Use of machine learning to improve global models on aerosol-cloud interactions without compromising their computing efficiency

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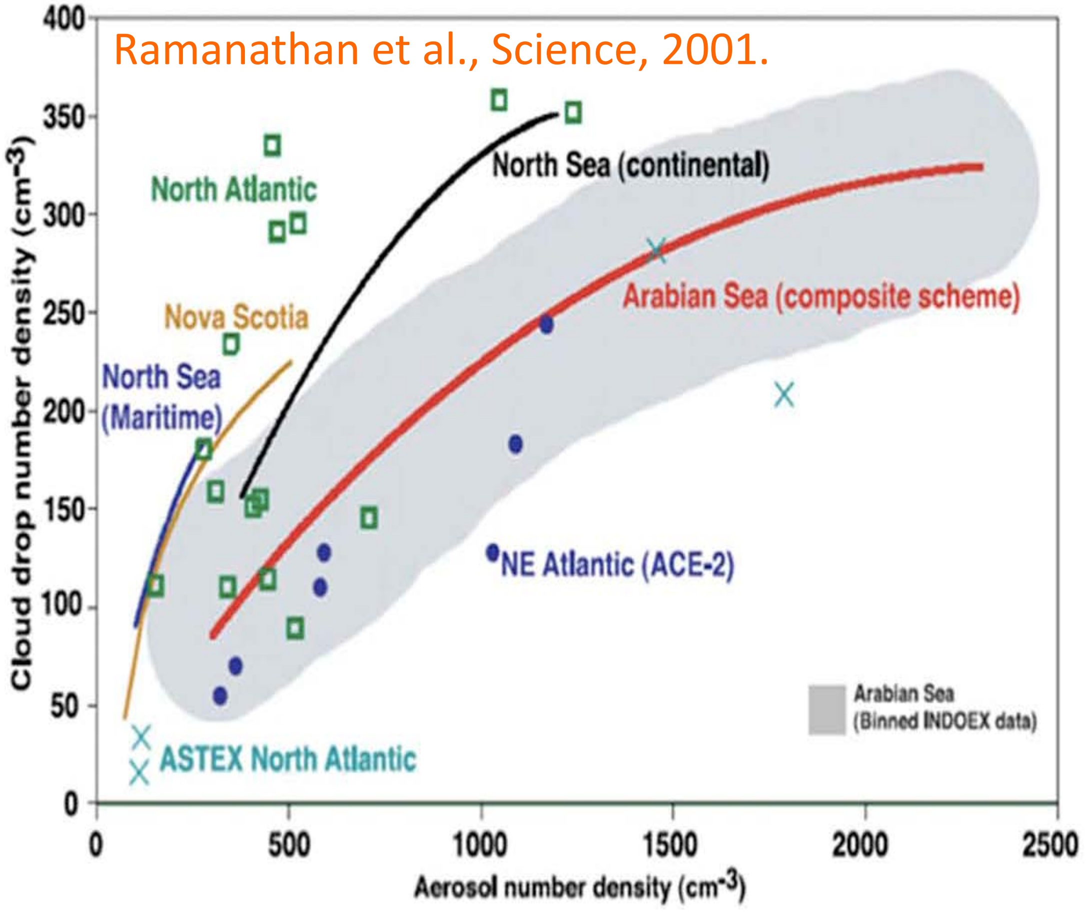
Motivation and Objective

Cloud droplet number concentration depends on particle number concentration (PNC)



PNC calculation simplified in climate models due to computing cost and challenges in including size-resolved particle microphysics.

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Fast responses on pre-industrial climate from present-day aerosols in a CMIP6 multi-model study

Prodromos Zanis[1], Dimitris Akritidis[1], Aristeidis K. Georgoulias[1], Robert J. Allen[2], Susanne E. Bauer[3], Olivier Boucher[4], Jason Cole[5], Ben Johnson[6], Makoto Deushi[7], Martine Michou[8], Jane Mulcahy[6], Pierre Nabat[8], Dirk Olivié[9], Naga Oshima[7], Adriana Sima[10], Michael Schulz[9], Toshihiko Takemura[11], and Konstantinos Tsigaridis[3,12]

Among 10 CMIP6 models compared by Zanis et al. (2020), 7 models employ bulk mass-based aerosol schemes while 3 models use mode aerosol schemes.

Here we employ simulations of a global size-resolved (sectional) aerosol microphysics model and a machine-learning tool to develop a computationally efficient and easy to use Random Forest Regression Model (RFRM) for PNC.

GEOS-Chem with APM (GC-APM)

Size-resolved (bin) advanced particle microphysics (APM) model

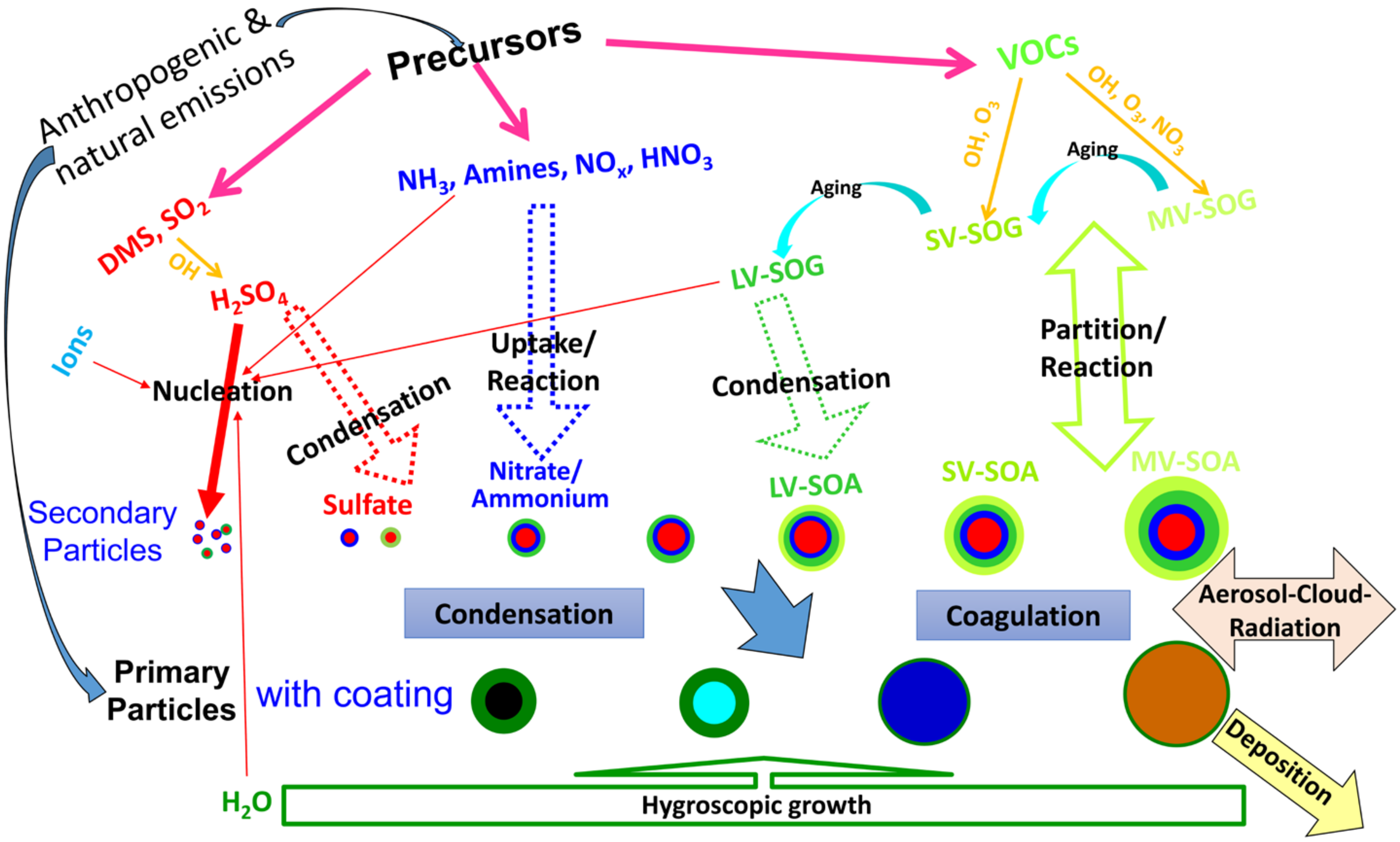
(Yu and Luo, ACP, 2009; Yu, ACP, 2011)

