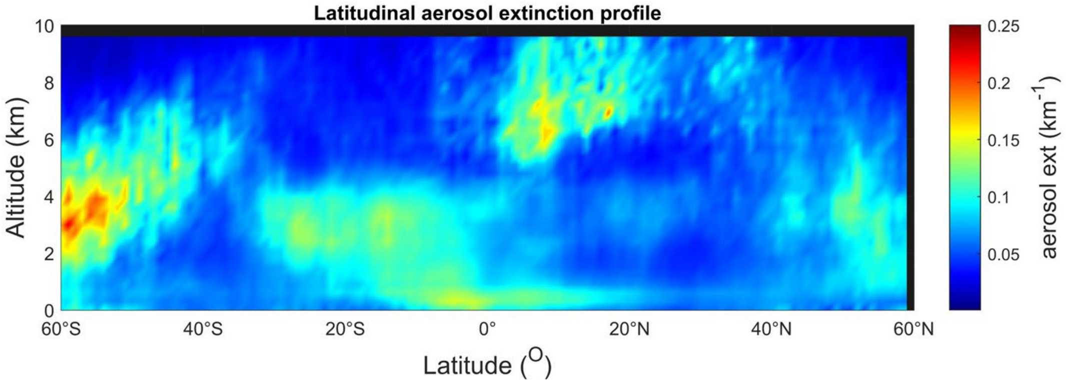


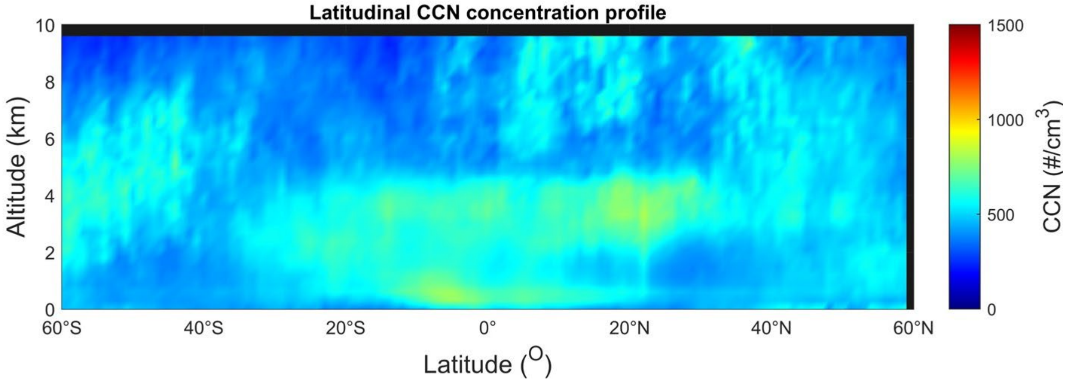
Latitudinal aerosol BSC/EXT/DEPOL in Version AC and derived CCN profiles

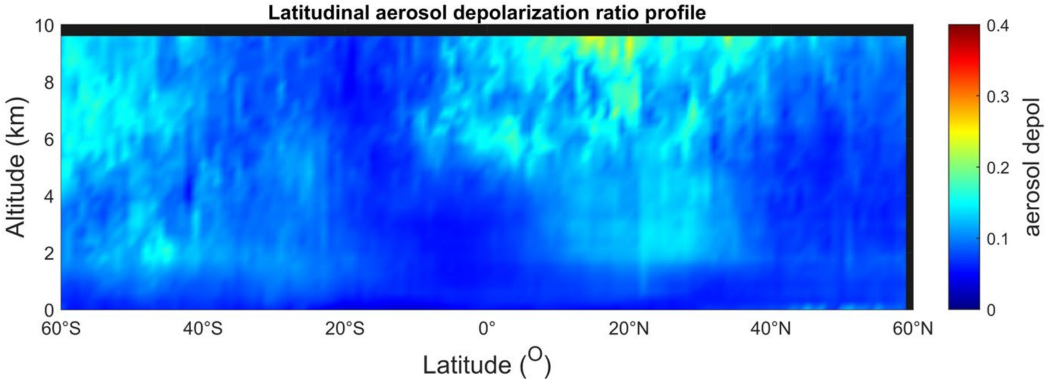
The Atlantic Domain:
60N – 60S, 75W-15E

- Retrieve CCN/ABS profiles from ATLID L2A EBD products for the period of Aug 11, 2024 – Jan 31, 2025.
- Compute the average CCN profiles across the 75ºW-15ºE longitude range, using 1-degree latitude & 300m vertical bins from 60ºN to 60ºS.







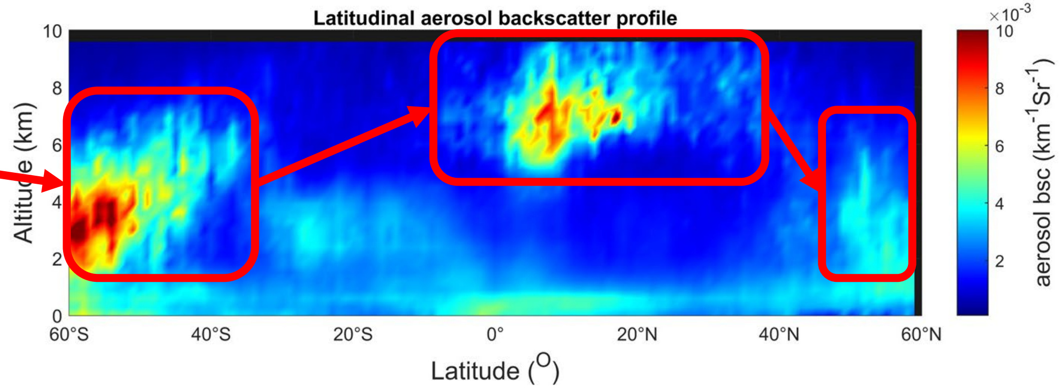


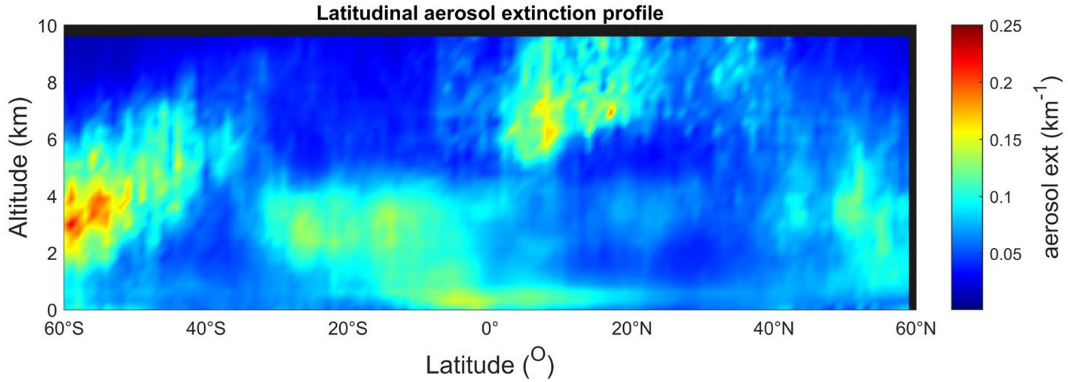
Latitudinal aerosol BSC/EXT/DEPOL in Version AC and derived CCN profiles

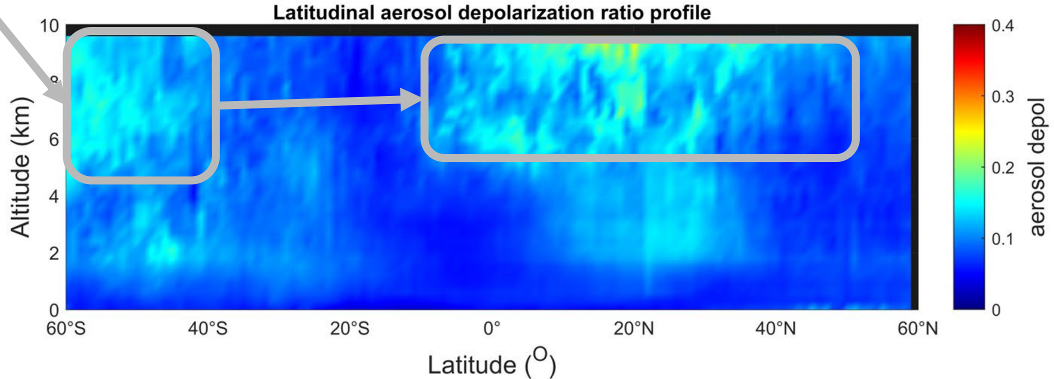
The Atlantic Domain:
60N – 60S, 75W-15E

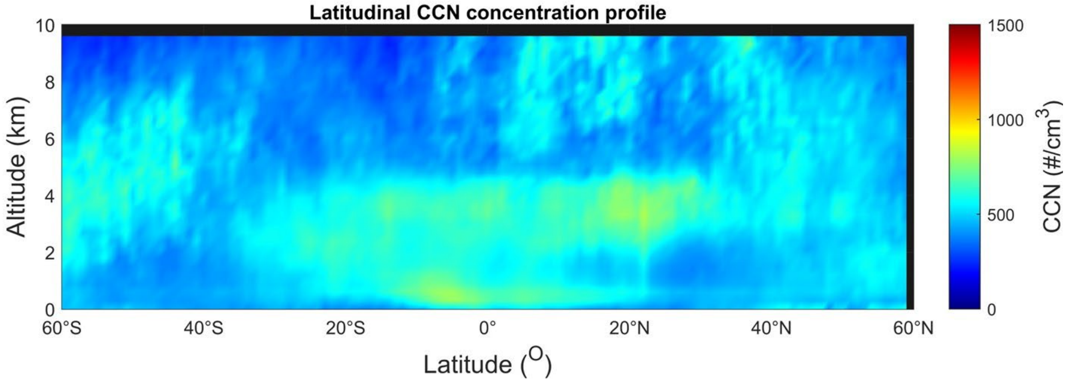
- Physically implausible high BSC/EXT features

- Physically implausible high DEPOL features









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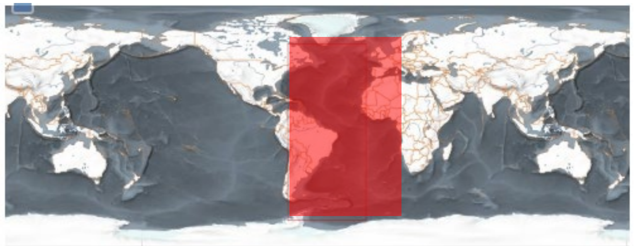
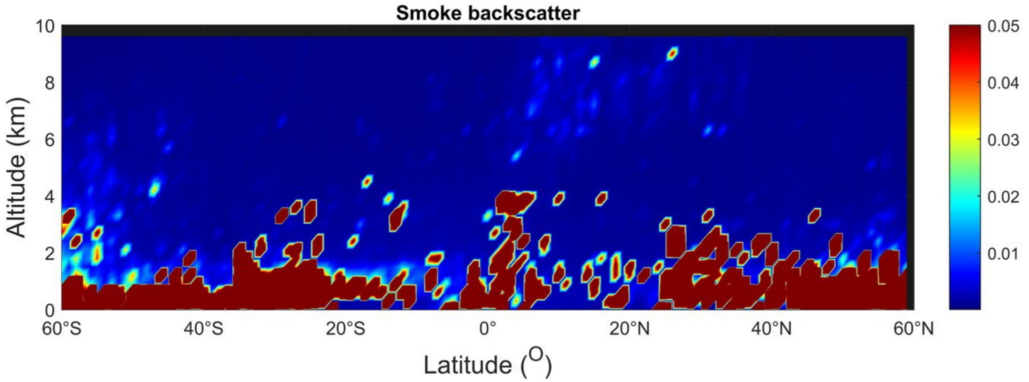
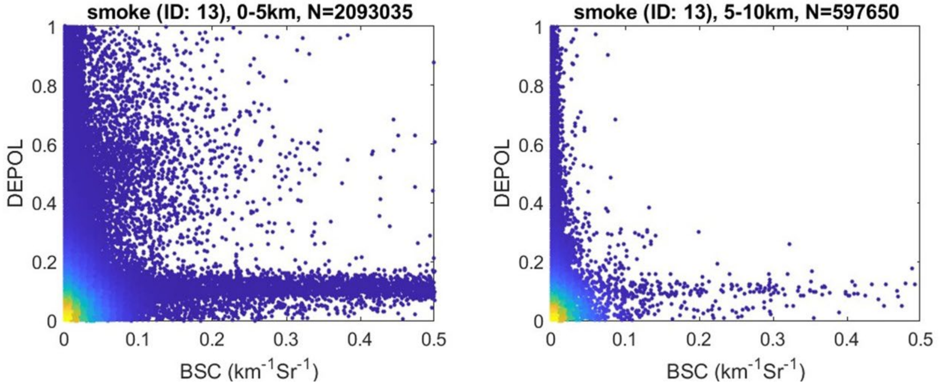
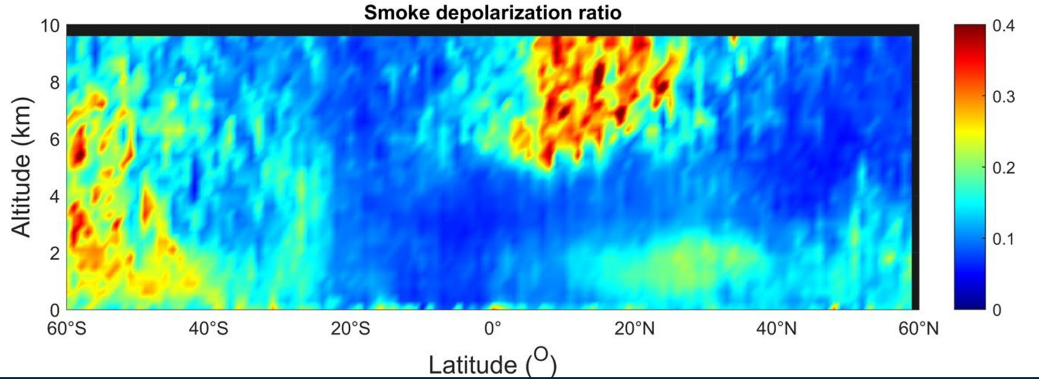
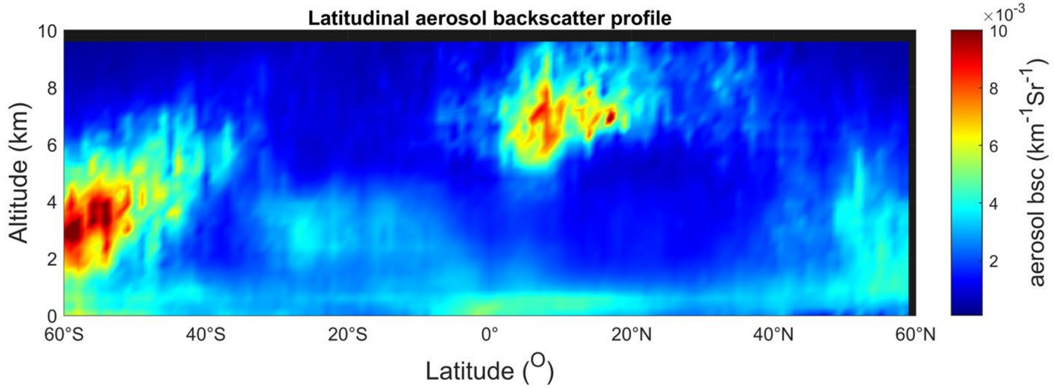


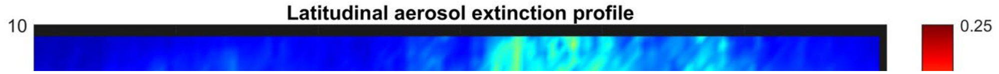
Smoke Target Category ONLY



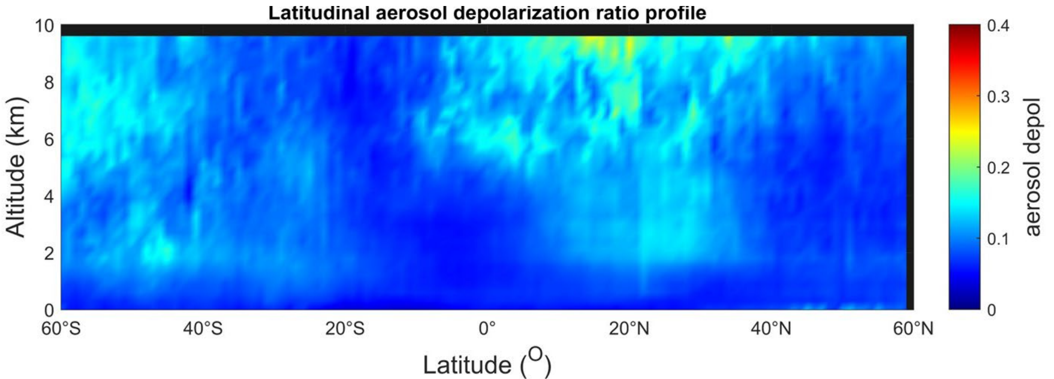






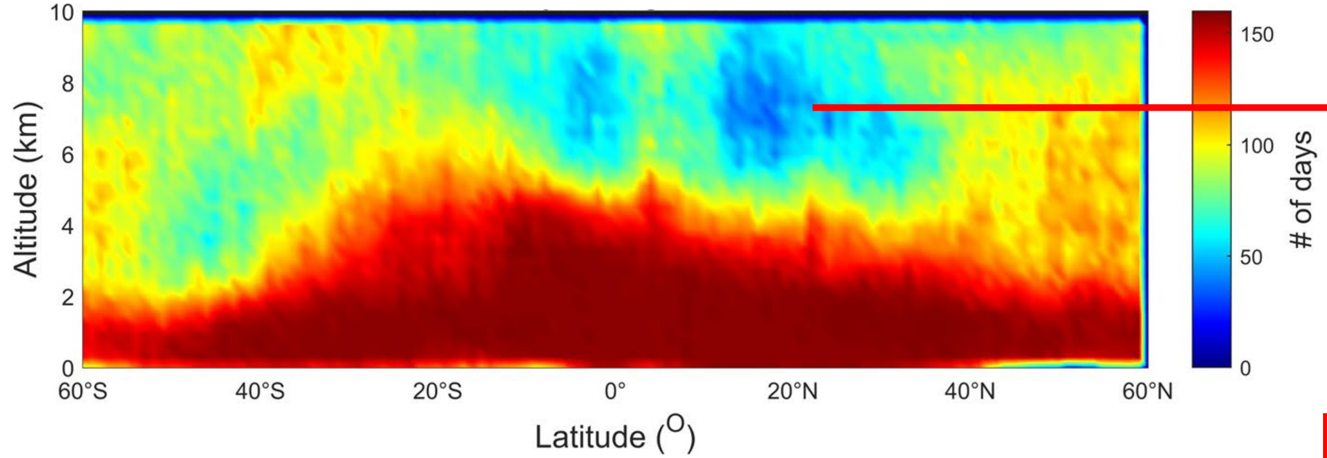


There are some, possibly unavoidable, target misclassifications
Also - target definition includes most probable target

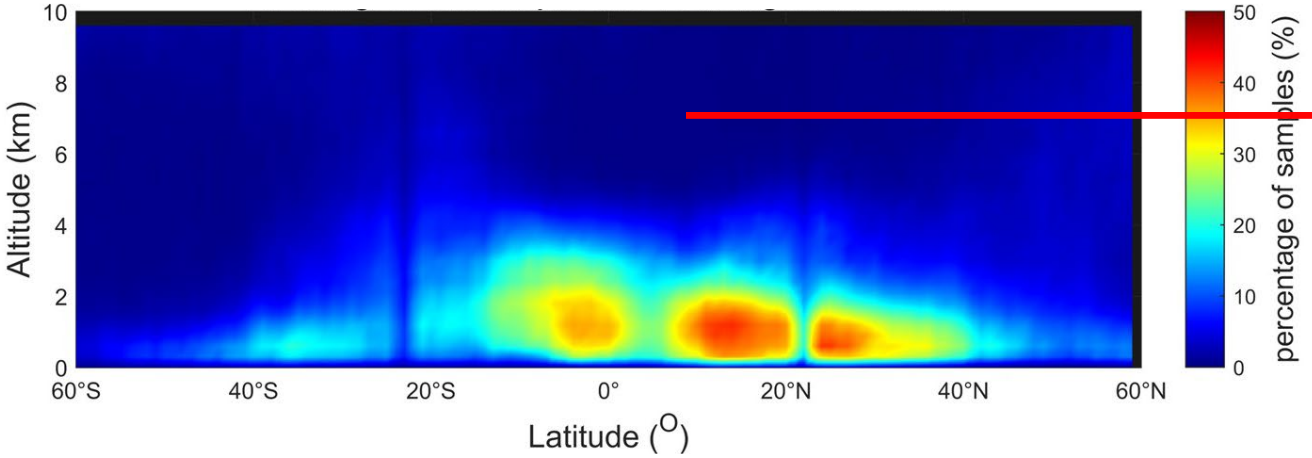


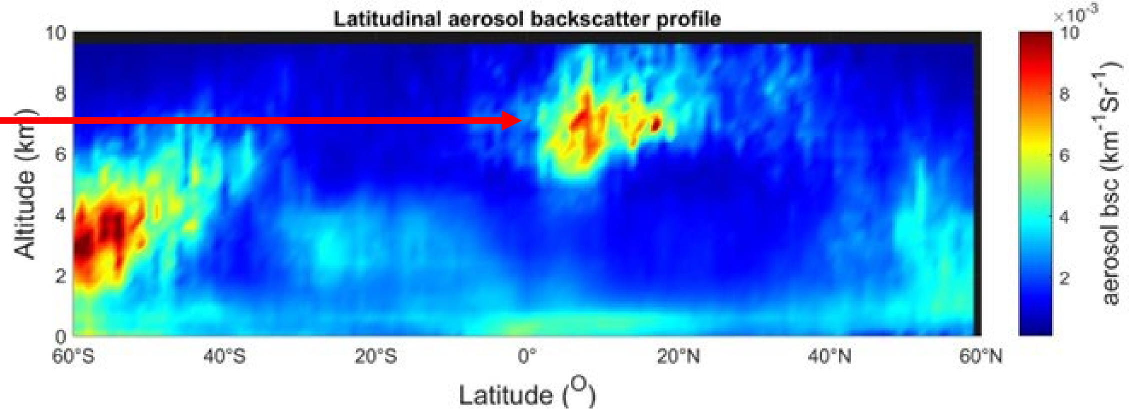
Analysis of sampling issues

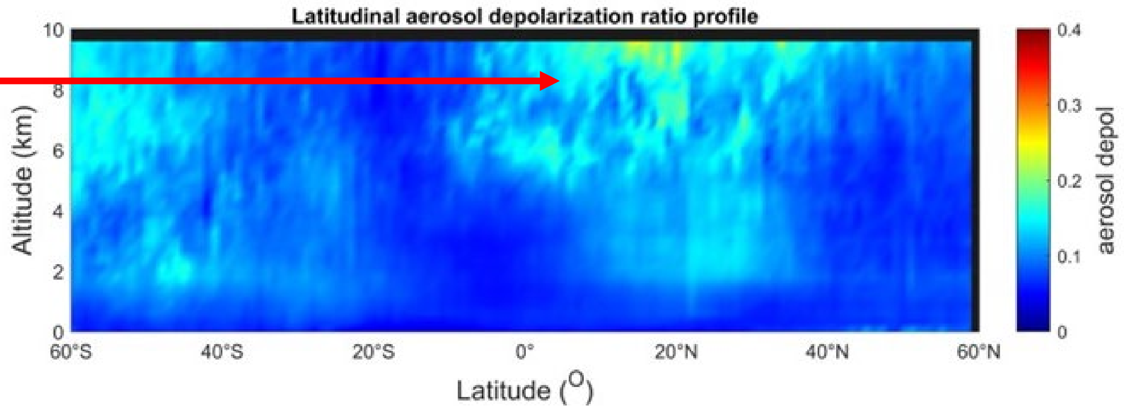
Number of days in 6-month period with valid obs in 1 deg lat and 300m vert bin



Percentage of valid obs after TC and QA screening in 1 deg lat and 300m vert bin







High depol/bsc occurred only on certain days or in a very small fraction of the samples

Percentage is defined as the number of valid ATLID pixels - after TC and QA screening - within the prescribed grid, divided by the total number of lidar pixels sampled within the same grid.

Latitudinal aerosol BSC/EXT/DEPOL in Version AC and derived CCN profiles

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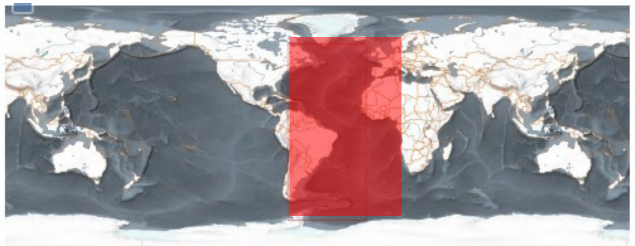

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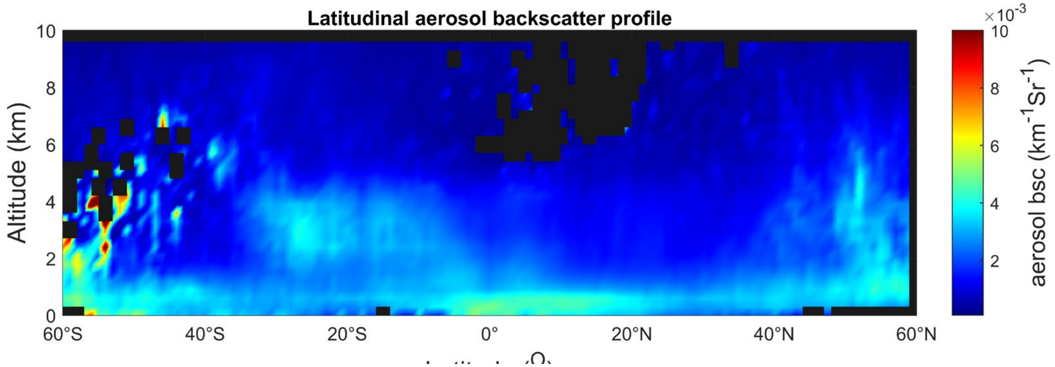
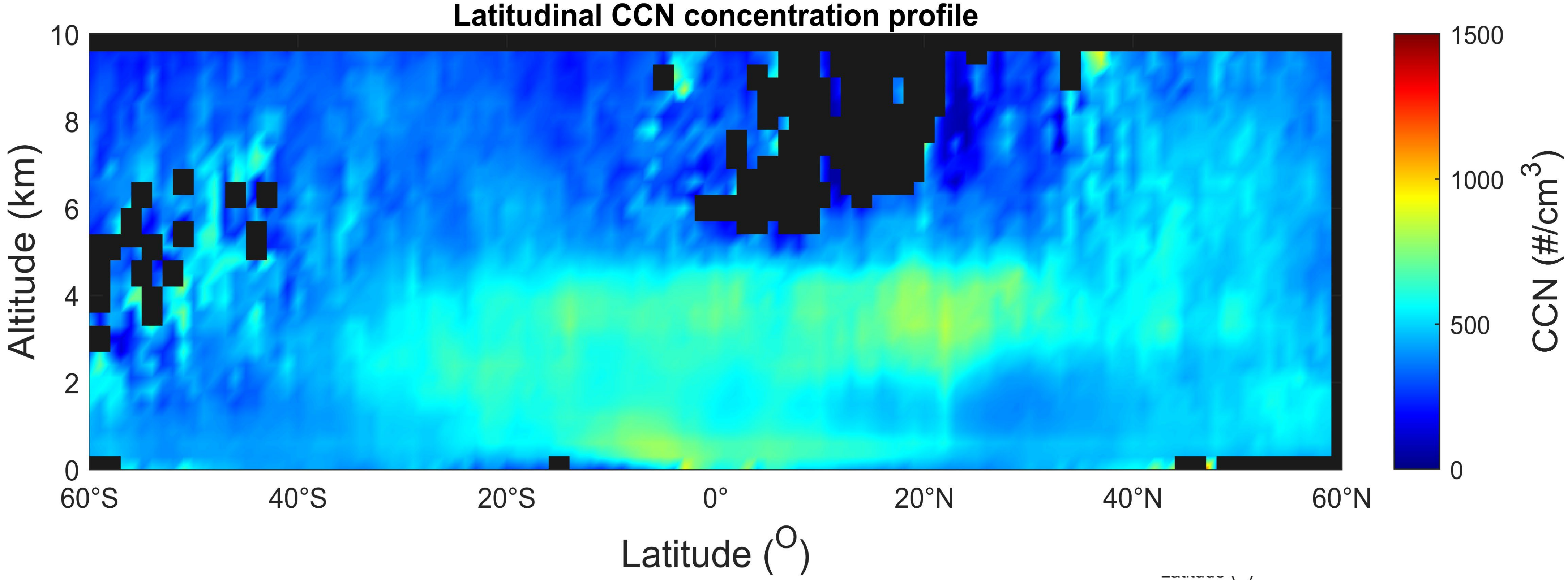
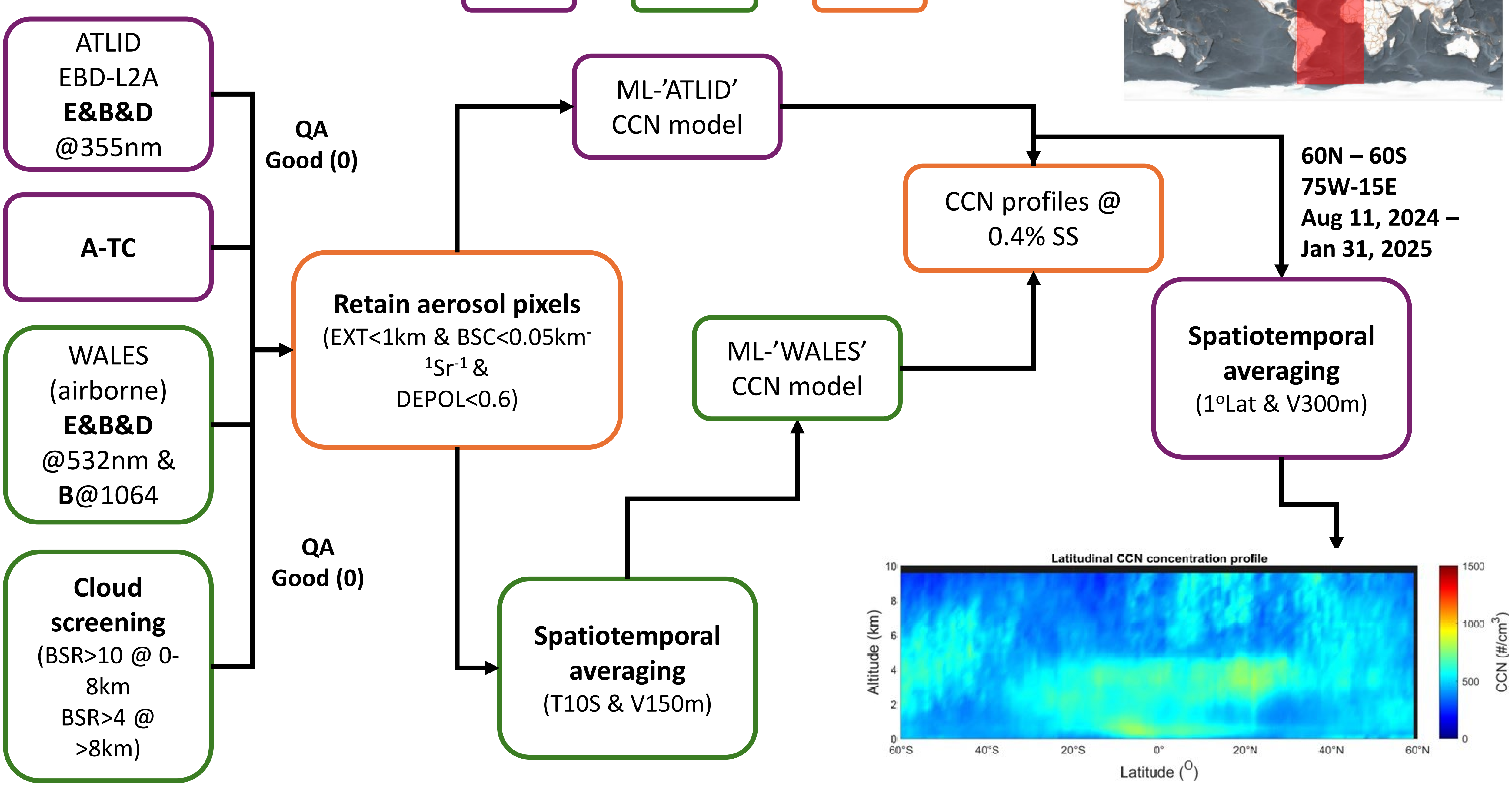
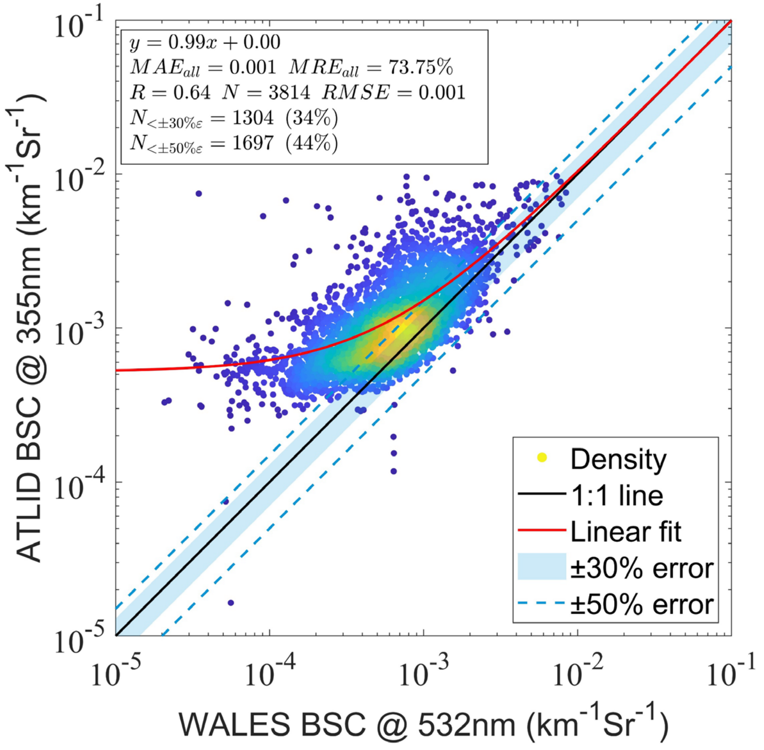


