CLouds · CLimatE · Aerosols · Radiation

NOVEL RETRIEVALS OF AEROSOL MICROPHYSICAL AND RADIATIVE PROPERTIES FROM LIDAR OBSERVATIONS IN FUTURE SATELLITE MISSIONS

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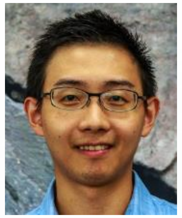
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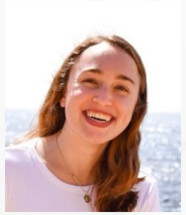
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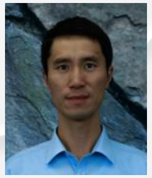
Feng Xu
Radiative Transfer

Motivation: Vertically resolved CCN

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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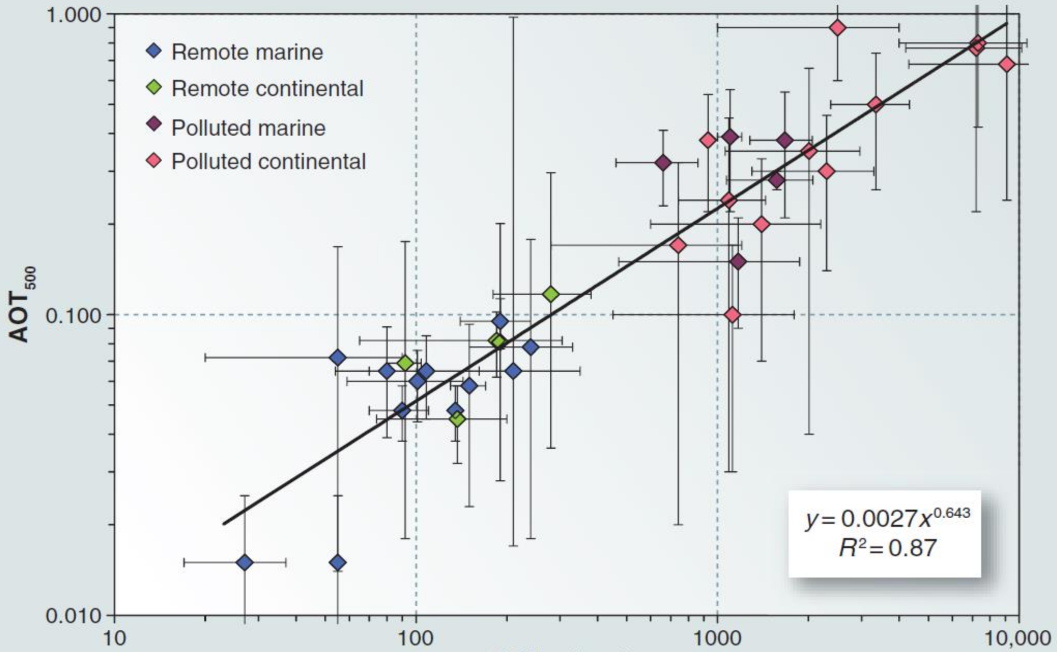
An urgent need for global observations of CCN(*S*) by remote sensing follows from these considerations. Because the microphysical and radiative effects of aerosols act simultaneously on a given cloud population and change the thermodynamic environment of cloud formation and the microphysical processes of the cloud development [*Rosenfeld et al.*, 2008a], the CCN(*S*) field should be observed simultaneously with aerosol light scattering and absorption properties. Since the effects of light scattering (cooling of the ground surface) and absorption (cooling at the ground combined with heating aloft) have different impacts on atmospheric stability, they must be observed independently. Here, quantitative measures of absorption are especially important.

- **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**

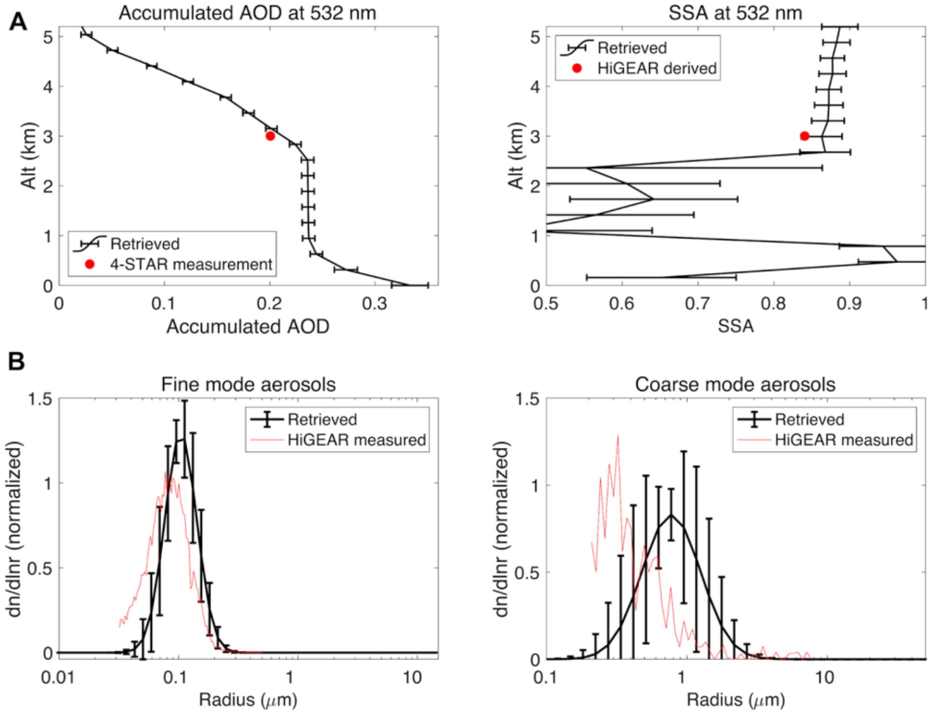


Rosenfeld, et al. *Science* 2008

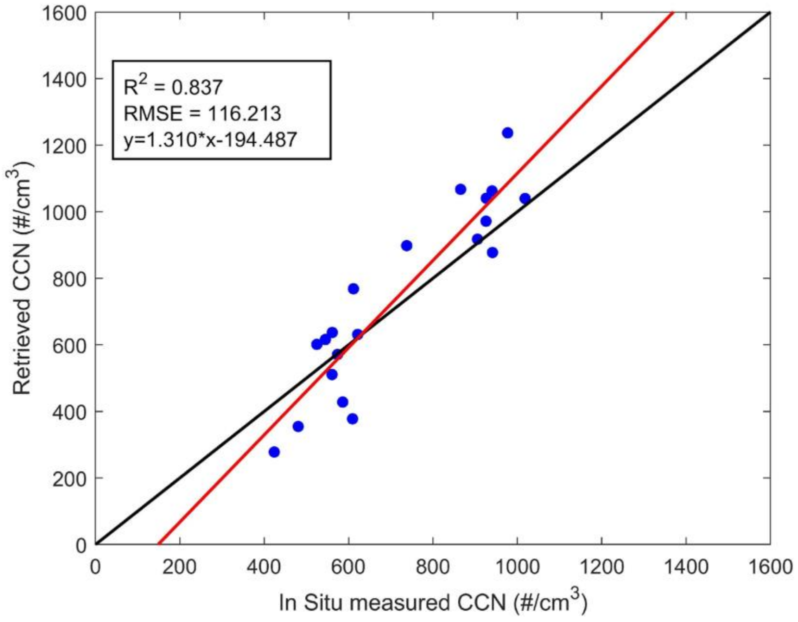
Stier, 2016: "…71 % of the area of the globe shows correlation coefficients between CCN0.2 % at cloud base and aerosol optical depth (AOD) below 0.5, i.e. AOD variability explains only 25 % of the CCN variance" – model-based, self-consistent.

Physics-based retrieval of CCN using lidar and polarimeter observations (Gao et al, AGU 2021)

- For NASA AOS retrieval simulations, we developed a physics-based optimal estimation (OE) approach for lidar+polarimeter retrieval of speciated aerosol profiles.
- Used aerosol reanalysis product to estimate the bulk hygroscopicity parameter for aerosol mixture.
- Applied κ-Köhler theory to calculate CCN concentration.



(Xu, F., Gao, L., Redemann, J., et al., 2021)

