https://ntrs.nasa.gov/search.jsp?R=20200002182 2020-05-24T04:35:42+00:00Z

Challenges in developing better observational constraints and models for aerosols : Emerging ideas for design and use of future observing systems

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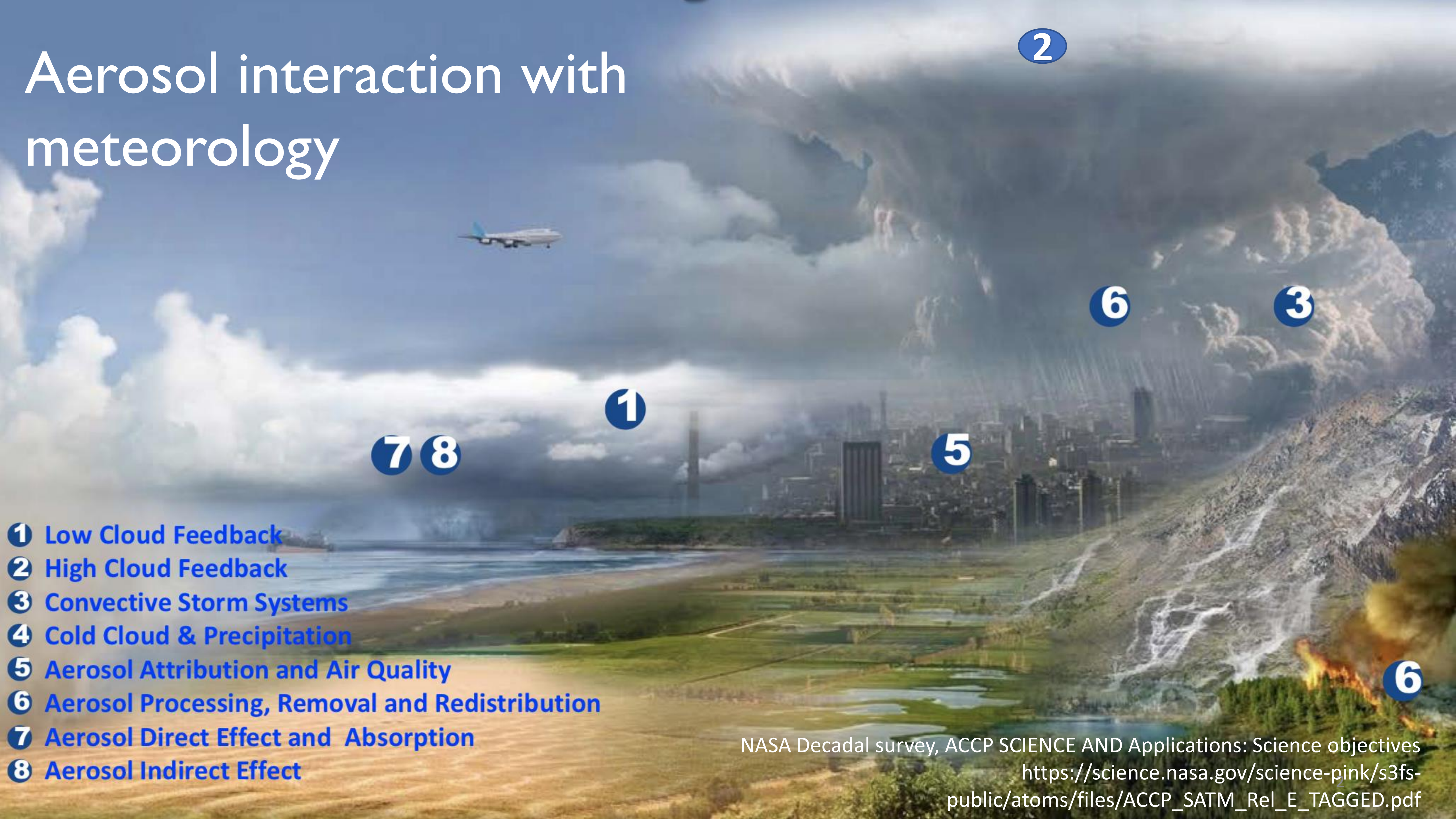
U.S. Naval Research Laboratory[6]

https://www.sciencemag.org/news/2016/08/nasa-aircraft-probe-namibian-clouds-solve-global-warming-puzzle

Aerosol interaction with meteorology



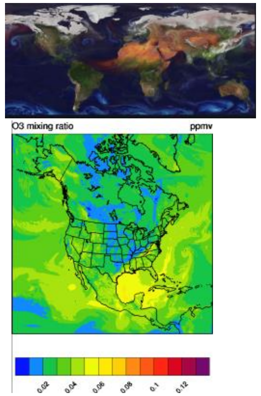
1. Low Cloud Feedback
2. High Cloud Feedback
3. Convective Storm Systems
4. Cold Cloud & Precipitation
5. Aerosol Attribution and Air Quality
6. Aerosol Processing, Removal and Redistribution
7. Aerosol Direct Effect and Absorption
8. Aerosol Indirect Effect

NASA Decadal survey, ACCP SCIENCE AND Applications: Science objectives
https://science.nasa.gov/science-pink/s3fs-public/atoms/files/ACCP_SATM_Rel_E_TAGGED.pdf

Aerosol modeling : Status and future

Observations

- Multi-platform multi-spectral aerosol retrievals from satellites
- In-situ aerosol mass and optical properties



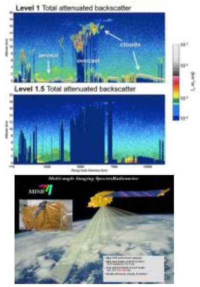
Aerosol modeling

- Best possible meteorology : Multi-model ensemble
- Aerosol mass, size distribution and optical properties

Data Assimilation

Obs + Model : Calculate increments

- Point by point observation uncertainty
- Choice of aerosol variables
- Clear sky radiance



Evaluation and development

- Use of aerosol variables not used in assimilation – process-based improvements to models

Observation constrained modeling

Good representation of atmospheric aerosol sources and sinks

AERONET

MAN

Lidar profiles

AOD

Dust AOD

Smoke AOD

Angstrom exponent

Depolarization ratio

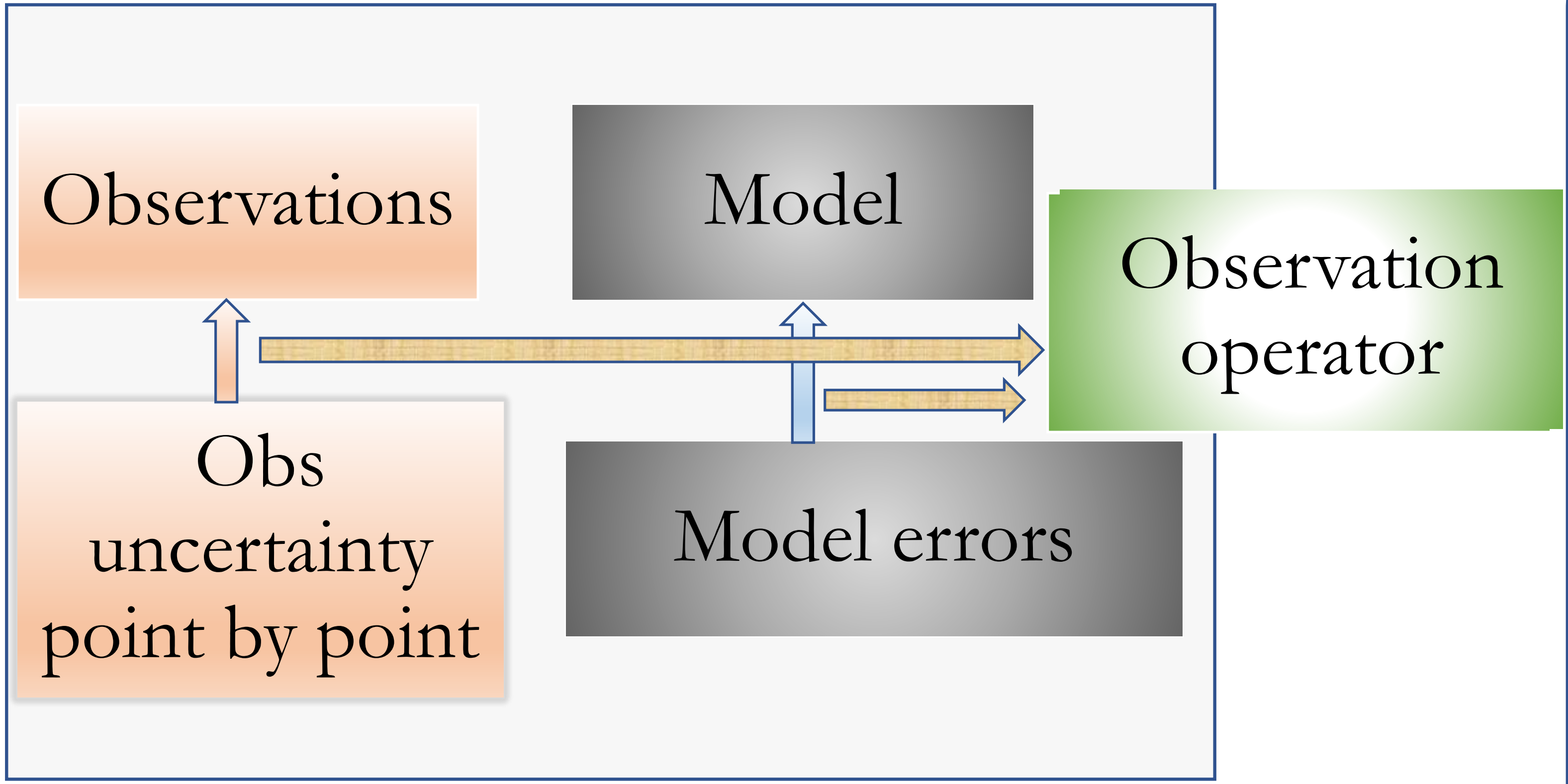
PM total

Speciation

Dual-pole radar

Passive microwave retrievals

Observation constrained modeling (Contd)