Full Chemistry;

Full size-resolved (bin) particle microphysics (40/15/15/20/15 bins for secondary particles/BC/POC/Sea salt/dust);

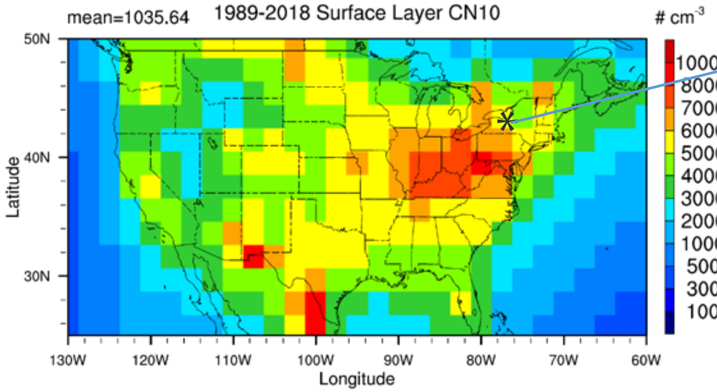
Coating of primary particles by secondary species tracked;

State-of-the-art nucleation mechanisms (Yu et al., ACP, 2017; Yu et al., GMD, 2020)

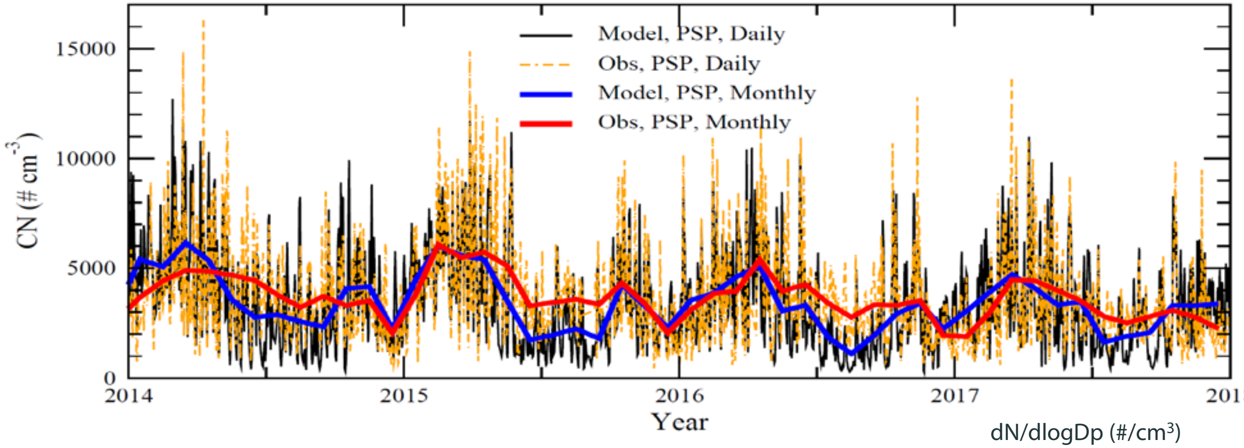


Simulation period: 1989-2018 (30 years), 2°×2.5°; detailed outputs used for machine learning training

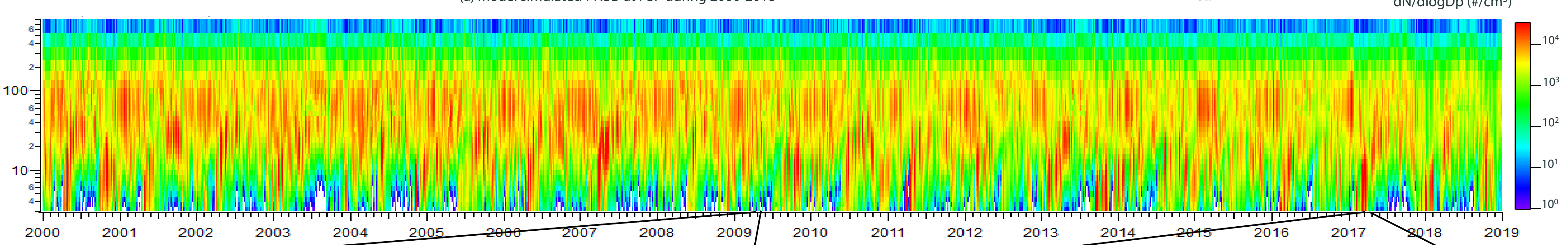
GC-APM: Comparison with surface observation



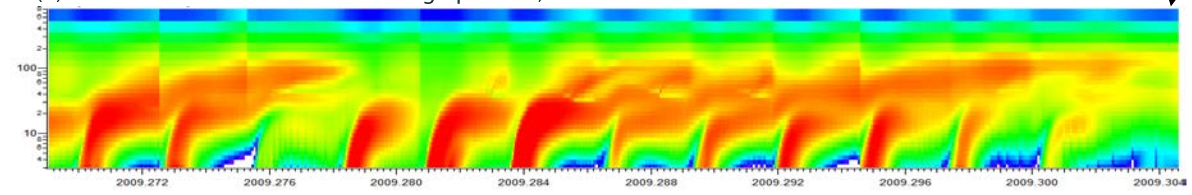
Pinnacle State Park, NY; Data Acknowledgements: James Schwab @UAlbany



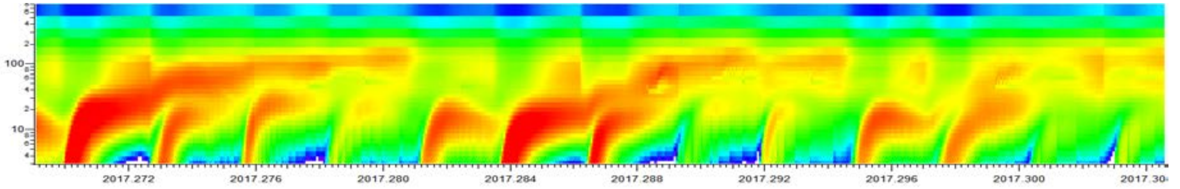
(a) Model simulated PNSD at PSP during 2000-2018