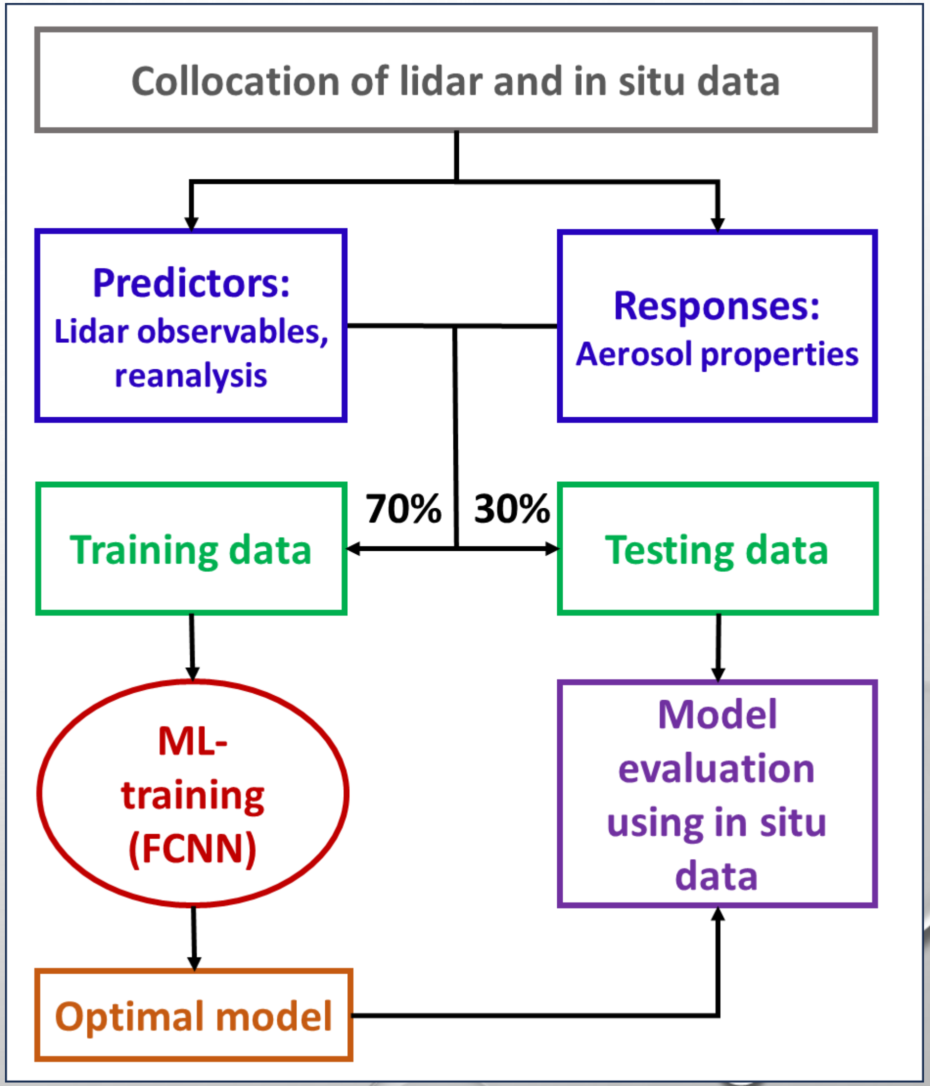


Limitations – AOS retrieval simulation "lessons learned"

- Great dependence on *a priori* information (aerosol size distribution and chemical composition) to retrieve CCN
- Computationally very expensive.

The Machine Learning alternative

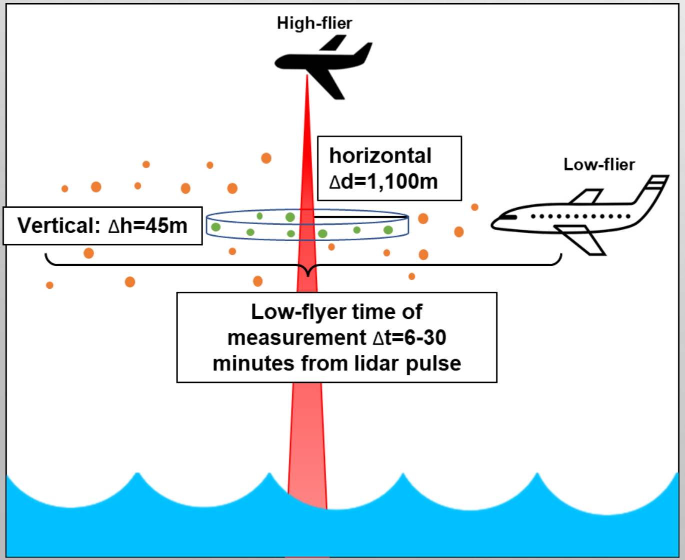
- Collocate HSRL-2 and in-situ measured CCN from multiple campaigns.
  - ✓ ACTIVATE, CAMP^{2}EX, DISCOVER-AQ, ORACLES
- Train neural networks for different sets of lidar observables (e.g., ATLID, NASA AOS).
  - ✓ HSRL-2: 3β + 2α + 3δ
  - ✓ HSRL-1: 2β + 1α + 2δ
  - ✓ EarthCARE/ATLID: 1β + 1α + 1δ
  - ✓ 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)

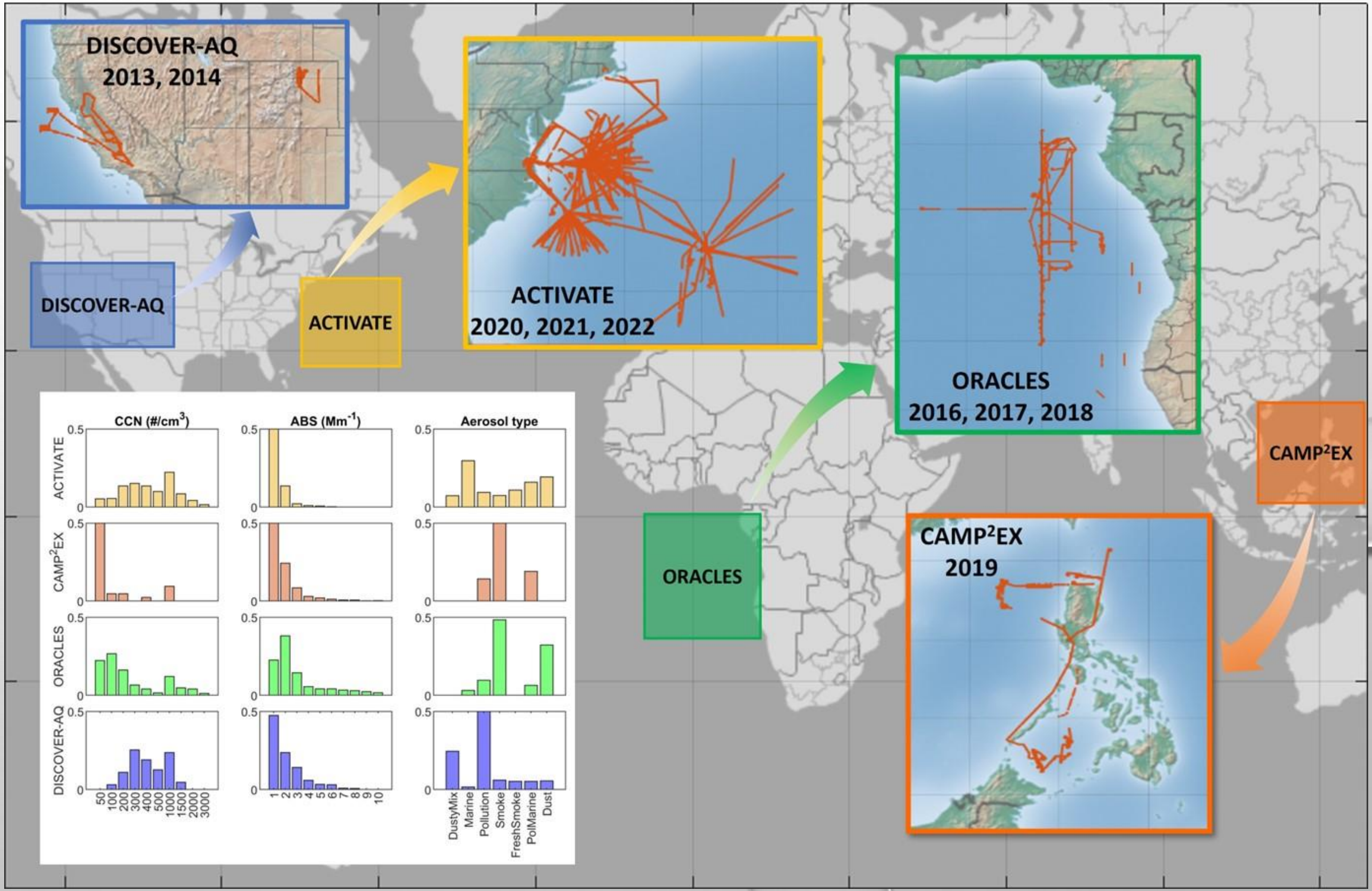


Training the ML model

- Aircraft observations (lidar and in situ) from multiple campaigns

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





MACHINE LEARNING - HOW TO DEAL WITH THE BLACK BOX…

”

Before machine learning:

- Remove data that has large uncertainties
  - Lidar
    - ✓ Negative lidar observables
    - ✓ Aerosol depolarization ratio greater than 1
  - In situ
    - ✓ CCN below 10 cm^{-3}
    - ✓ ABS below 0.1 Mm^{-1}

Algorithm selection:

- Supervised regression learning problem with large number of numerical features.
- Fully-Connected Neural Network (FCNN) regression model

Architecture setup:

- Training data: 70%, Testing data: 30%
- 10-fold cross validation
- Hyperparameters are tuned iteratively during the training using Bayesian optimization