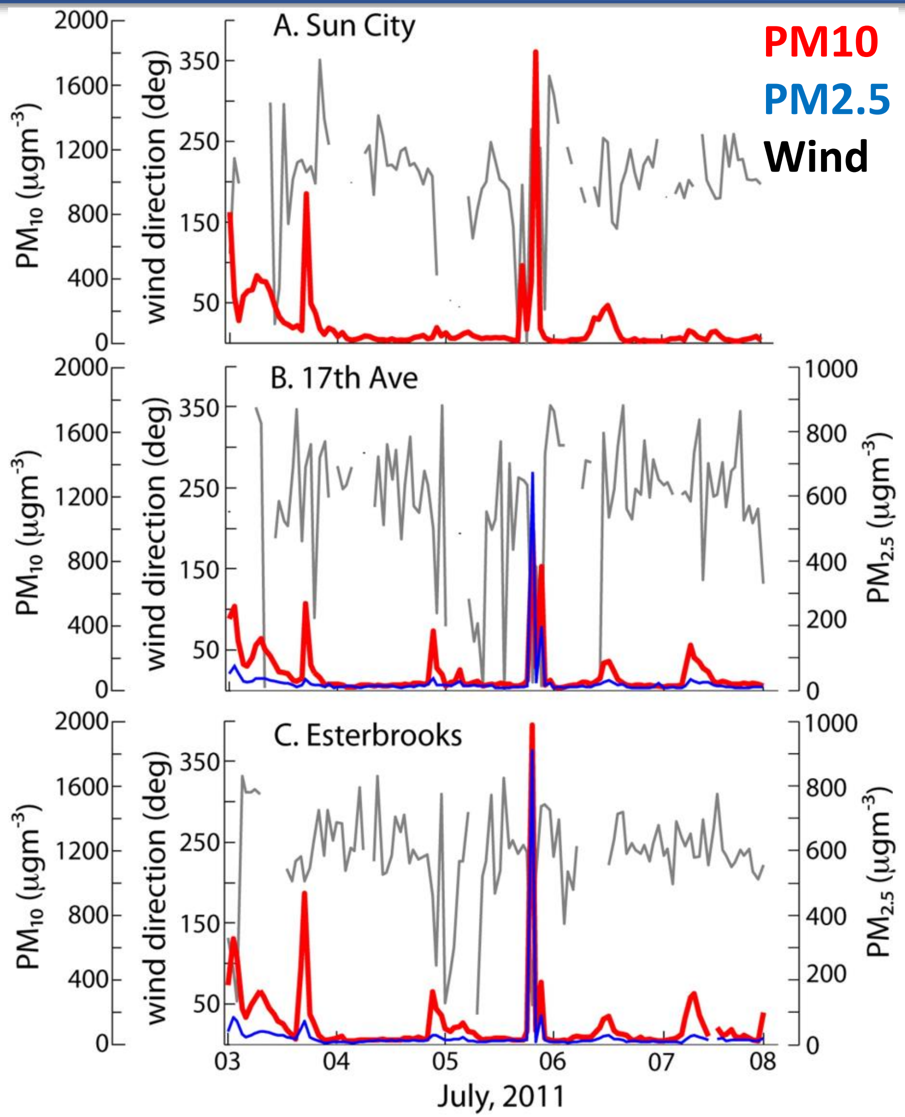


- Improvements to parameters [Johnson et al. 2019]
- Direct assimilation (e.g. AOD)
- Inversion for emission
- Identify key mechanisms for aerosols

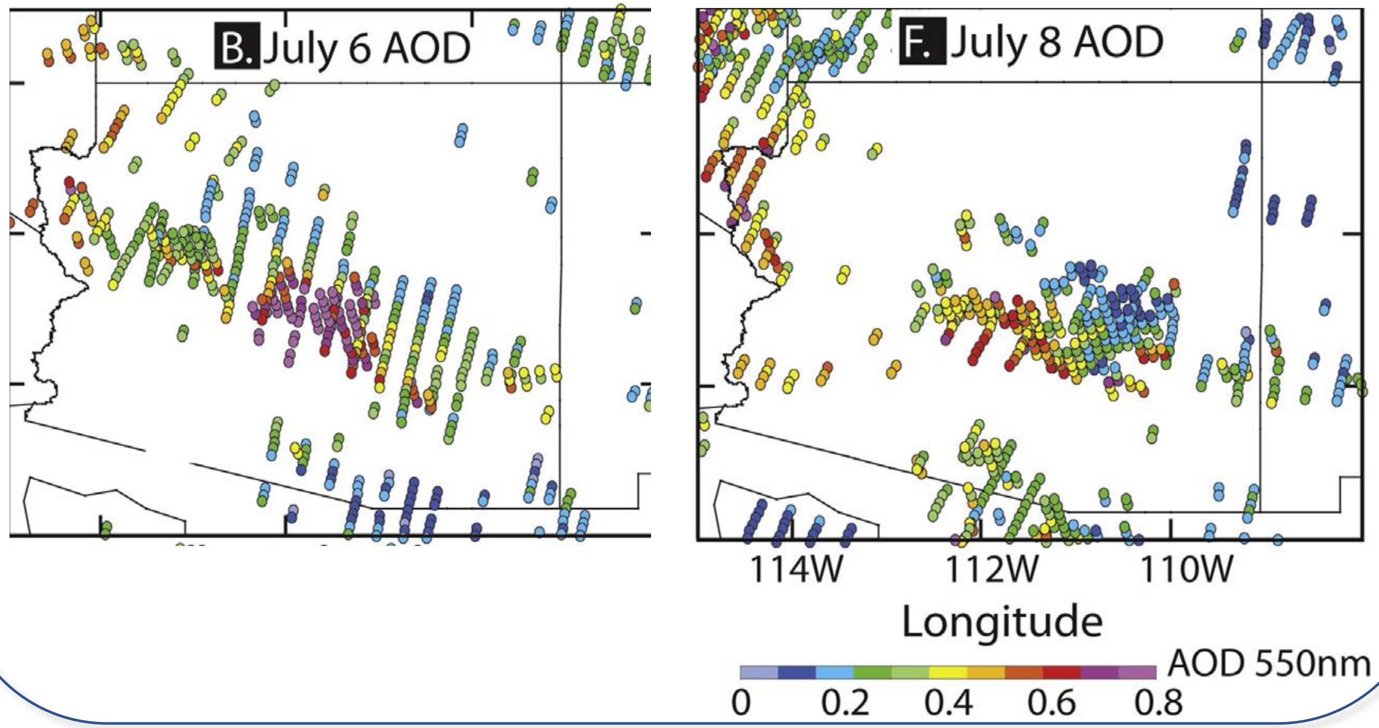
Aerosol regional modeling

Case study of dust storms in Arizona : Mile high wall of dust hits Phoenix

Aerosol optical properties, dust concentrations, and transport

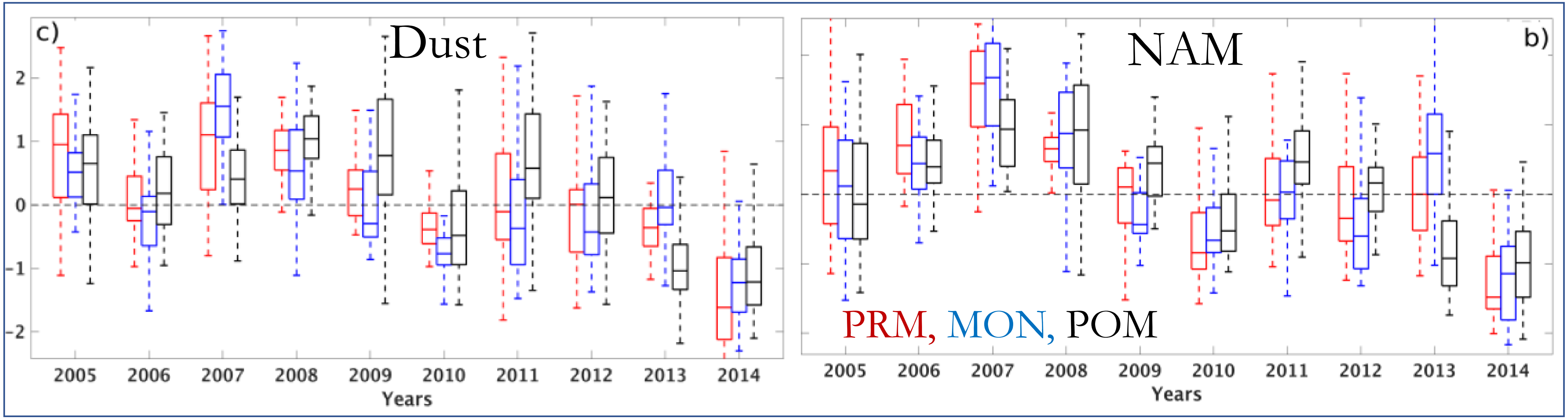


MODIS AOD (Terra + Aqua)



A. Raman et al., 2014

Aerosol trends over the dusty SouthWest

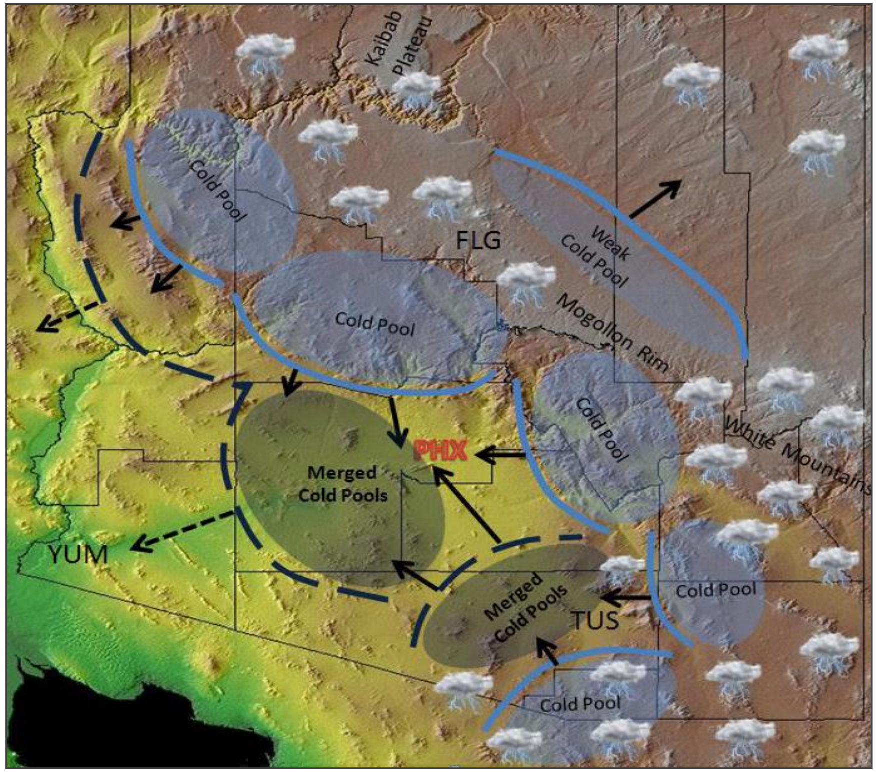


Change in TERRA AOD Standardized anomaly over a decade shows statistically significant decrease in anomalies over dusty hotspots and North American Monsoon (NAM) alley for pre-monsoon and monsoon.