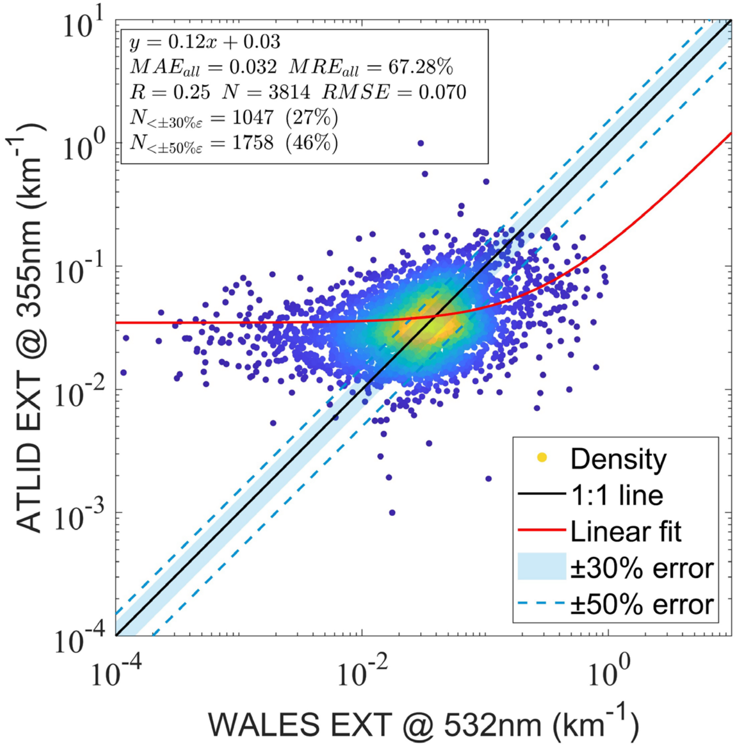


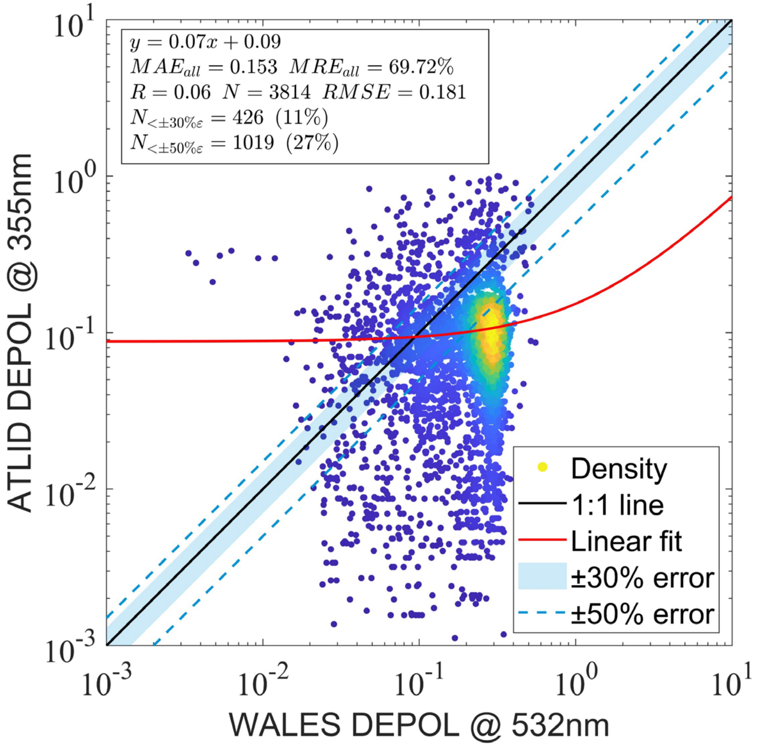
Algorithm flowchart



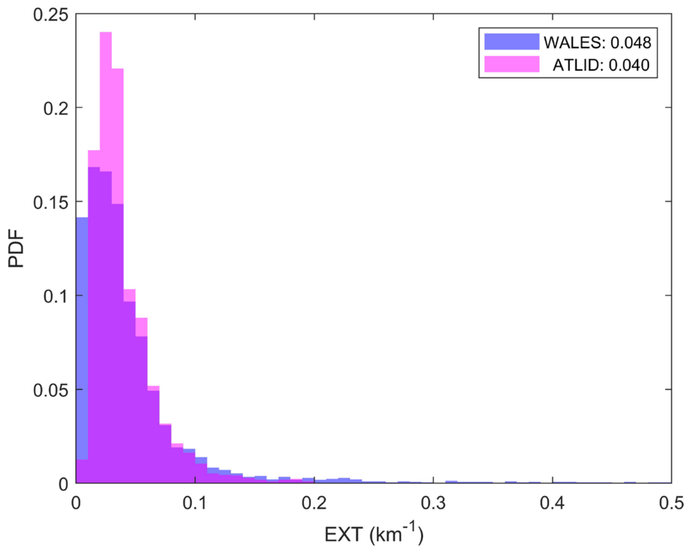
Simple comparison of E&B&D between WALES and ATLID, with noted **caveats**.

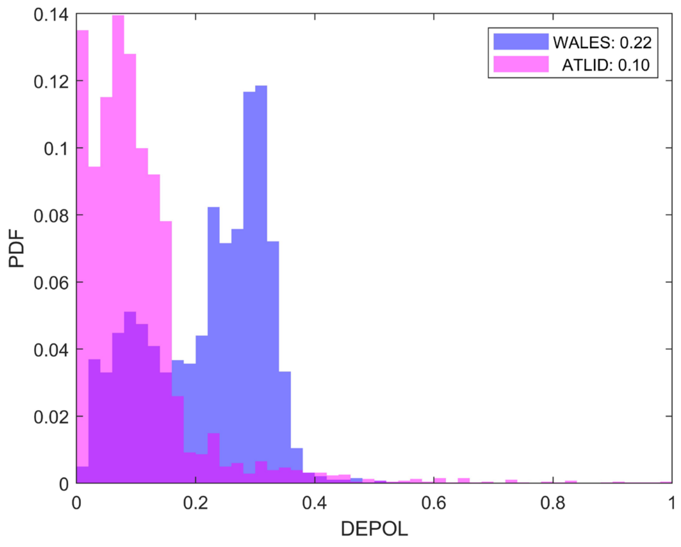






- On average, WALES EXT532 is slightly larger than ATLID EXT355 due to EXT532>0.2km^{-1} range, still some cloud contamination
- Most WALES DEPOL532 values, particularly in the hotspot area, are higher than ATLID DEPOL355, known dust depol issue in V AC





Flowchart of the WALES CCN retrieval

WALES
E&B&D @532nm & B@1064

↓

Quality status
Good data (Flag=0)

↓

Spatiotemporal averaging
10S & 150m

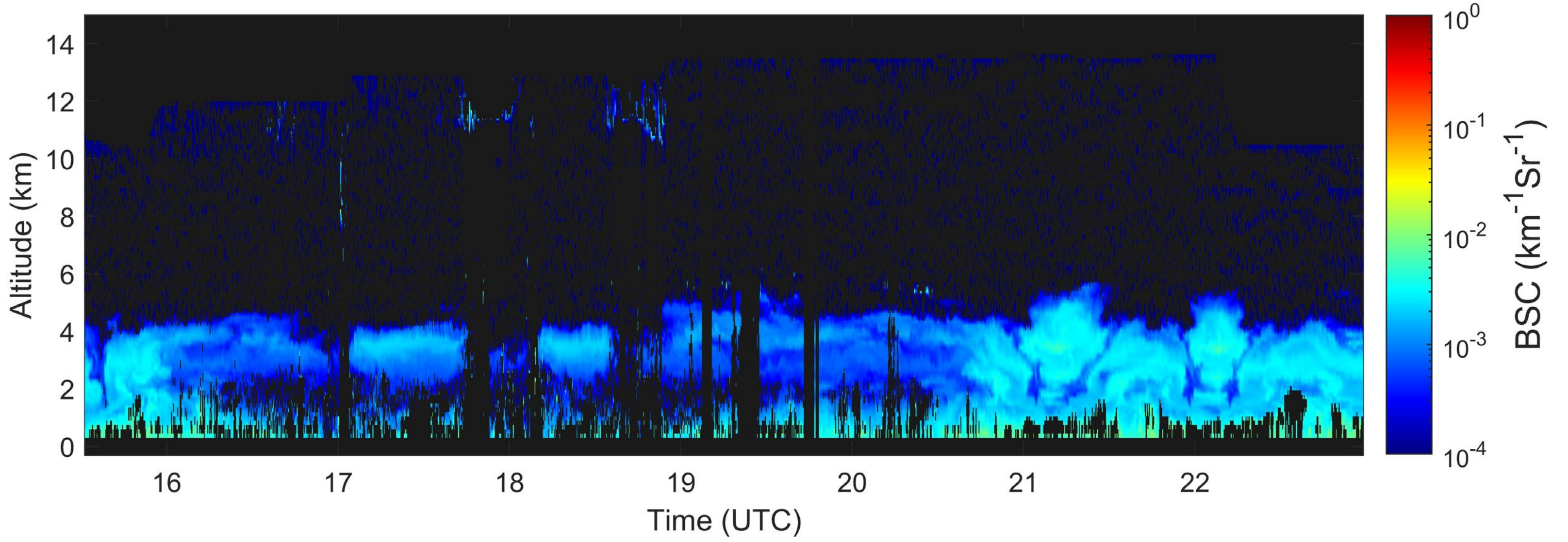
↓

Retain only 'aerosol' pixels (arbitrary)
EXT>1km^{-1}&BSC>0.05km^{-1}Sr^{-1}

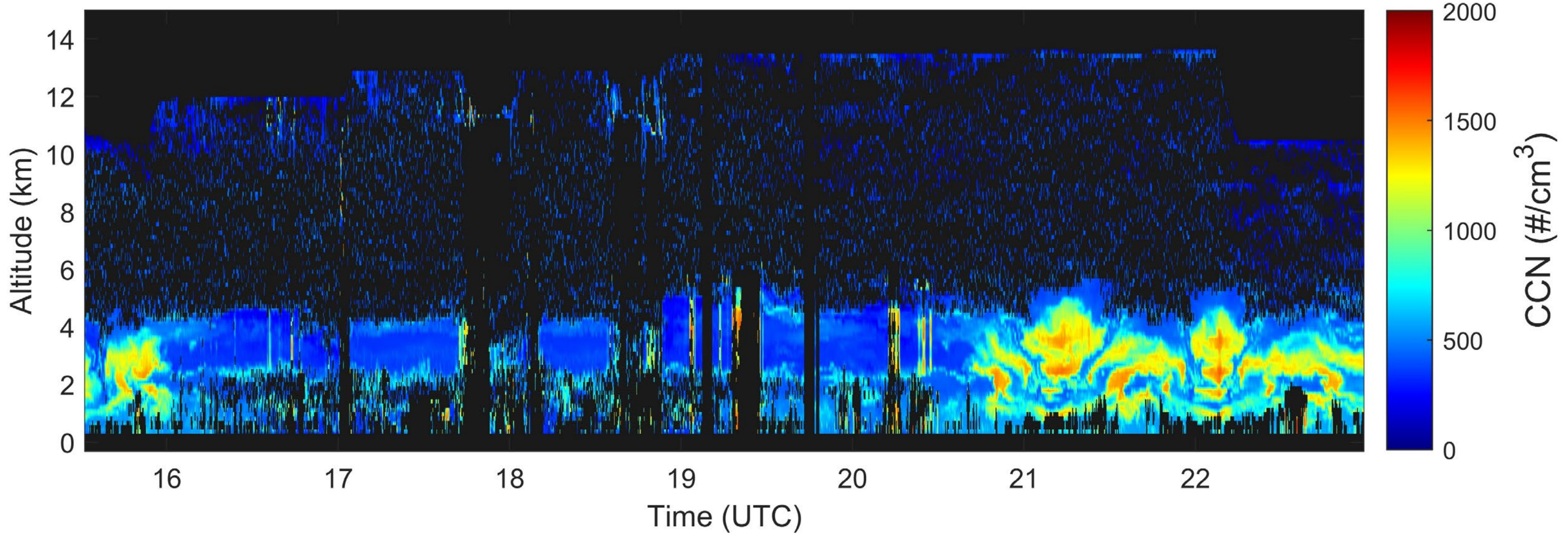
↓

ML-CCN algorithm

WALES 'aerosol' BSC on 20240813



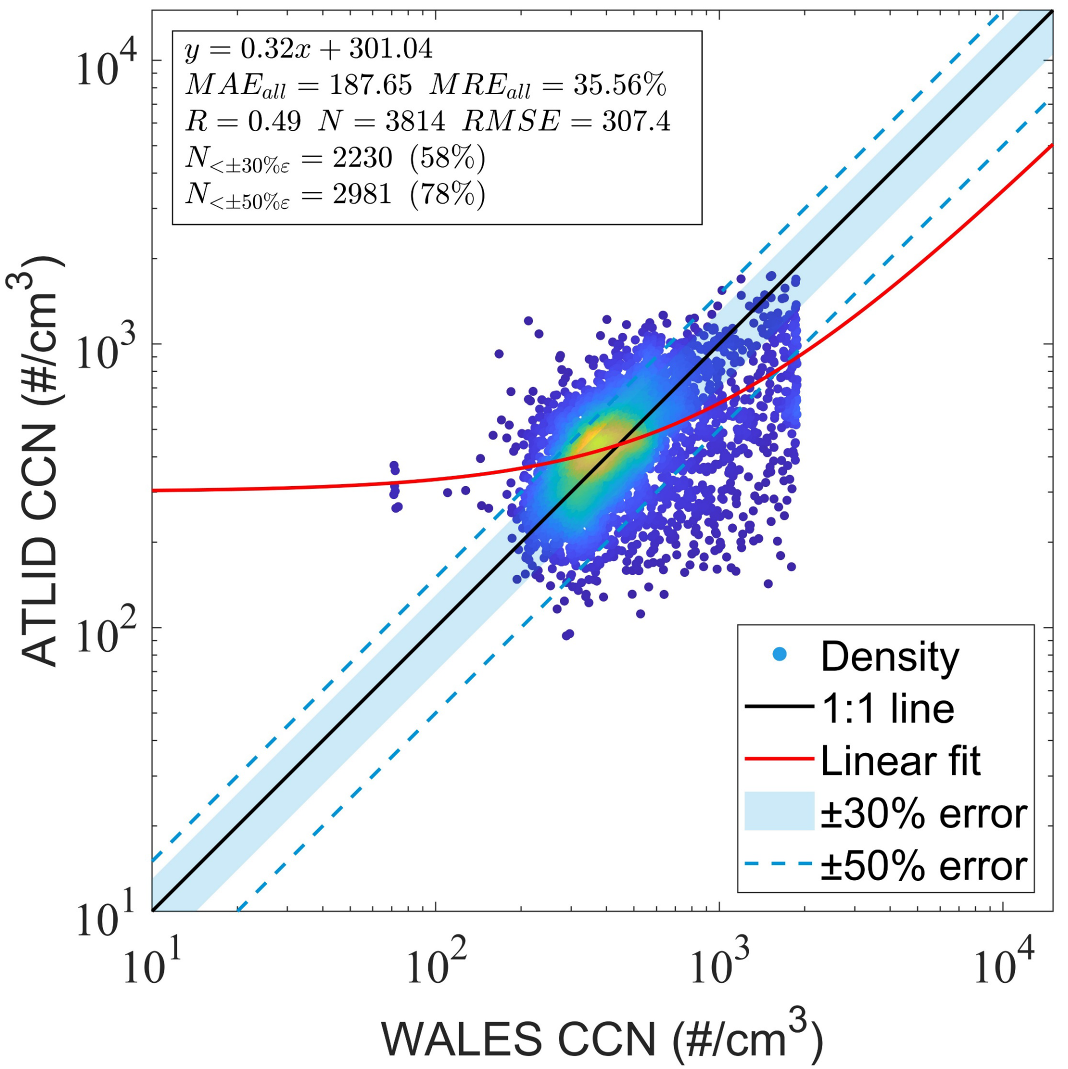
WALES retrieved CCN on 20240813

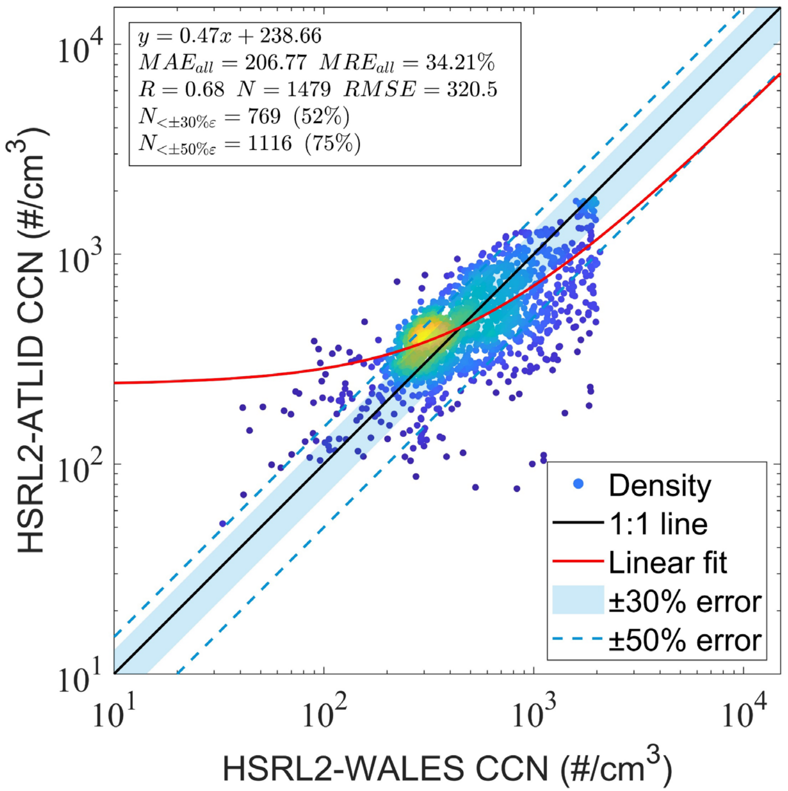


Comparison of retrieved CCN from WALES and EarthCARE-ATLID

- WALES: 10S & 150m average
- ATLID: individual L2A-EBD profile, ~100m vertical
- Exclude EXT>1km^{-1}, BSC>0.05km^{-1}Sr^{-1}, minimize cloud contamination (arbitrary, need to apply cloud mask)
- Time < 15 mins
- Horizontal distance < 2 km
- Vertical distance < 100

CCN retrievals using WALES and ATLID observations





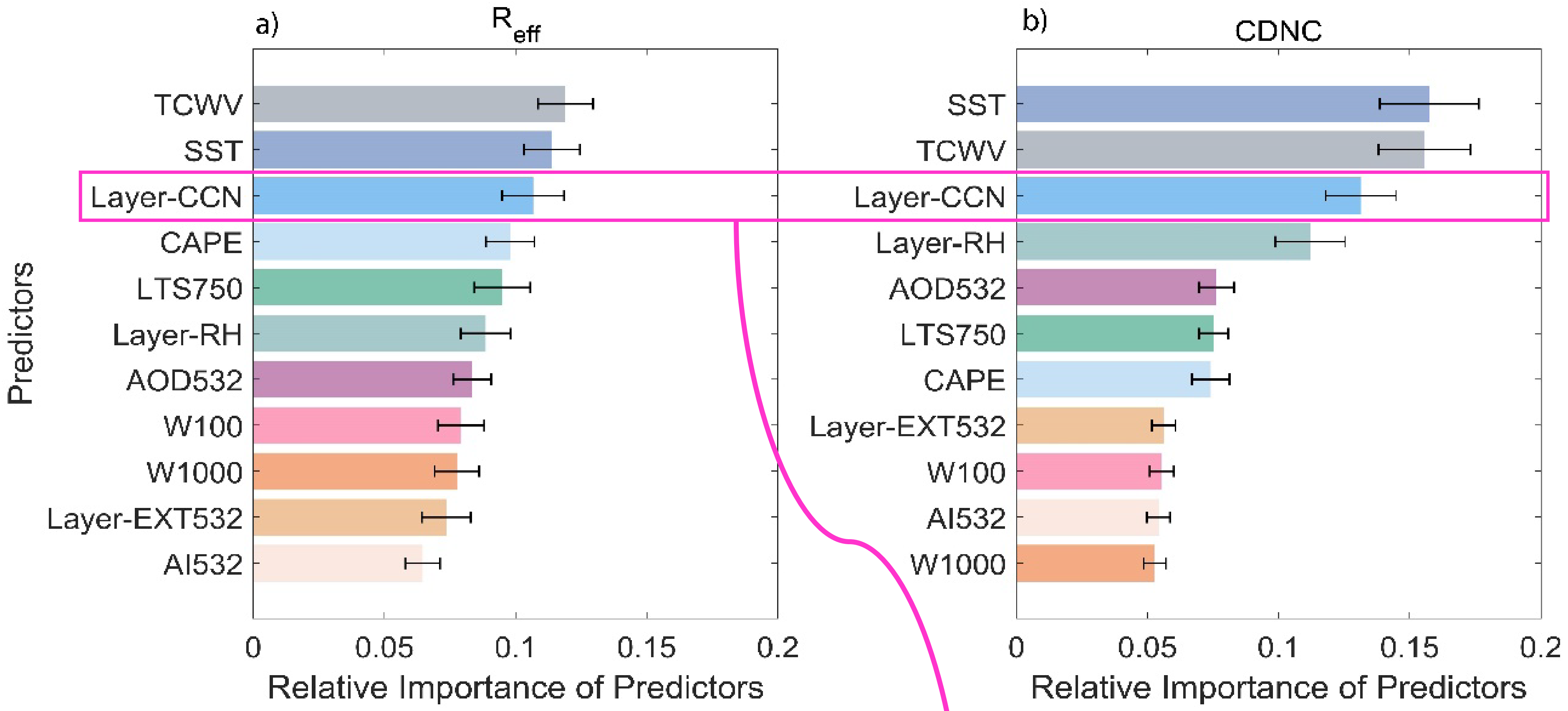
CCN retrievals from HSRL-2 data using WALES and ATLID observables in HSRL-2 dataset

Science Applications for Higher-level Aerosol Property Retrievals from ATLID obs

Conclusions

1. ATLID observations have unprecedented potential to provide crucial, vertically-resolved aerosol and cloud properties to help constrain Earth System Models.
2. Machine-Learning (ML) algorithms will be part of the future of filling in observational gaps.
3. ML-derived, value-added, vertically-resolved aerosol products can be used to study:
   A. aerosol-cloud interactions where the ATLID observations reach relevant cloud-inflow regions (i.e., below-cloud, near-cloud, above-cloud);
   B. regional, vertically-resolved radiation budgets;
   C. carbonaceous aerosol life cycle (as manifested in the evolution of ABS).
4. These measurements and retrievals are necessary but not sufficient to constrain ESMs.
5. Possible target misclassifications and sampling issues have to be heeded in use of all ATLID products, but certainly in the ML value-added products, as they only represent a fraction of data.
6. We have a NASA proposal pending which would facilitate the production of 1-year of global, value-added CCN and ABS from the low res ATLID data

Strength of using below cloud CCN to study aerosol-cloud interaction



Gao et al., submitted to Geophysical Research Letters, 2025GL115821

Random Forrest Analysis indicates **Layer-CCN is most important predictor** of CDNC and R_{eff} **after** SST and TCWV

Mean Absolute (Relative) Error of CCN and ABS predictions for all and pristine conditions with oversampling lower range

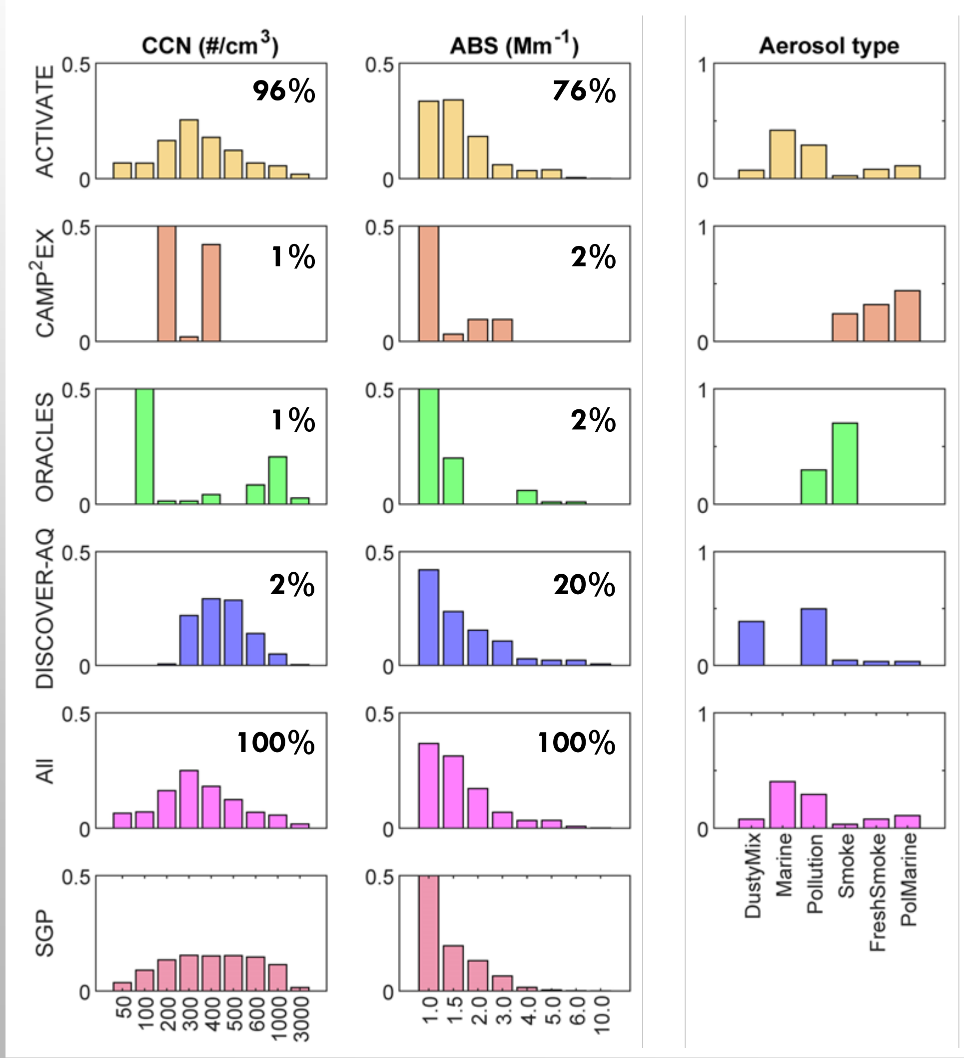
Predictor Data set →	ATLID observables		**ATLID** observables + Reanalysis Data		**ATLID** observables + 50% noise + Reanalysis Data	
Predictor Indicator →	**Mean Absolute Error (Relative)**					
	All conditions	Pristine 0<CCN<100 0<ABS<0.5	All conditions	Pristine 0<CCN<100 0<ABS<0.5	All conditions	Pristine 0<CCN<100 0<ABS<0.5
CCN [1/cm^3]	210.5 (33.4%)	136.7 (244.7%)	102.2 (16.2%)	69.8 (125.0%)	134.3 (21.3%)	76.5 (137.0%)
ABS [10^{-6} m^{-1}]	0.56 (32.1%)	0.28 (103.7%)	0.40 (23.2%)	0.25 (92.5%)	0.49 (27.3%)	0.23 (86.2%)

ATLID: ATmospheric LIDar on EarthCARE

The Machine Learning augmentation… to physics-based aerosol retrievals

Redemann and Gao, Nature Communications, 2024

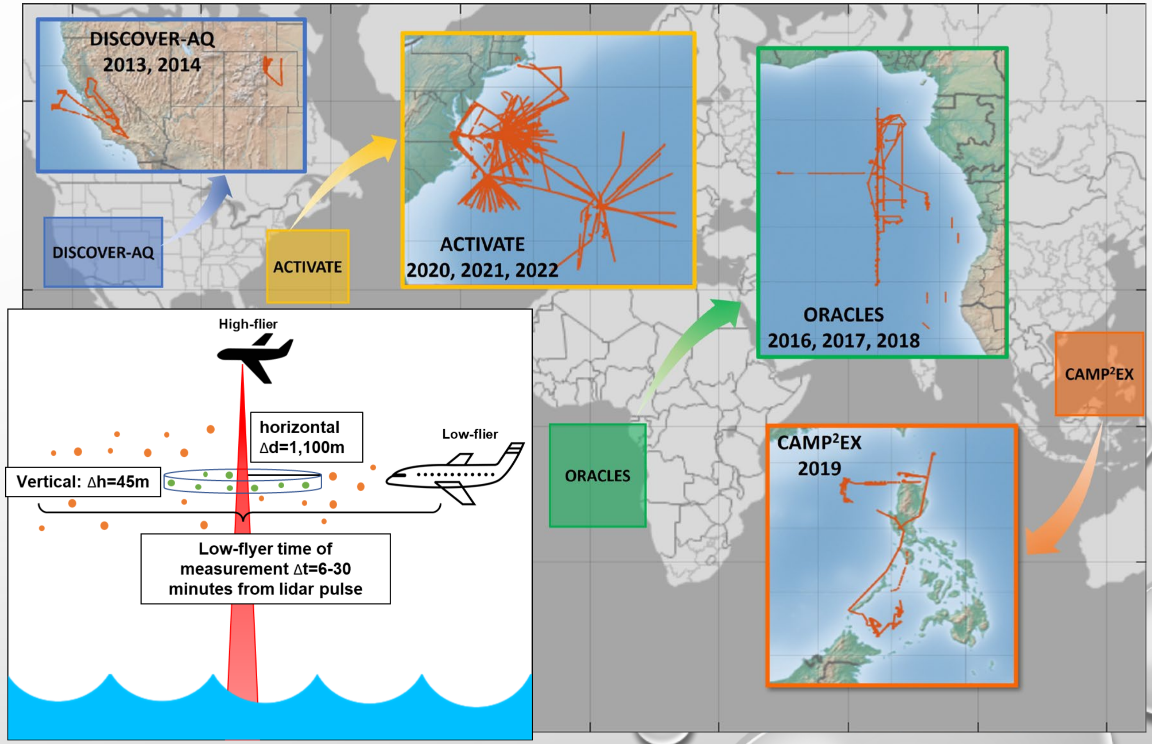
Machine Learning models to estimate CCN and ABS from HSRL and reanalysis data as predictors



How representative is 4-campaign training data?