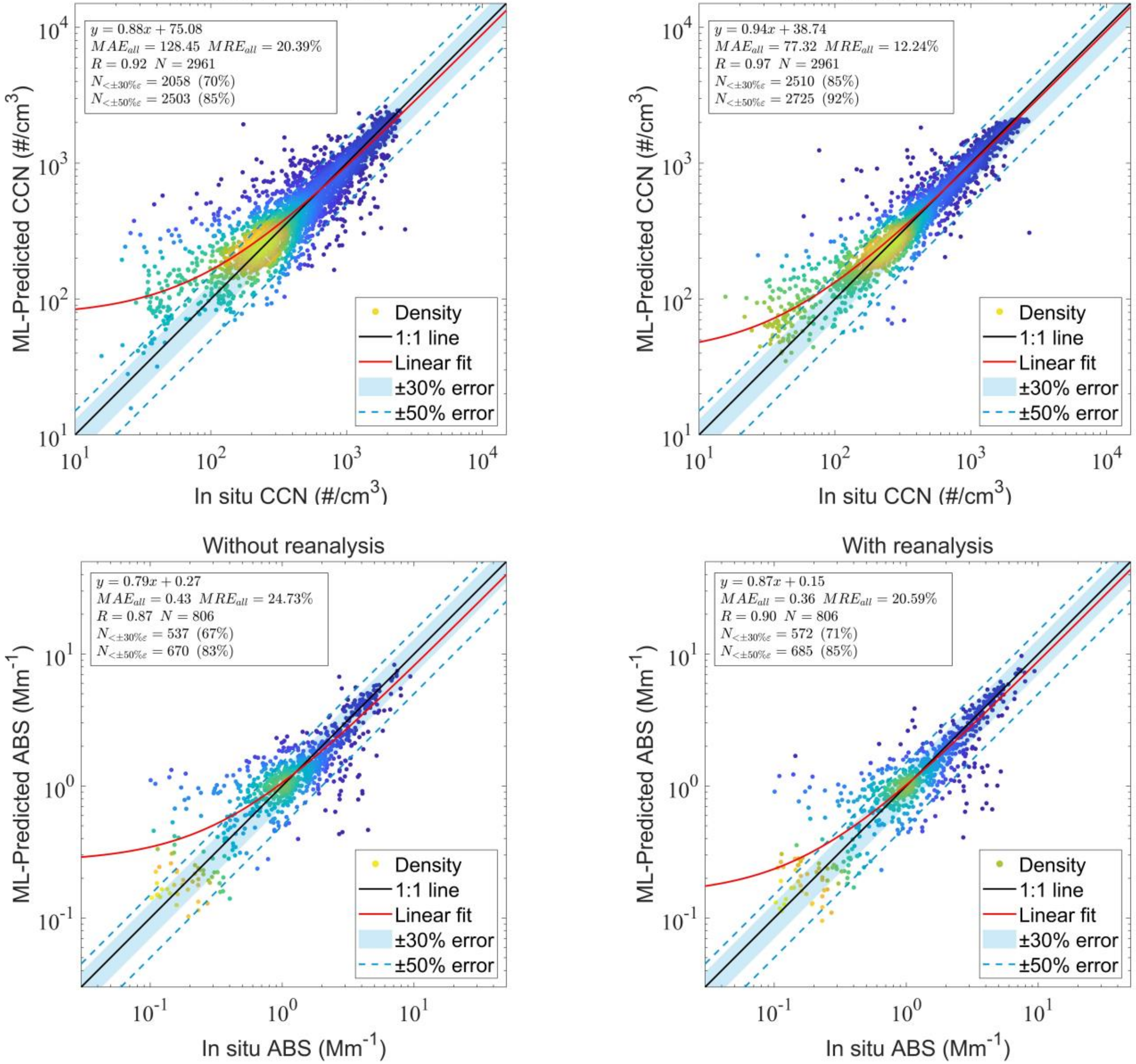
Simulation of ML retrievals: CCN/ABS for full set of HSRL-2 observables (3β + 2α + 3δ)

WITHOUT Reanalysis

WITH Reanalysis

CCN

ABS

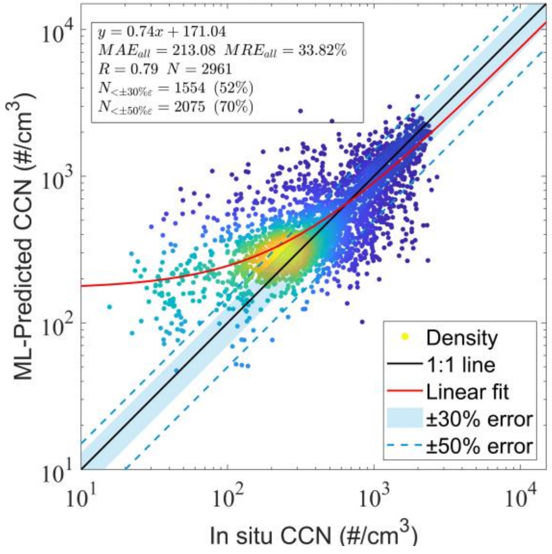


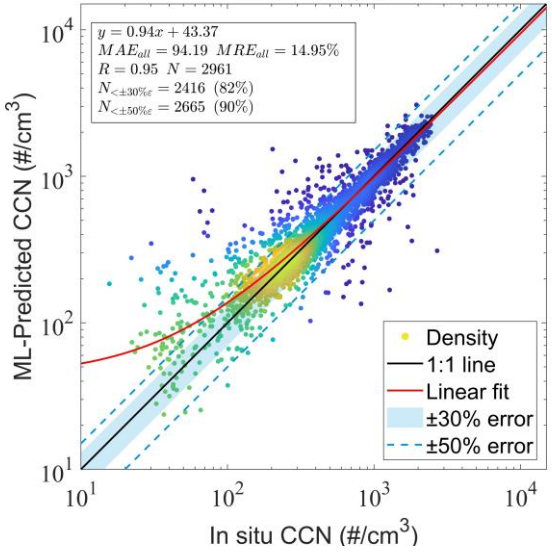
Simulation of ML retrievals: CCN/ABS for EarthCARE/ATLID observables (1β + 1α + 1δ)