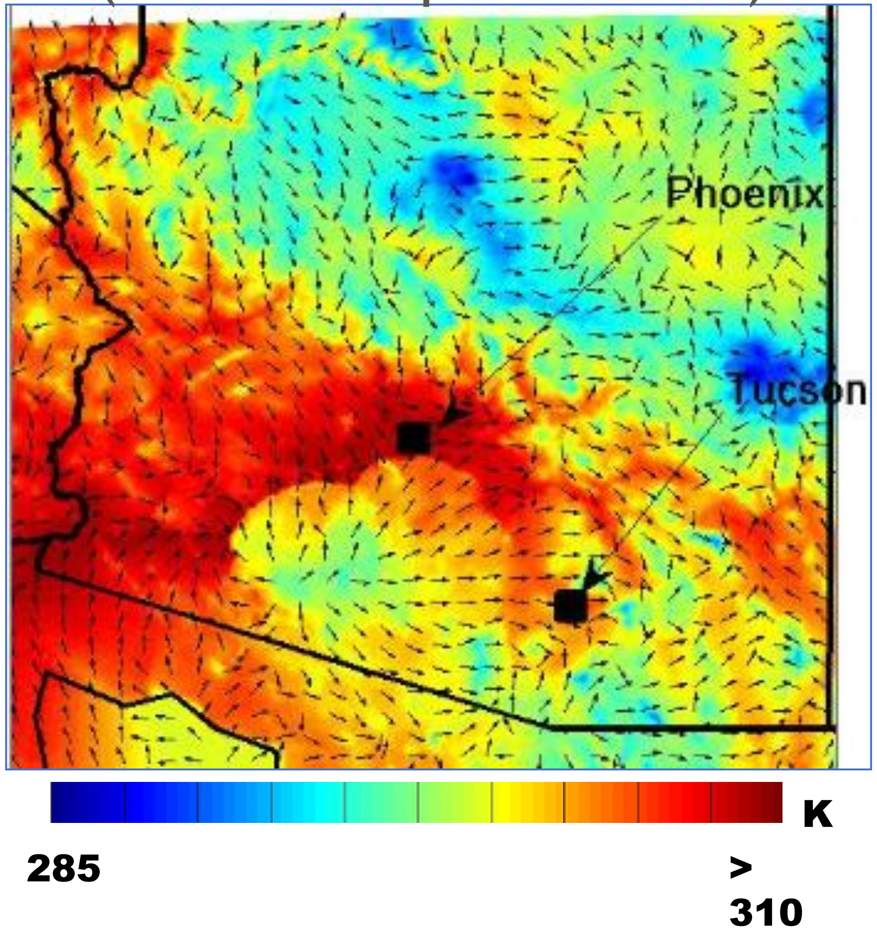
A. Raman et al., 2016

Modeling of Arizona dust storms

Conceptual Diagram of Cold Pool Formation and Movement



WRF-Chem Simulated Cold Pool (2011/07/05 8pm Local Time)



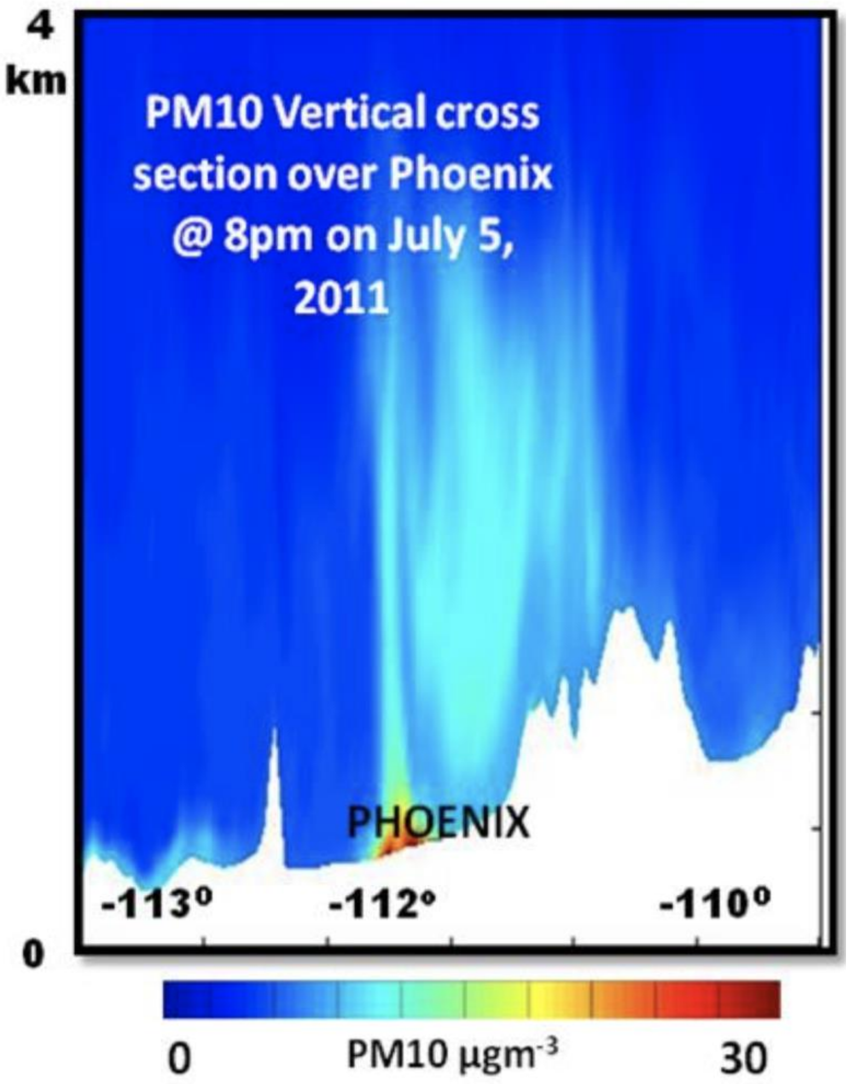
WRF-Chem 1.2 km inner domain simulation of July 5, 2011 haboob

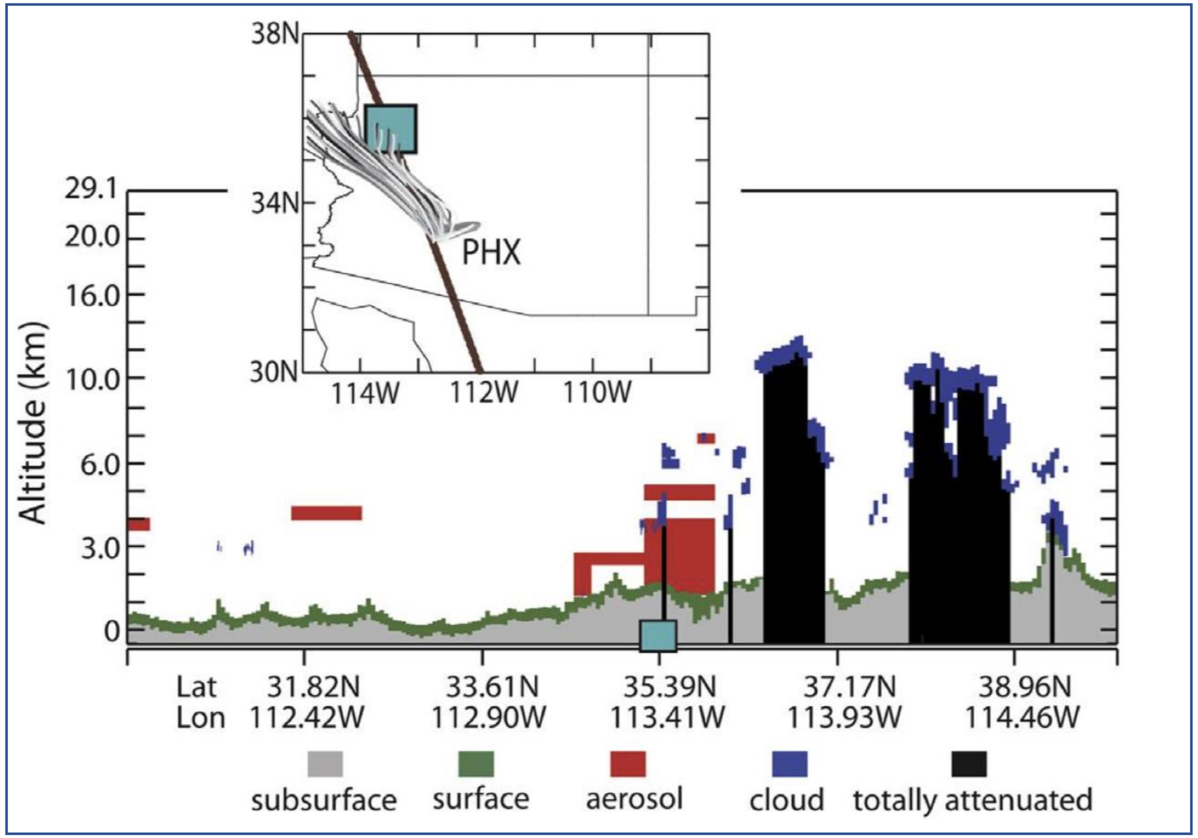
- Decrease in 2m temperature
- Downbursts and surface divergence
- Dust uplift

Strong SE winds 23-25ms^{-1} and cold pool development !

Lader, G., A. Raman et al., 2016 NOAA Tech memo NWS-WR 290

Modeling of Arizona dust storms (Contd)



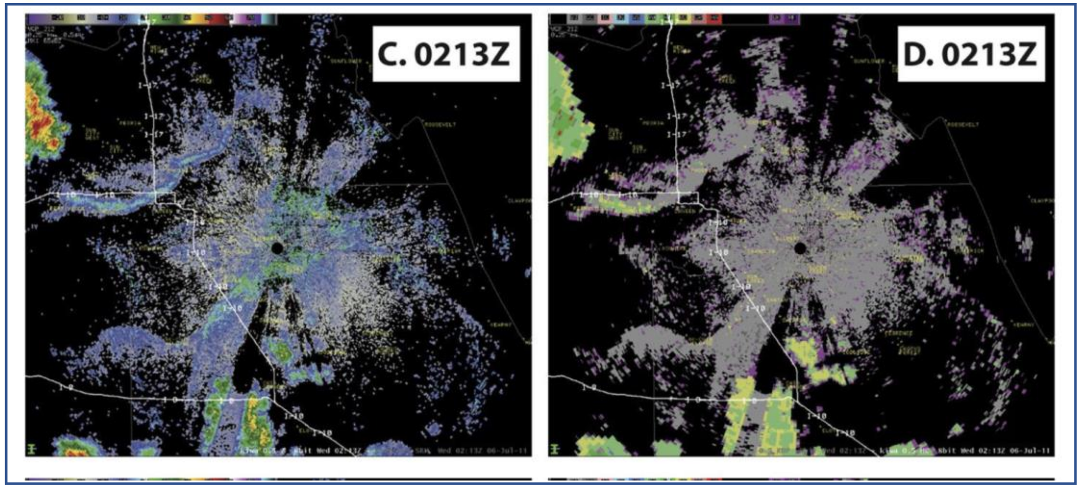


HYSPLIT ensemble trajectories of dust transported from Phoenix to Northwestern AZ. Also seen from CALIPSO aerosol classification