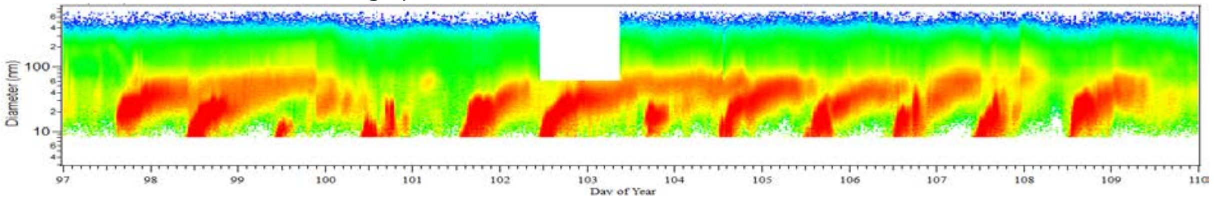
(b) Model simulated PNSD at PSP during April 8-20, 2009



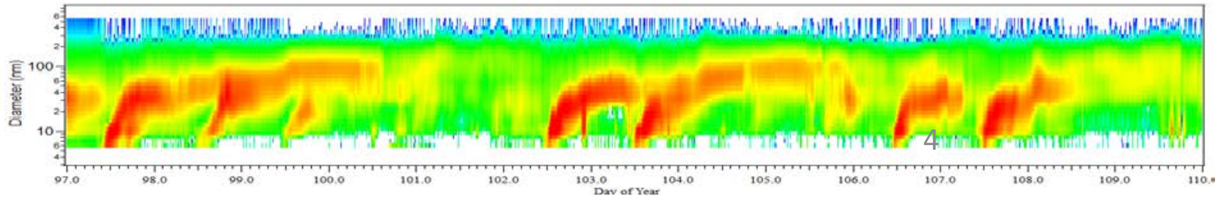
(c) Model simulated PNSD at PSP during April 8-20, 2017



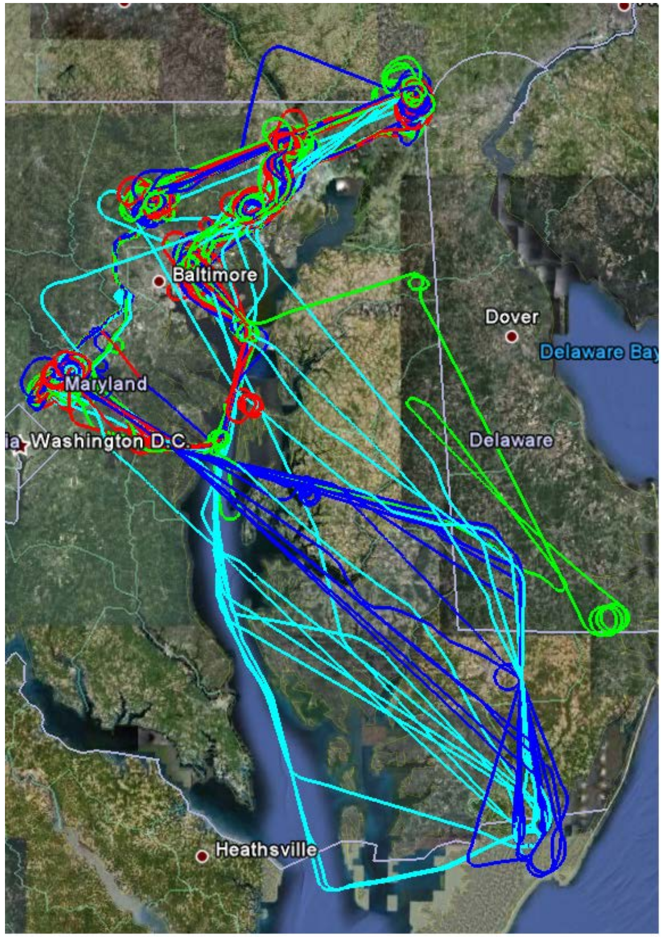
(d) Measured PNSD at PSP during April 8-20, 2009



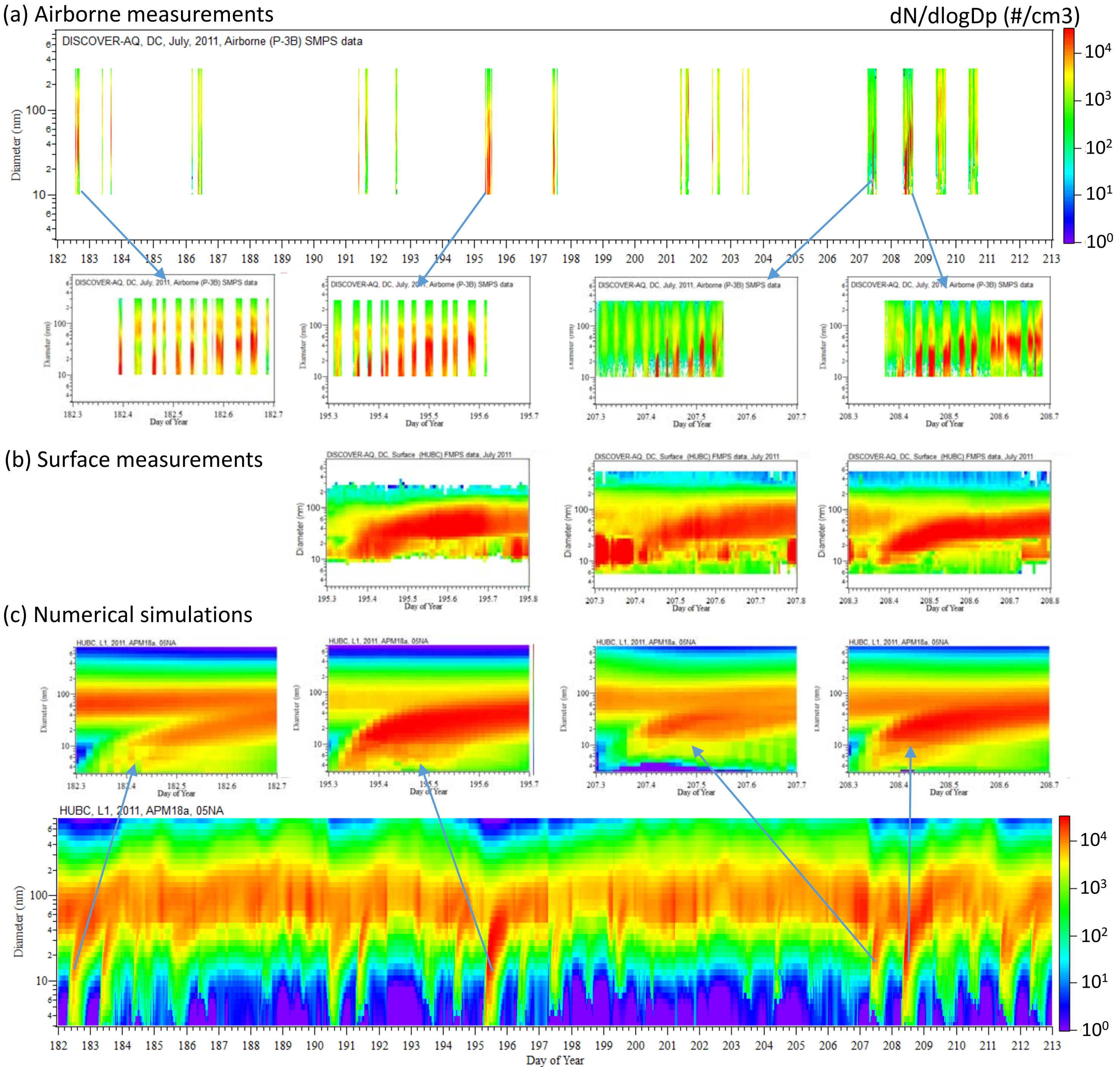
(e) Measured PNSD at PSP during April 8-20, 2017