WITHOUT Reanalysis

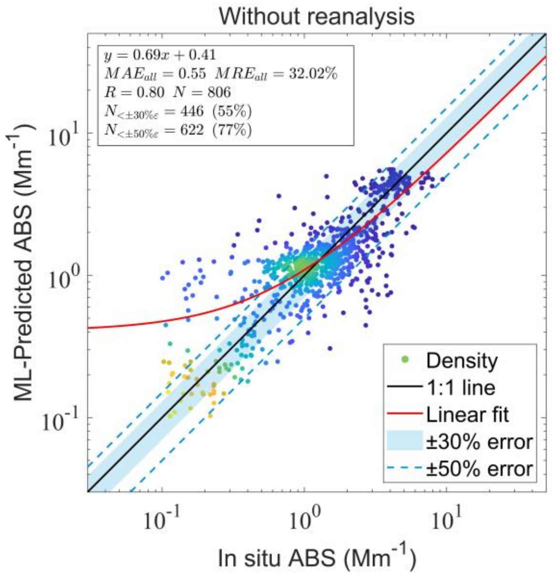
WITH Reanalysis

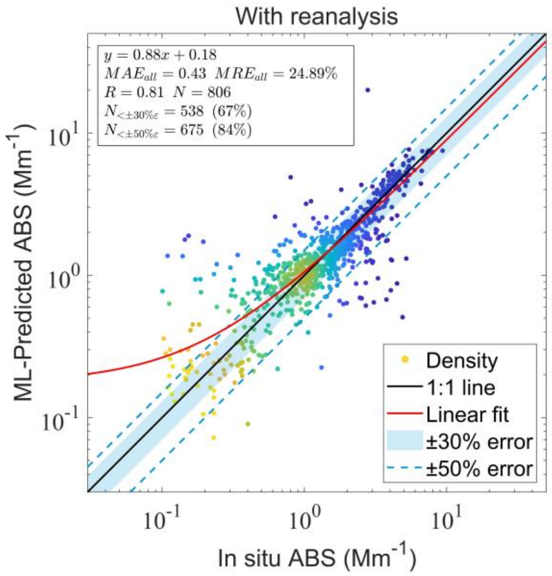
CCN



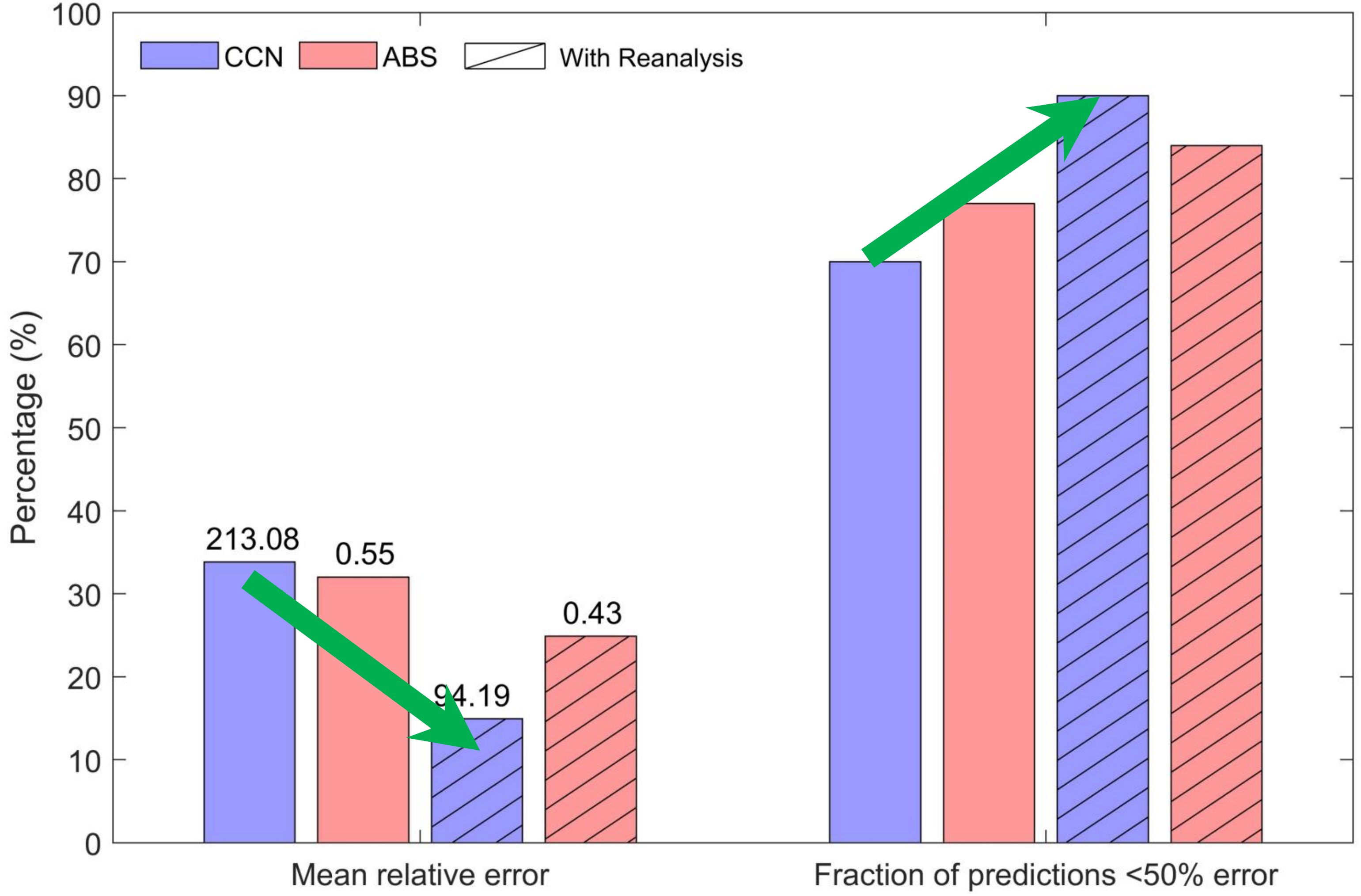


ABS





Mean relative error and fraction of predictions within 50% uncertainty

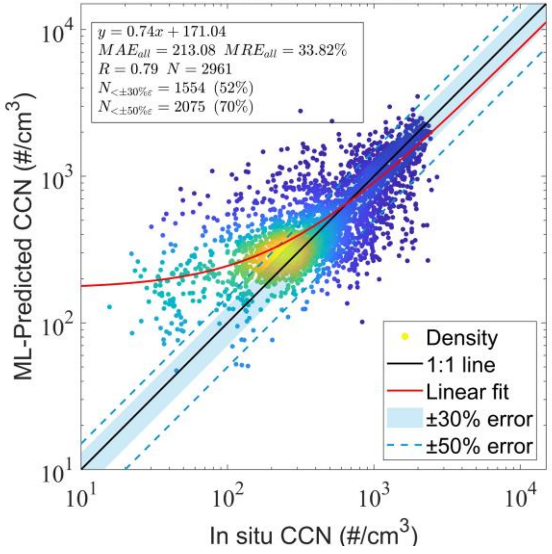


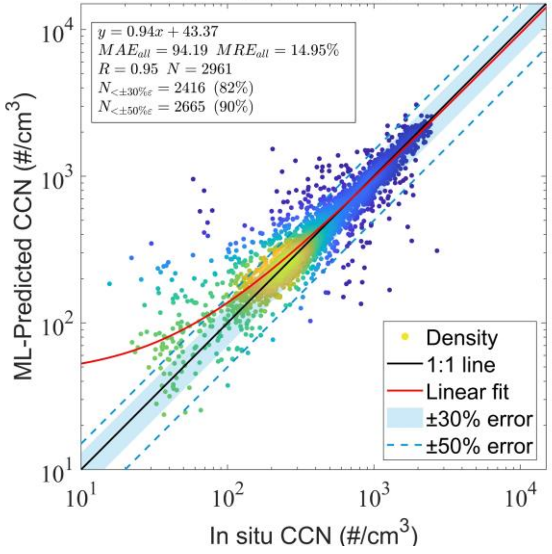
Significant Boost in retrieval performance for ATLID from adding reanalysis data (T, RH) as constraints

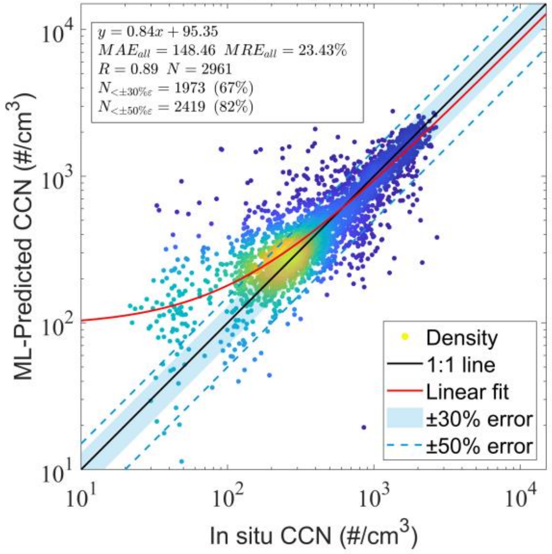
Simulation of ML retrievals: CCN/ABS for EarthCARE/ATLID observables (1β + 1α + 1δ)