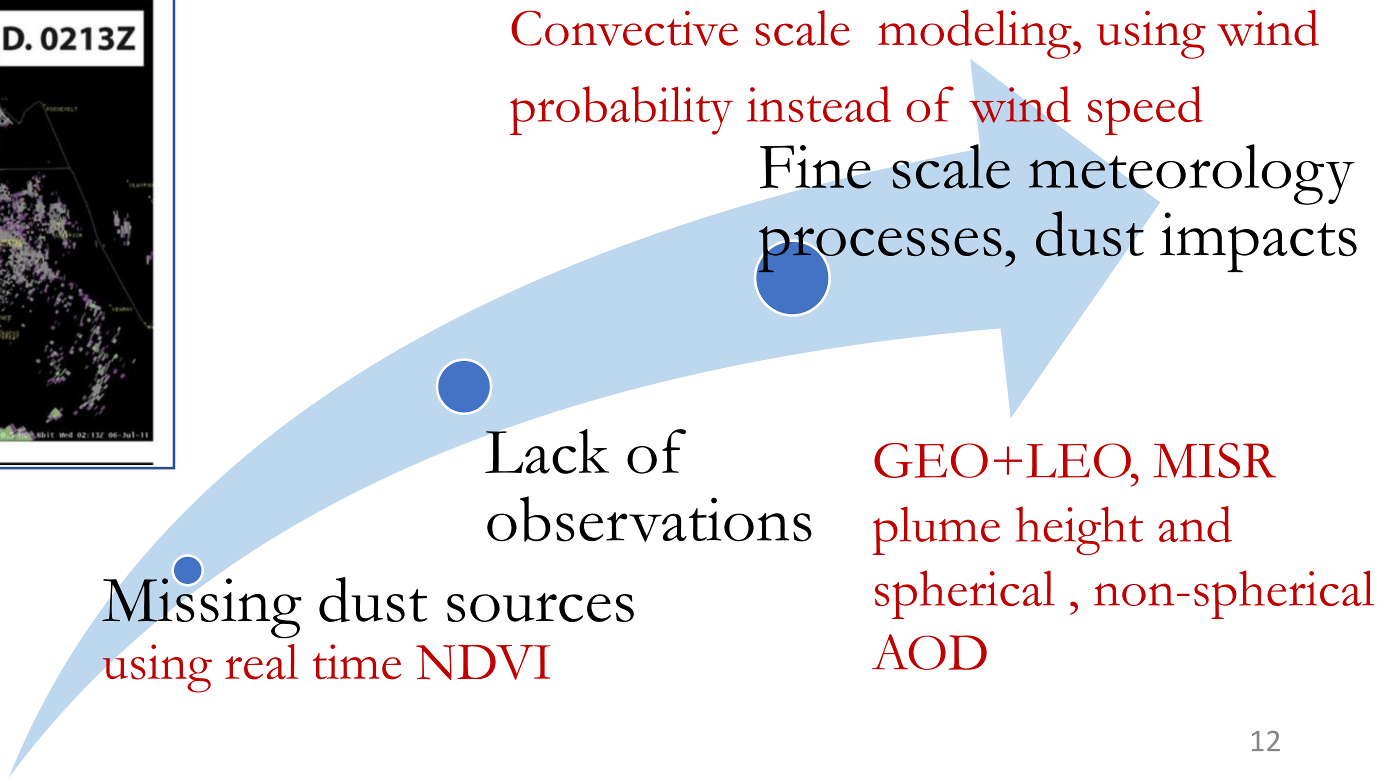
Limitations and future direction

$$F = CSsp\,(u_{10} - u_{*t})\,u_{10}^2 \quad if\ u_{10} > u_{*t}$$

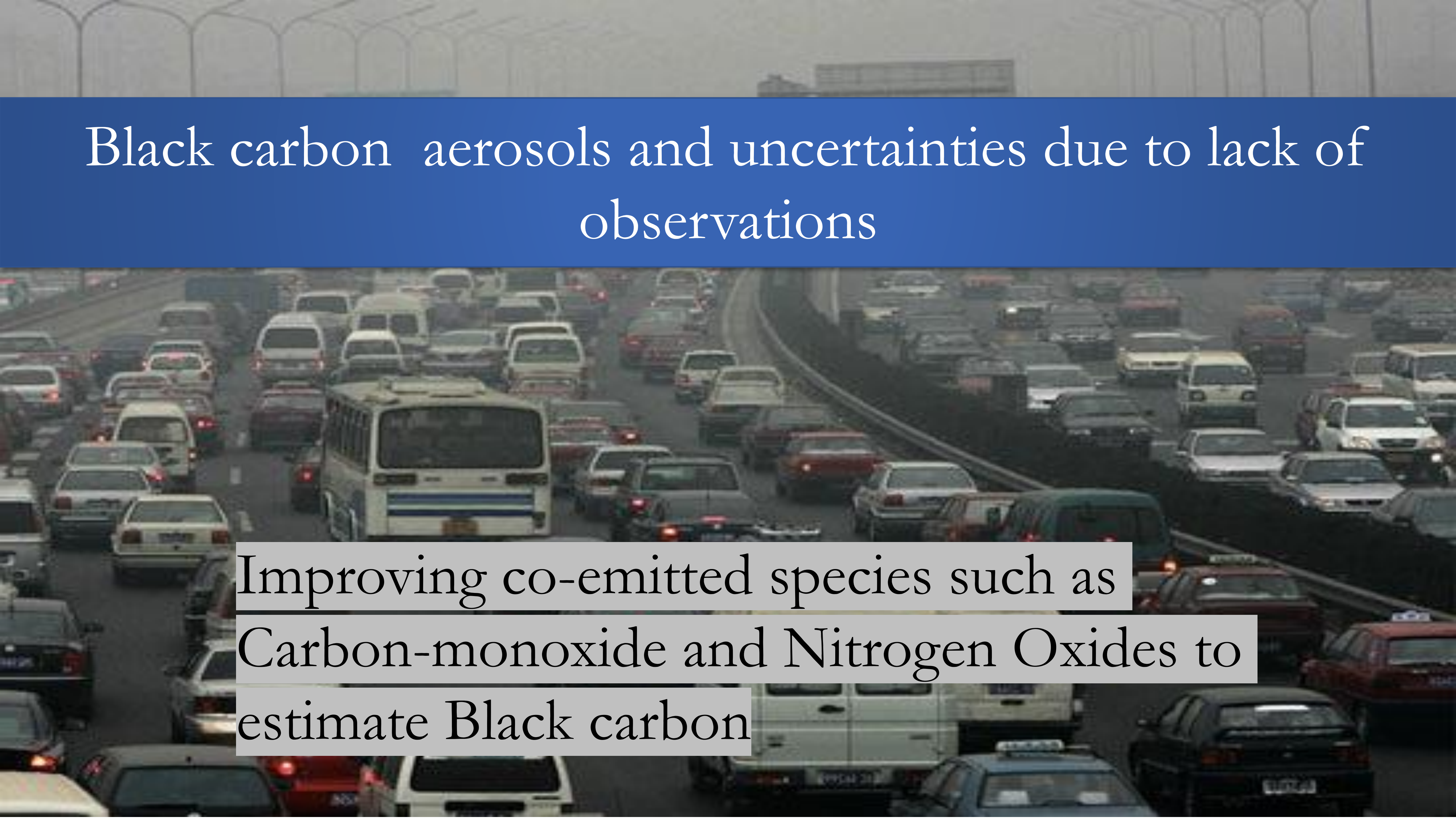
S is the erodibility, sp is the fraction of soil composition, u10 is the 10m wind speed, u*t is the threshold wind friction velocity, and C is a tunable constant