Summary of Dataset for ML training

5-years of ARM SGP site data

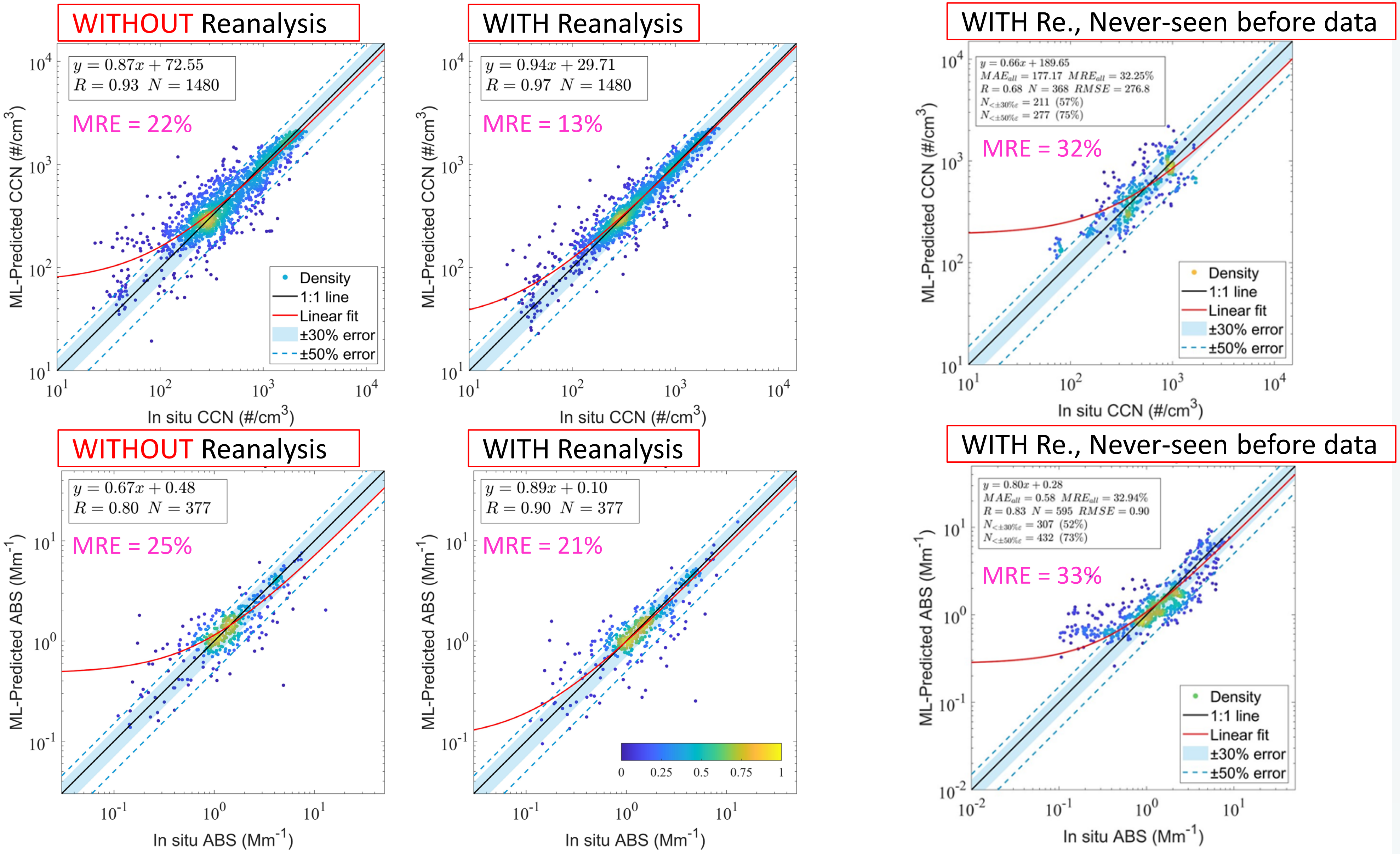


Lidar observables	EXT_{355}, EXT_{532}, BSC_{355}, BSC_{532}, BSC_{1064}, $DEPO_{355}$, $DEPO_{532}$, $DEPO_{1064}$
Reanalysis	Relative humidity (RH), Temperature (T)
In situ	CCN concentration at 0.4% SS (~9,900) Absorption, ABS (~2,700)

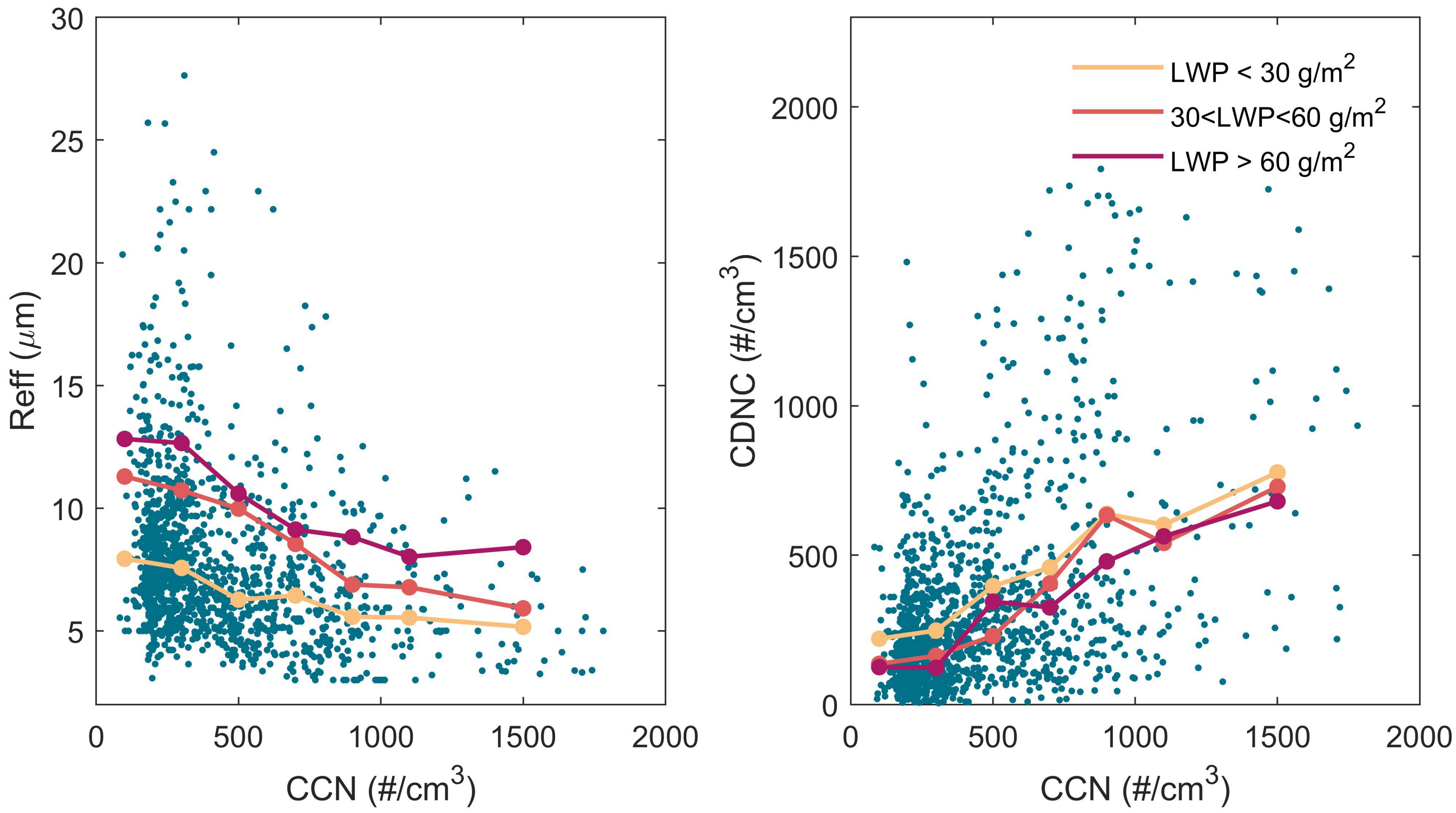
Simulation of ML retrievals: CCN/ABS for full set of HSRL-2 observables (3β + 2α + 3δ)

CCN

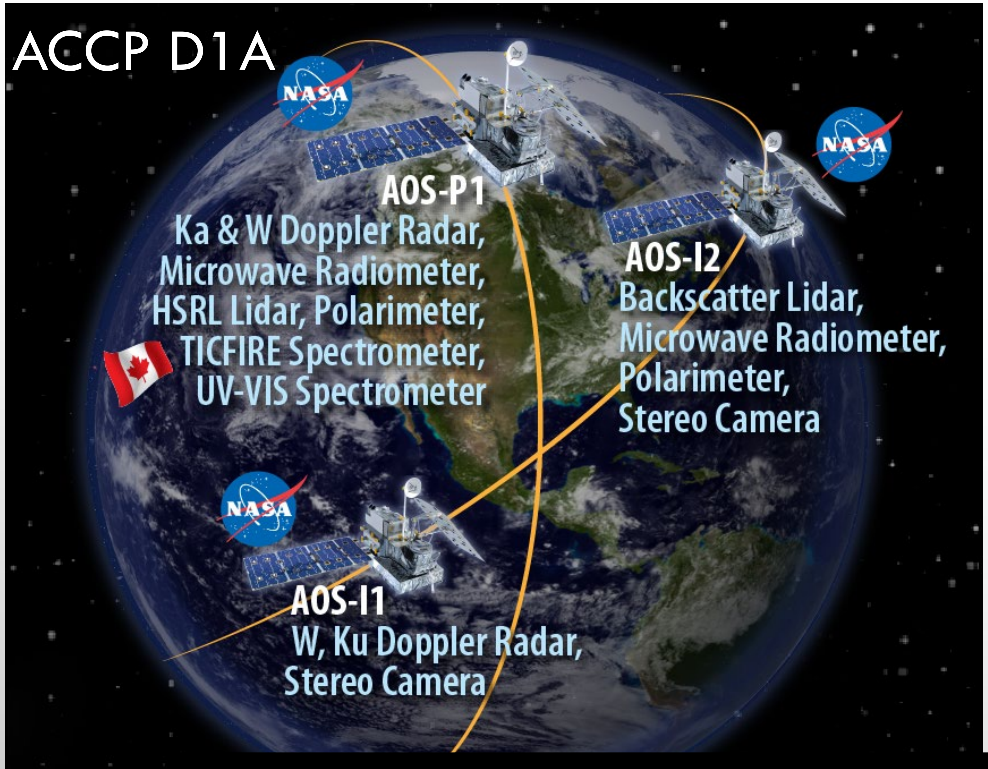
ABS

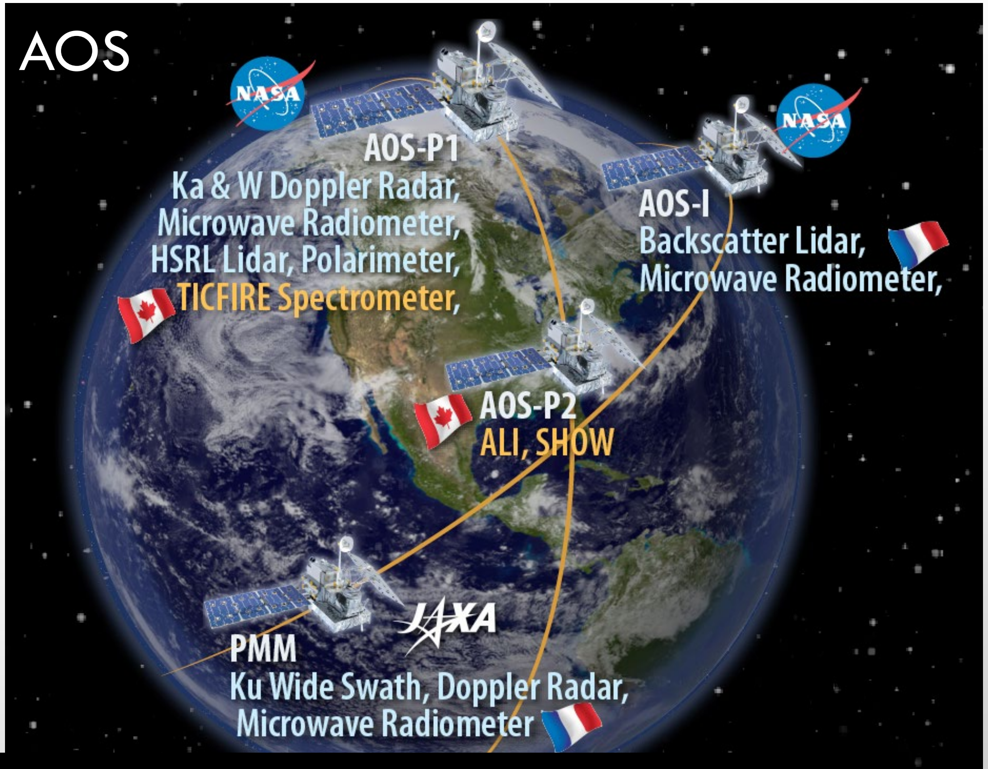


Methodology yields consistent results for different LWP ranges



MODIFICATIONS TO ACCP D1A DUE TO TECHNICAL AND COST MATURATION

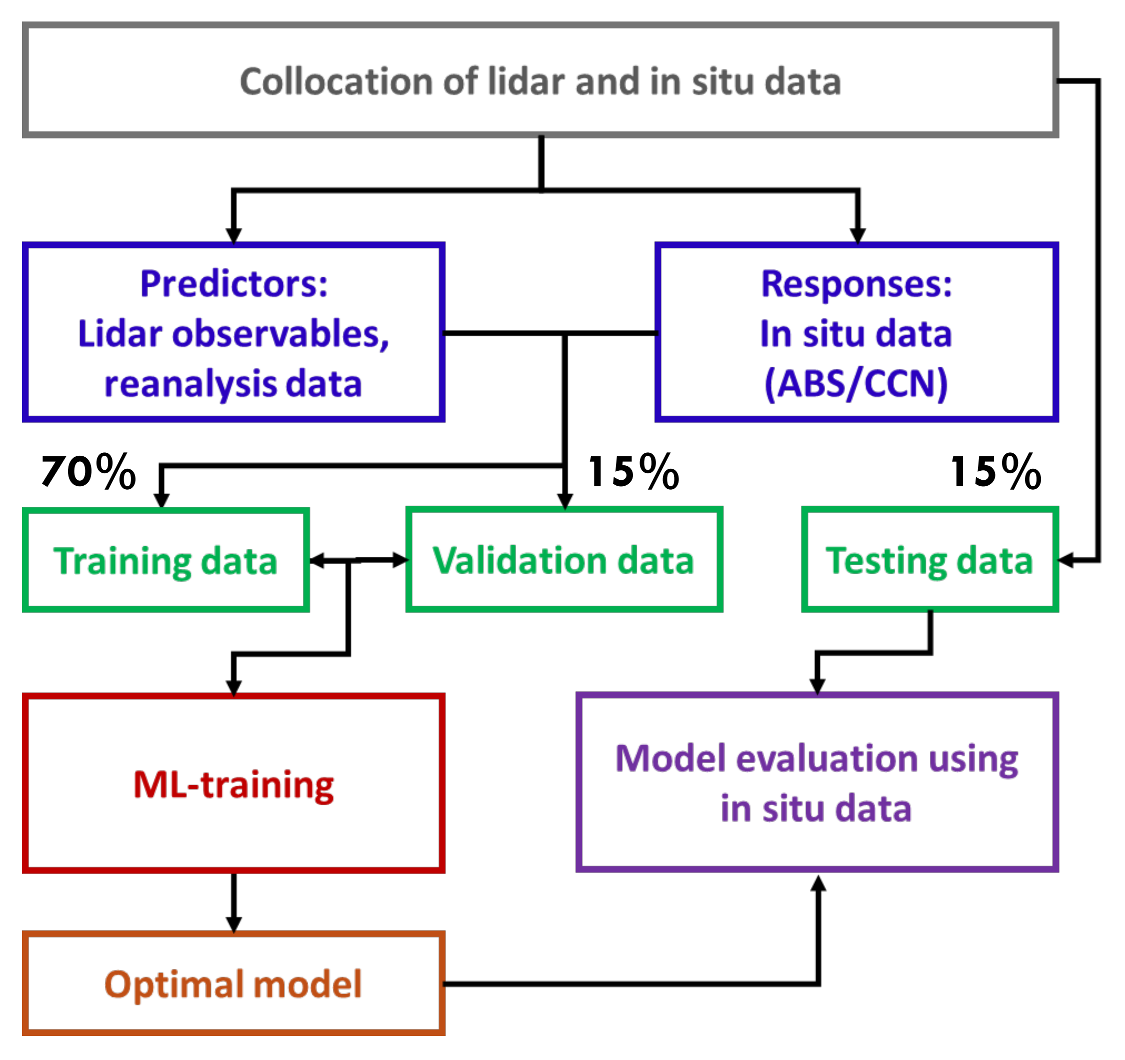




Lost (Inclined, Polar)	Gained (Inclined, Polar)
U.S. Ku, W-band radar	JAXA wide-swath Ku radar
Polarimeter	CNES tandem radiometers
Tandem stereo cameras	CSA aerosol and moisture limb sounding
SW spectrometer, lidar photon detector	

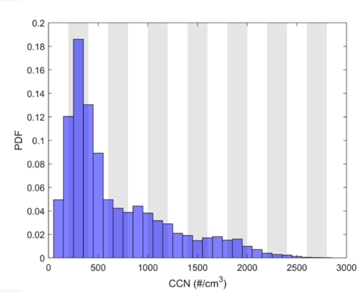
The Machine Learning alternative

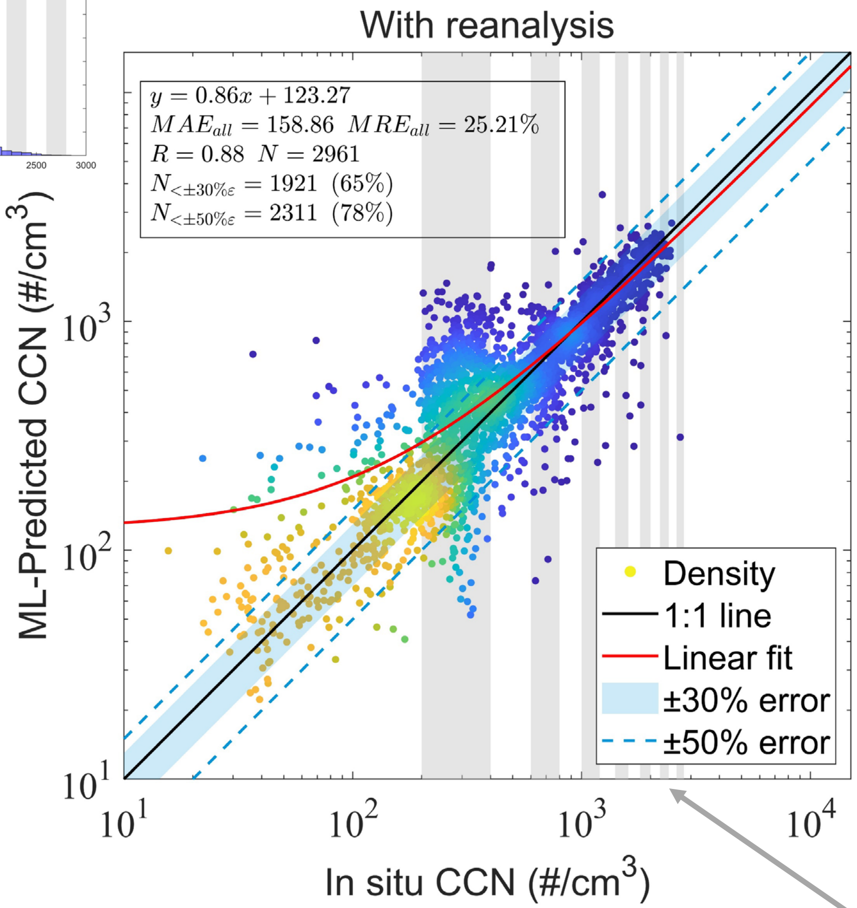
- Collocate HSRL-2 and in-situ measured CCN from multiple campaigns.
  - ✔ ACTIVATE, CAMP^{2}EX, DISCOVER-AQ, ORACLES
- Train neural networks for different sets of lidar observables (e.g., ATLID, NASA AOS).
  - ✔ HSRL-2: 3β + 2α + 3δ
  - ✔ HSRL-1: 2β + 1α + 2δ
  - ✔ EarthCARE/ATLID: 1β + 1α + 1δ
  - ✔ Simulated-Elastic-Backscatter (SEBL): 2β + 2δ
- Evaluate model prediction using in-situ measured CCN or ABS
  - ✔ Correlation coefficient (R)
  - ✔ Mean absolute error (MAE)
  - ✔ Mean relative error (MRE)

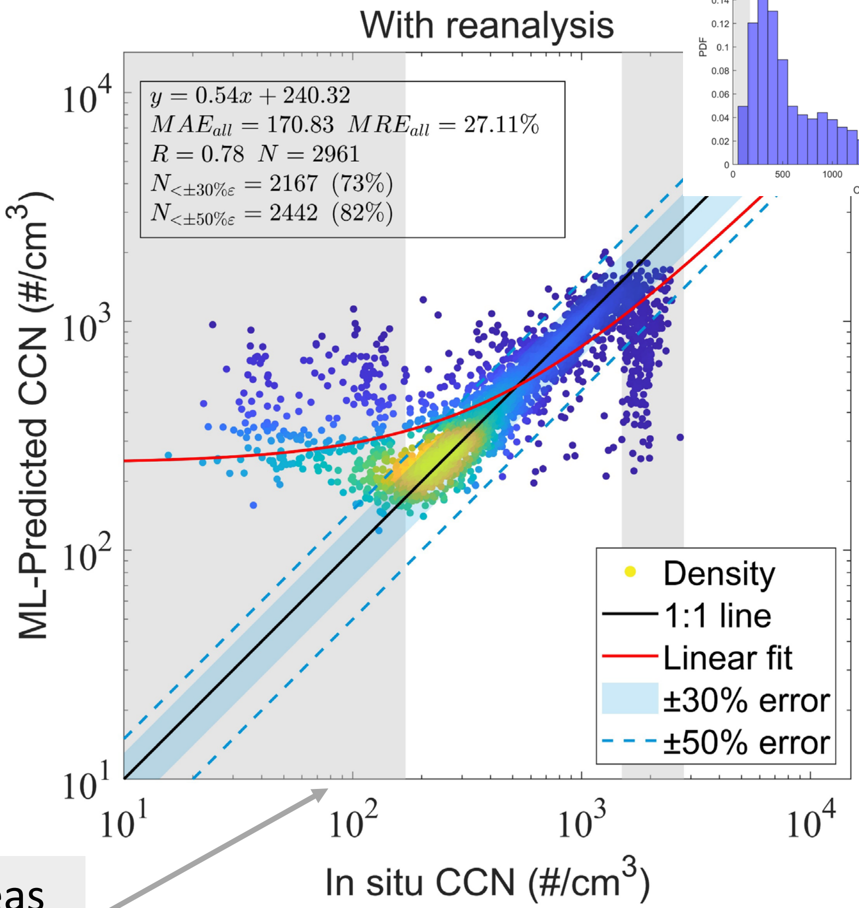


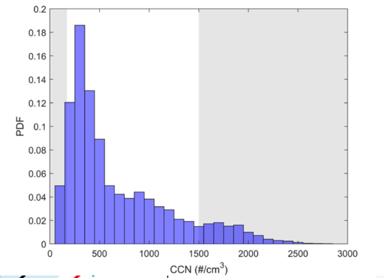
Test for ATLID observables with incomplete training data

ML model trained with incomplete training data has
good interpolation skills, but no extrapolation skills.