GC-APM: Comparison of predicted particle size distributions with airborne and surface measurements



DISCOVER-AQ 2011 ALL P3B July1-July29



Data Acknowledgements: Bruce Anderson and Luke Ziemba @NASA; Everette Joseph @NCAR

Machine-learning -- Random Forest Regression Model (RFRM)

INPUT

(commonly available in bulk aerosol models)

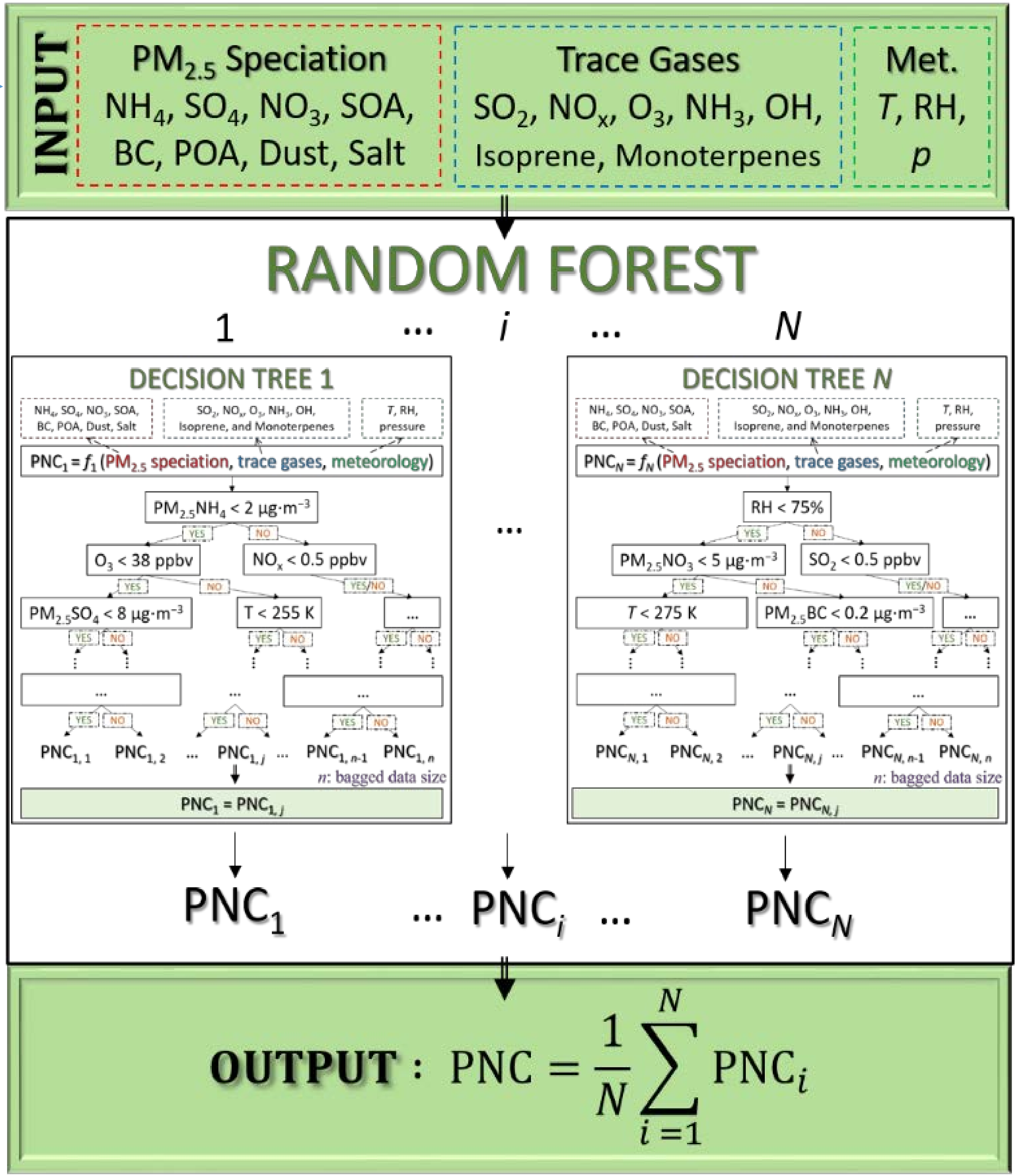
OUTPUT

(parameters important for aerosol radiative forcing)

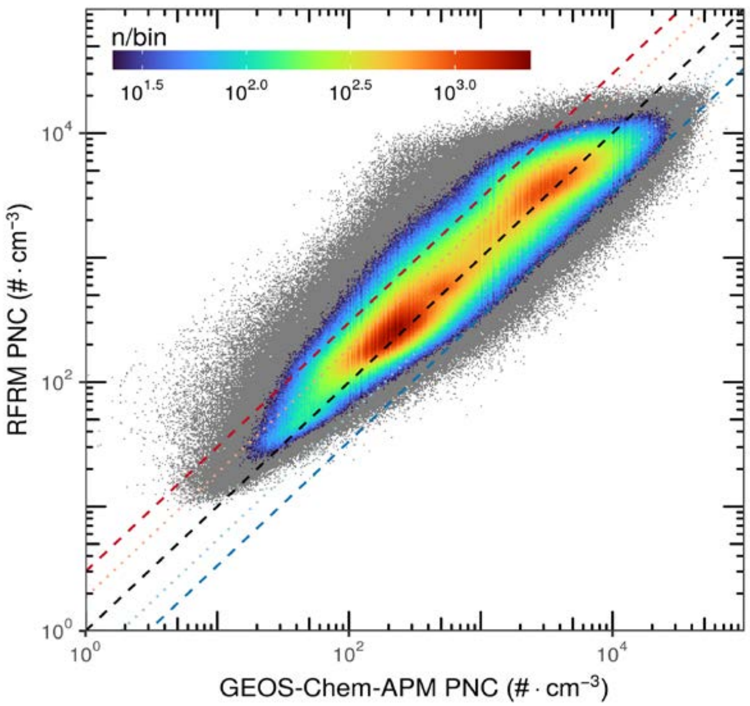
Cloud Condensation Nuclei at S=0.4% (CCN0.4) (Nair and Yu, ACP, 2020)

Aerosol Extinction Coefficient (AEC)

Condensation Nuclei larger than 10 nm (CN10) or **Particle Number Concentration (PNC)**