Dual-pole radar reflectivities and hydrometeor classification



Black carbon aerosols and uncertainties due to lack of observations

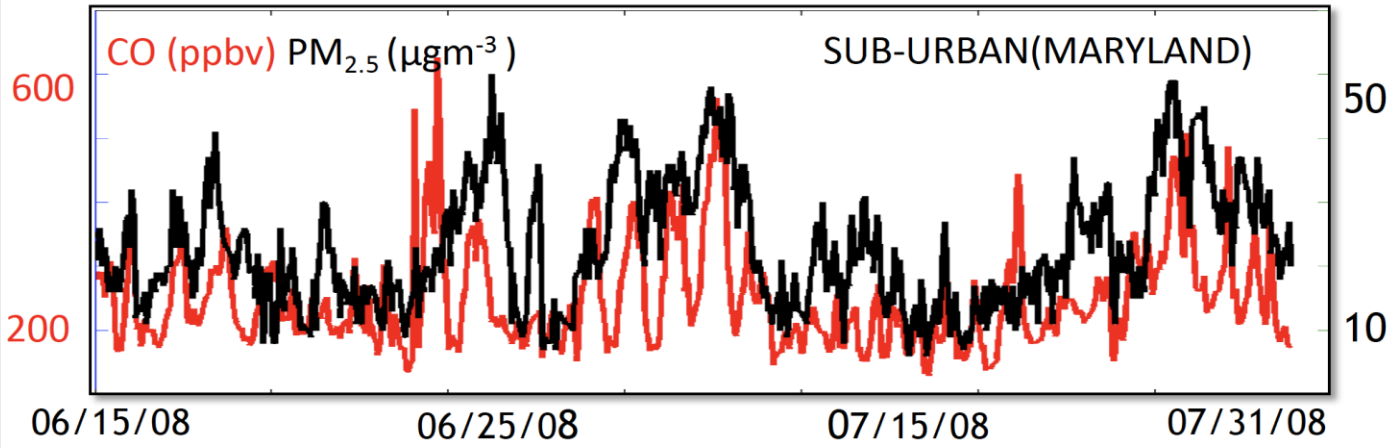


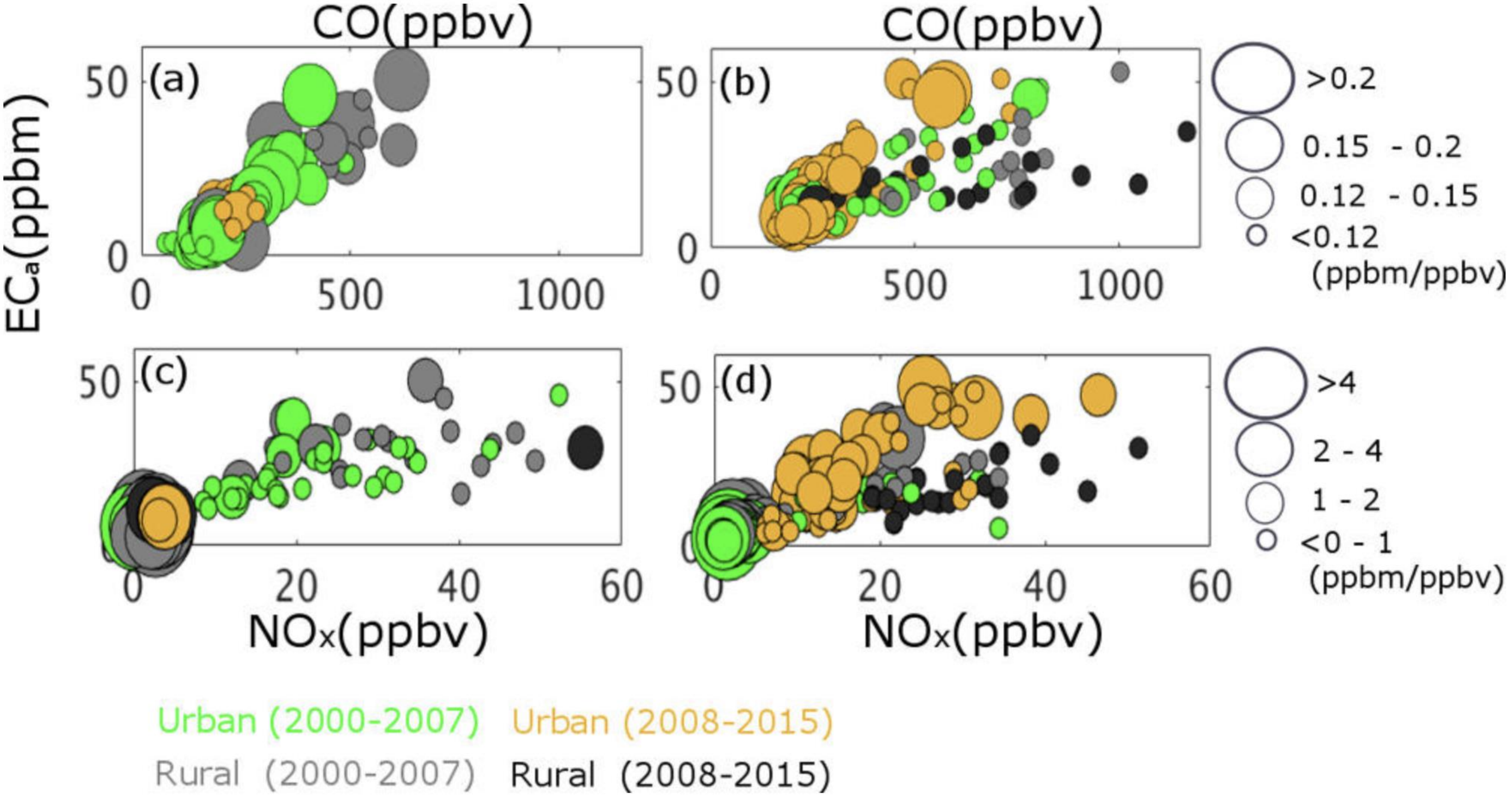
Improving co-emitted species such as Carbon-monoxide and Nitrogen Oxides to estimate Black carbon

Black carbon aerosols : Requirements for observations

- Reductions in BC, $PM_{2.5}$ (PM 2.5 µm or less in diameter) emissions from on-road diesel engines have not been significant (e.g. Dallmann, T. R. and Harley, R. A, 2010).
- Large uncertainties in BC mixing state in aerosol models.

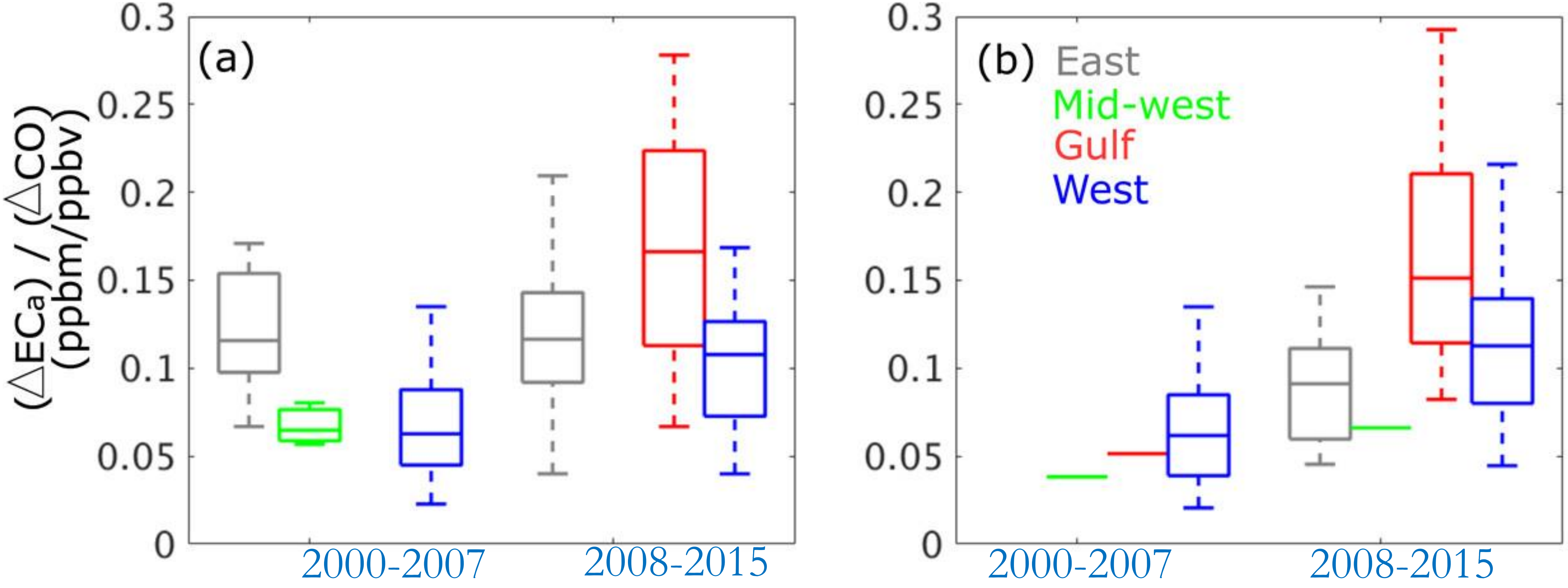
Using co-emitted species





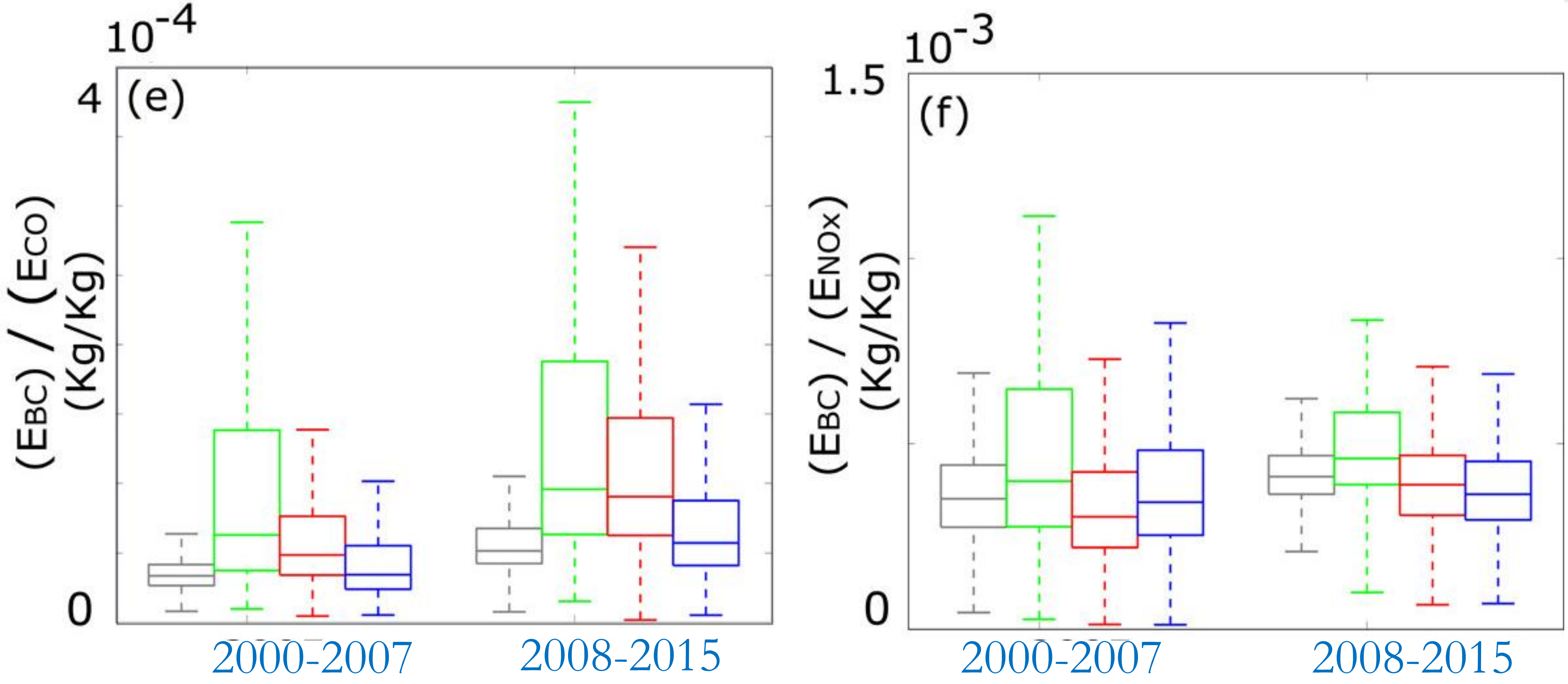
A. Raman and A.F. Arellano., 2017

Co-emitted gases : Utility in Elemental carbon enhancement trends



A. Raman and A.F. Arellano., 2017

Co-emitted gases : Utility in BC emission trends (Contd)