Grey-shaded areas
excluded in training

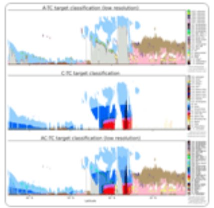
Search

https://doi.org/10.5194/amt-16-2795-2023

Article | Assets | Peer review | Metrics | Related articles

Research article | 06 Jun 2023

The classification of atmospheric hydrometeors and aerosols from the EarthCARE radar and lidar: the A-TC, C-TC and AC-TC products



Abdanour Irbah, Julien Delanoë, Gerd-Jan van Zadelhoff, David P. Donovan, Pavlos Kollias, Bernat Puigdomènech Treserras, Shannon Mason, Robin J. Hogan, and Aleksandra Tatarevic

Class numbers	A-TC classes
−3	Missing data
−2	Sub-surface
−1	Attenuated
0	Clear
1	Liquid
2	Supercooled liquid
3	Ice
10	Dust
11	Sea salt
12	Continental pollution
13	Smoke
14	Dusty smoke
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20	STS (PSC type I)
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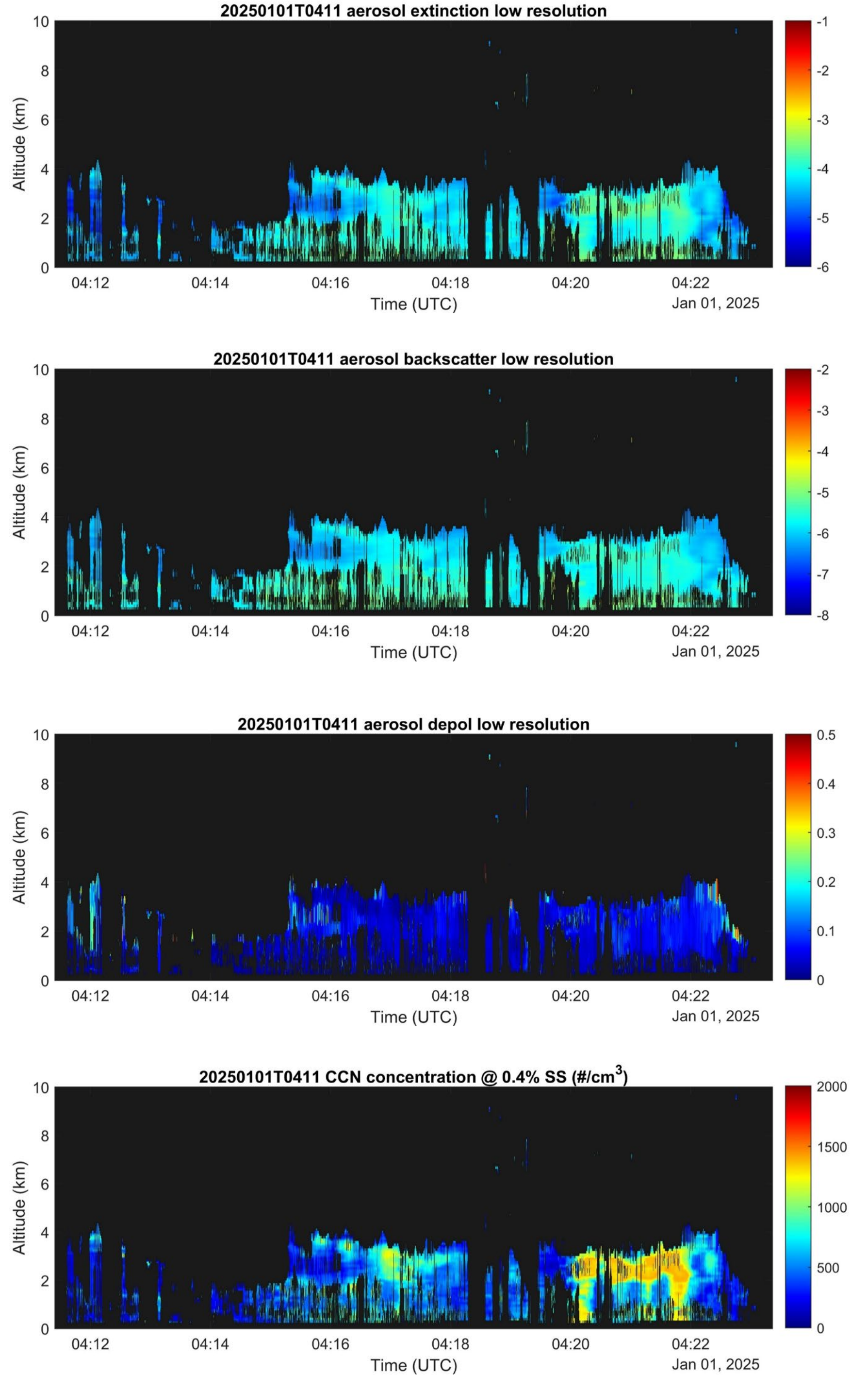
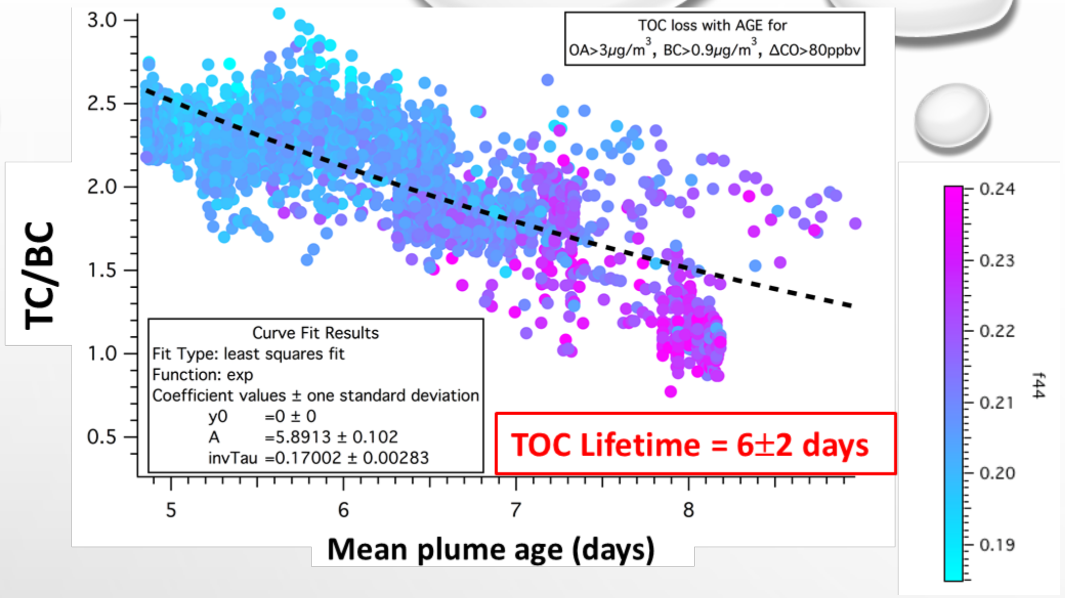


ORACLES-2016&2017: total organic carbon (TOC) loss/lifetime

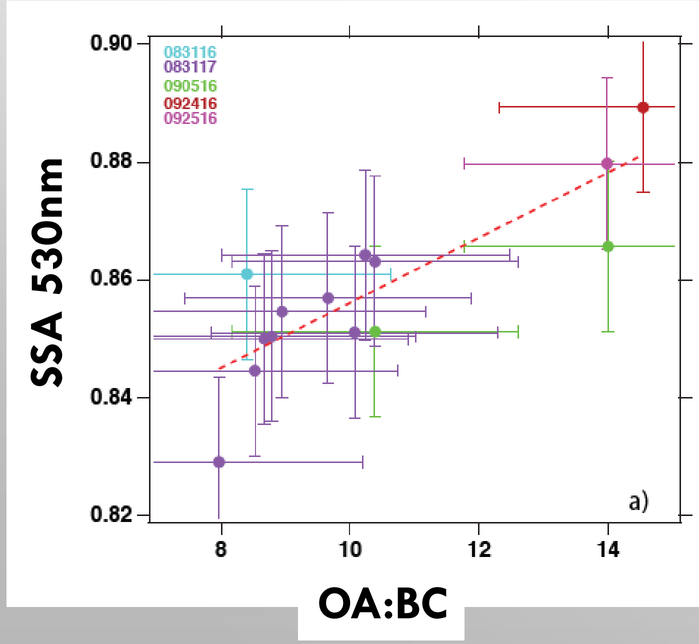


- Plume age: WRF-Chem model, corroborated by AMS f44 – parameter = highly oxygenated OA
- Can use f44 as a qualitative tracer for aerosol age (Cubison et al., 2010)
- TC from AMS, BC from SP2 instruments
- Data suggests that

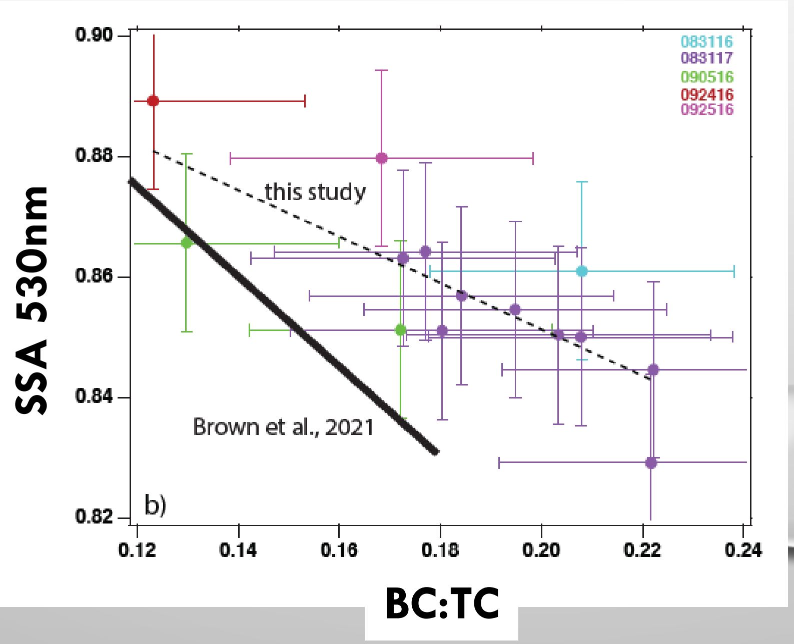
•OA:BC decreases with aging, as does SSA

SSA= 0.801+0.0055*(OA:BC)

← Increasing Age



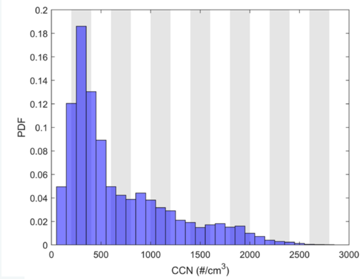
Increasing Age →

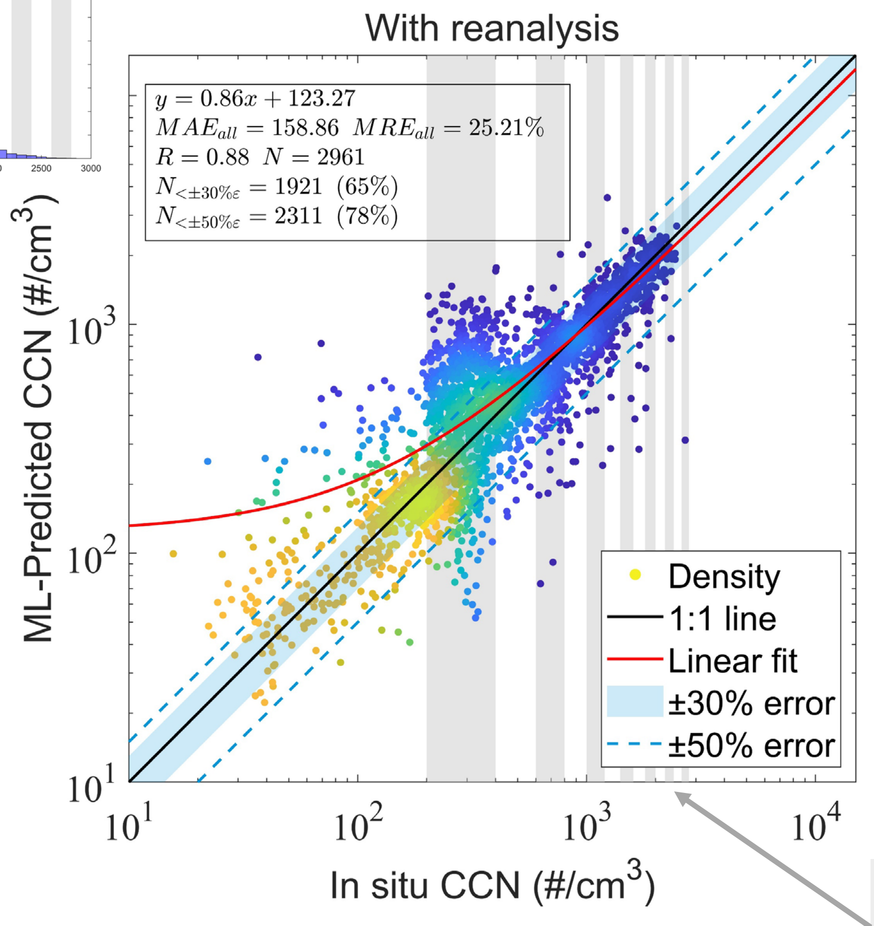


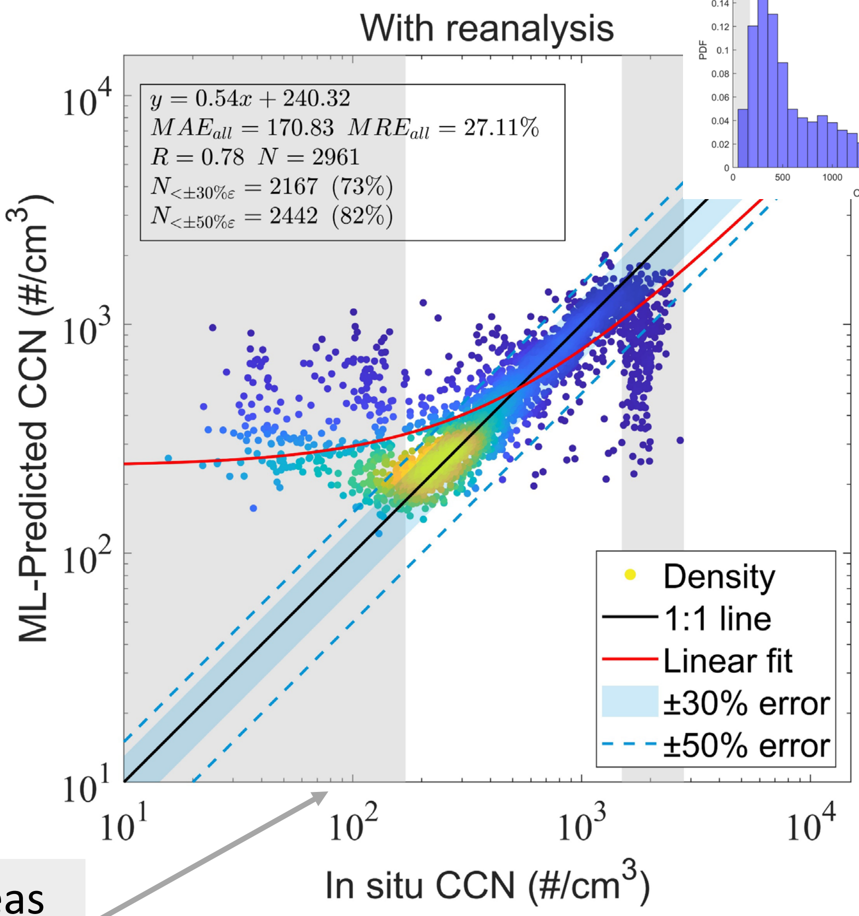
Dobracki et al.: An attribution of the low single-scattering albedo of biomass burning aerosol over the southeastern Atlantic, Atmos. Chem. Phys., 23, 4775–4799, https://doi.org/10.5194/acp-23-4775-2023, 2023.

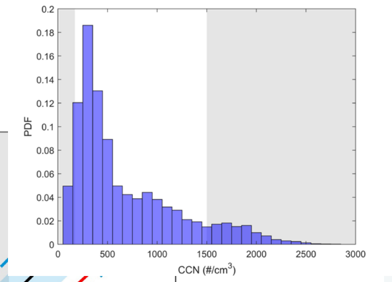
Test for ATLID observables with incomplete training data

ML model trained with incomplete training data has good interpolation skills, but no extrapolation skills.



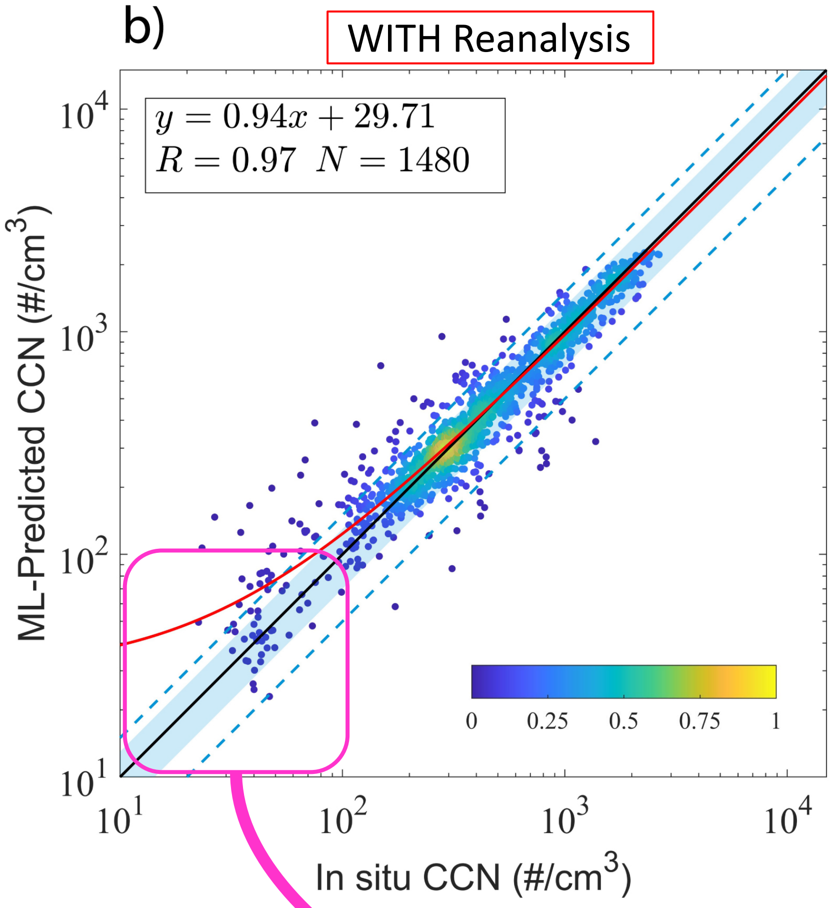


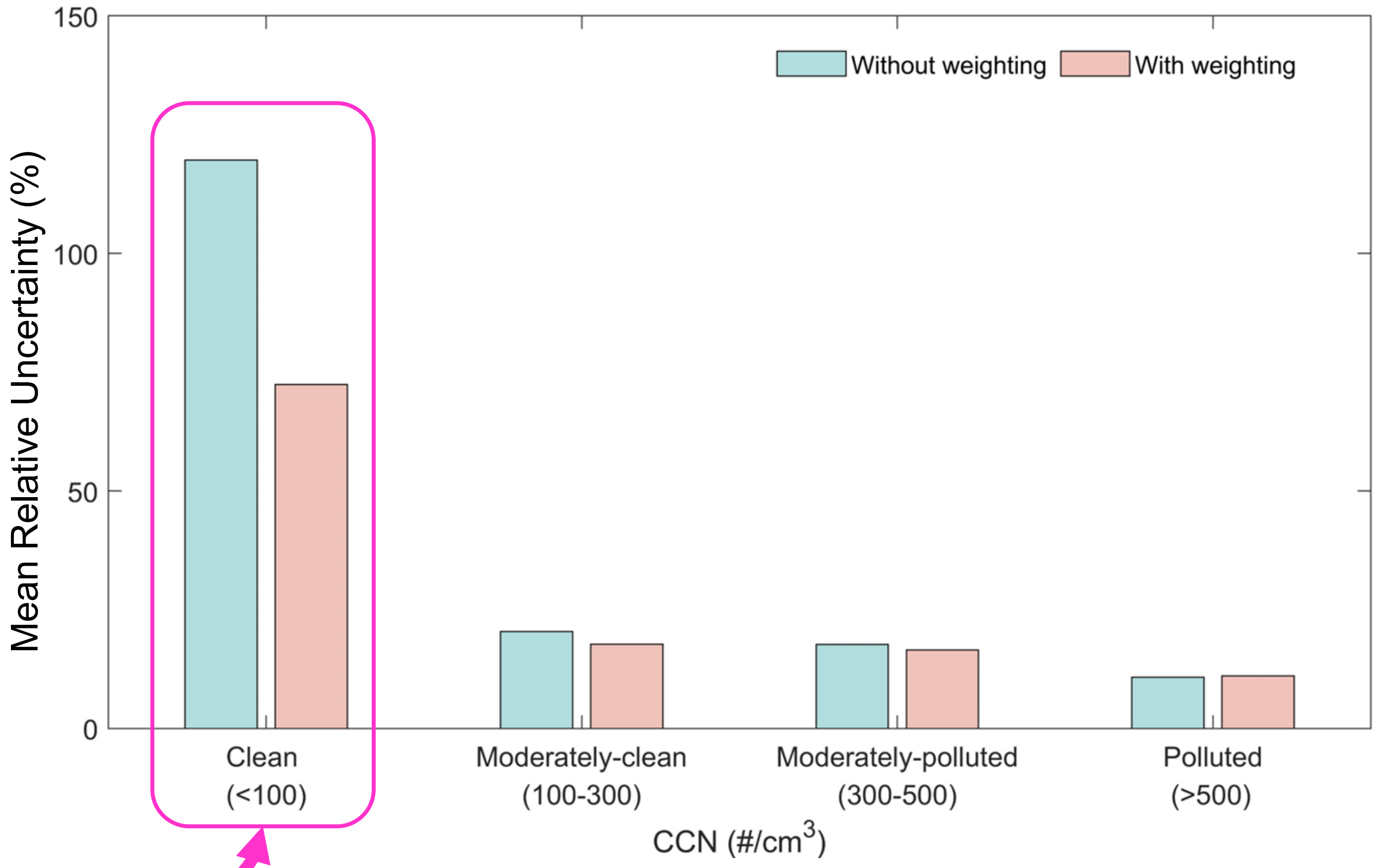




Grey-shaded areas excluded in training

SIMULATION OF ML RETRIEVALS: CCN FOR FULL SET OF HSRL-2 OBSERVABLES (3β + 2α + 3δ)



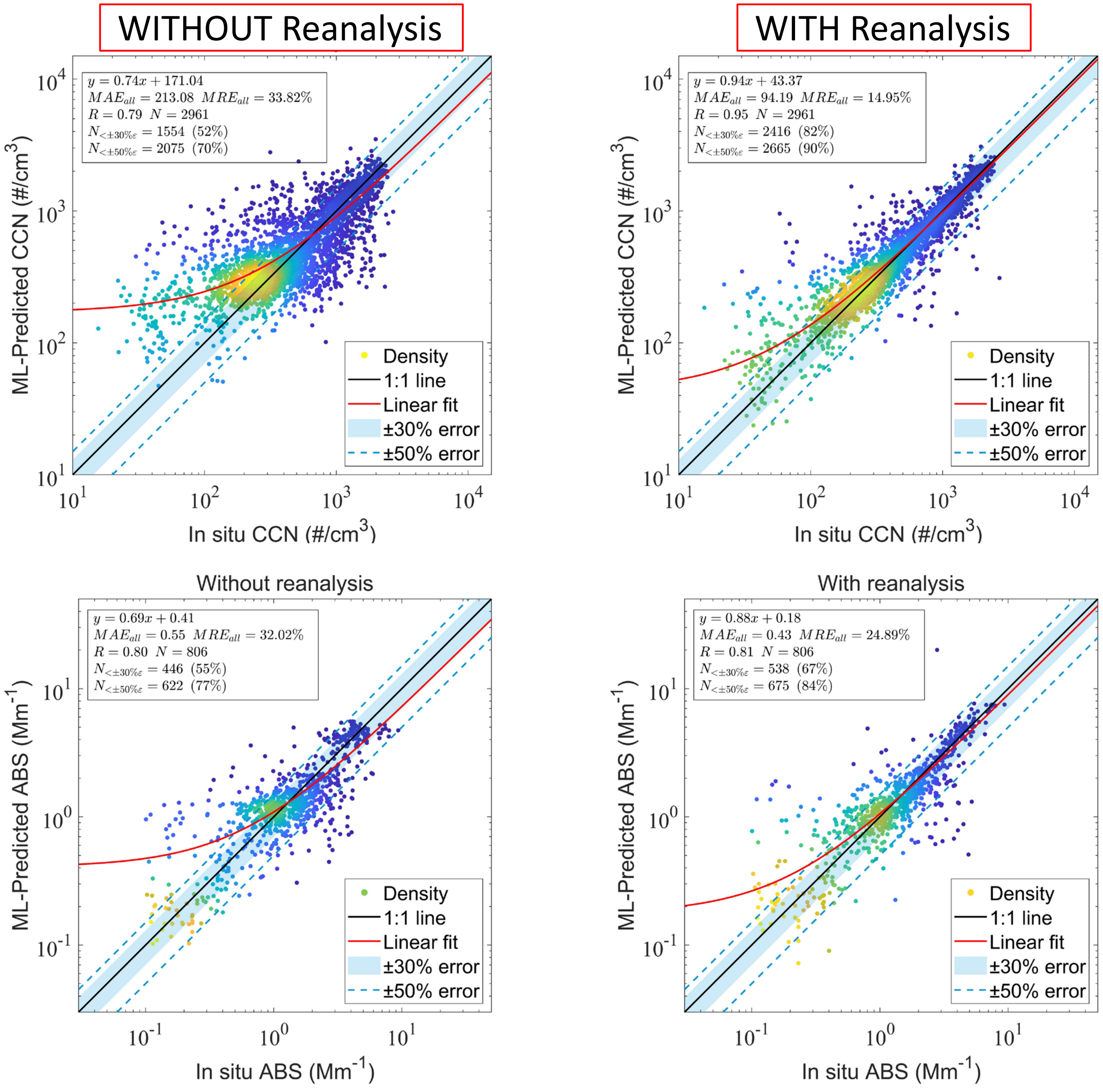


We need more training data in clean conditions, CCN<100/cm^3)

Simulation of ML retrievals: CCN/ABS for EarthCARE/ATLID observables (1β + 1α + 1δ)

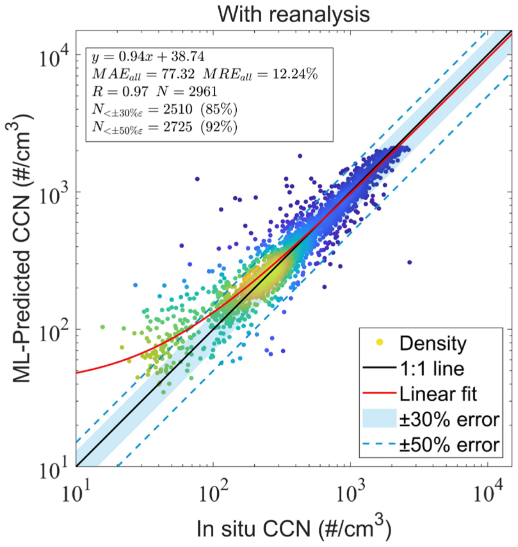
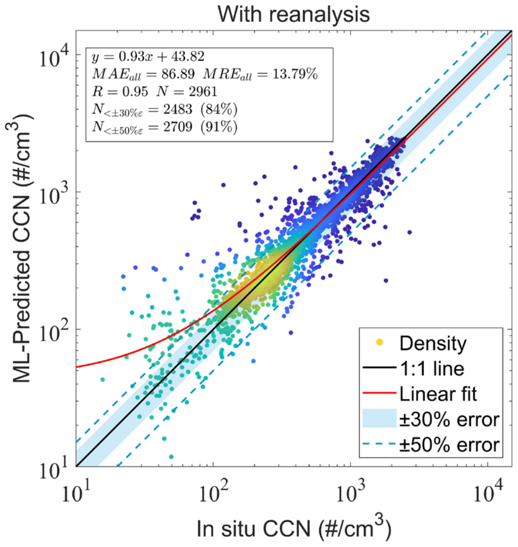
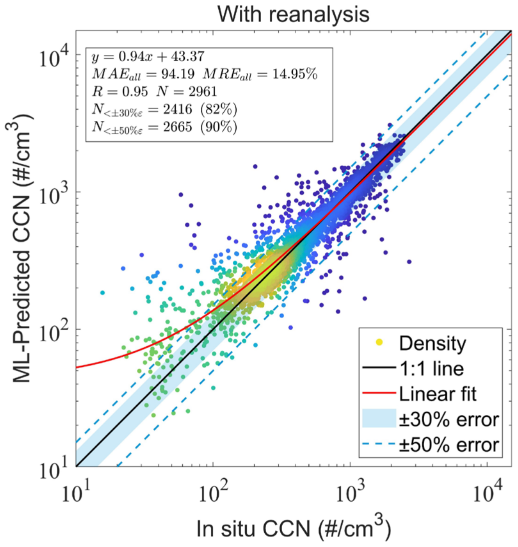
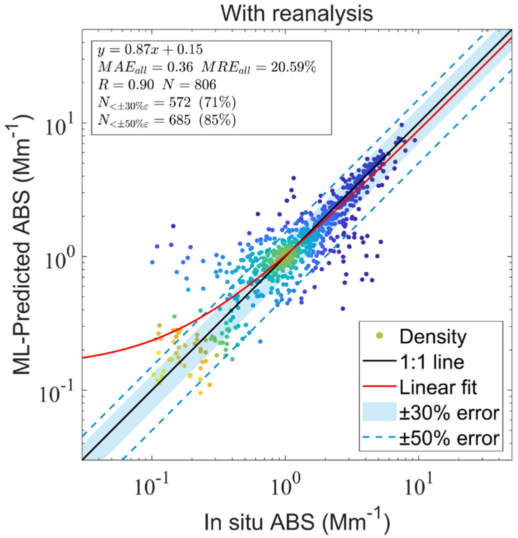
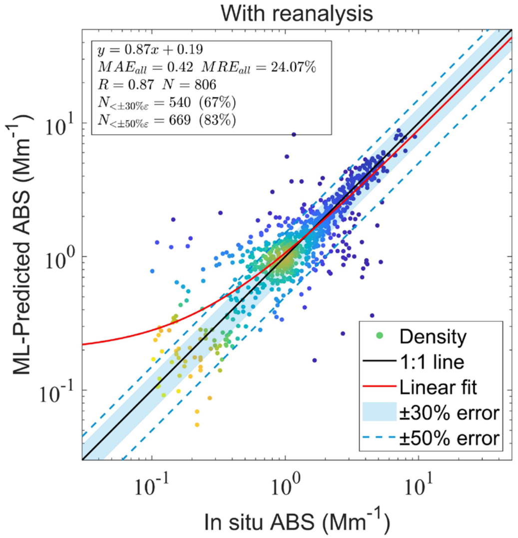
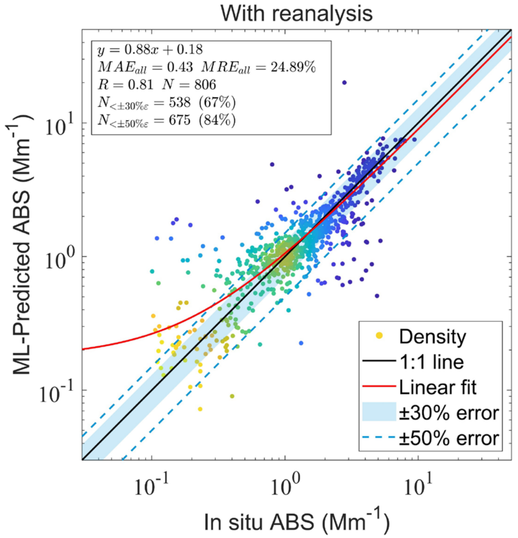
CCN

ABS



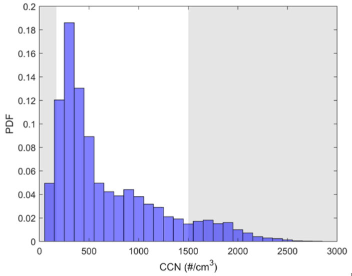
Reanalysis data of RH and T provide larger aid for lidars with lesser information content