GC-APM vs GC-RFRM PNC



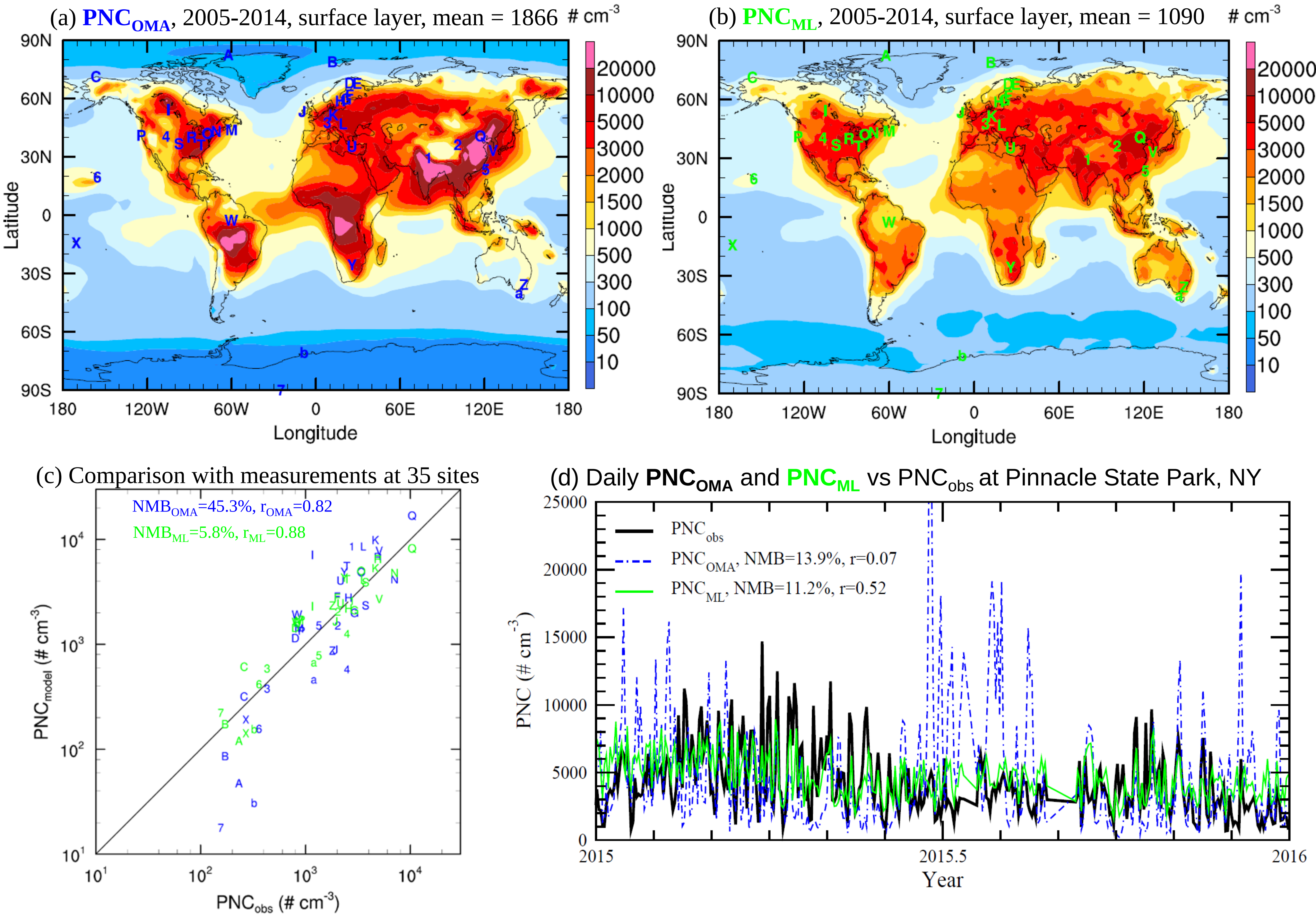
Correlation (τ): 0.77

Median Mean Fraction Bias: 0.19

% with |MFB| < 0.6: 78%

PNC_{OMA}:

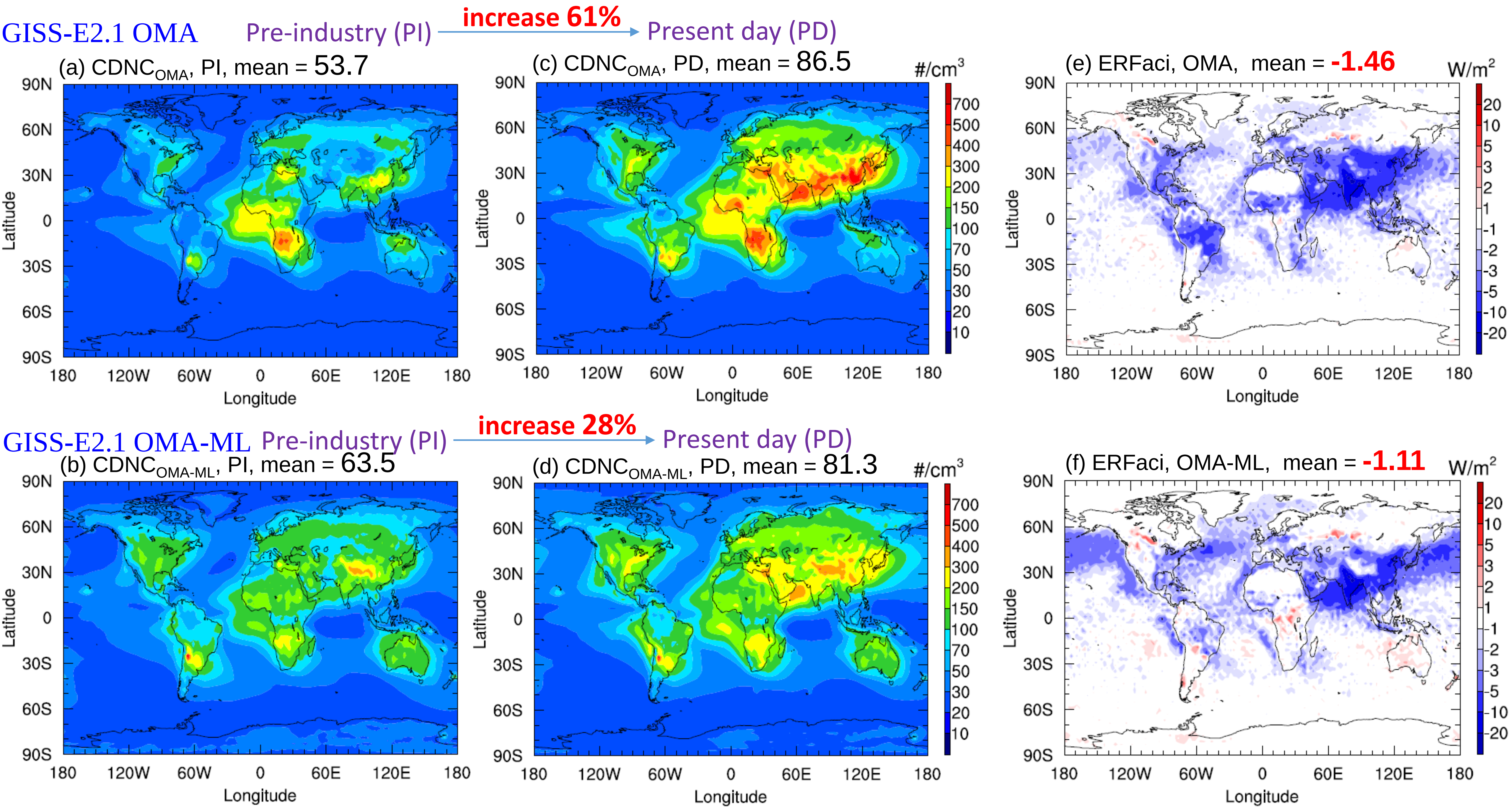
GISS-E2.1-OMA with prescribed mass to number coefficients



PNC_{ML}:

GISS-E2.1-OMA with machine learning PNC RFRM (computing cost = ~5%)

Cloud-cover weighted mean CDNC under PI & PD emissions and ERFaci based on GISS-OMA and GISS-OMA-ML