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

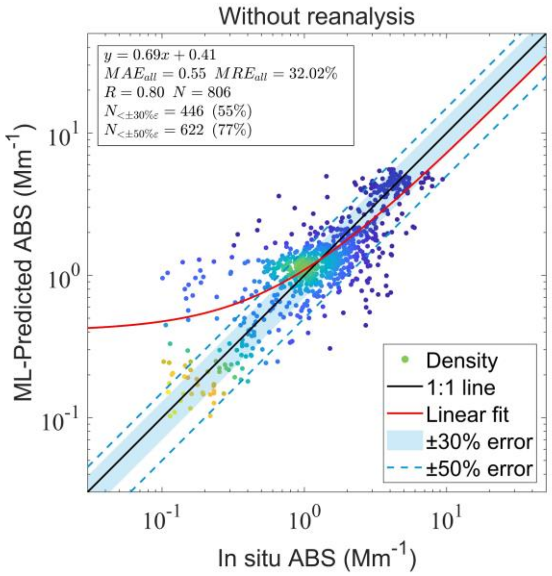
CCN

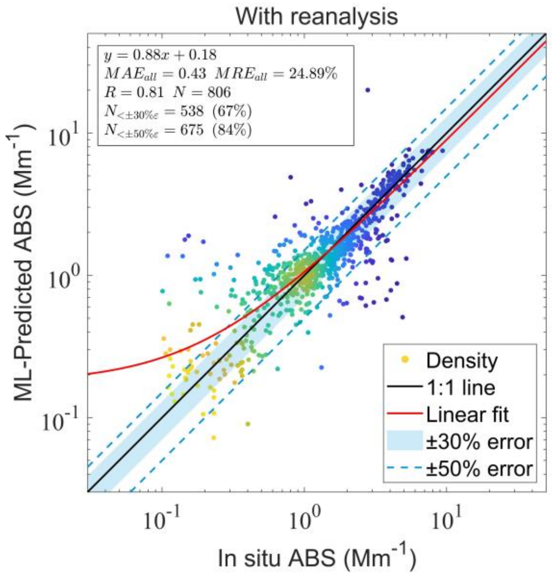


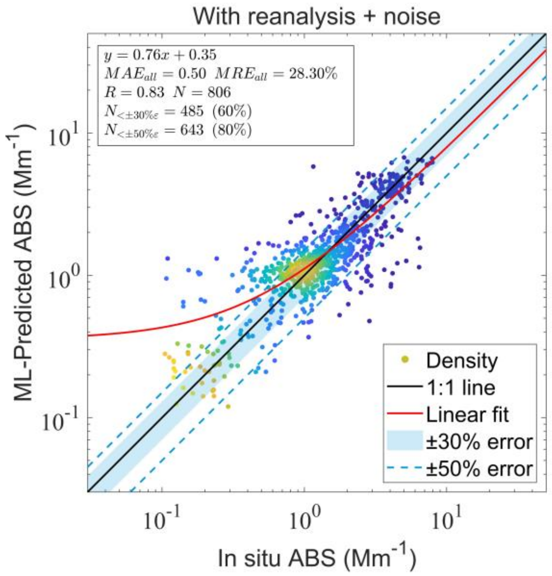




ABS

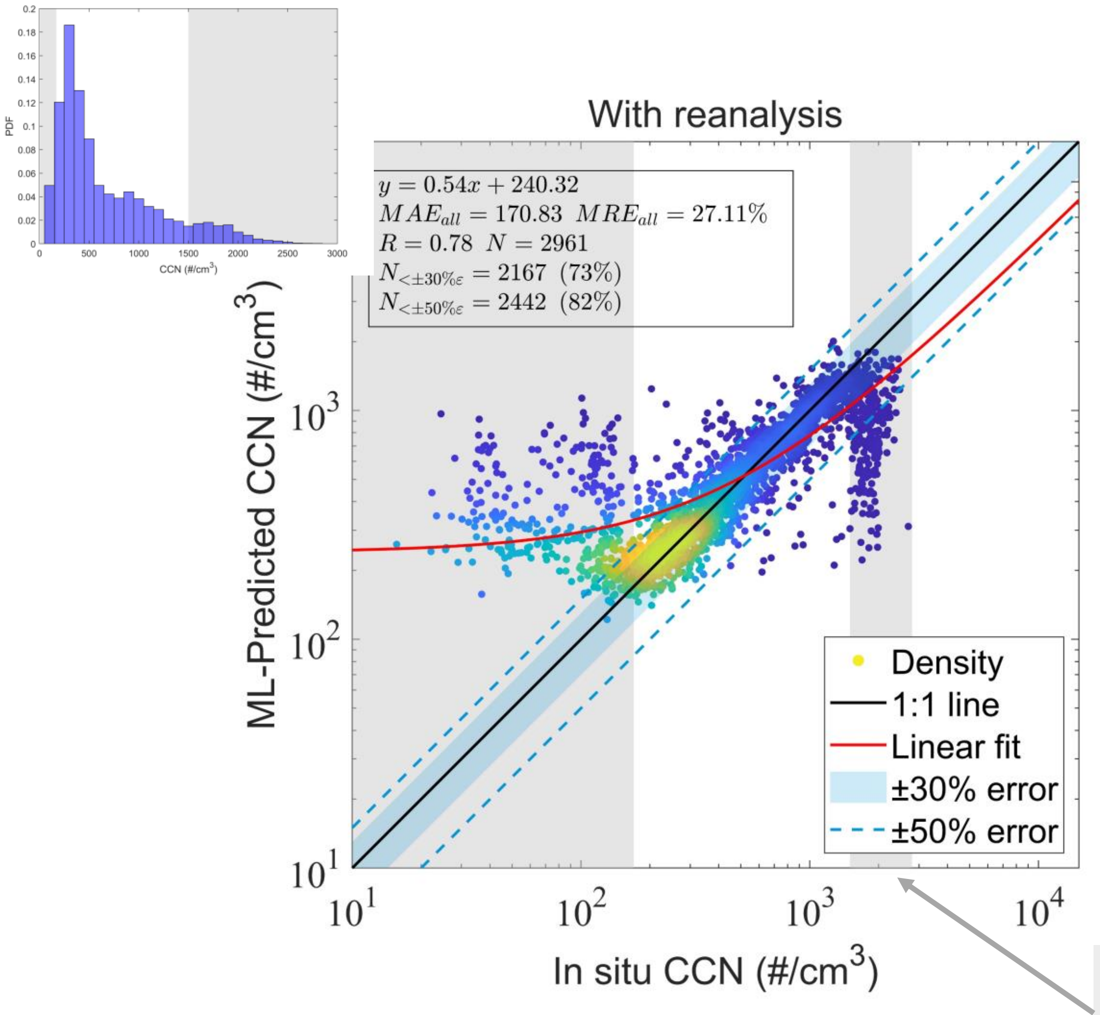


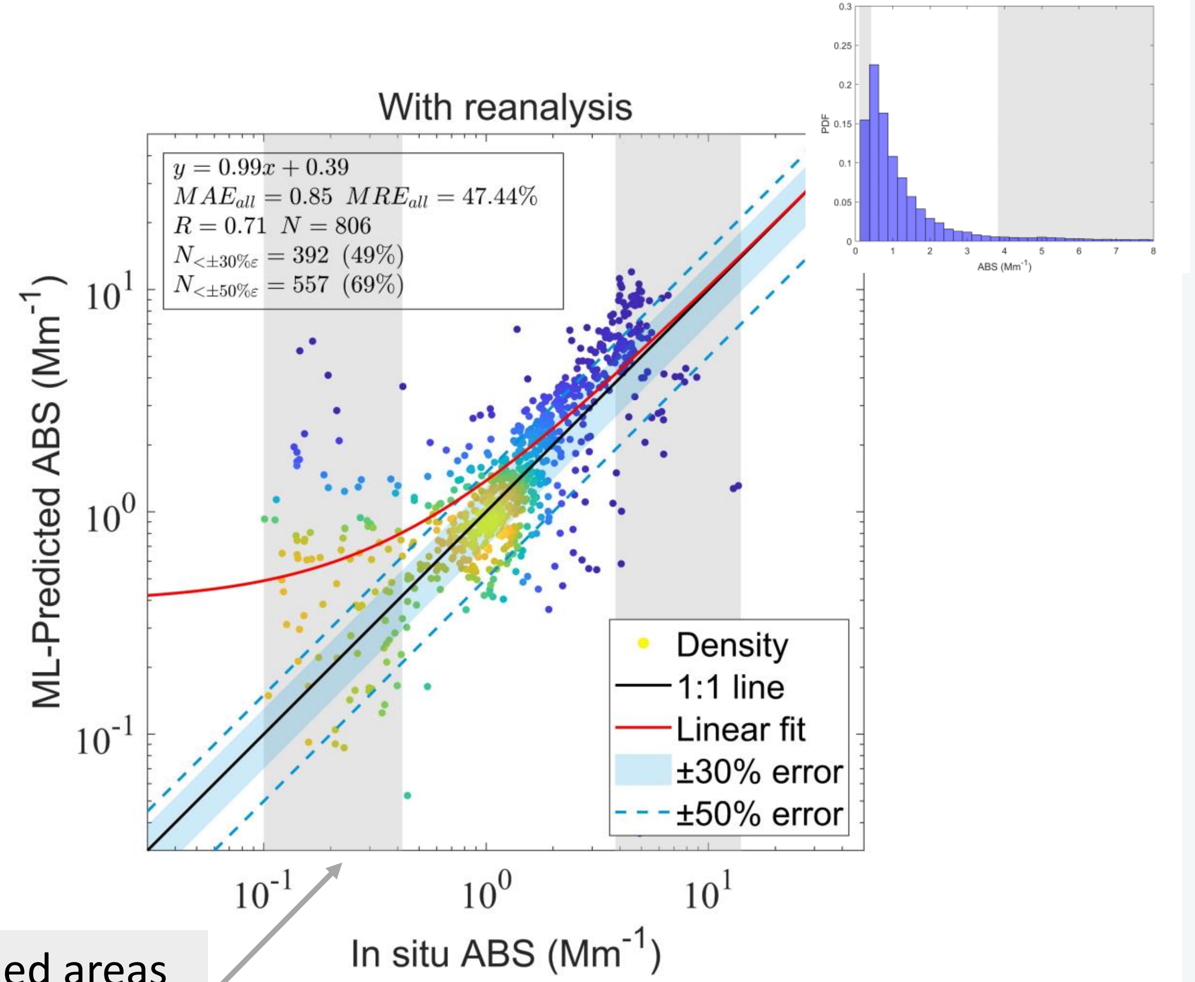




Test for ATLID observables with incomplete in situ data: limited range of training data