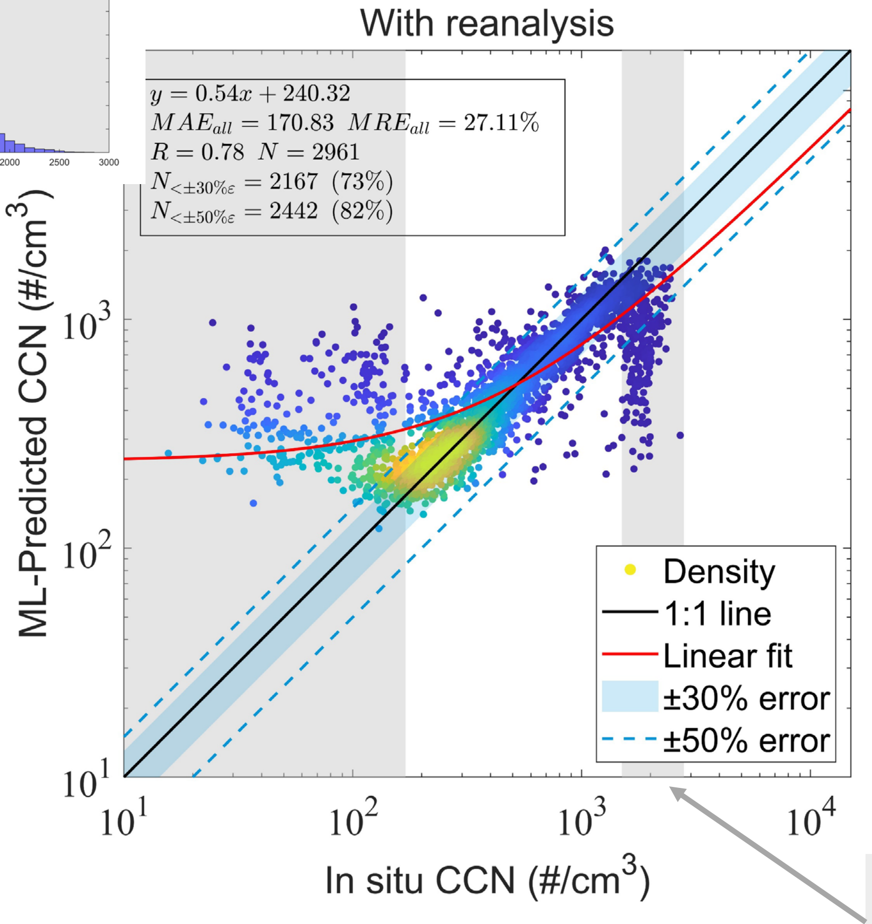
CCN/ABS for HSRL-2, HSRL-1 and EarthCARE/ATLID observables with reanalysis

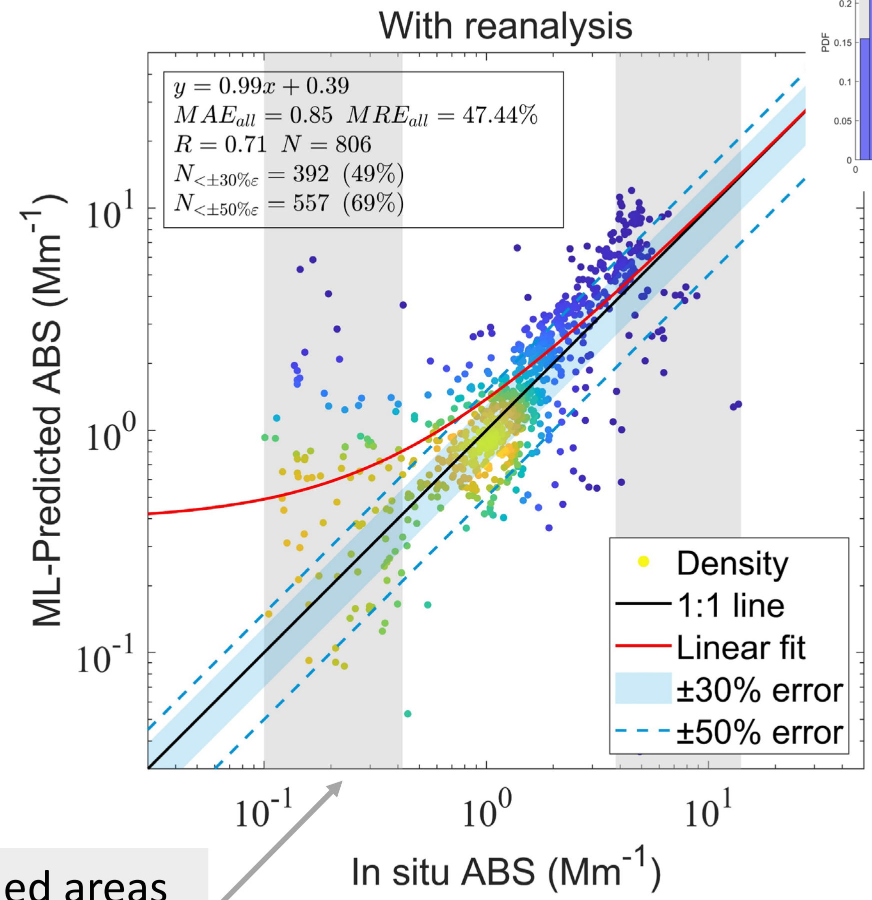
	HSRL-2: 3β + 2α + 3δ	**HSRL-1**: 2β + 1α + 2δ	**ATLID**: 1β + 1α + 1δ
CCN			
ABS			

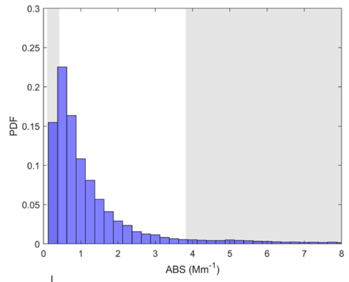
Test for ATLID observables with incomplete in situ data: limited range of training data

Provide only center 80% of CCN for training , but attempt prediction for full range of CCN pdf



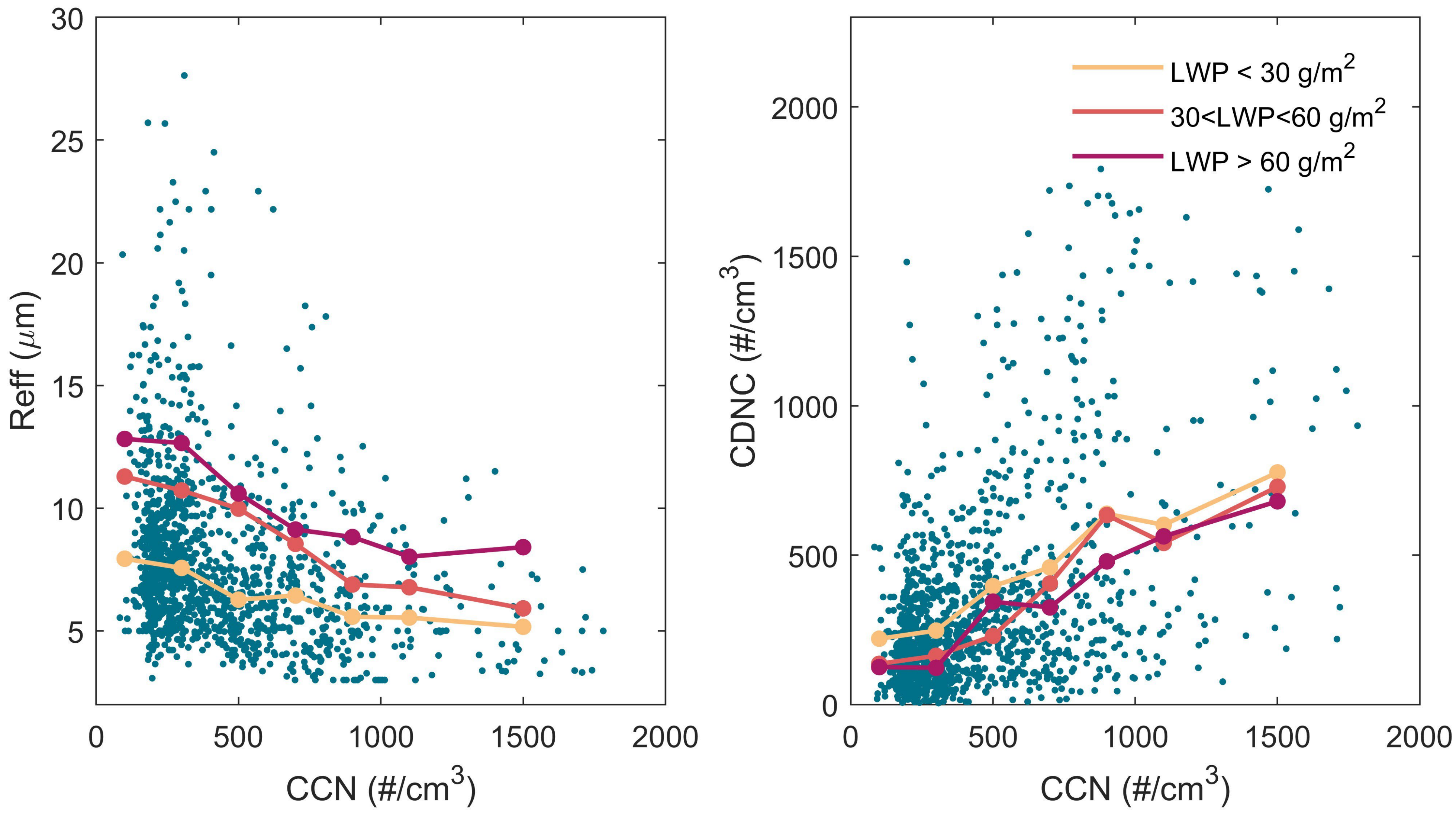






Grey-shaded areas excluded in training

Aerosol-cloud interaction for different LWP ranges

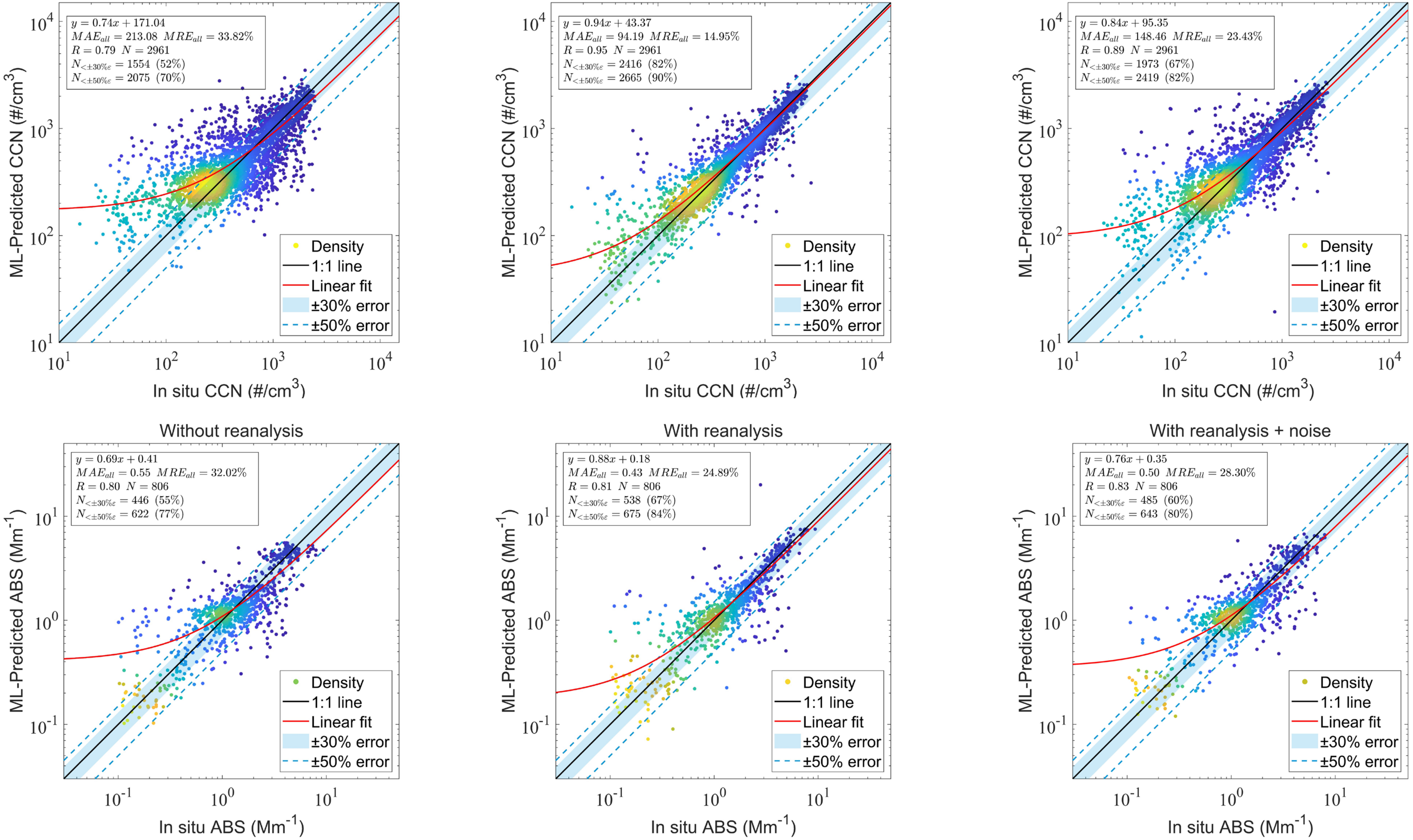


Simulation of ML retrievals: CCN/ABS for EarthCARE/ATLID observables (1β + 1α + 1δ)

WITHOUT Reanalysis | WITH Reanalysis | WITH 50% noise & Reanalysis

CCN

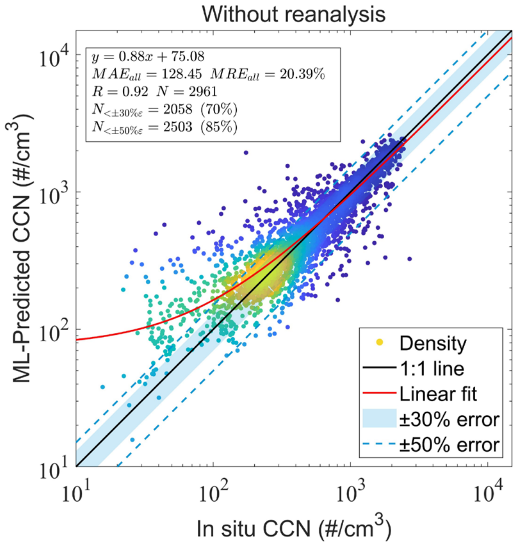
ABS

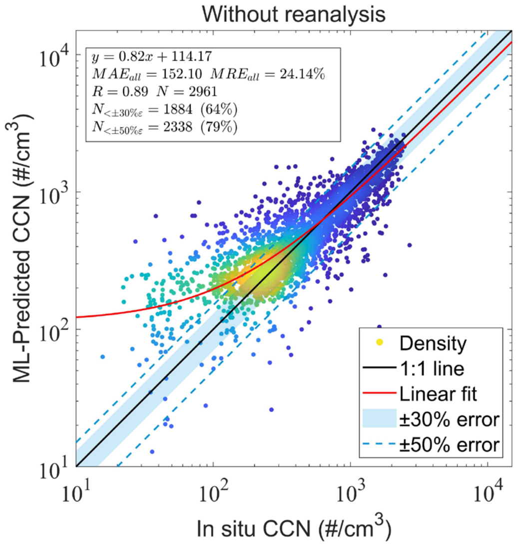


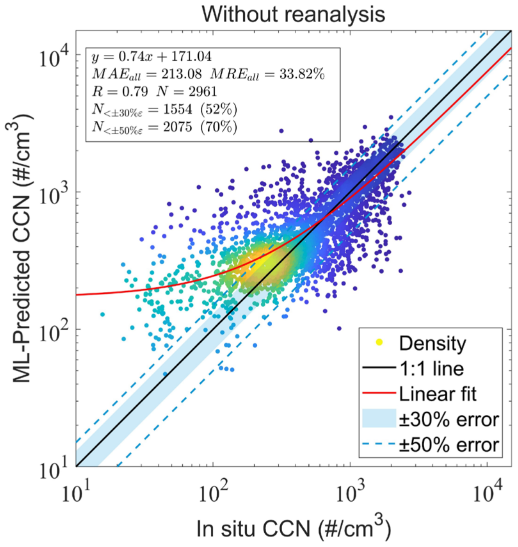
CCN/ABS for HSRL-2, HSRL-1 and EarthCARE/ATLID observables without reanalysis

HSRL-2: 3β + 2α + 3δ | **HSRL-1**: 2β + 1α + 2δ | **ATLID**: 1β + 1α + 1δ

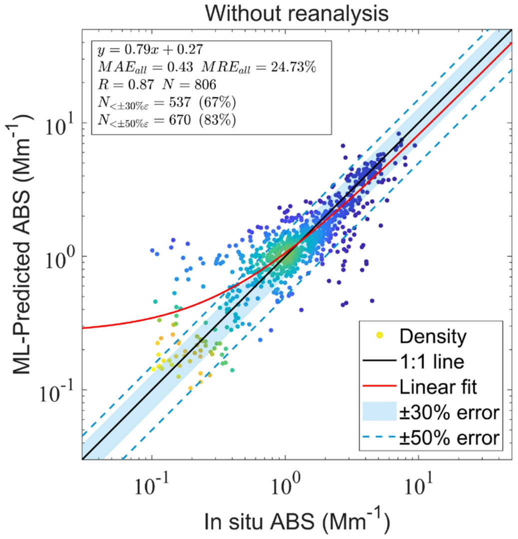
CCN

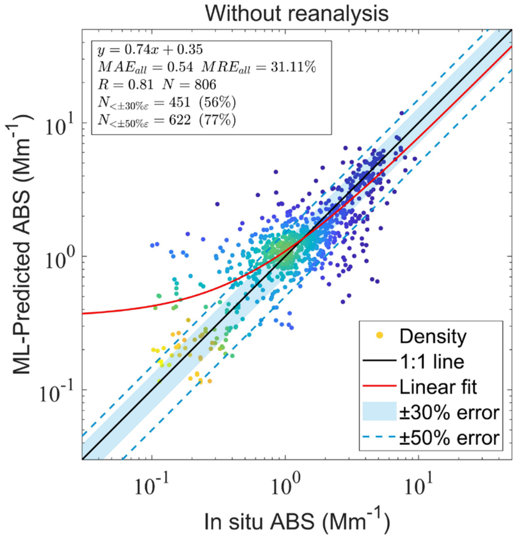


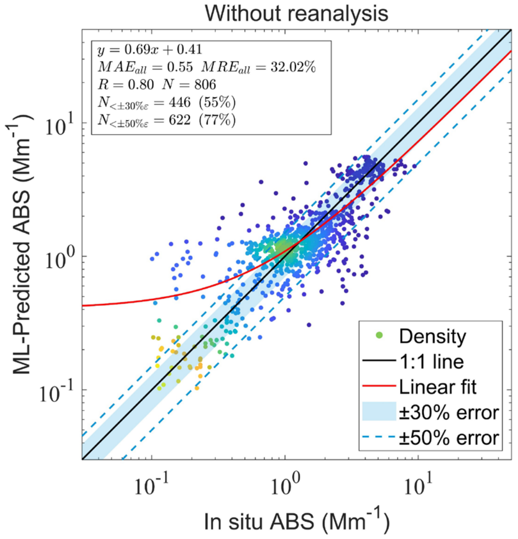




ABS







Mean Absolute (Relative) Error of CCN and ABS predictions for all and pristine conditions

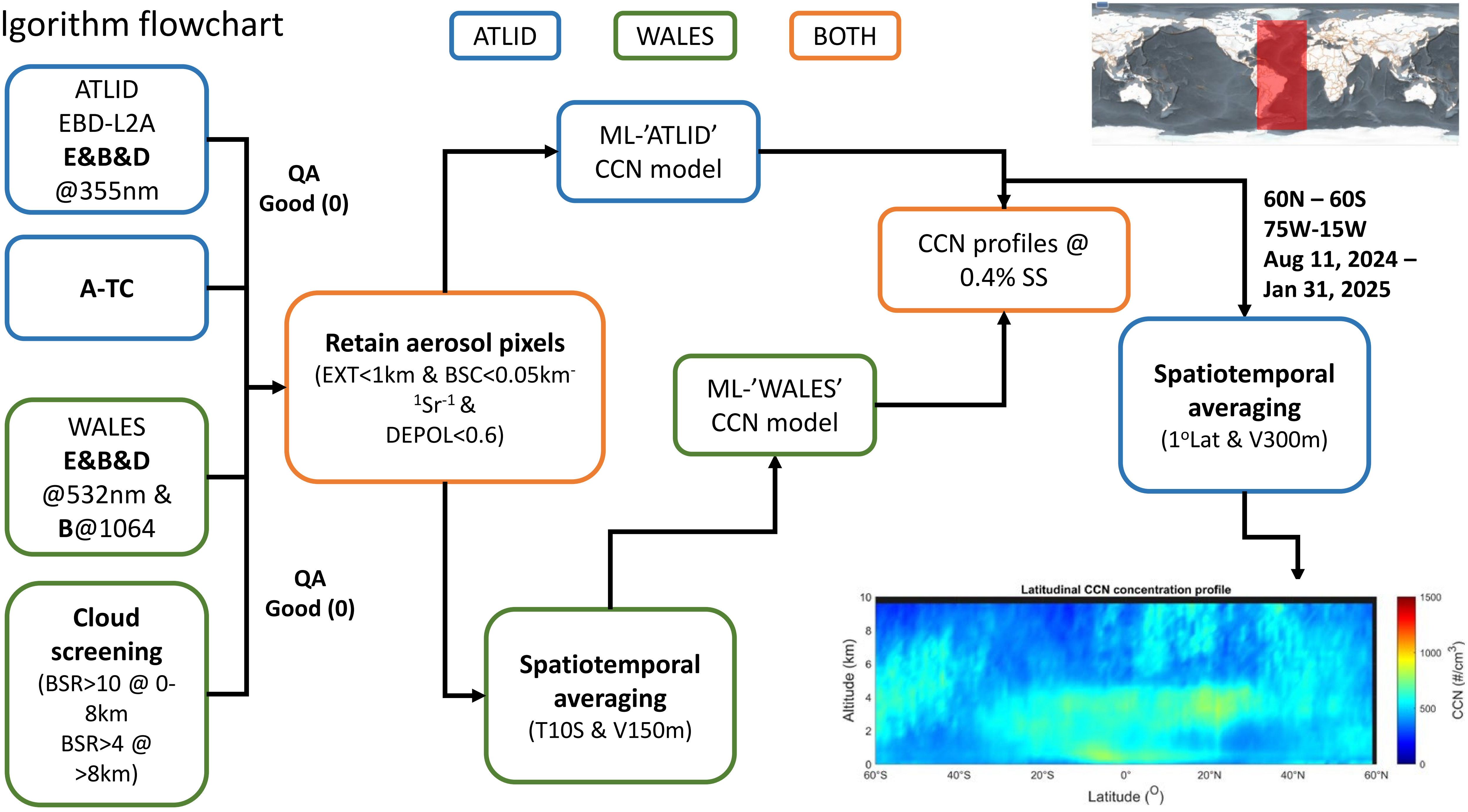
Predictor Data set →	ATLID observables		**ATLID** observables + Reanalysis Data		**ATLID** observables + 50% noise + Reanalysis Data	
Predictor Indicator →	**Mean Absolute Error (Relative)**					
	All conditions	Pristine 0<CCN<100 0<ABS<0.5	All conditions	Pristine 0<CCN<100 0<ABS<0.5	All conditions	Pristine 0<CCN<100 0<ABS<0.5
CCN [1/cm^3]	213.1 (33.8%)	192.5 (345%)	94.2 (15.0%)	79.6 (143%)	148.5 (23.4%)	146.1 (268%)
ABS [10^{-6} m^{-1}]	0.55 (32.0%)	0.29 (104%)	0.43 (24.9%)	0.26 (93%)	0.5 (28.3%)	0.31 (109%)

ATLID: ATmospheric LIDar on EarthCARE

Latitudinal CCN Vertical Distributions from EarthCARE ATLID Observations and ML Algorithm

- ML CCN retrievals from ATLID observations
- Intercomparison of ATLID CCN VS. WALES CCN
- Latitudinal cross section of CCN vertical distributions

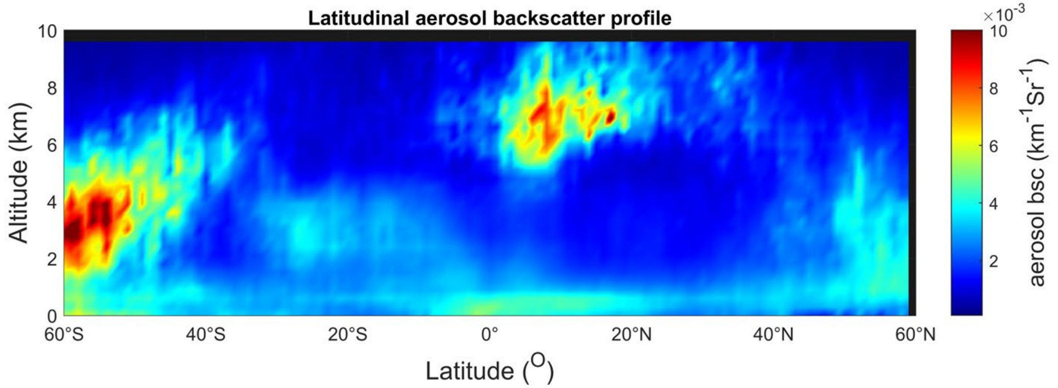
Algorithm flowchart

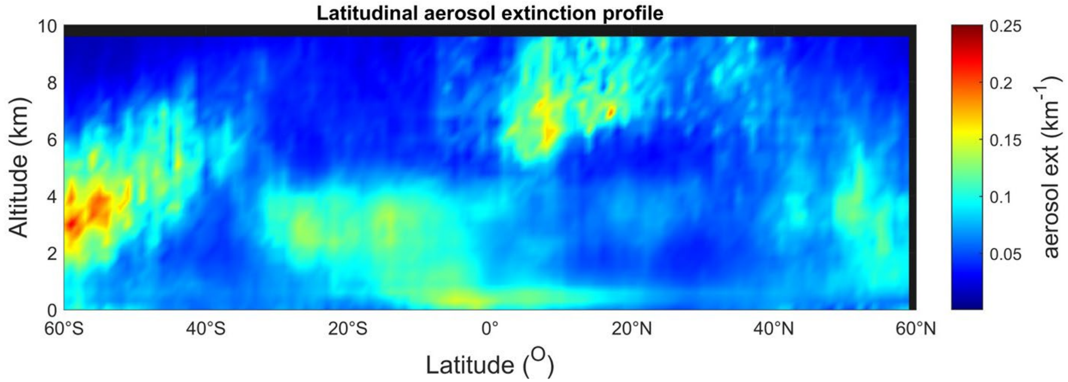


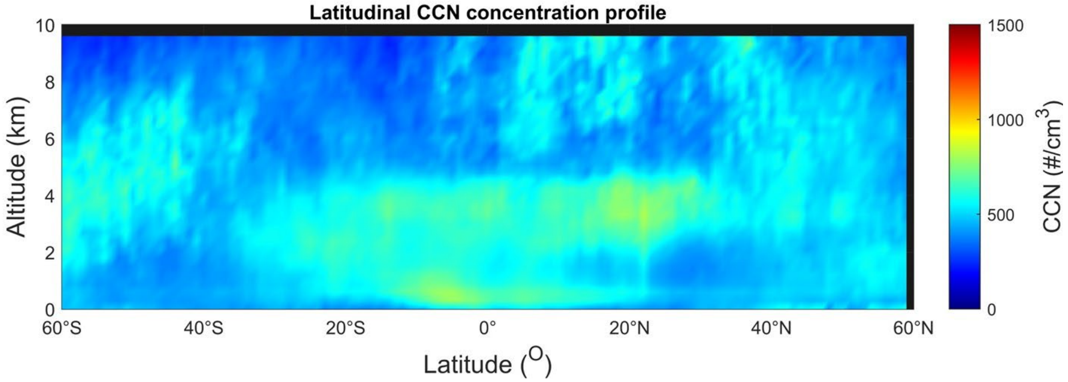
Latitudinal aerosol backscatter and CCN profiles

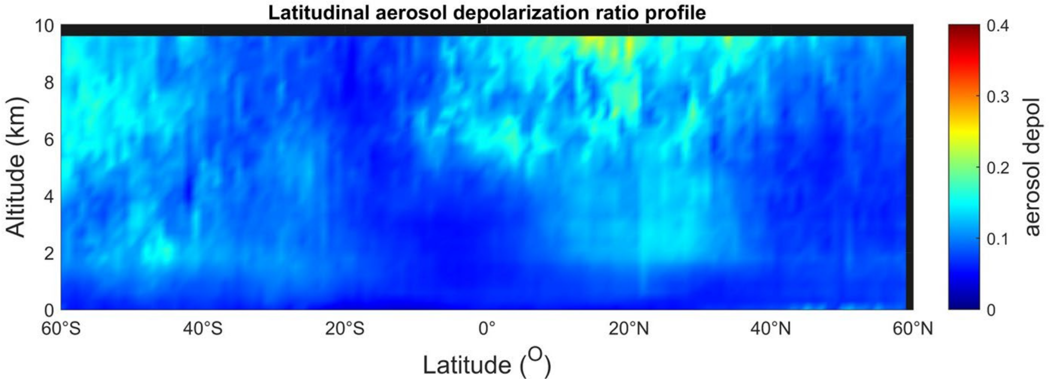
- Retrieve CCN profiles from ATLID L2A EBD products for the period of Aug 11, 2024 – Jan 31, 2025.
- Compute the average CCN profiles across the 75°W-15°W longitude range, using 1-degree latitude bins from 60°N to 60°S.
- Perform vertical averaging of CCN profiles in 300m bins.