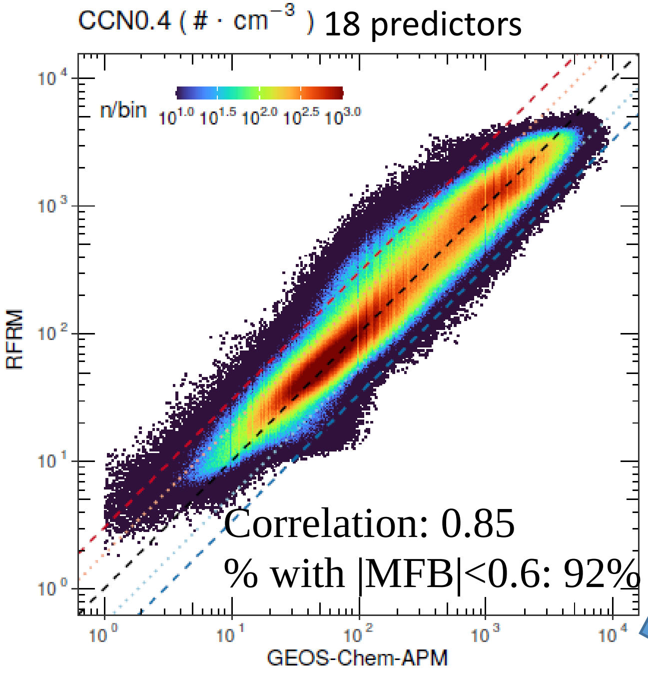


RFRM for CCN0.4

INPUT

$PM_{2.5}$ Speciation	Trace Gases	Met.
NH_4, SO_4, NO_3, SOA, BC, POA, Dust, Salt	SO_2, NO_x, O_3, NH_3, OH, Isoprene, Monoterpenes	*T*, RH, *p*

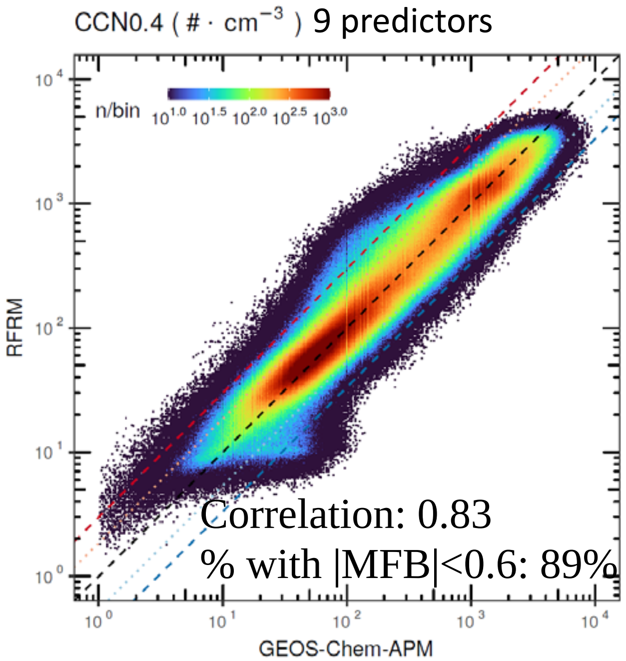
18 predictors



9 predictors

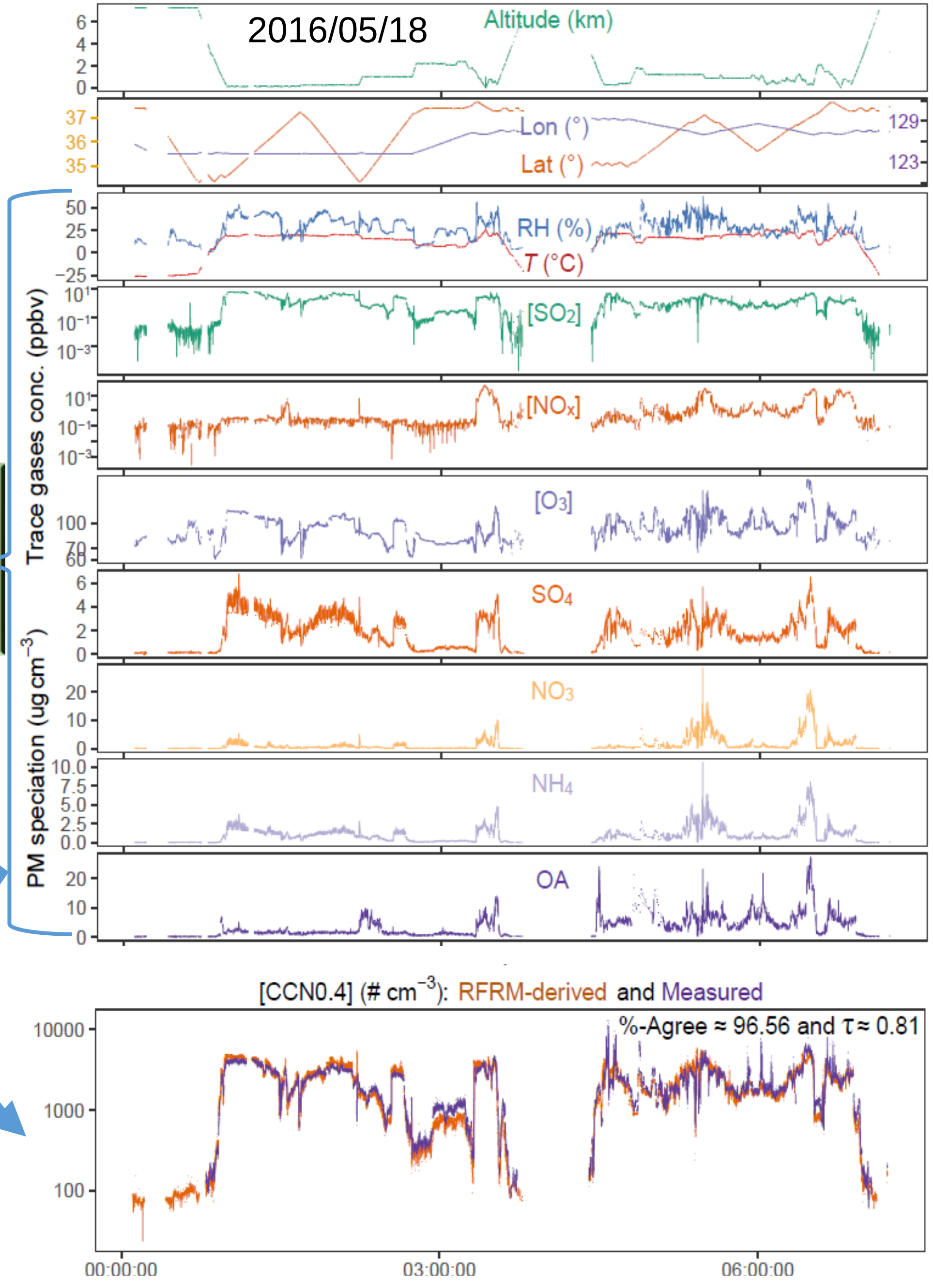
INPUT

$PM_{2.5}$ Speciation	Trace Gases	Met.
NH_4, SO_4, NO_3, OA	SO_2, NO_x, O_3	*T*, RH



$$\textbf{OUTPUT} : \mathrm{CCN} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{CCN}_i$$