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

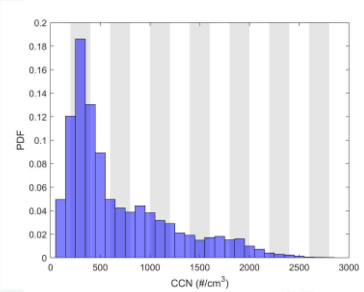


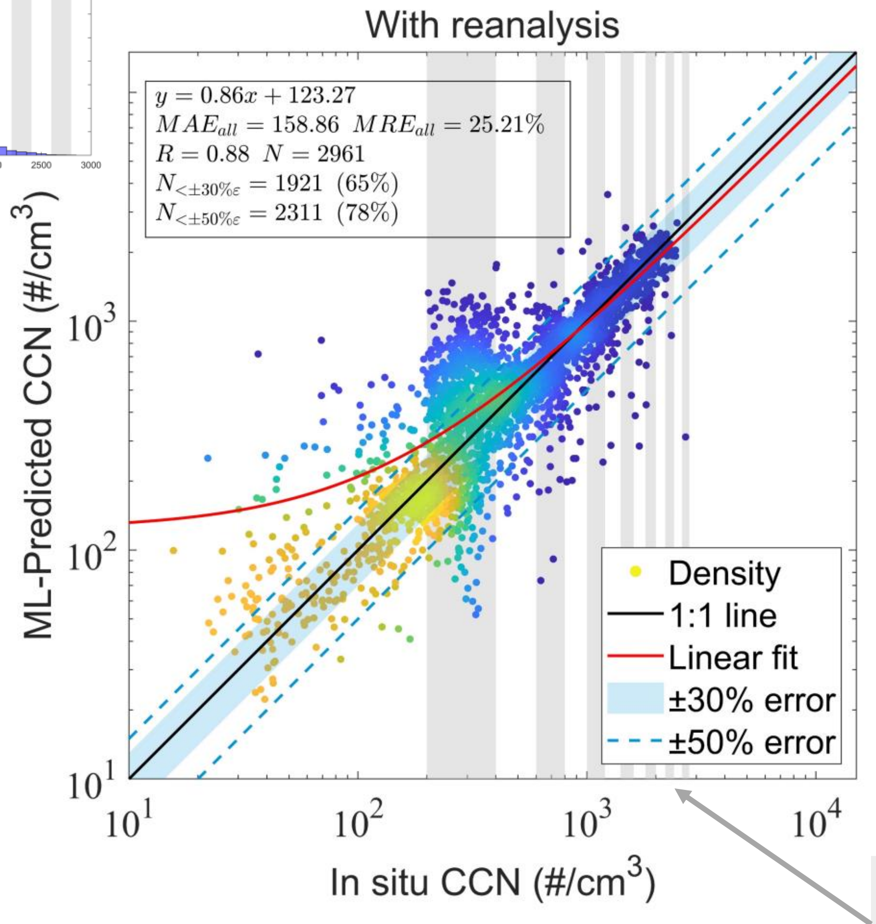


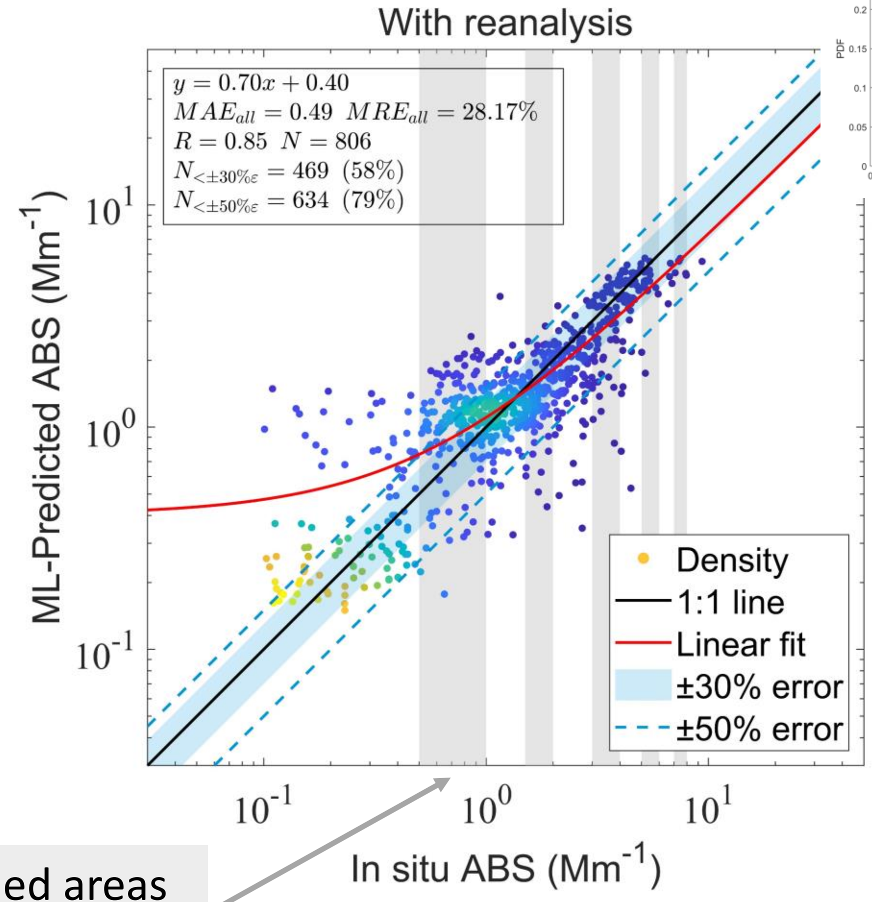
Grey-shaded areas
excluded in training

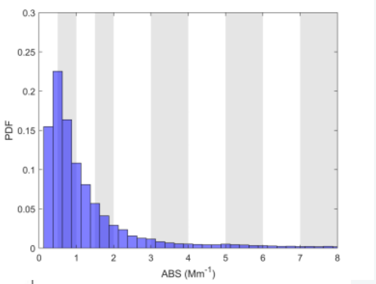
Test for ATLID observables with incomplete in situ data: Discontinuous training data

Provide only intermittent of CCN for training, but attempt prediction for full range of CCN pdf









Grey-shaded areas excluded in training

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

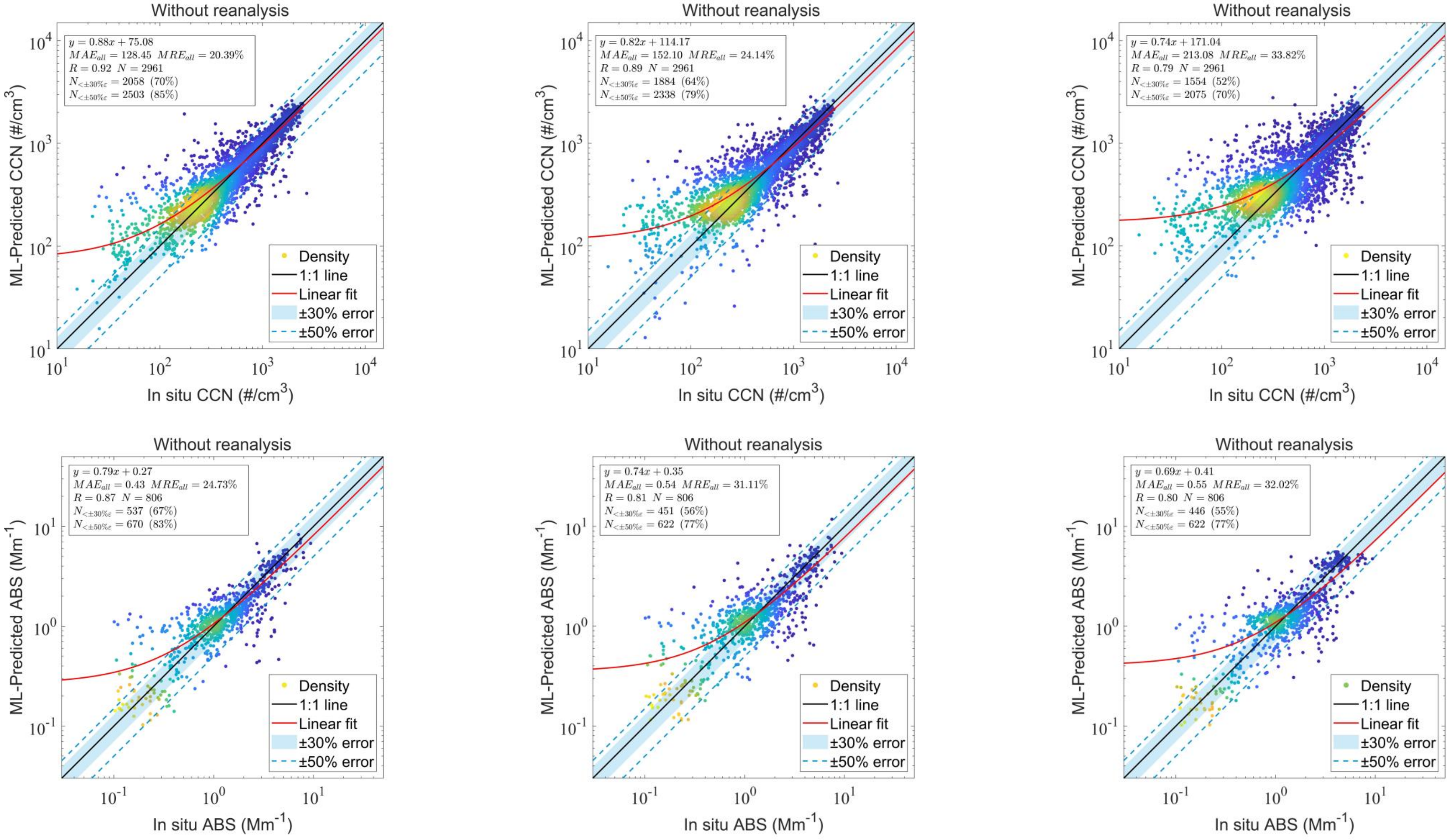
HSRL-2: 3β + 2α + 3δ

HSRL-1: 2β + 1α + 2δ

ATLID: 1β + 1α + 1δ

CCN

ABS



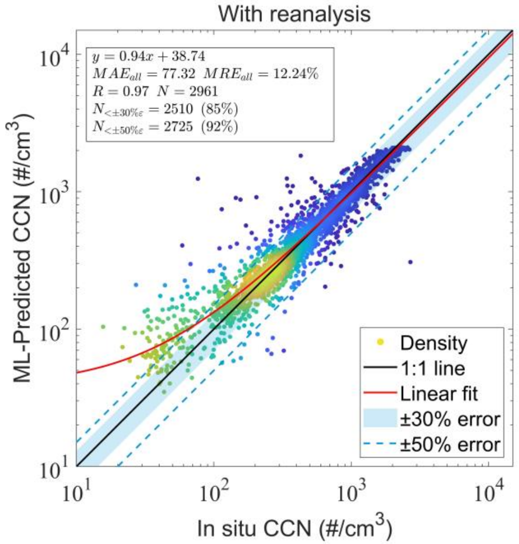
CCN/ABS for HSRL-2, HSRL-1 and EarthCARE/ATLID observables with reanalysis