The Atlantic Domain:
60N – 60S, 75W-15W

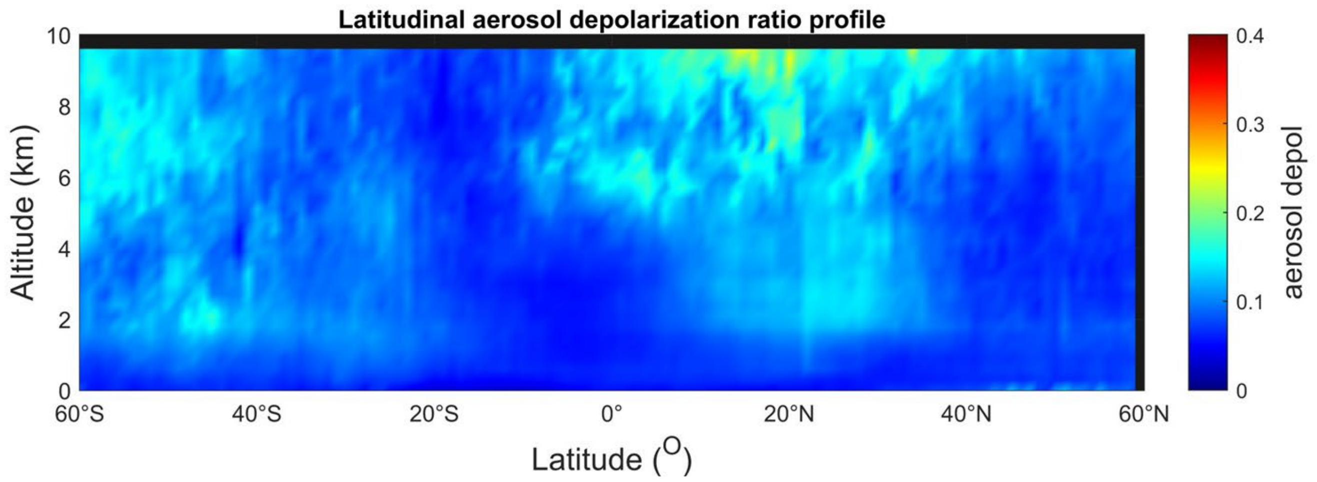


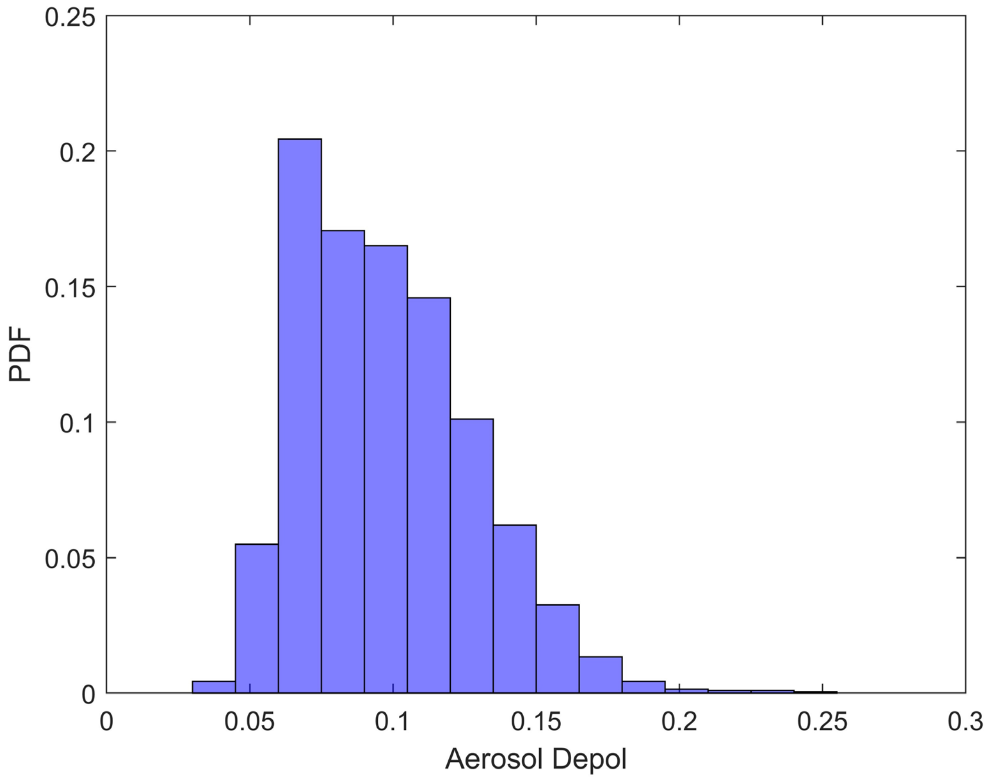






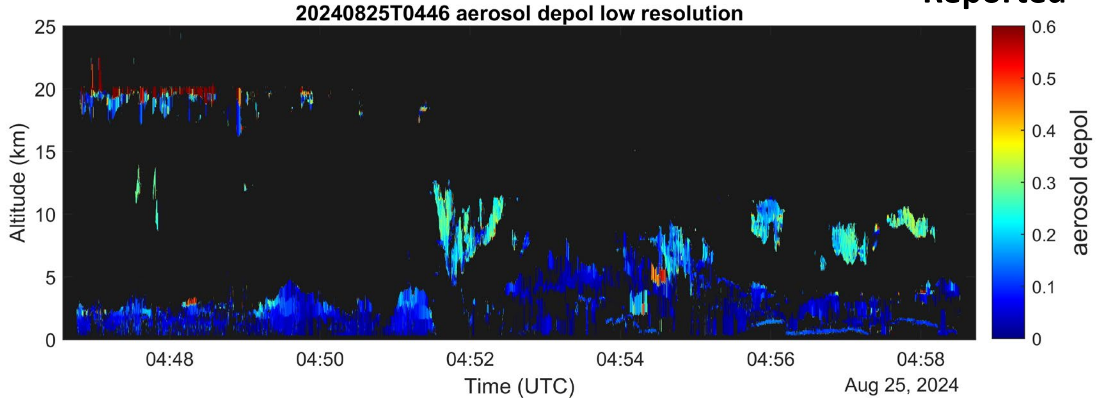
- The calculated mean of depol 355nm is about 0.09.
- The depol values are higher than the aerosol depolarization used in our training dataset (mean: 0.06).
- There are some pixels with very high aerosol depol in the upper level even after applying the TC classification to exclude cirrus contamination.



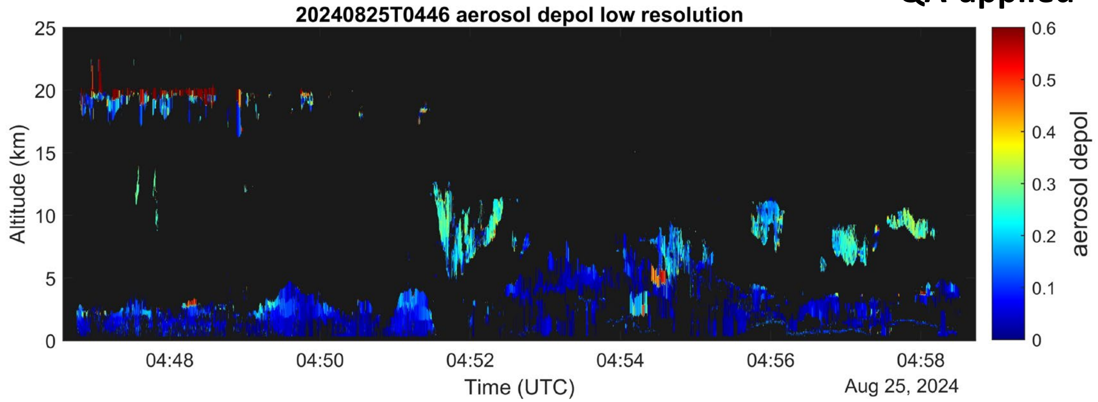


Why some ATLID aerosol depol are high?

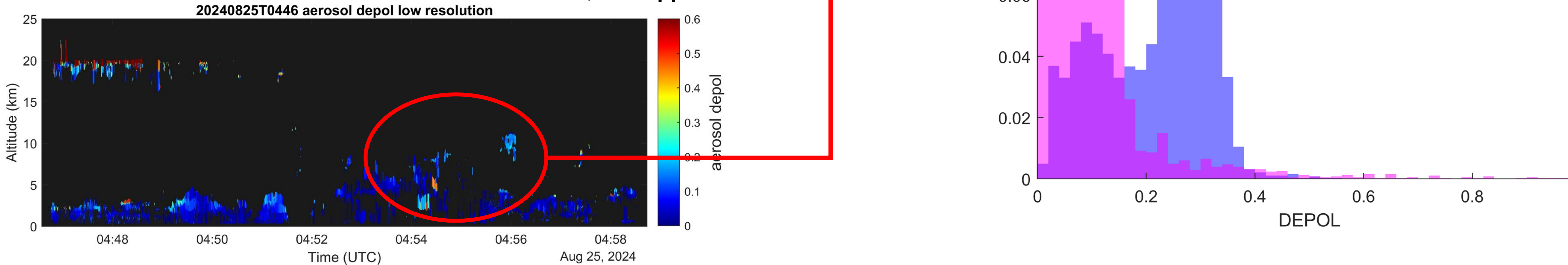
Reported

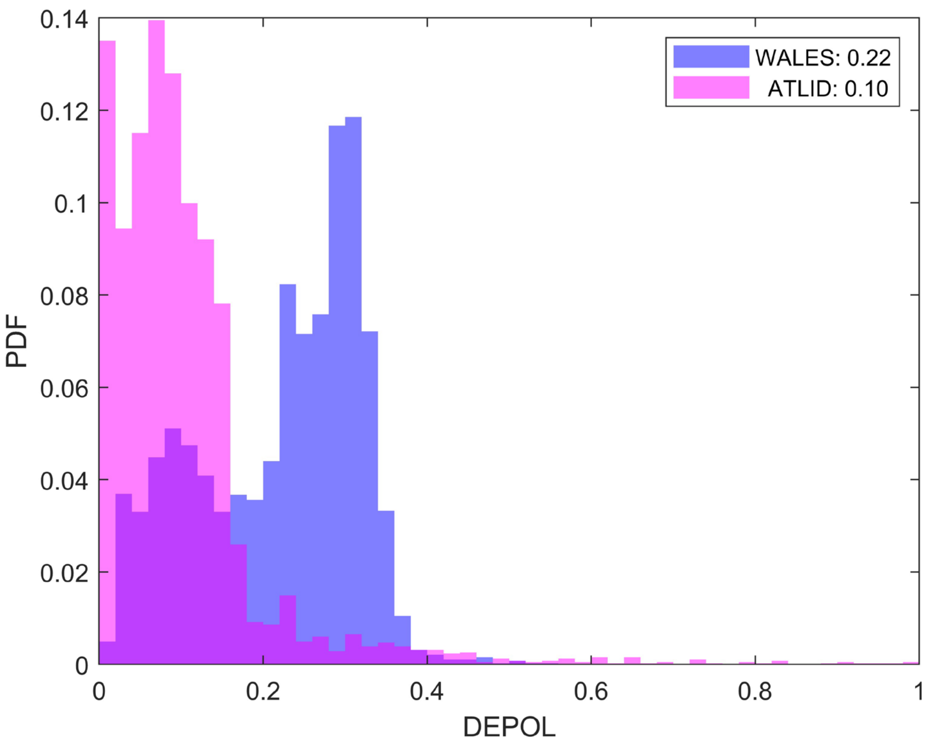


QA-applied

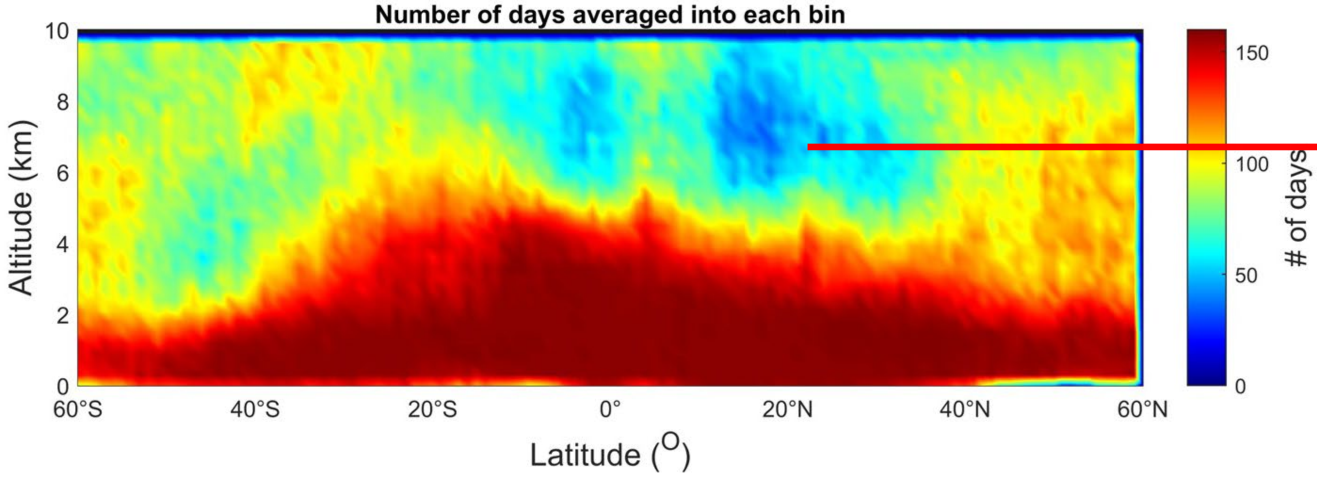


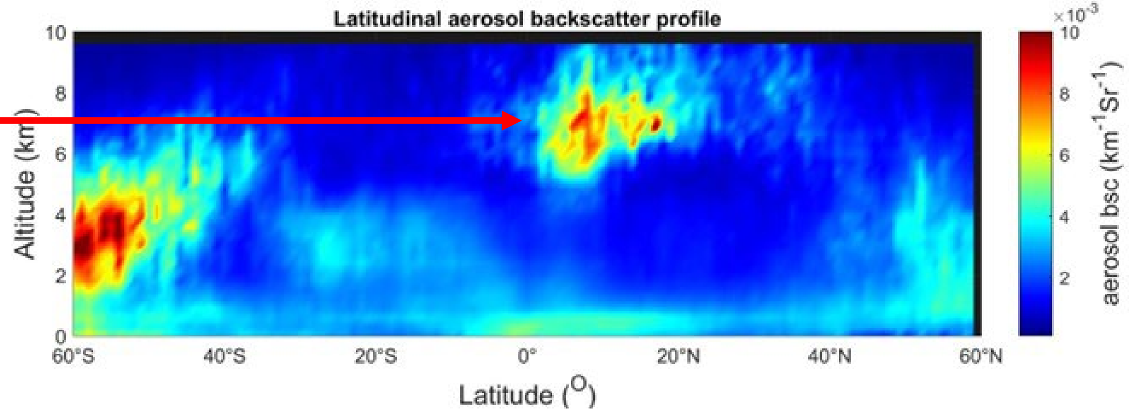
QA-TC-applied

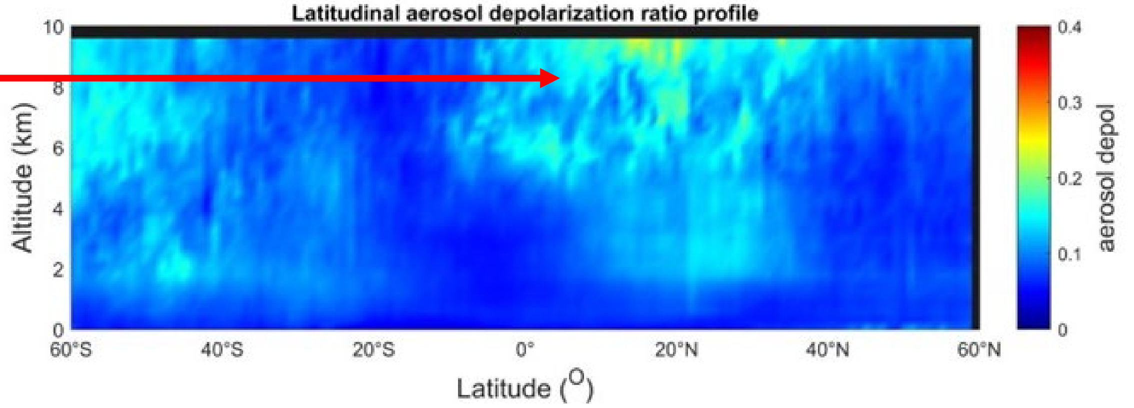


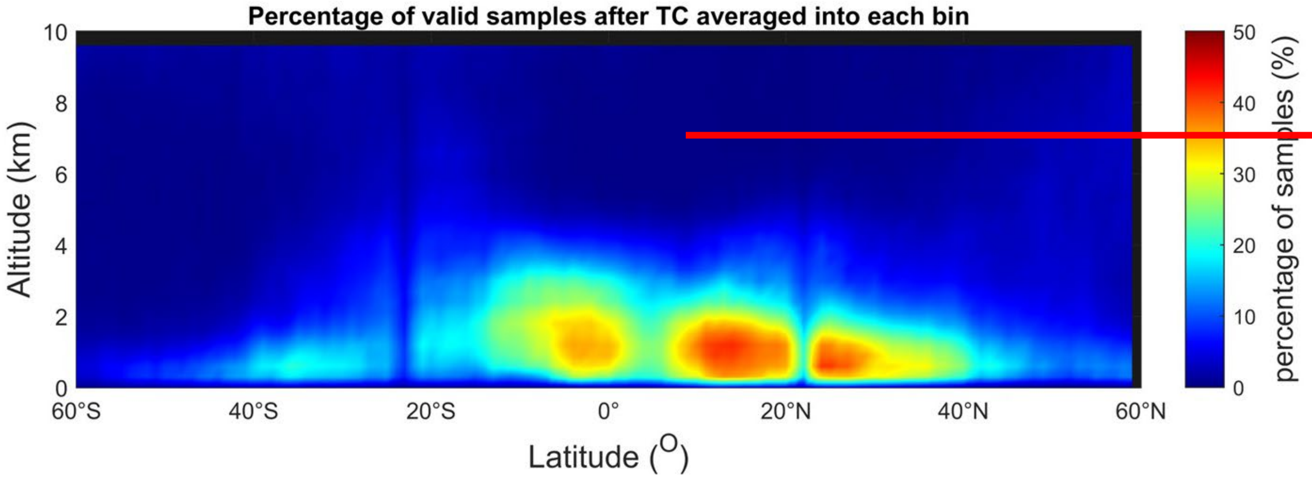


Analysis sampling issue?









High depol/bsc occurred only on certain days or in a very small fraction of the samples

Percentage is defined as the number of valid ATLID pixels - after TC and QA screening - within the prescribed grid, divided by the total number of lidar pixels sampled within the same grid.

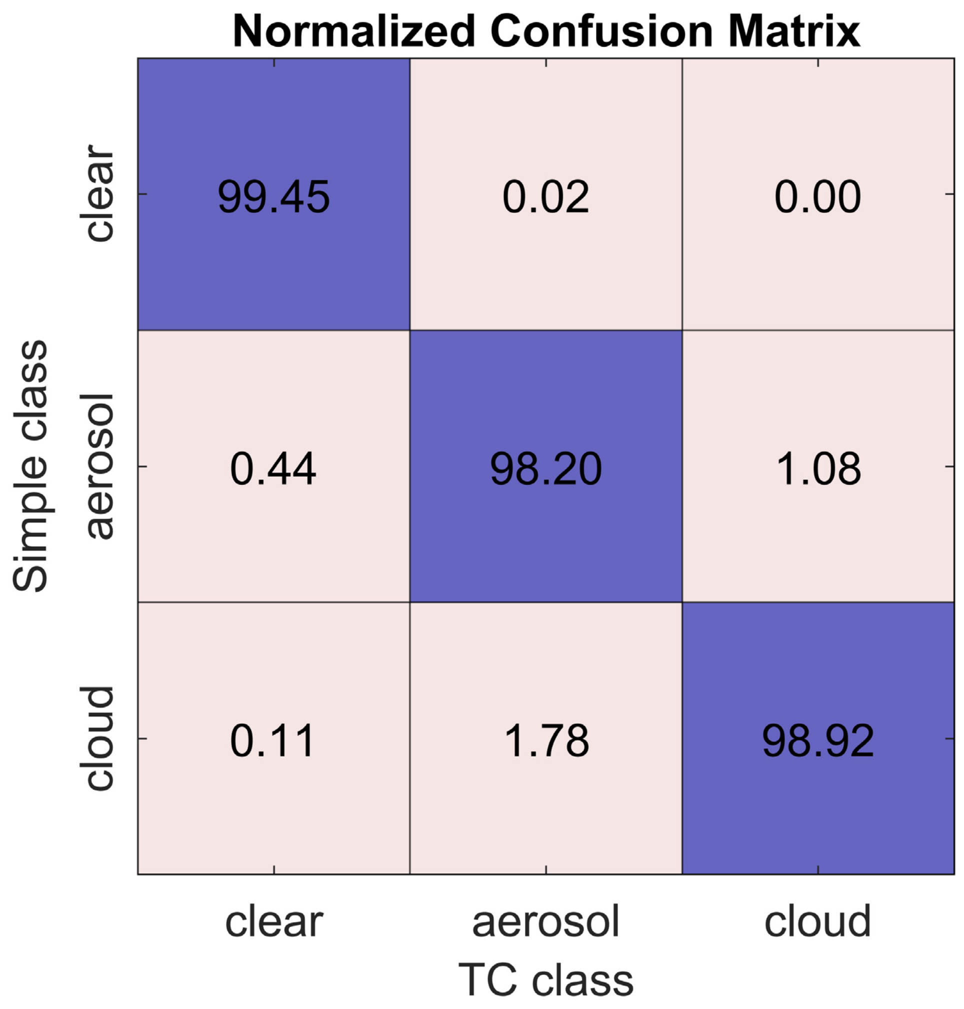
Notes:

There are two variables: ‘quality_status’ and ‘extended_data_quality_status’, I previously only applied ‘quality_status’ to the data, but I noticed that some pixels in the TC_low still showed missing values. These pixels were removed after additionally applying the ‘extended_data_quality_status’.

In some cases, even after applying QA to both depol and TC, there are no depol 355 low-res values but there is TC index. While TC indicates ‘0’ for clear sky pixels, the depol values remain as high as ~0.7-0.8, undetected cirrus or low SNR?
(ECA_EXAC_ATL_TC__2A_20240811T142701Z_20241210T143640Z_01161F.h5 &
ECA_EXAC_ATL_EBD_2A_20240811T142701Z_20241210T143640Z_01161F.h5)

TC VS simple classification

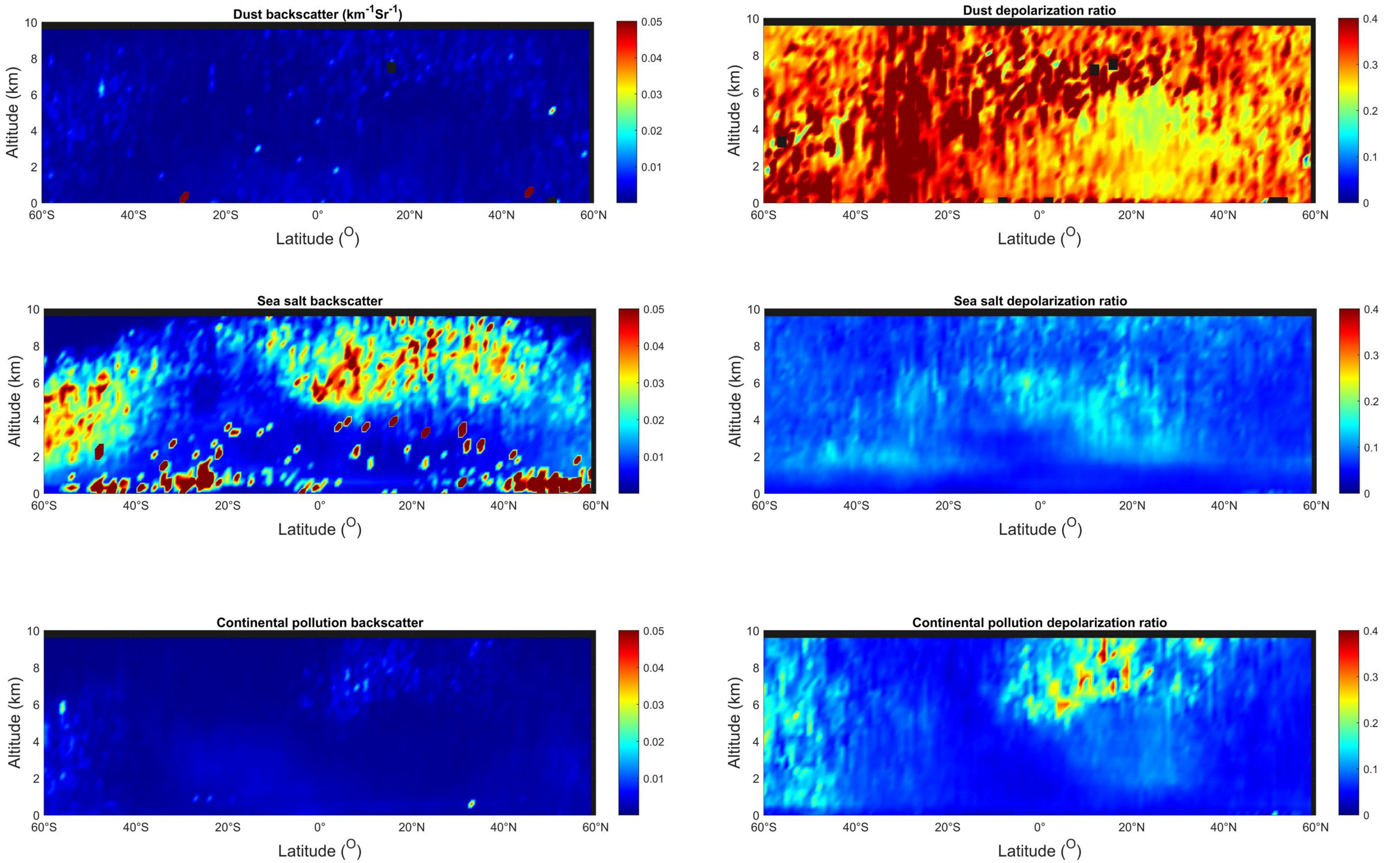
Class numbers	A-TC classes
−3	Missing data
−2	Sub-surface
−1	Attenuated
0	Clear
1	Liquid
2	Supercooled liquid
3	Ice
10	Dust
11	Sea salt
12	Continental pollution
13	Smoke
14	Dusty smoke
15	Dusty mix
20	STS (PSC type I)
21	NAT (PSC type II)
22	Stratospheric ice
25	Stratospheric ash
26	Stratospheric sulfate
27	Stratospheric smoke