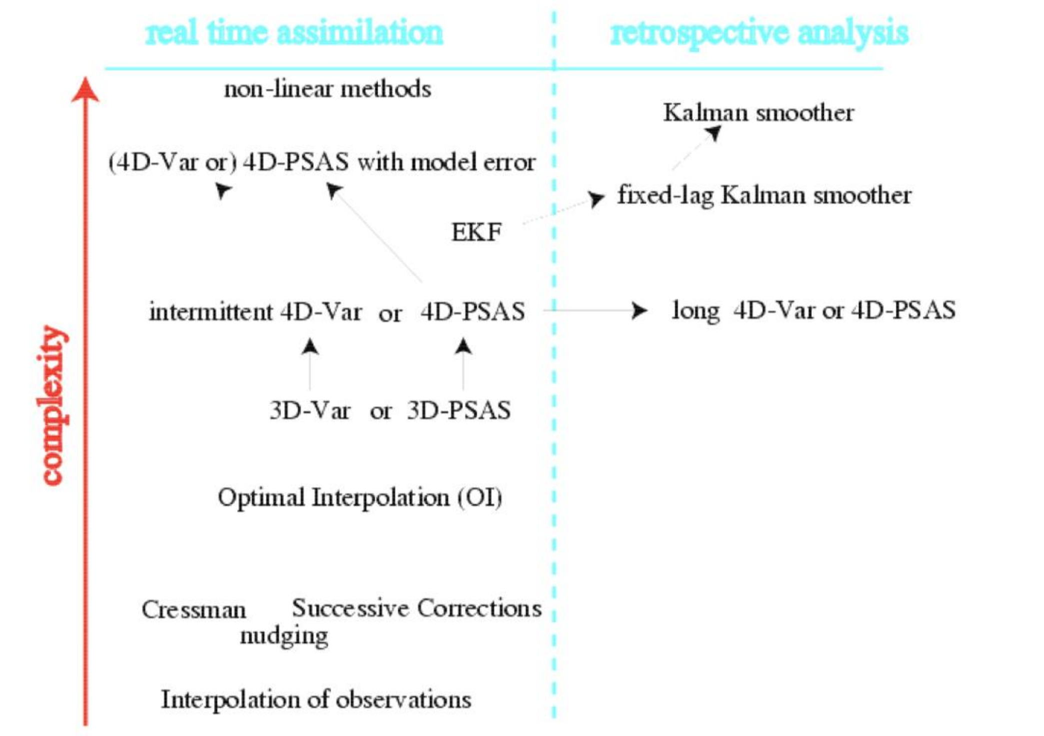


A. Raman and A.F. Arellano., 2017

Take home messages

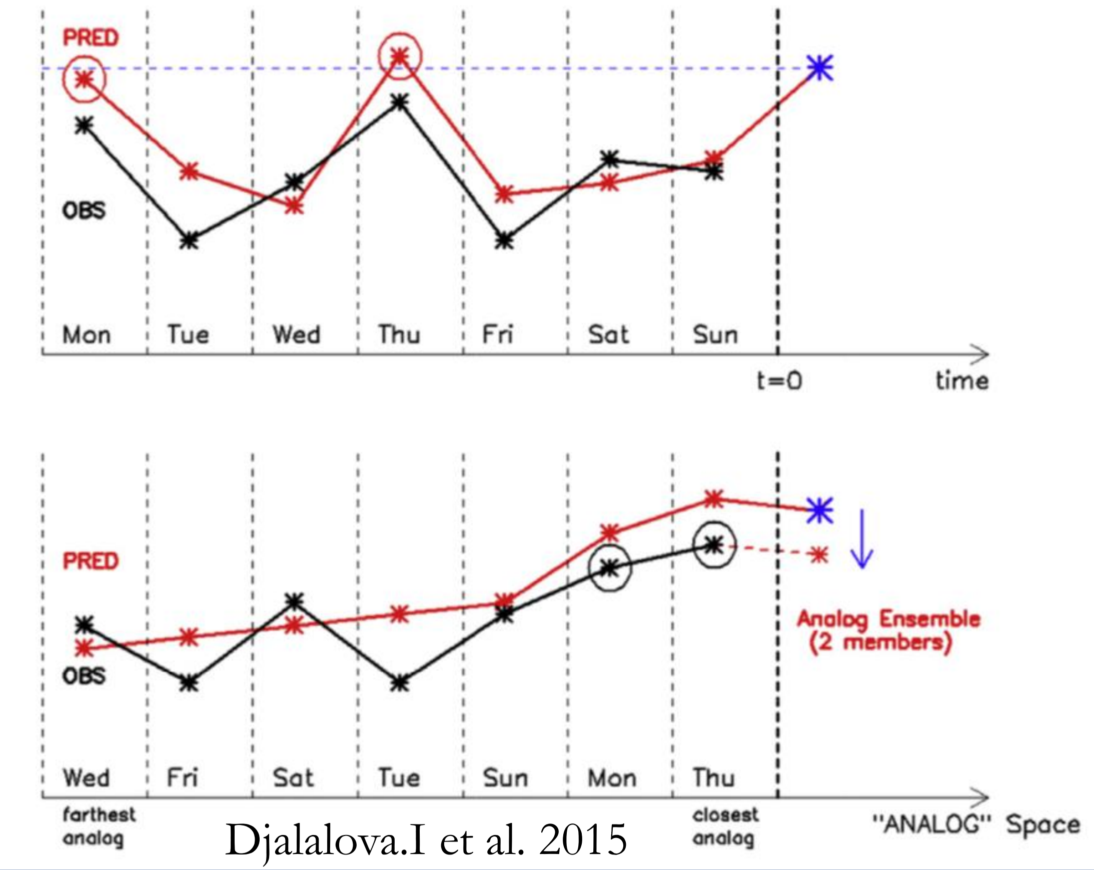
- CO and NO_x provide a novel pathway to improve observational coverage for sparsely measured , co-emitted aerosol species like Black Carbon.
- Such approach can significantly improve characterization of black carbon aerosol sources from satellite retrievals due to ample measurements of CO and NO_x from space.
- Developing tracers for regional and sectoral CO in addition to total CO can improve source attribution and emission fluxes for black carbon aerosol in models.

Combining models and observations



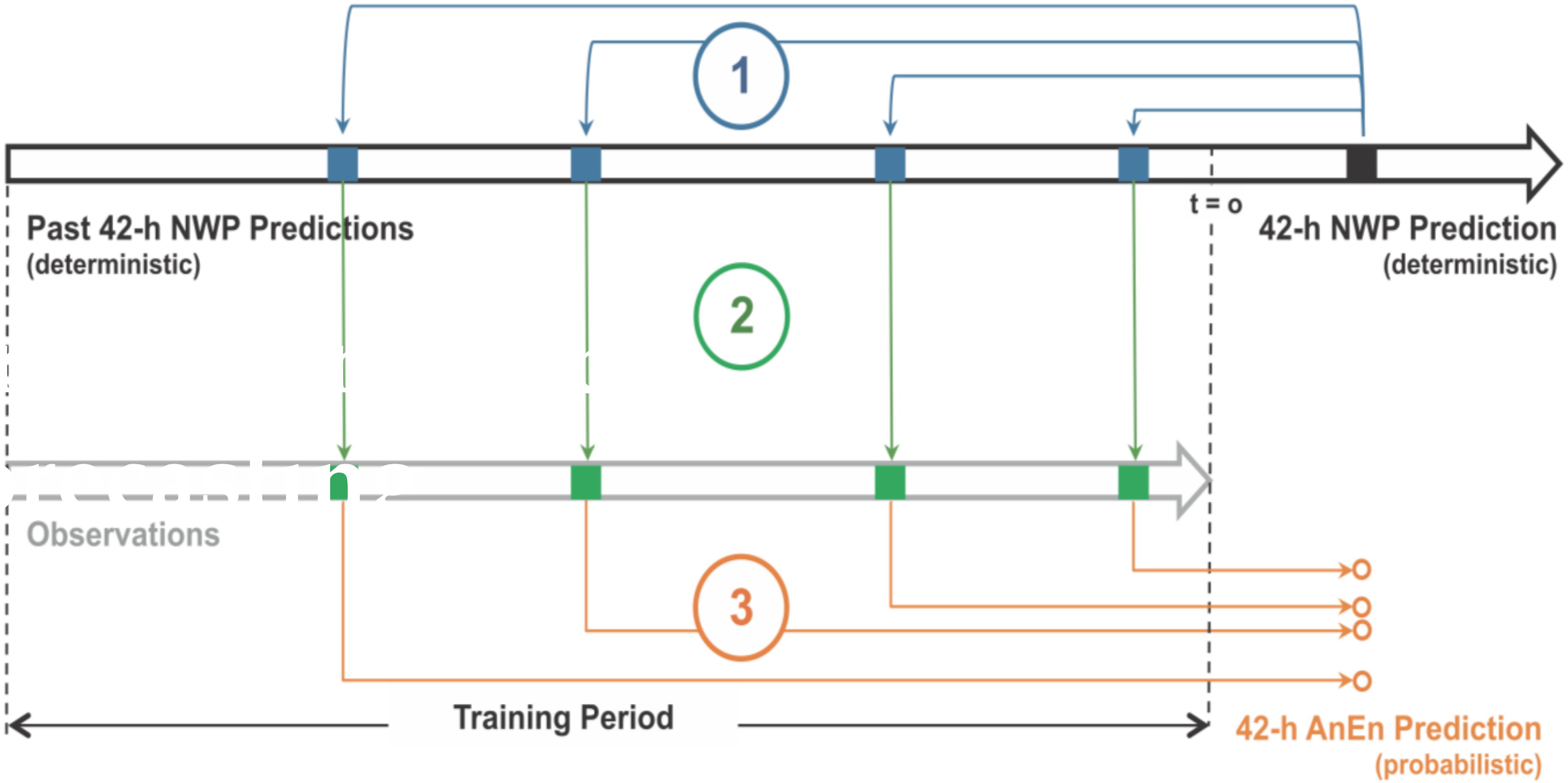
Bouttier and Courtier, 1999

Analog Ensemble Forecasting



Djalalova.I et al. 2015

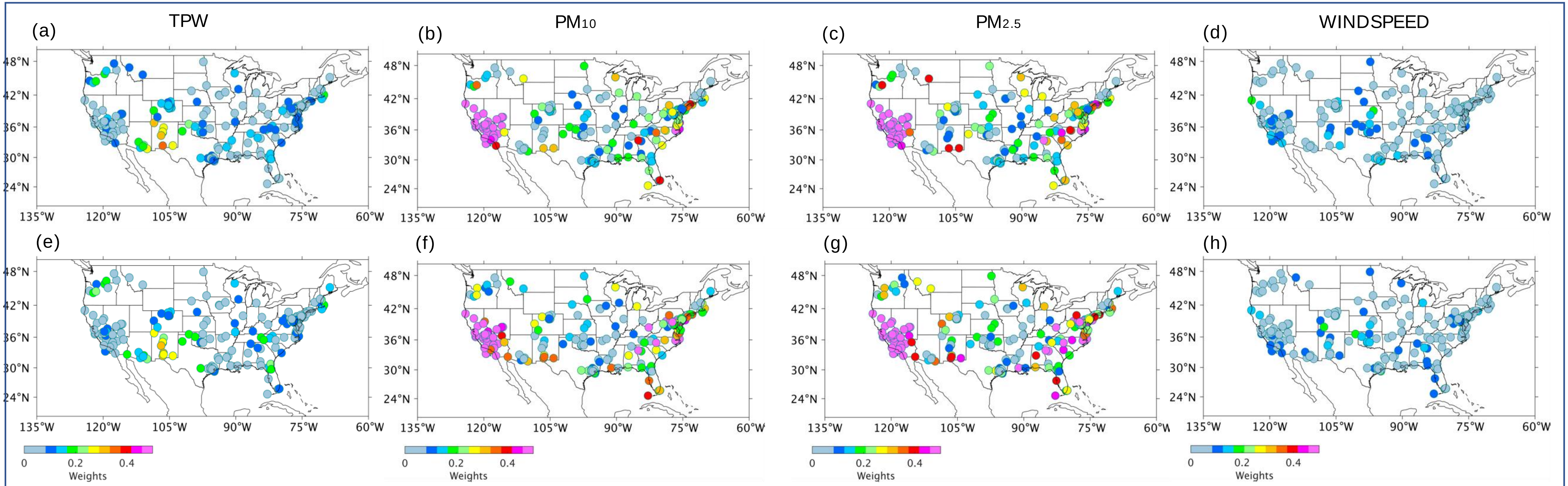
Analog Ensemble Forecasting



Analog Kalman Filter operates on the analog set of forecasts and the predicted errors in the historical forecasts