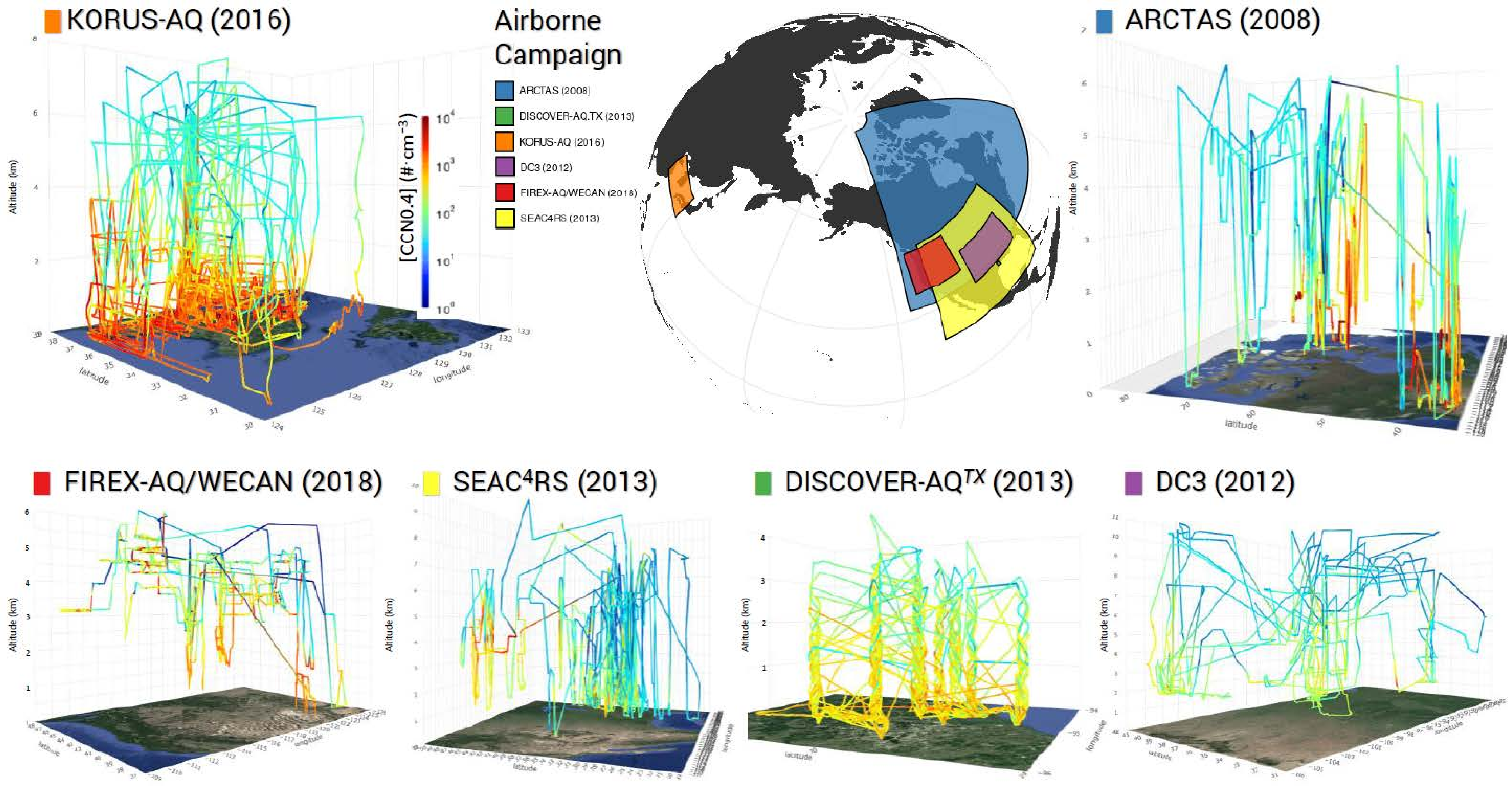
CCN0.4 RFRM (9 predictors) vs KORUS-AQ Measurements



Data Acknowledgements: NASA KORUS-AQ Measurement Team

CCN0.4 observed at six airborne campaigns

Data Acknowledgements:
NASA Airborne Campaigns Measurement Teams



CCN0.4 RFRM (9 predictors) vs Airborne Measurements

INPUT

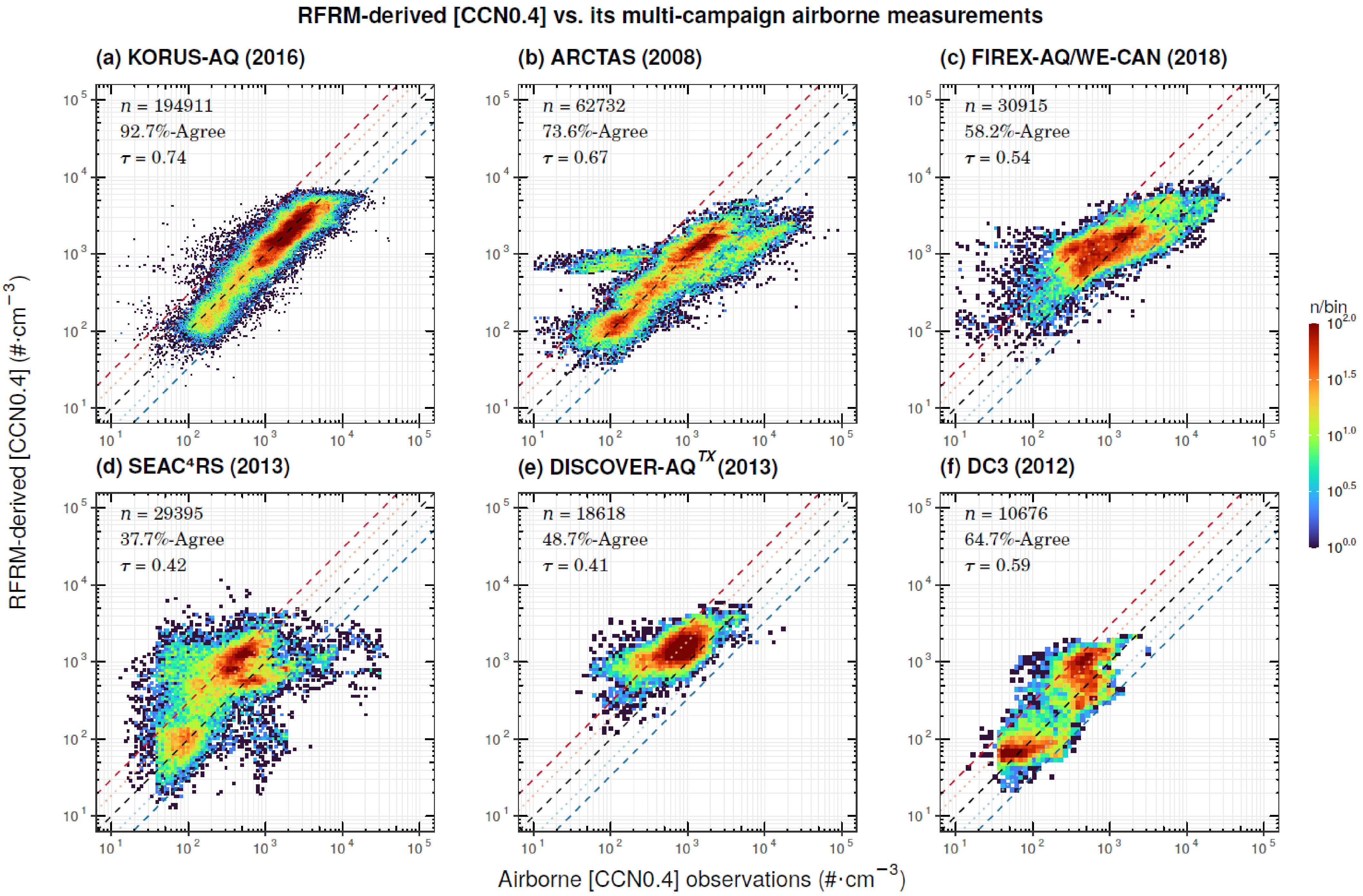
$PM_{2.5}$ Speciation:
NH_4, SO_4, NO_3, OA