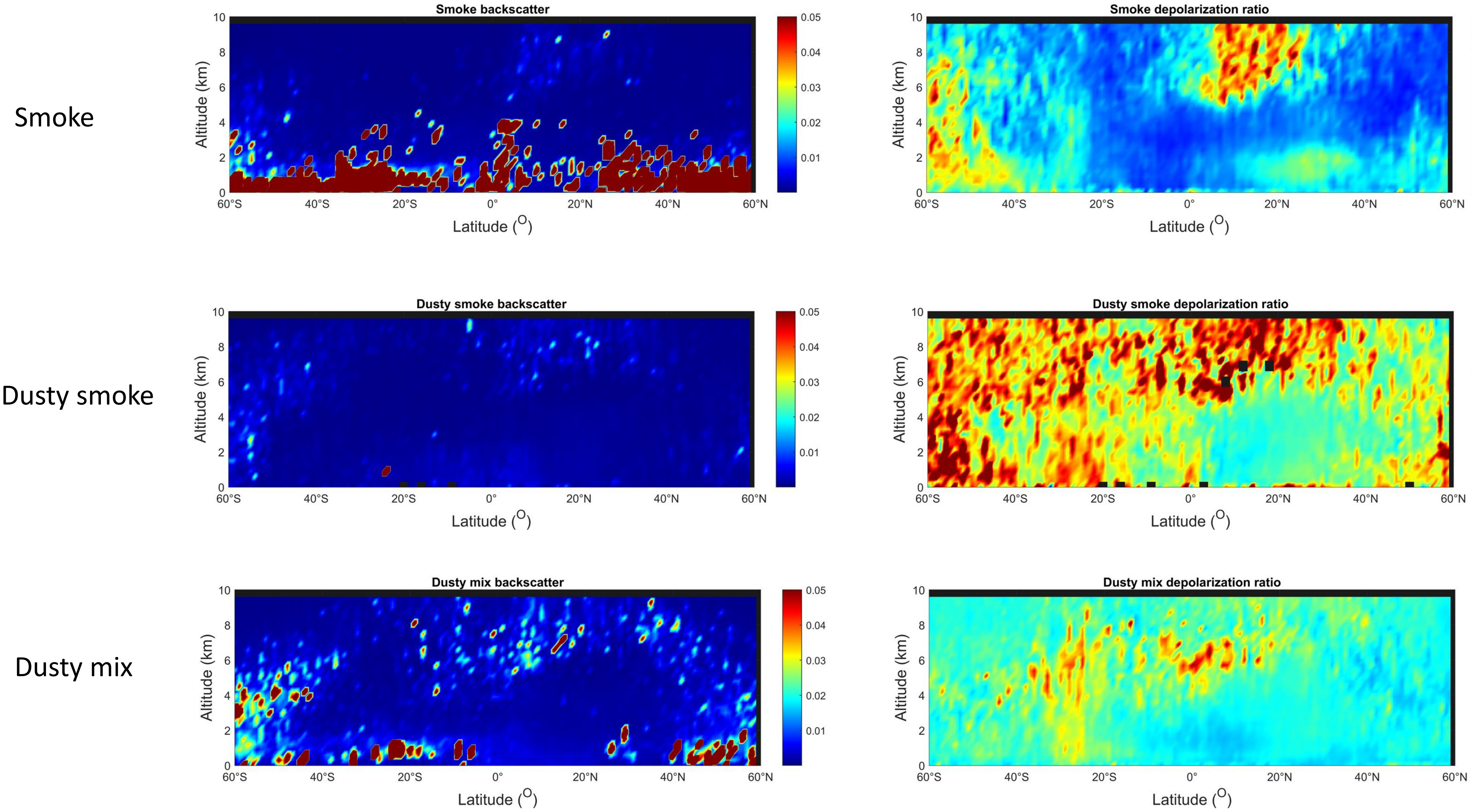


Dust

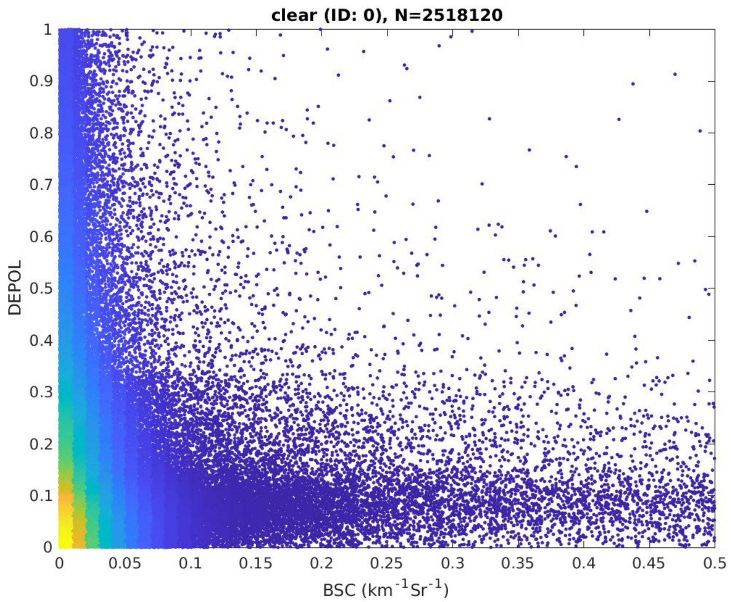
Sea salt

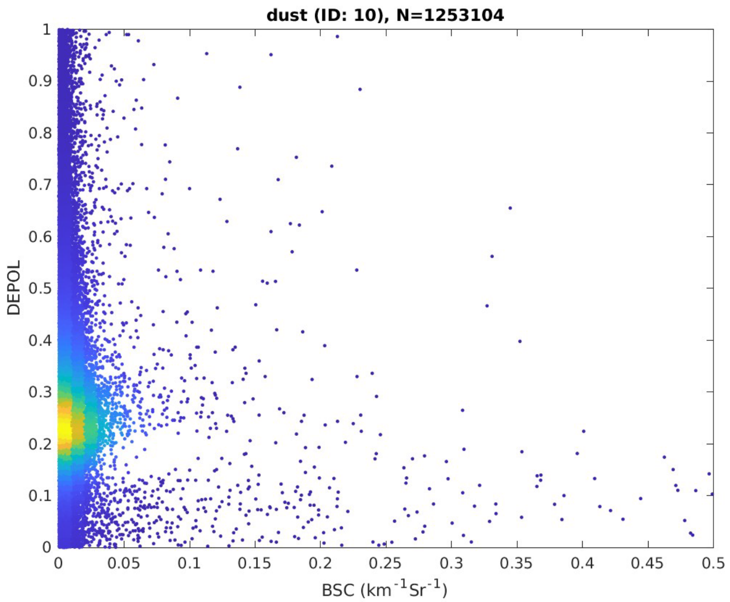
Continental pollution

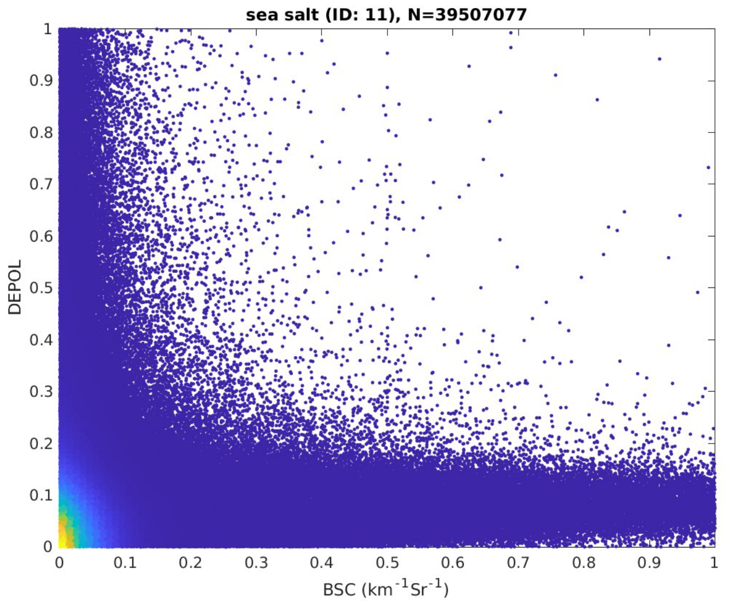



Smoke
Dusty smoke
Dusty mix
Smoke backscatter
Smoke depolarization ratio
Dusty smoke backscatter
Dusty smoke depolarization ratio
Dusty mix backscatter
Dusty mix depolarization ratio
Altitude (km)
Latitude (O)
60°S
40°S
20°S
0°
20°N
40°N
60°N
0
2
4
6
8
10
0.01
0.02
0.03
0.04
0.05
0.1
0.2
0.3
0.4

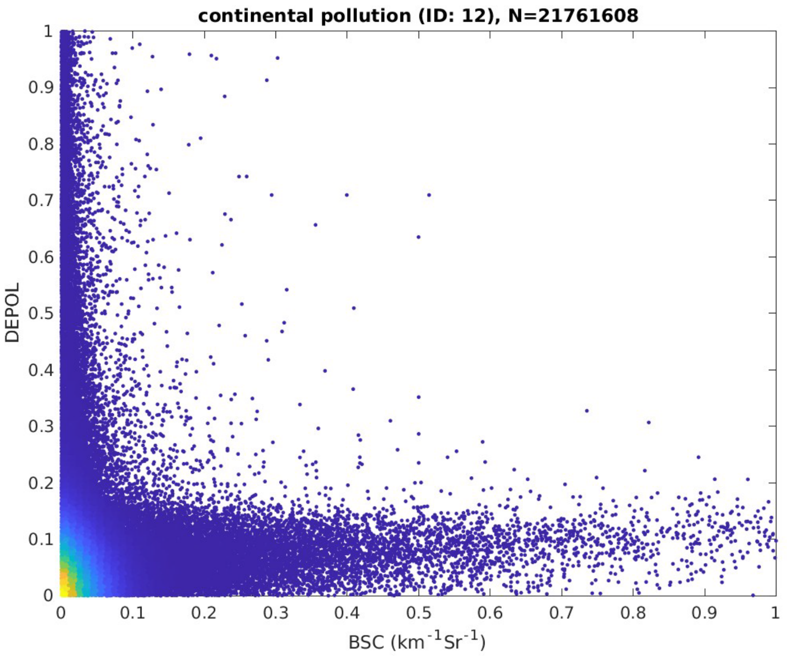
ATLID BSC VS. DEPOL for individual lidar pixels before any averaging

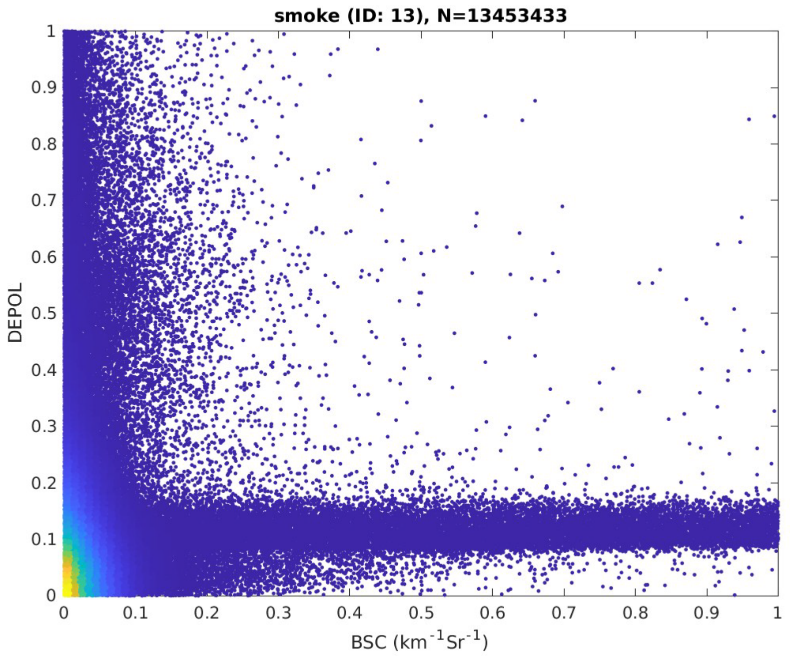


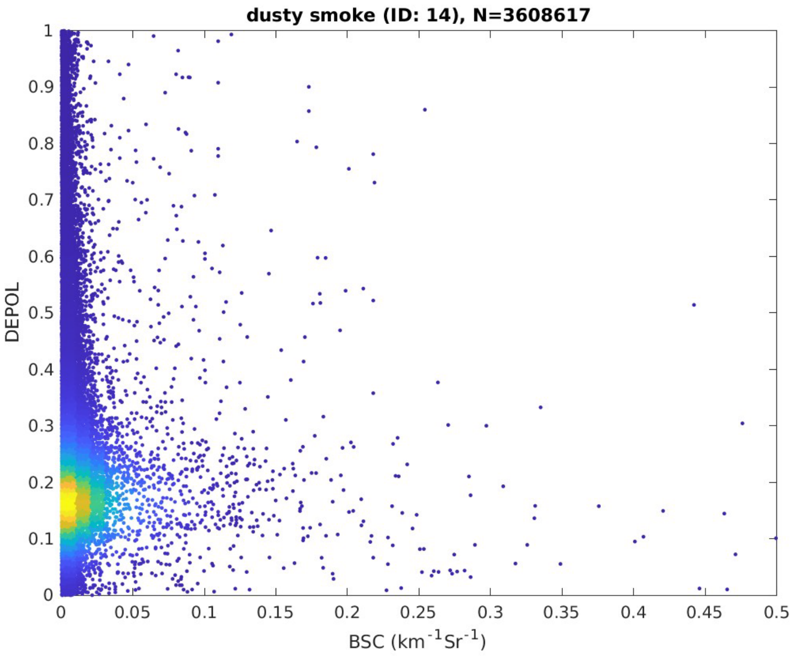


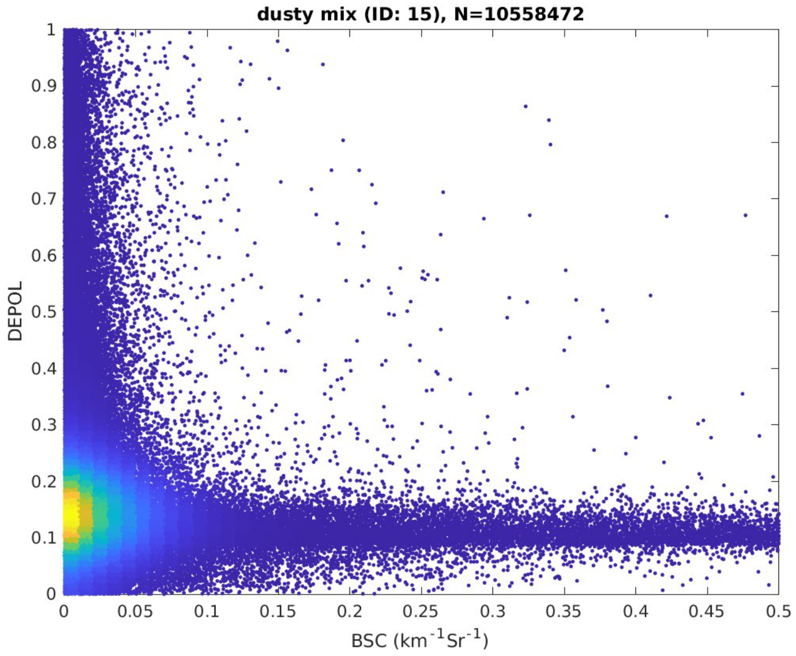


- QA and TC are applied to remove bad-quality data and to classify the remaining samples by aerosol type.
- Figure titles indicate the pixel type and number of samples.

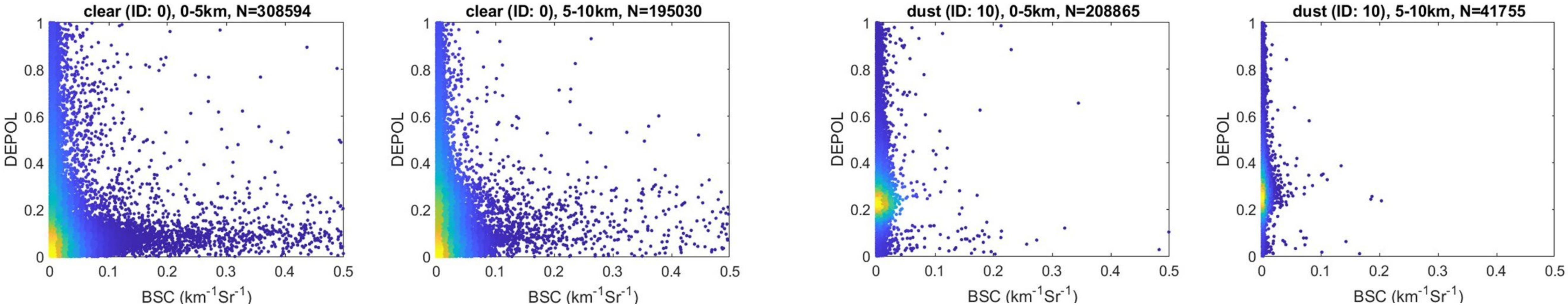

continental pollution (ID: 12), N=21761608
DEPOL
BSC (km^{-1}Sr^{-1})

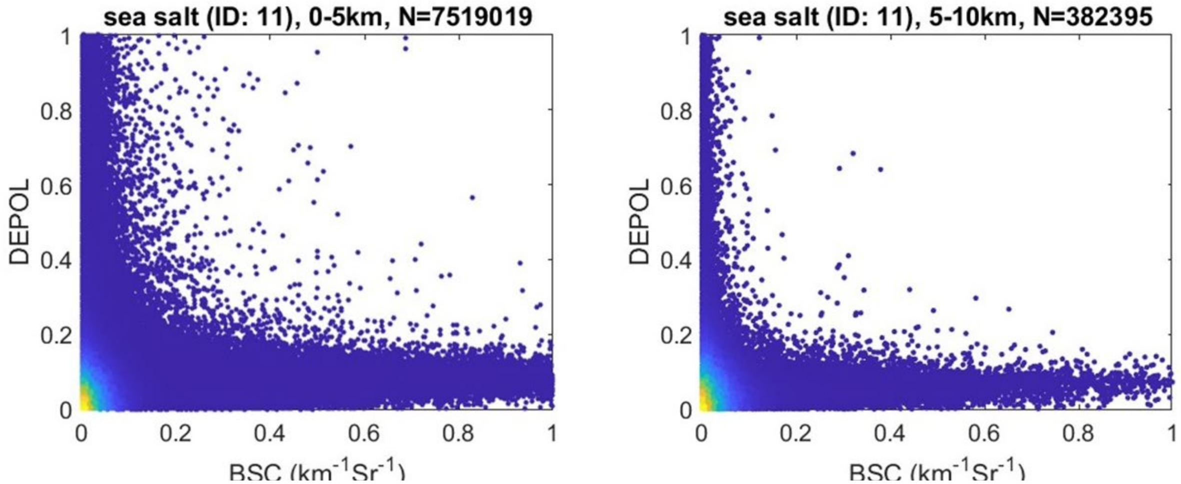

smoke (ID: 13), N=13453433
DEPOL
BSC (km^{-1}Sr^{-1})


dusty smoke (ID: 14), N=3608617
DEPOL
BSC (km^{-1}Sr^{-1})

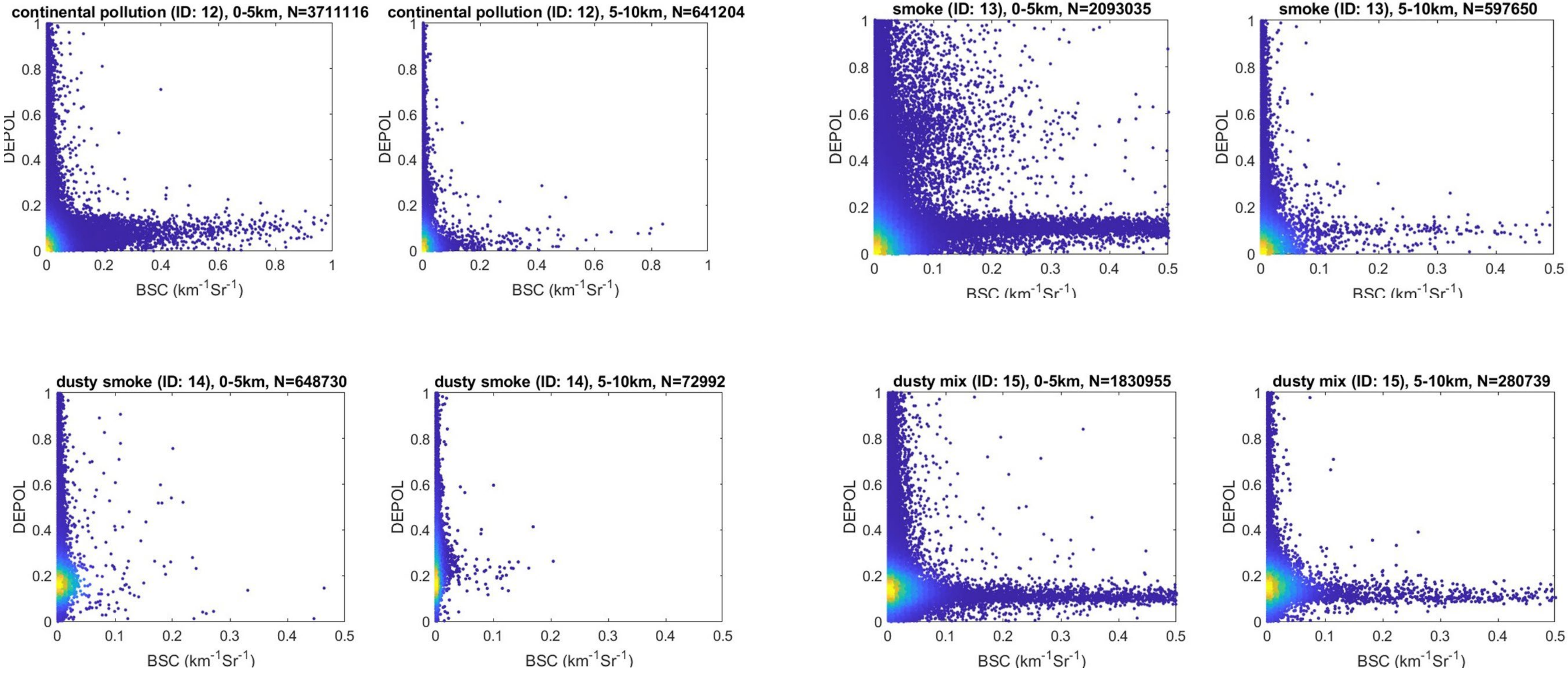

dusty mix (ID: 15), N=10558472
DEPOL
BSC (km^{-1}Sr^{-1})

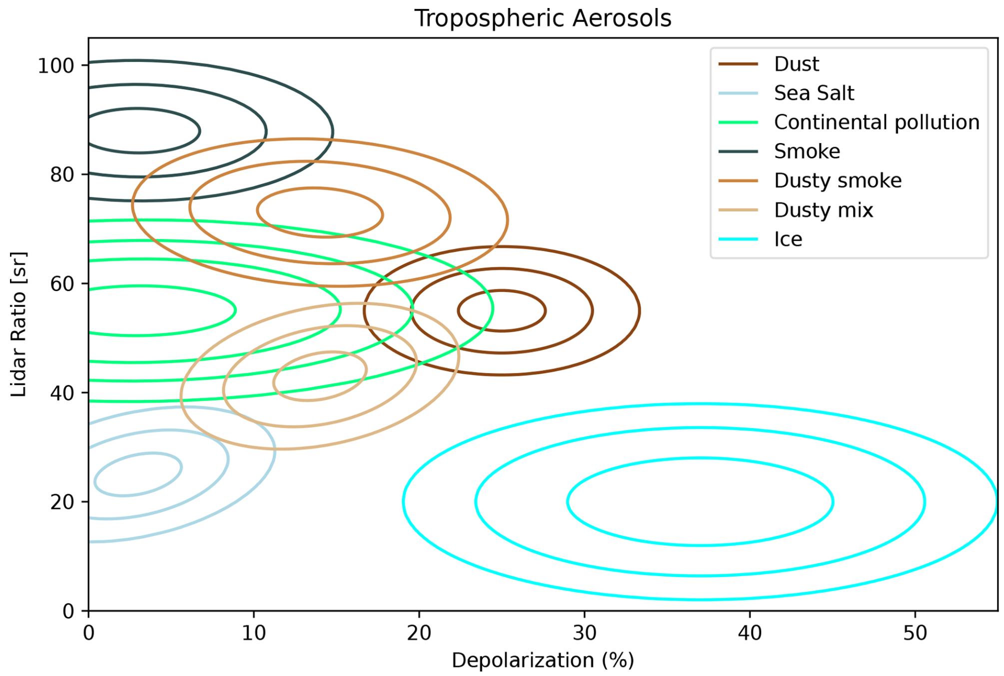
ATLID BSC VS. DEPOL for individual lidar pixels before any averaging





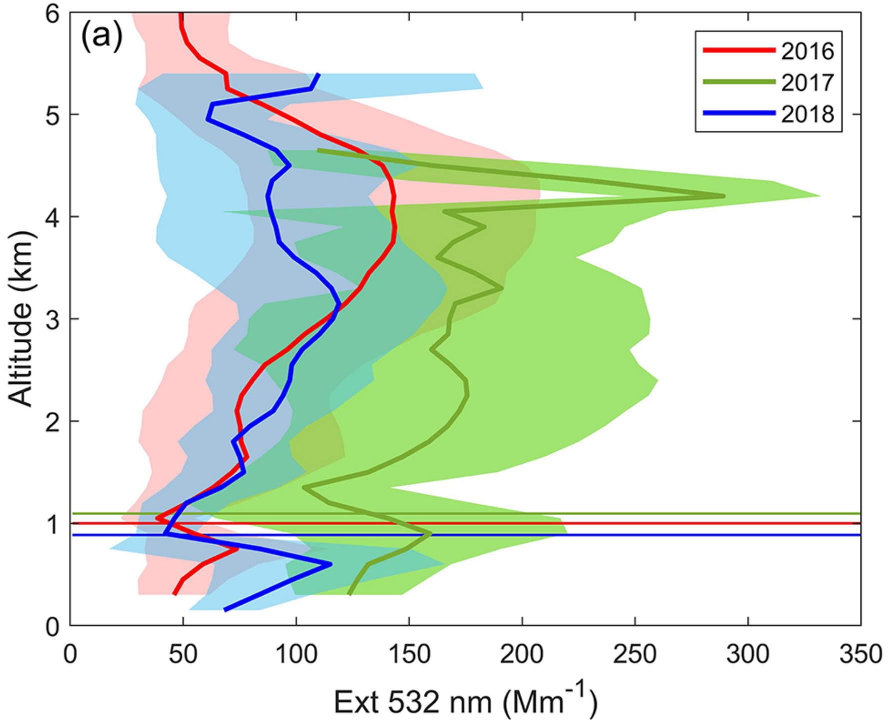
- QA and TC are applied to remove bad-quality data and to classify the remaining samples by aerosol type.
- Figure titles indicate the pixel type and corresponding altitude range.
- Due to the large data volume, only 20% of the total samples are randomly selected for plotting in each panel.

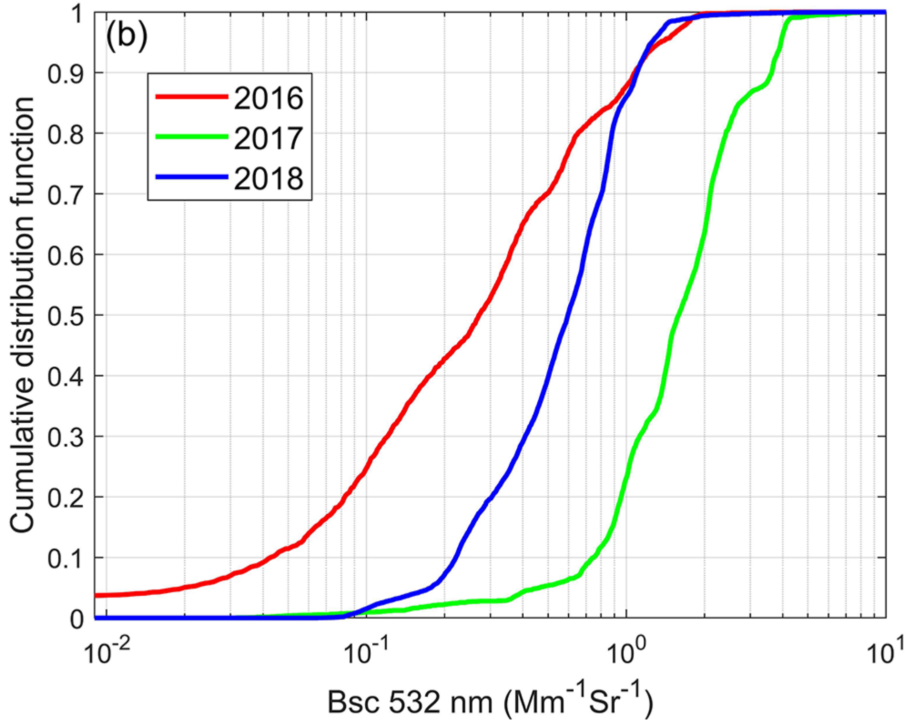

continental pollution (ID: 12), 0-5km, N=3711116
continental pollution (ID: 12), 5-10km, N=641204
smoke (ID: 13), 0-5km, N=2093035
smoke (ID: 13), 5-10km, N=597650
dusty smoke (ID: 14), 0-5km, N=648730
dusty smoke (ID: 14), 5-10km, N=72992
dusty mix (ID: 15), 0-5km, N=1830955
dusty mix (ID: 15), 5-10km, N=280739
DEPOL
BSC (km-1Sr-1)



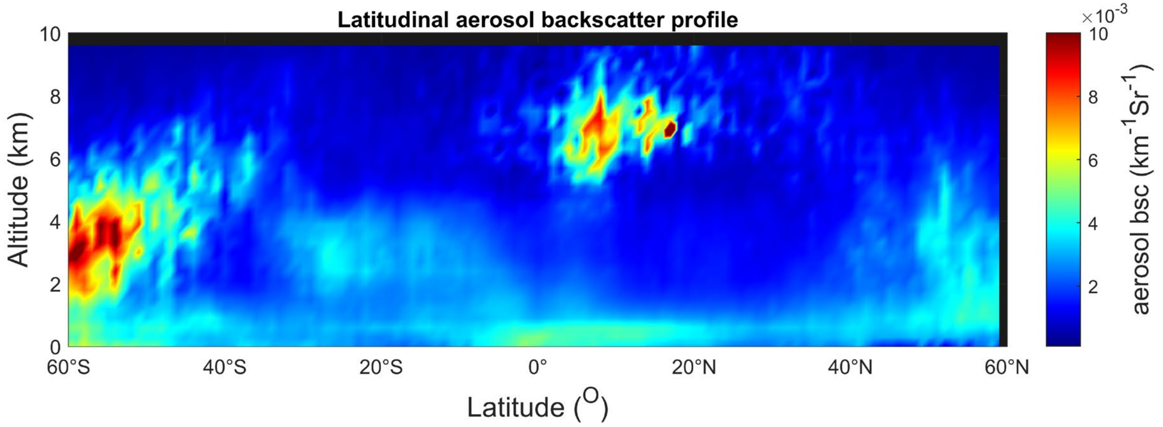
From TC paper

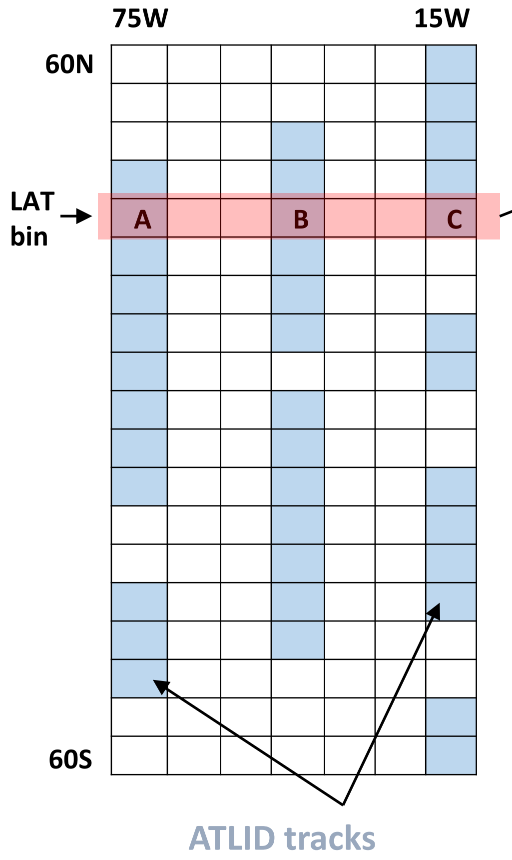
ORACLES

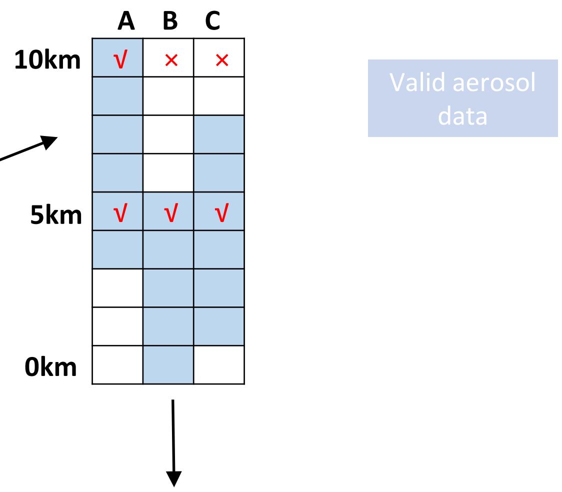




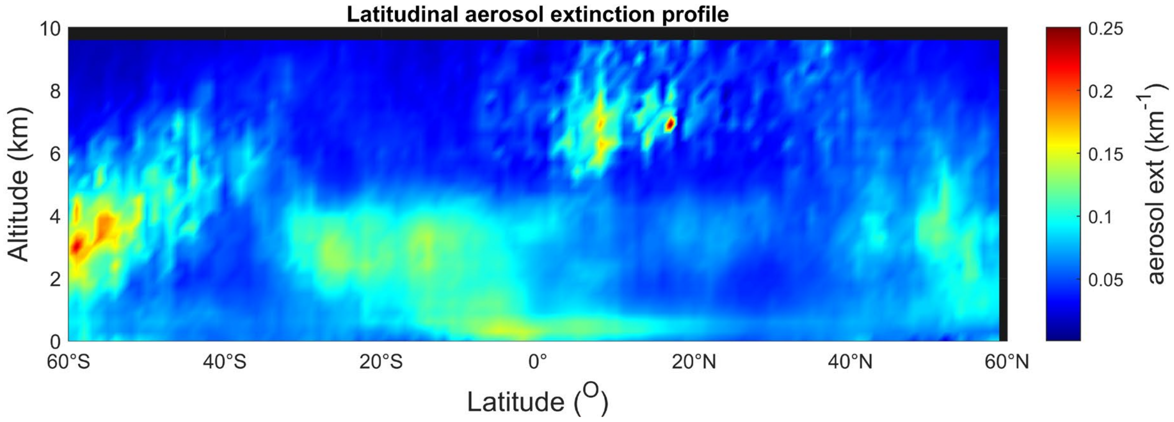
Filtering out grids with fewer than 20 samples per day (may not be sufficient)