Delle Monache et al. 2011
Delle Monache et al. 2006

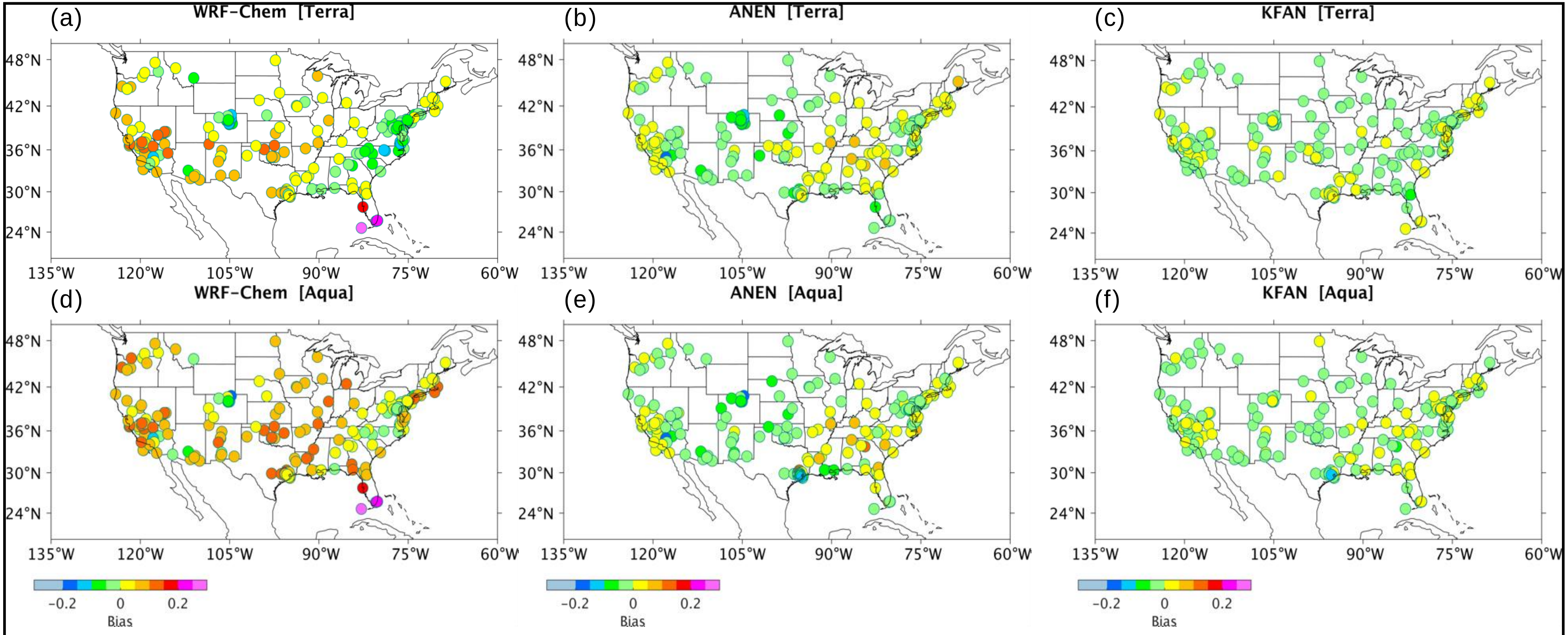
Predictor weights correspond to AOD-predictor correlation in the model



Correlation values of AOD and predictors . (a) AOD Vs Total Precipitable Water, (b) AOD Vs PM_{10} , (c) AOD Vs $PM_{2.5}$, and (d) AOD Vs Horizontal windspeed at the surface collocated for Terra overpass time. (e) - (h) Similar to (a) - (d) but for Aqua over pass time

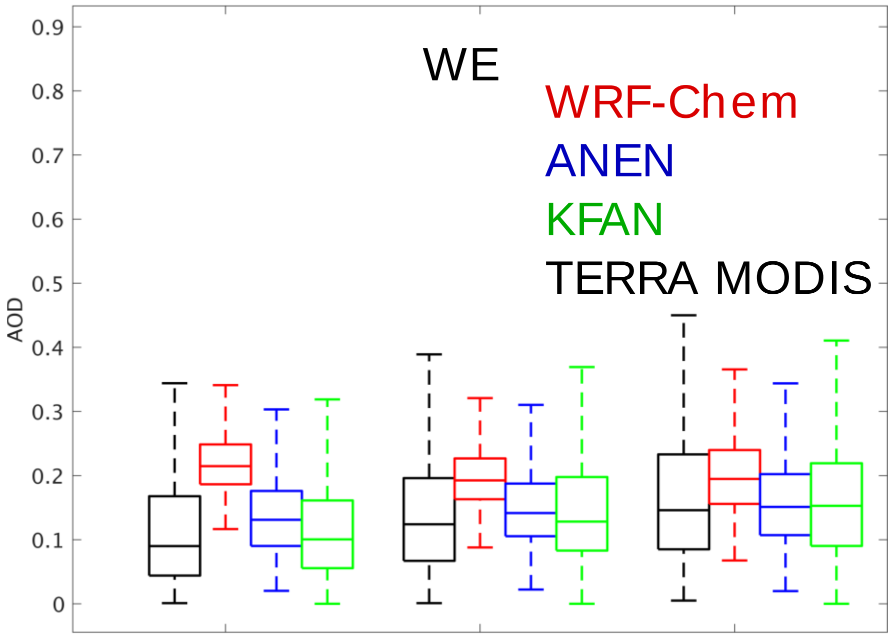
A. Raman et al., in prep

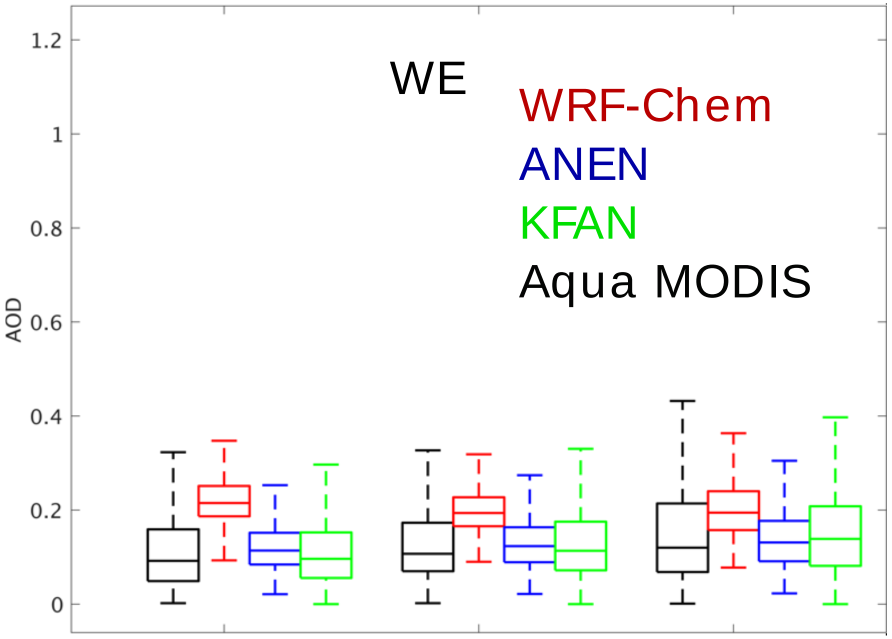
Analog Ensemble Forecasting : Results



Mean bias (Model - Observation) for June - august, 2012 from WRF-Chem (a,d), ANEN (b,e), and KFAN (c,d) for points collocated with Terra (top) and Aqua (bottom) respectively.

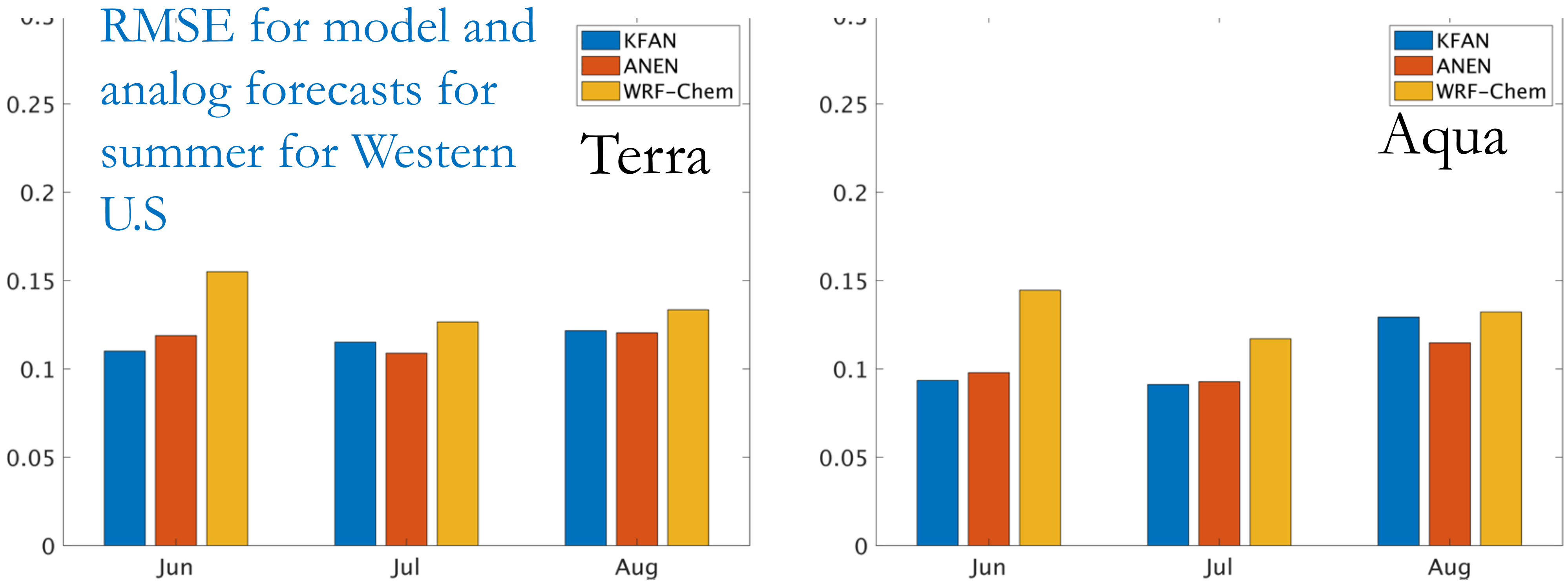
Analog Ensemble Forecasting : Meteorology driven aerosols





Boxplot of AOD from MODIS, WRF-Chem , ANEN, and KFAN for June-August, 2012
Midline in the boxplot represents the median of AOD , top and bottom lines of the box represents 25th and 75th percentile, and top and bottom lines outside the box represents maximum and minimum values of AOD that are not outliers. The boxplots are shown for different EPA regions and outliers are not shown here.

Analog Ensemble Forecasting : Meteorology driven aerosols



Change in RMSE is ~ 30% for June and July. Smaller reduction for August is due to the higher relative humidity (RH) during this period across U.S and the model errors in accurately predicting the total precipitable water and effects of higher on RH on model AOD.

Take home messages

- Analog Ensemble forecasting with a combination of Kalman Filter provides improvement in AOD in seasons when AOD is mostly driven by wind and aerosol emissions.

- Despite the strong dependence on observations, analogs are heavily driven by the choice and quality of the predictors which is evident from the case of U.S East coast where during the month of August, errors in model predictions of precipitable water and wet scavenging prohibits improvement to AOD.