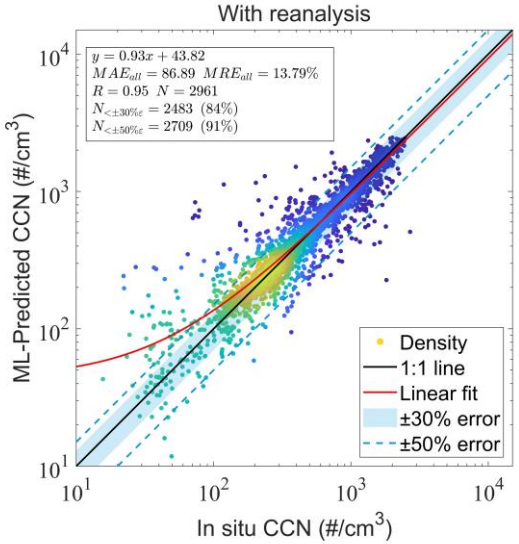
HSRL-2: 3β + 2α + 3δ

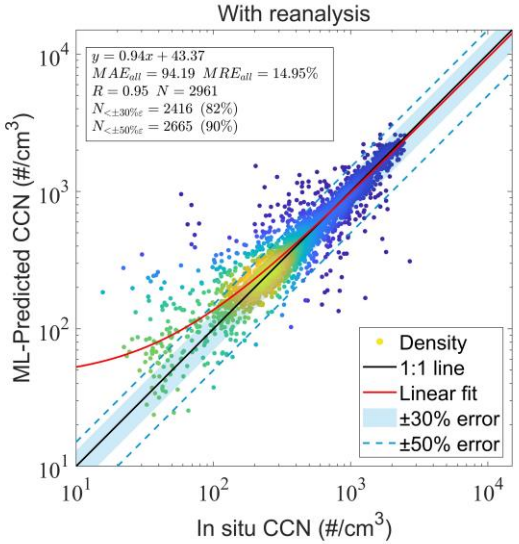
HSRL-1: 2β + 1α + 2δ

ATLID: 1β + 1α + 1δ

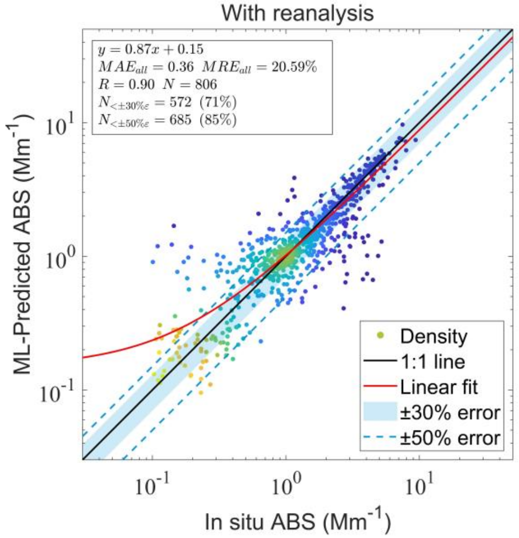
CCN

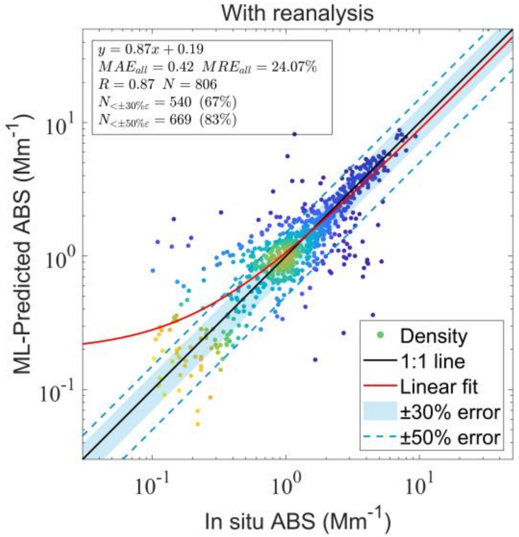


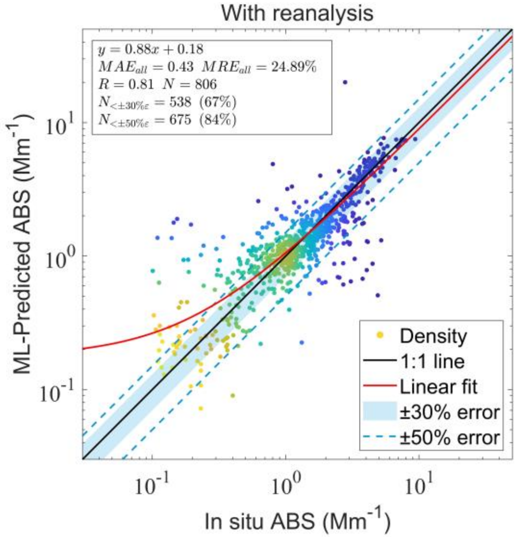




ABS

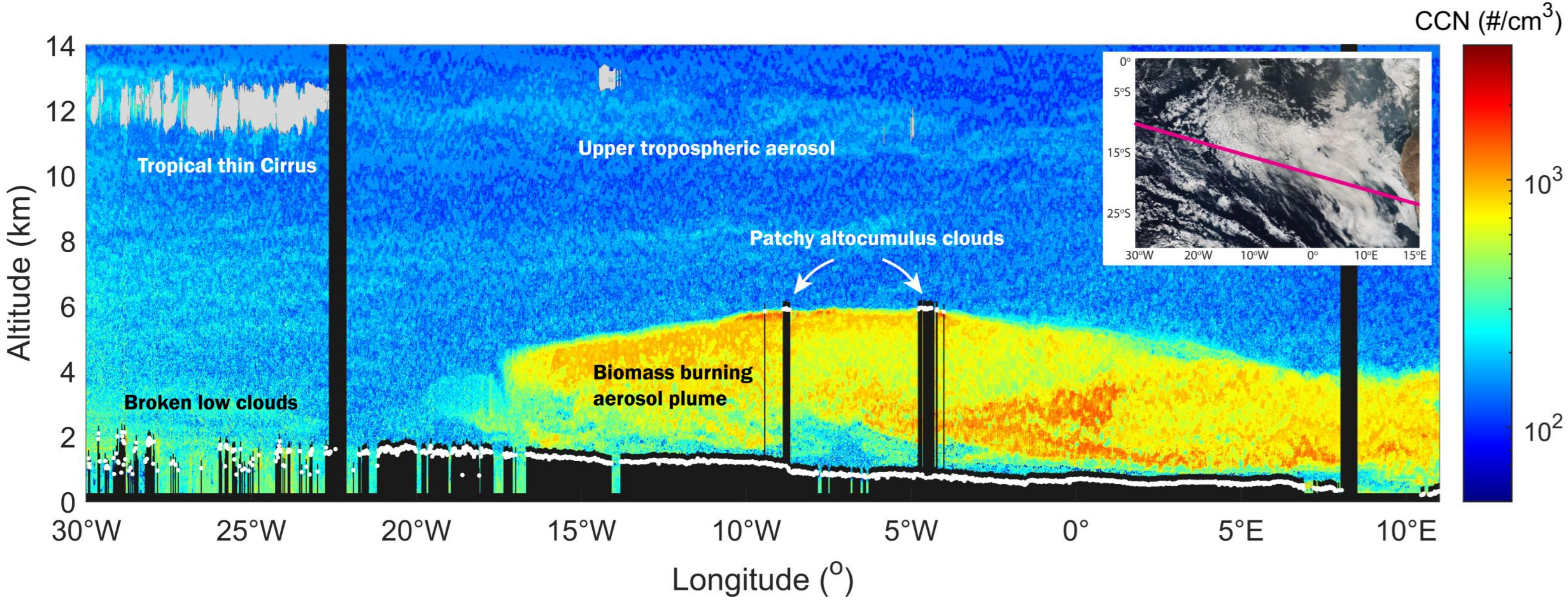






Will be submitted to Science this week

CCN predicted by ML model for ER-2 flight across Southeast Atlantic - Aug. 26, 2016



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 (142.5%)	148.5 (23.4%)	146.1 (268.4%)
ABS [10^{-6} m^{-1}]	0.55 (32.0%)	0.29 (104.4%)	0.43 (24.9%)	0.26 (93.1%)	0.5 (28.3%)	0.31 (109.3%)

Novel Retrievals of Aerosol Microphysical and Radiative Properties from Lidar

Conclusions

1. We trained ML algorithms using airborne HSRL-2 observations collocated with in situ CCN (N≈9,900) and ABS (N≈2,700) measurements to predict CCN/ABS from lidar observables.
2. ML models have been adapted to many sets of future spaceborne lidar obs, incl. EarthCARE/ATLID, and tested with high-accuracy HSRL-2 data as input (overly optimistic, but necessary).
3. For ATLID observables, ML models predict CCN and ABS with mean relative errors of 30-35%.
4. Adding reanalysis data (T, RH) boosts CCN errors to ~15% and ABS to ~25%.
5. Performance depends greatly on completeness of training data.
6. For pristine conditions, CCN/ABS retrieval errors are much higher (partly due to sparse training data).
7. Actual retrieval errors for spaceborne systems will depend on error characteristics.
8. Philosophically, the paradigm should use the airborne HSRL-trained ML models, as the low uncertainties provide maximum likelihood for ML models to discover non-linear and multi-variate correlations between lidar observables and other aerosol properties.