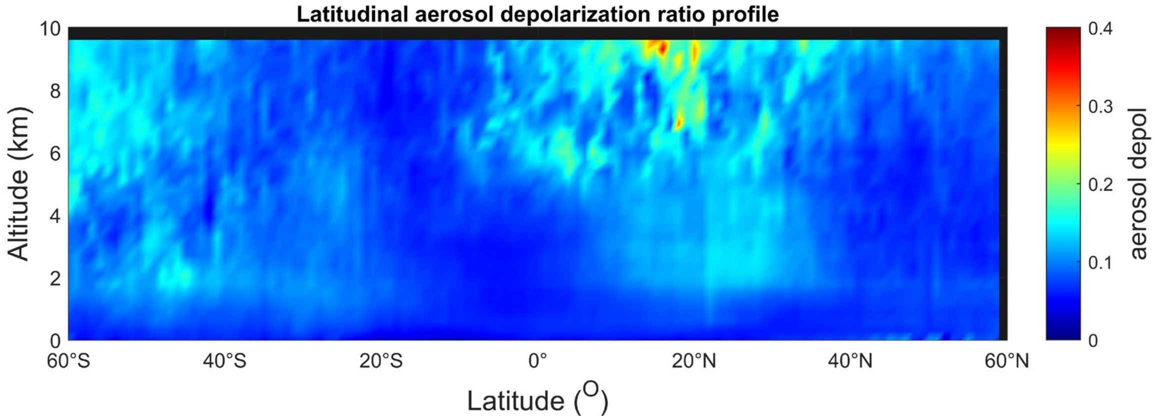


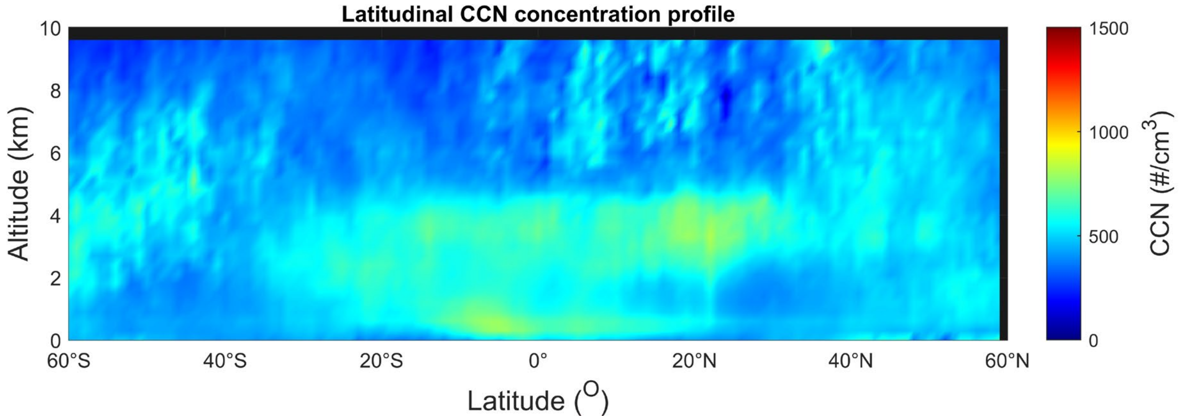




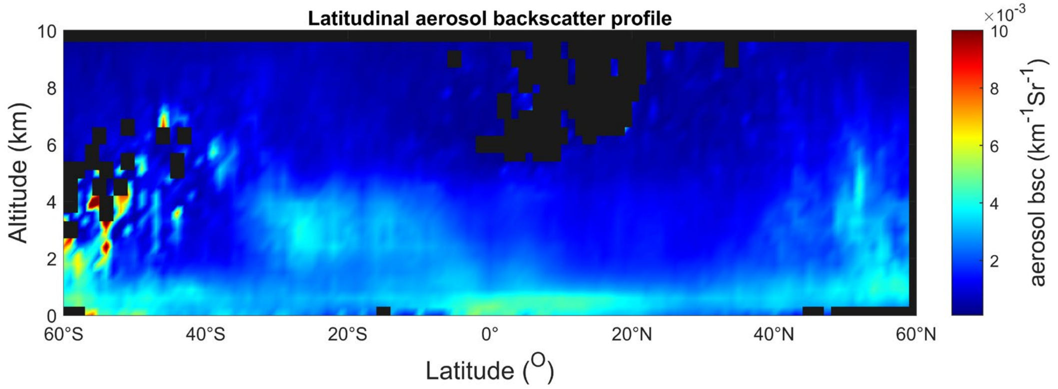
E.g.: If the required number of samples is greater than 2, then 10 km samples within the designated latitude bin will be excluded, while the 5 km samples will be retained.

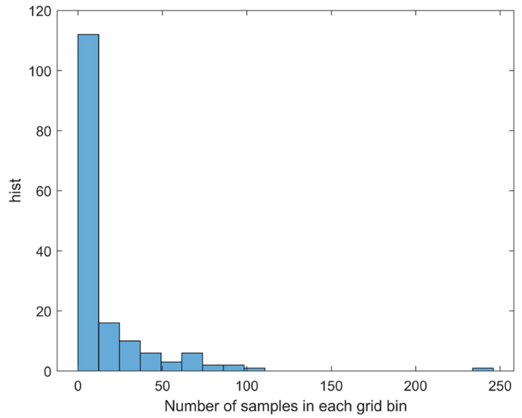


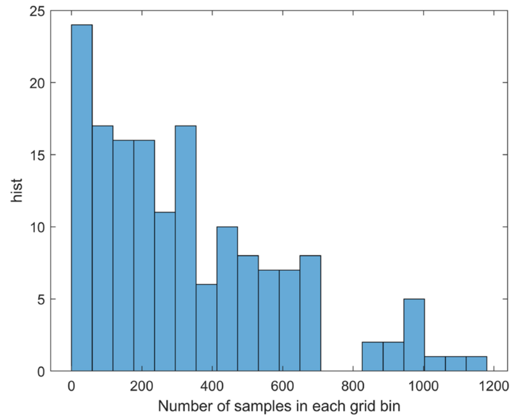


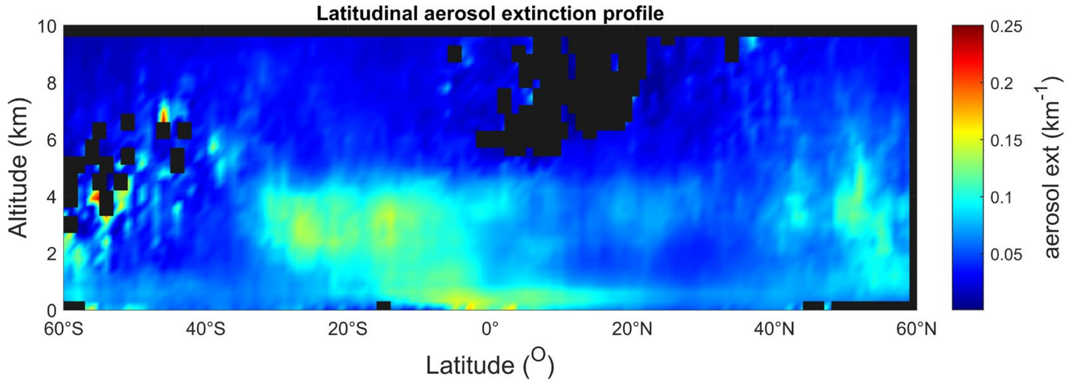


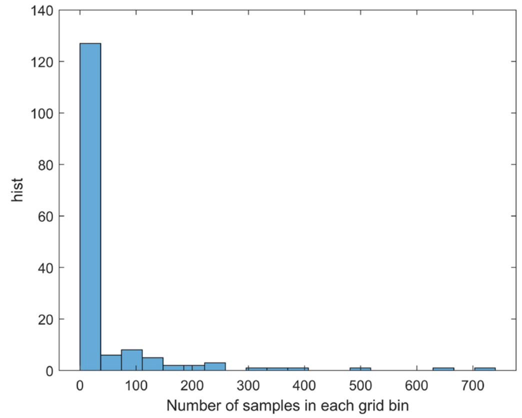
Filtering out grids with fewer than 100 samples per day

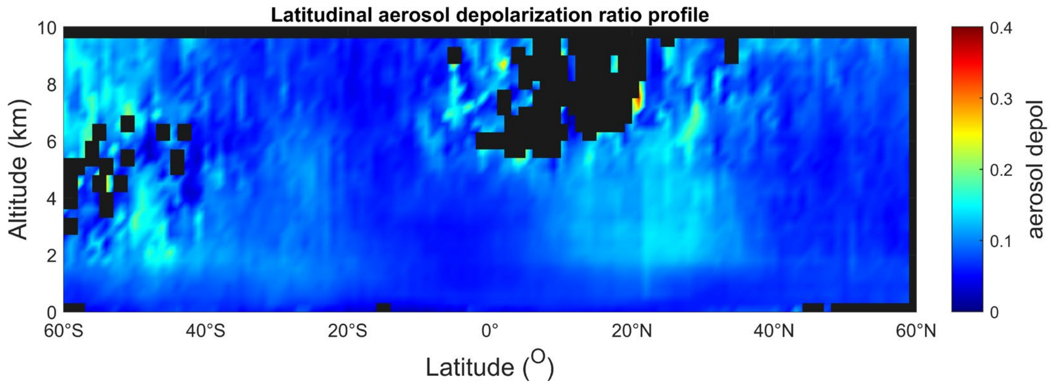


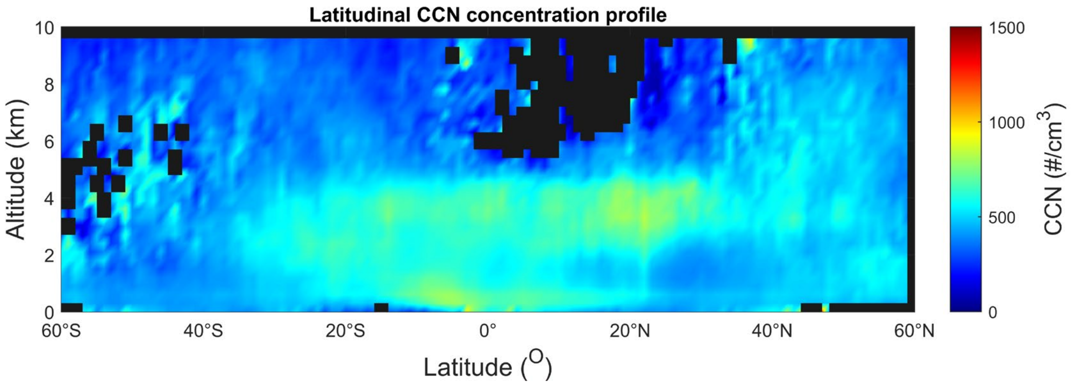












CCN retrievals from collocated ATLID and WALES measurements

$$\sigma(\lambda) = \frac{24\pi^3(n_s^2 - 1)^2}{\lambda^4 N_s^2(n_s^2 + 2)^2}\left(\frac{6 + 3\rho_n}{6 - 7\rho_n}\right)$$

$$\beta(\lambda, z) = N(z)\sigma(\lambda)$$

$$\beta = \beta_s \frac{N}{N_s} = \beta_s \frac{P}{P_s}\frac{T_s}{T}$$

$$\beta(\theta, \lambda, z) = \frac{\beta(\lambda, z)}{4\pi} P_{\mathrm{ray}}(\theta, \lambda)$$

$$P_{\mathrm{ray}}(\theta) = \frac{3}{4(1 + 2\gamma)}[(1 + 3\gamma) + (1 - \gamma)\cos^2\theta]$$

$$\gamma = \frac{\rho_n}{2 - \rho_n}$$

Rayleigh-scattering calculations for the terrestrial atmosphere

Anthony Bucholtz

Rayleigh-scattering cross sections and volume-scattering coefficients are computed for standard air; they incorporate the variation of the depolarization factor with wavelength. Rayleigh optical depths are then calculated for the 1962 U.S. Standard Atmosphere and for five supplementary models. Analytic formulas are derived for each of the parameters listed. The new optical depths can be 1.3% lower to 3% higher at midvisible wavelengths and up to 10% higher in the UV region compared with previous calculations, in which a constant or incorrect depolarization factor was used. The dispersion of the depolarization factor is also shown to affect the Rayleigh phase function slightly, by approximately 1% in the forward, backscattered, and 90° scattering-angle directions.

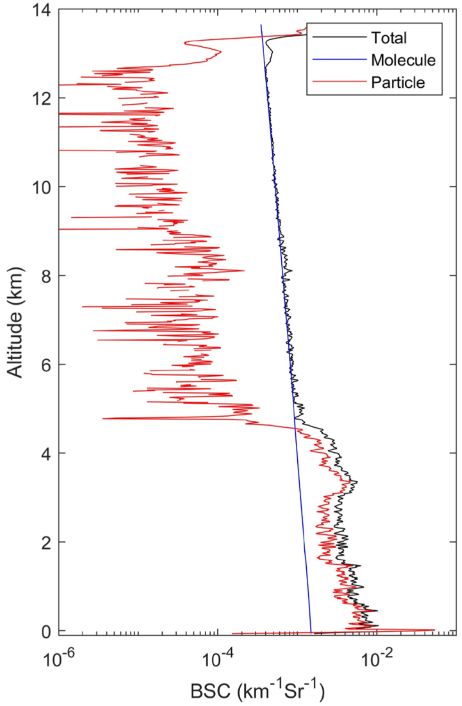
Key words: Rayleigh scattering, Rayleigh optical depth, Rayleigh cross section.

n_s: refractive index for standard air (1013.25 hPa, 15°C)
N_s: molecular number density (2.54743×10^{19} cm^{-3})
ρ_n : depolarization factor
P_{ray} : Rayleigh phase function considering molecular anisotropy

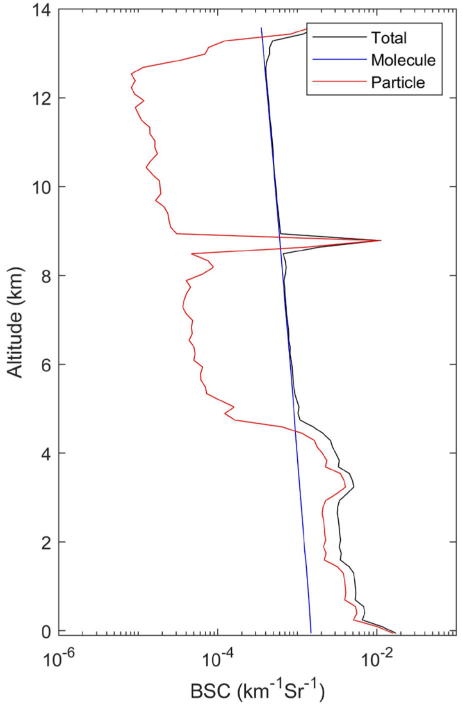
Bucholtz, A., 1995. Rayleigh-scattering calculations for the terrestrial atmosphere. Applied optics, 34(15), pp.2765-2773.

Derive particle backscattering from WALES 20240811 flight

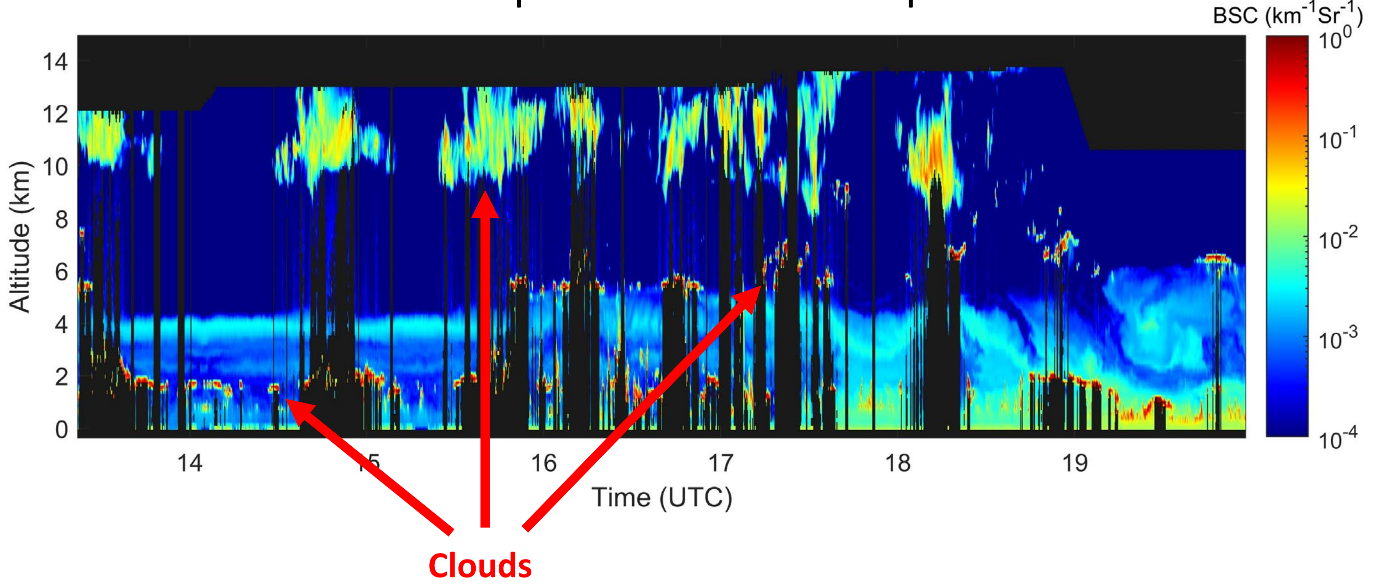
1S BSC

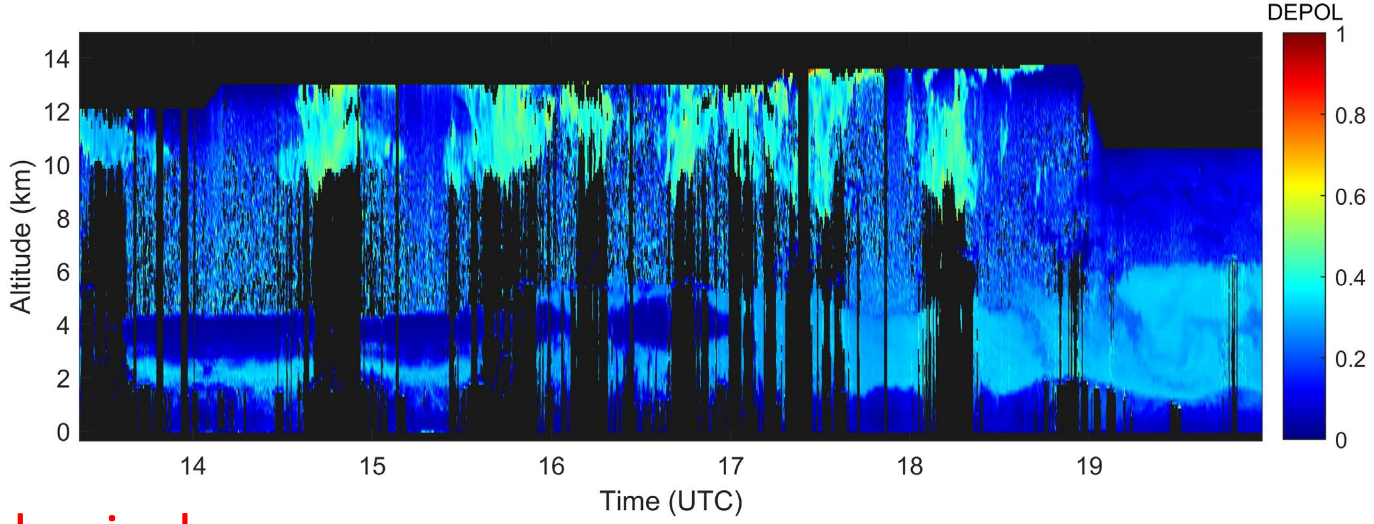


10S & 150m averaged BSC



Derived particle backscatter profile





Name	Value
'units'	[]
'long_name'	'backscatter ratio'
'coordinates'	'altitude longitude latitude'
'description'	'Total backscatter coefficient relative to the one caused by molecular scattering from a given volume.'

Need to apply feature mask to exclude cloudy pixels.

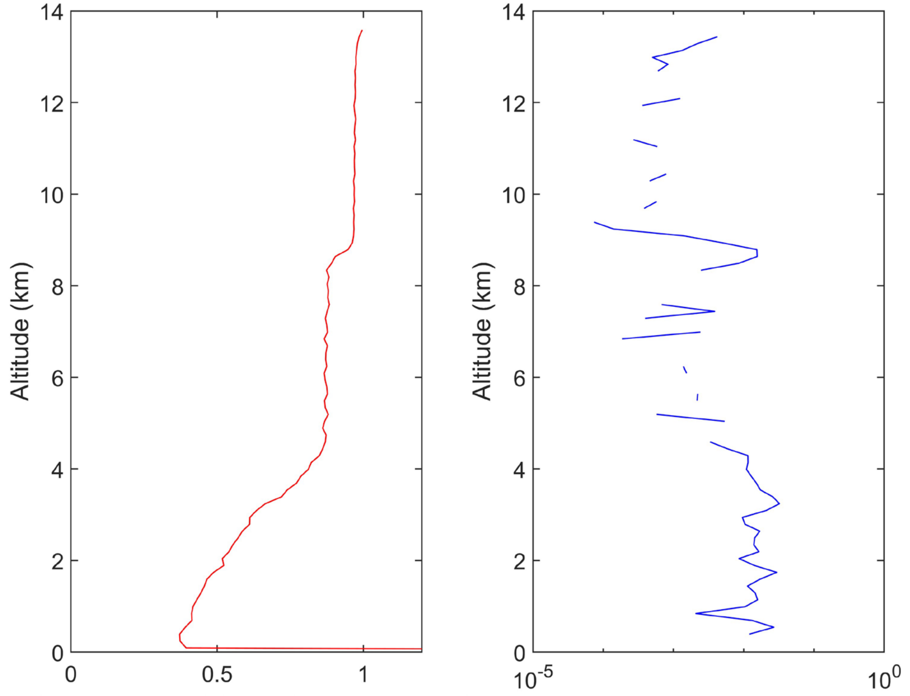
Derive extinction from WALES 20240811 flight

$$\alpha(z) = -\frac{1}{2}\frac{\frac{dT}{dz}}{T}$$

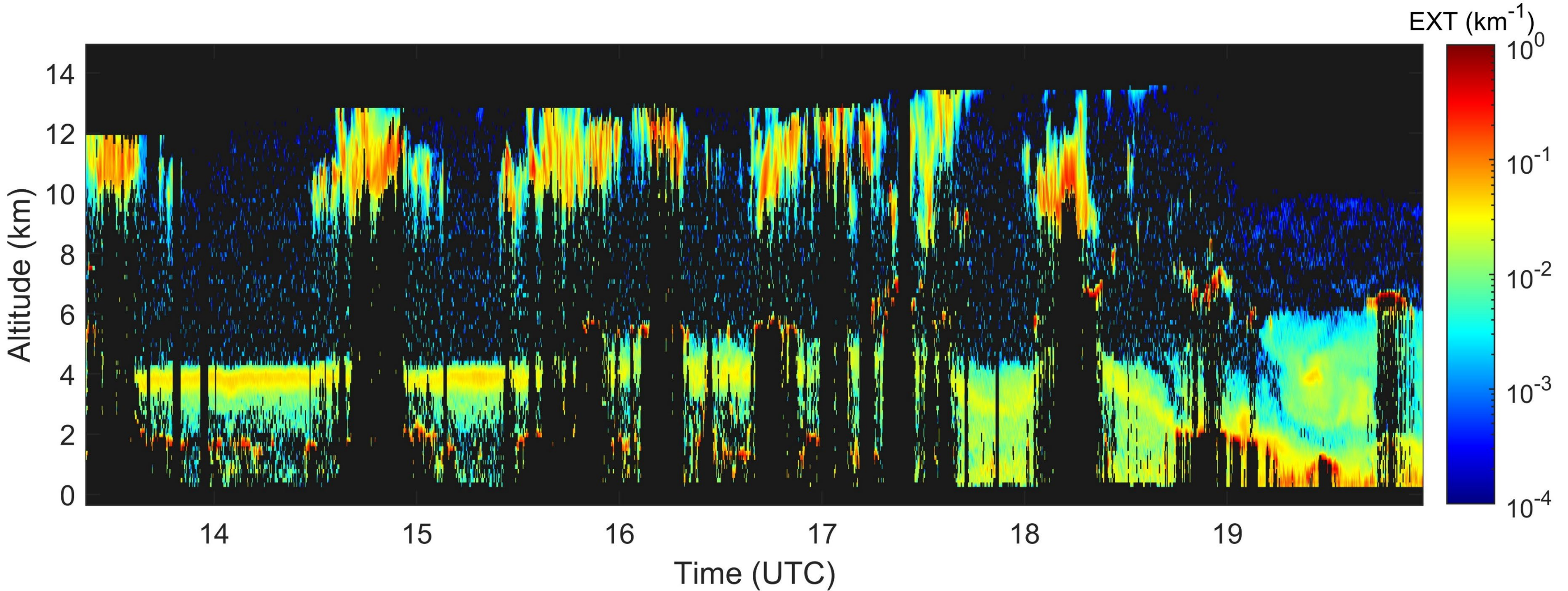
Apply Savitzky-Golay Derivative

Name	Value
'units'	[]
'long_name'	'two way aerosol optical transmission'
'coordinates'	'altitude longitude latitude'
'description'	'Two way transmission of the optical layer between the lidar and a given point in the atmosphere which is due to aerosol. '

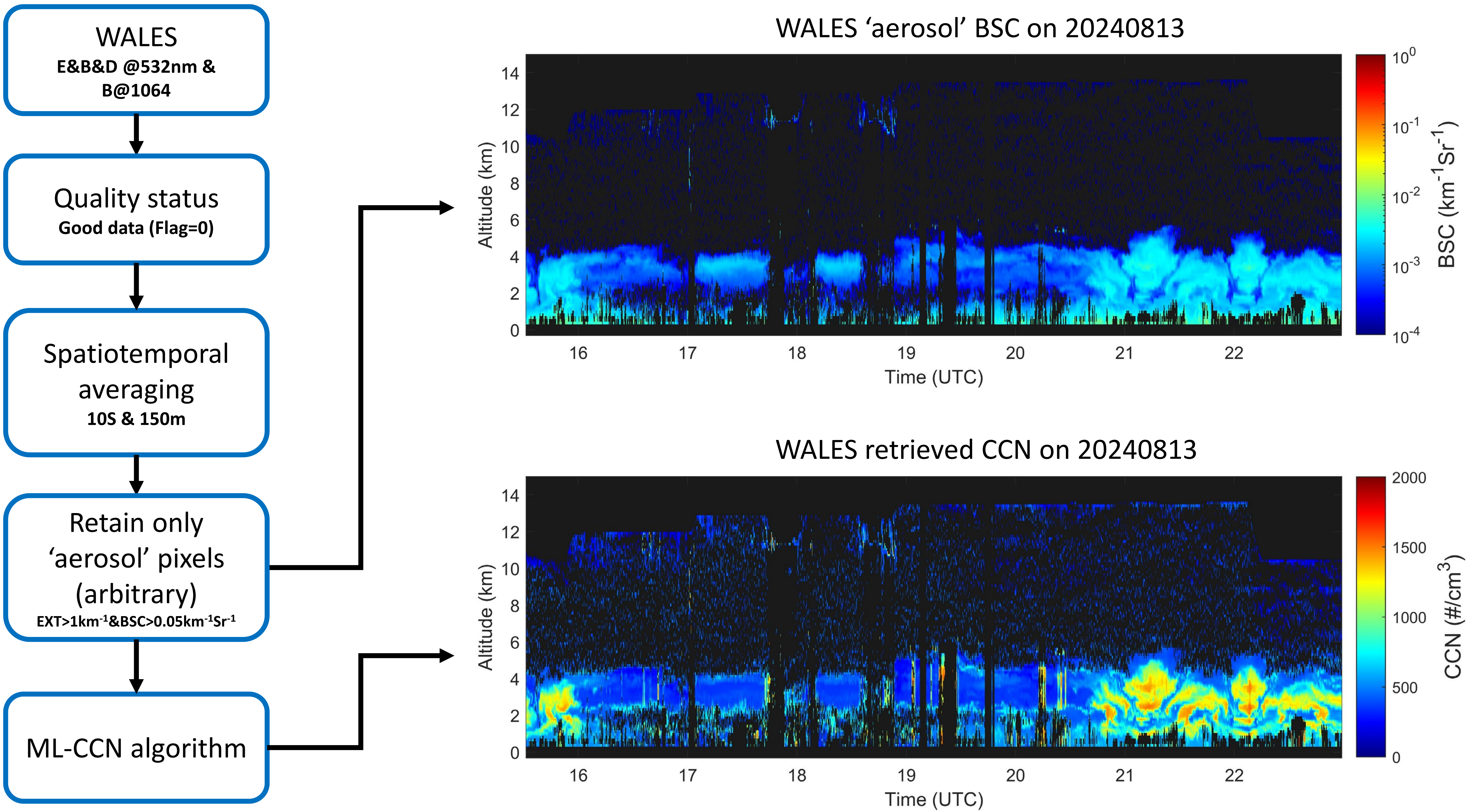
10S & 150m averaged extinction coefficient



Really aerosol ext?



Flowchart of the WALES CCN retrieval



Exclude pixels with BSR > 10 below 8 km and BSR > 4 above 8 km.