Trace Gases:
SO_2, NO_x, O_3

Met.:
T, RH

OUTPUT

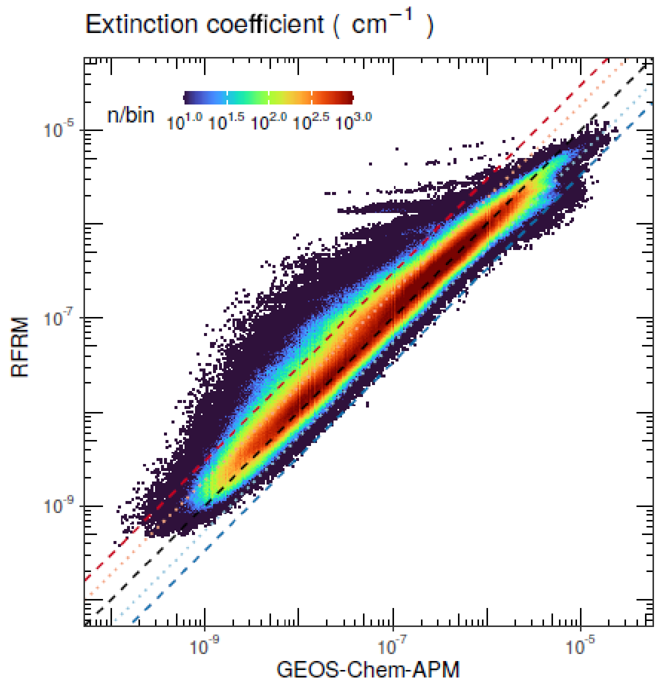
CCN0.4



Data Acknowledgements: NASA Airborne Campaigns Measurement Teams

Summary

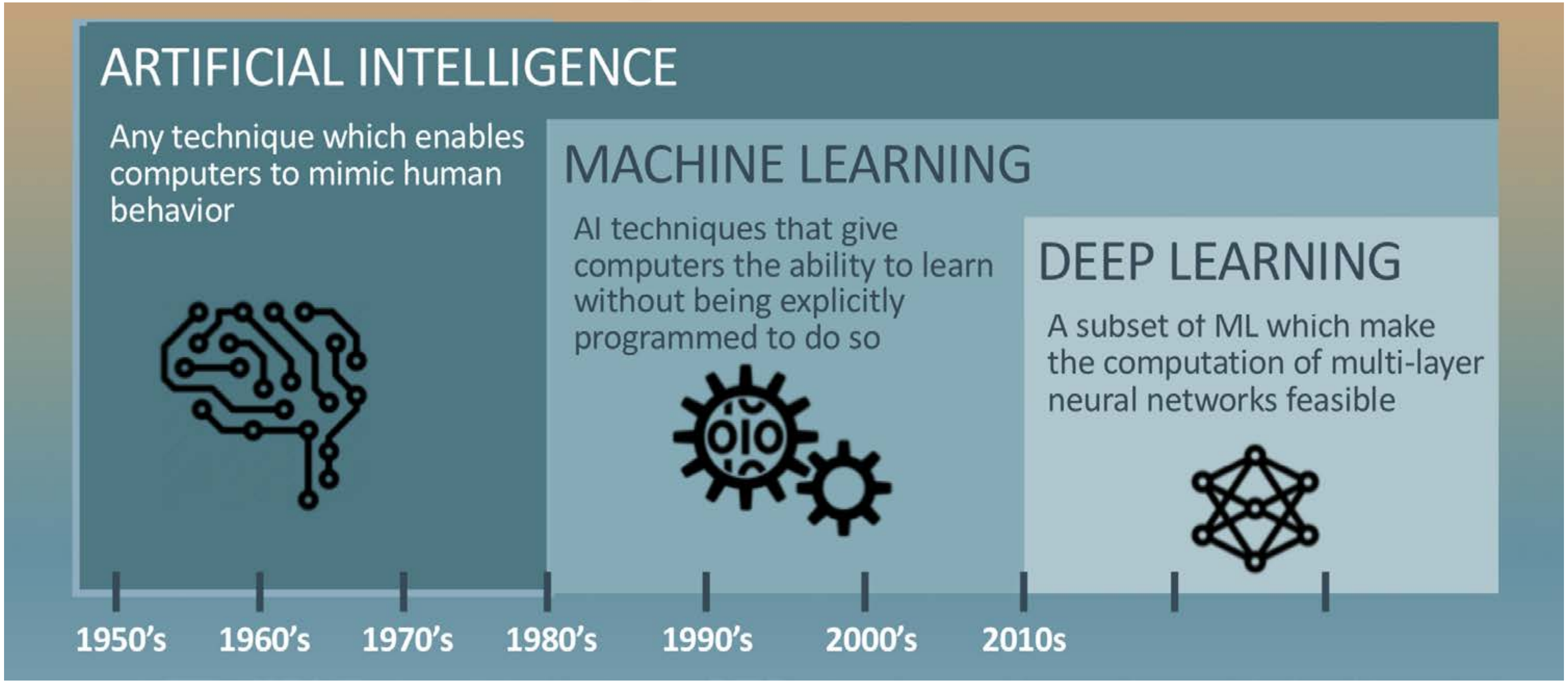
- Particle number concentration (PNC), one of the key parameters affecting ERFaci, is generally simplified in climate models. Here we employ outputs from long-term (30-years) simulations of a global size-resolved aerosol microphysics model and a machine-learning (ML) tool to develop a Random Forest Regression Model (RFRM) for PNC.
- We implemented the PNC RFRM in GISS-ModelE2.1-OMA model, which significantly improves the agreement of its predicted PNC with measurements, weakens the relative changes of cloud droplet number concentration (CDNC) associated with changes of emissions from pre-industry to present-day, and reduces the ERFaci from $-1.46\ W{\cdot}m^{-2}$ to $-1.11\ W{\cdot}m^{-2}$.
- ML is promising in improving climate models in predicting more accurately aerosol properties important for radiative forcing (PNC, CCN, CDNC, extinction coefficient, AOD, AAOD, etc.), and thus can reduce uncertainties in the aerosol radiative forcing calculation without having to deal with the complexity of size-resolved particle microphysics and without compromising their computing efficiency.



- Future work: (1) improve and validate model outputs used for ML training, (2) improve, optimize, and validate ML algorithms, and (3) apply and evaluate ML algorithms in climate models.

Additional slides

Machine Learning



Source: blogs.oracle.com/bigdata/difference-ai-machine-learning-deep-learning

- Machine Learning is a subset of AI
- Simply put, ML is the science (art) of getting computers to learn from their own experience without explicit instructions

GEOS-Chem-APM **GEOS-Chem-ML (RFRM)**