Fig.S1: flowchart

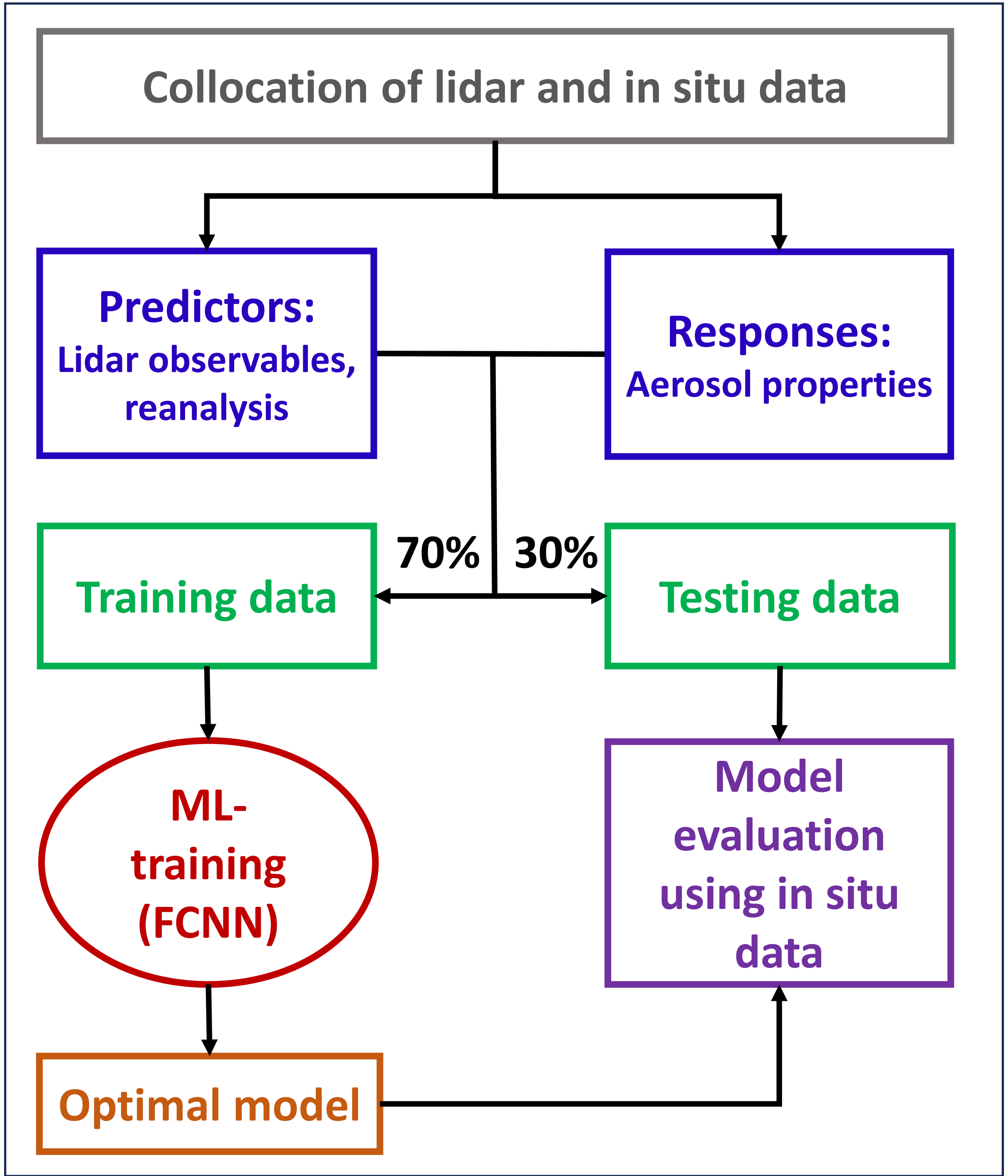


Table1: List of lidar systems and aerosol variables used in this study

Lidar system	Aerosol variables and wavelengths (nm)		
	Extinction	Backscatter	Depolarization ratio
HSRL-2 ($3\beta + 2\alpha + 3\delta$)	355, 532	355, 532, 1064	355, 532, 1064
HSRL-1 ($2\beta + 1\alpha + 2\delta$)	532	532, 1064	532, 1064
Elastic-backscatter-lidar ($2\beta + 2\delta$)	-	532, 1064	532, 1064
EarthCare-like-lidar ($1\beta + 1\alpha + 1\delta$)	355	355	355

New paradigm for aerosol retrievals from lidar

General ML model

- Trained with collocated suborbital HSRL-2 (all λ's) & in situ data
- Augmented with reanalysis data
- Tested with HSRL/in situ data

"Best case"

$3\beta + 2\alpha + 3\delta$

Accuracy of aerosol retrievals depends on **HSRL uncertainties** & information content

Optimized ML model

- Retrained for specific lidar observables
- Augmented with reanalysis data
- Tested with HSRL/in situ data

Lidar-type specific, e.g.

$1\beta + 1\alpha + 1\delta$

Accuracy of aerosol retrievals depends on **HSRL uncertainties** & information content

Application to ANY Lidar

- Applied to
  - EarthCARE
  - AOS
  - Ground-based
  - Airborne
- Tested with in situ ?

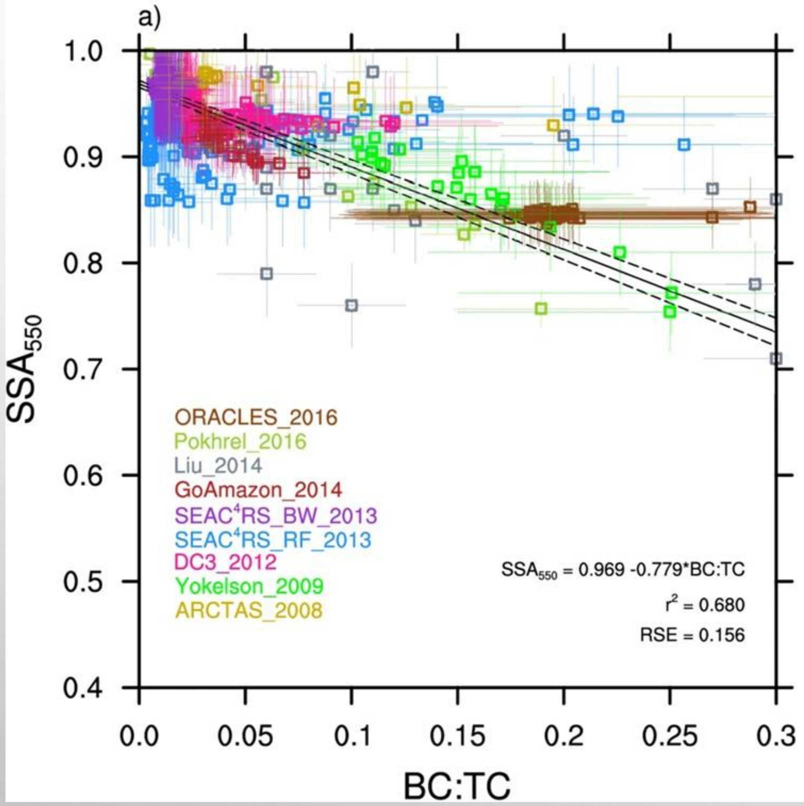
Lidar-system specific, e.g.

$1\beta + 1\alpha + 1\delta$

Accuracy of aerosol retrievals depends on **system-specific uncertainties** & information content

Some deficiencies in climate models

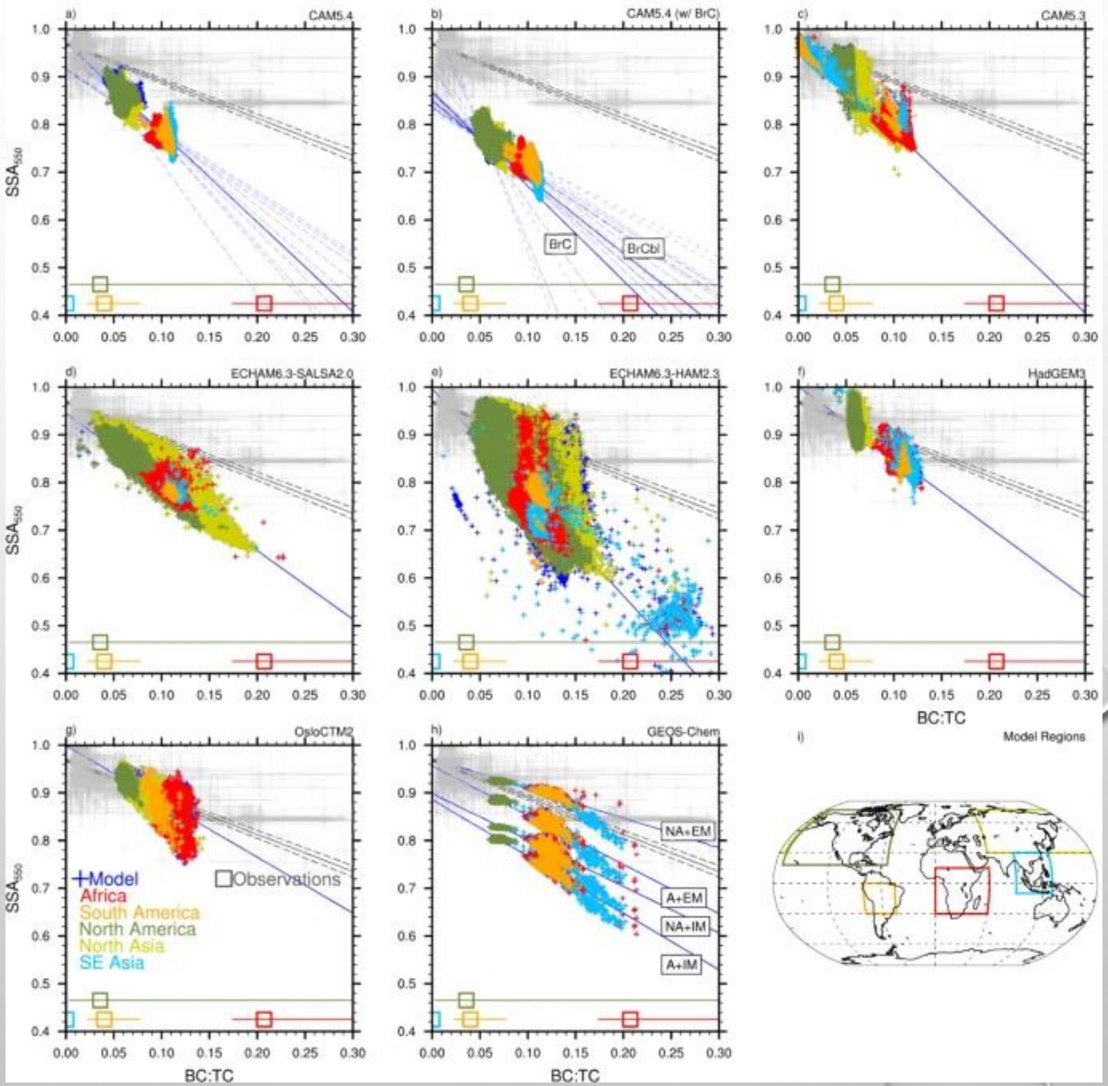
Black/brown carbon and associated absorption



Aerosol Single Scattering Albedo (SSA)

$$SSA = \frac{k_{scattering}}{k_{extinction}} = \frac{k_{scattering}}{k_{scattering} + k_{absorption}}$$

$$SSA = \frac{k_{extinction} - k_{absorption}}{k_{extinction}} = 1 - \frac{k_{absorption}}{k_{extinction}}$$



→ Treatment of carbonaceous aerosol lifecycle (and its impact on absorption) is vastly different between models

Brown et al., 2021