Aerosol global modeling

Implementing a process driven sea salt aerosol emission parameterization in GEOS

Whitecap fraction : Area of the ocean surface covered by active wave breaking (Stage A or active) and mature foam (stage b).

Sea salt emissions =

$f\ (Whitecap\ fraction)$

f (Size distribution of sea salt particles)

Whitecap models : Wind dependence

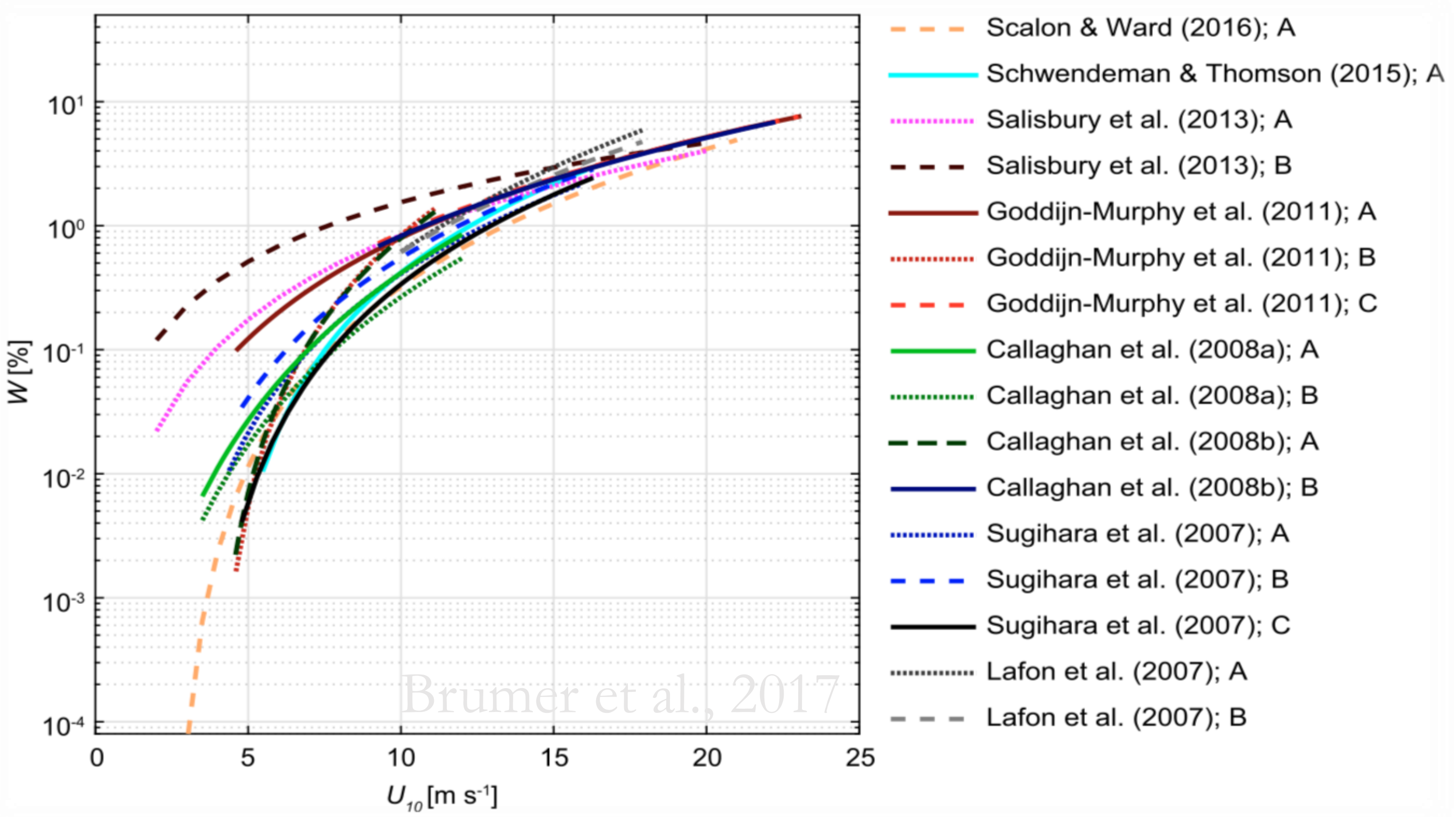
At a given wind speed, W variability is ~1-2 orders of magnitude

(e.g. Monahan, 1971)

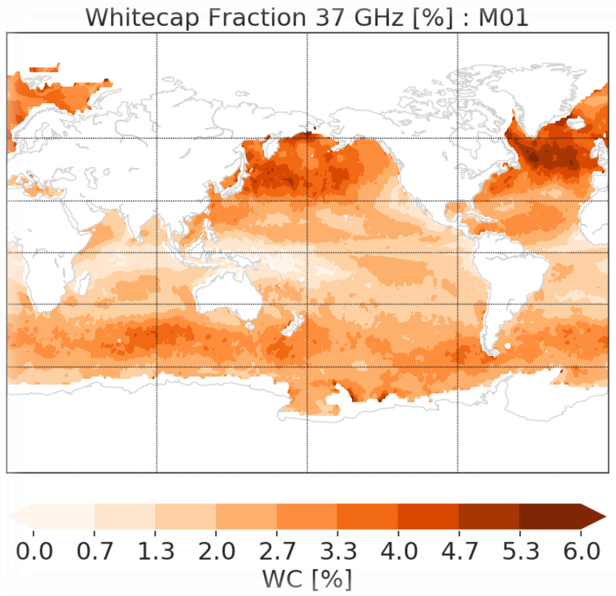
(e.g. Wu, 1988)

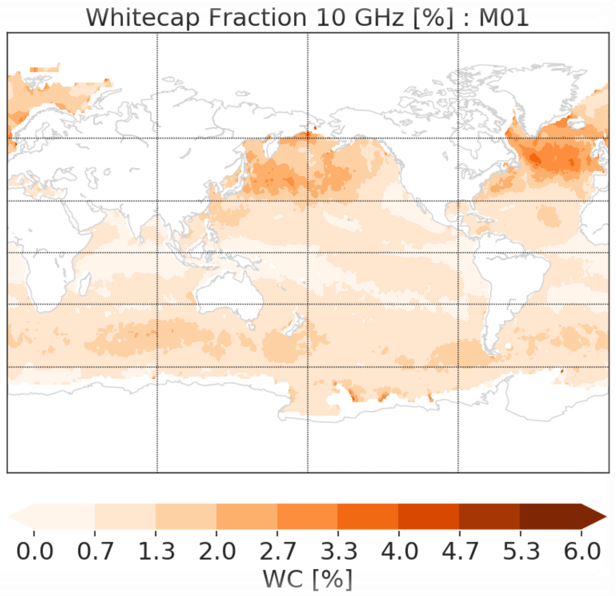
(Goddijn-Murphy et al. (2011))

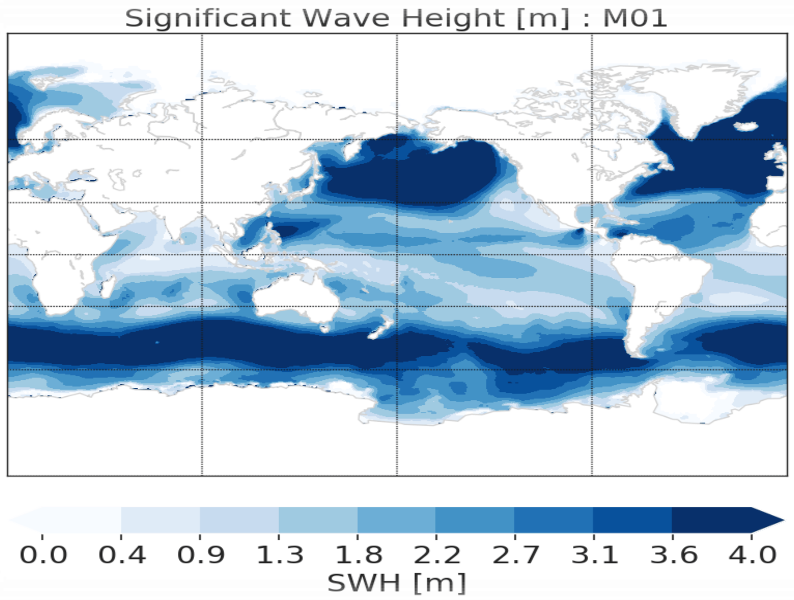
(e.g. Callaghan et al., 2008)



Observation constrained modeling





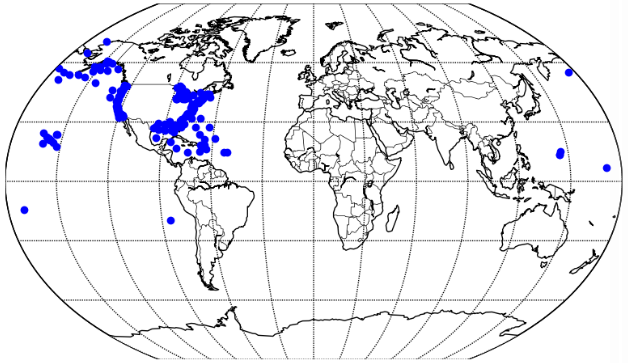


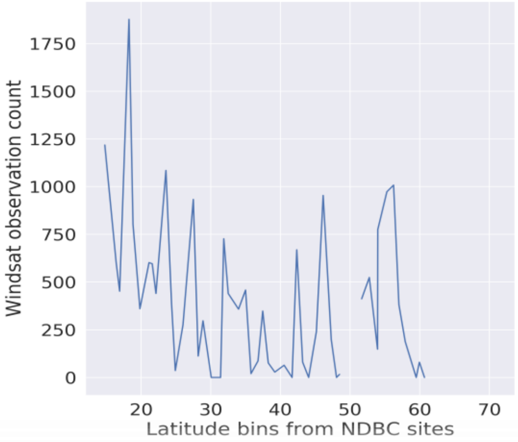
- Windsat W : 1° x 1° multi –frequency retrievals [Anguelova et al., 2019]
- 10 GHz includes more active W and 37 GHz include fresh + mature (foam) W

- GEOS-UMWM
  - 0.5° x 0.5° resolution runs for 2014 replayed to MERRA-2
  - Wind, sea-ice, air density input to UMWM from GEOS

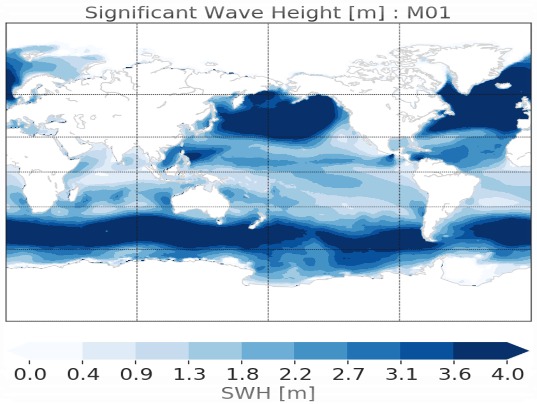
W parameterization development

NDBC Wind/wave collocated stations





Sample GEOS-UMWM at NDBC



Model fitting

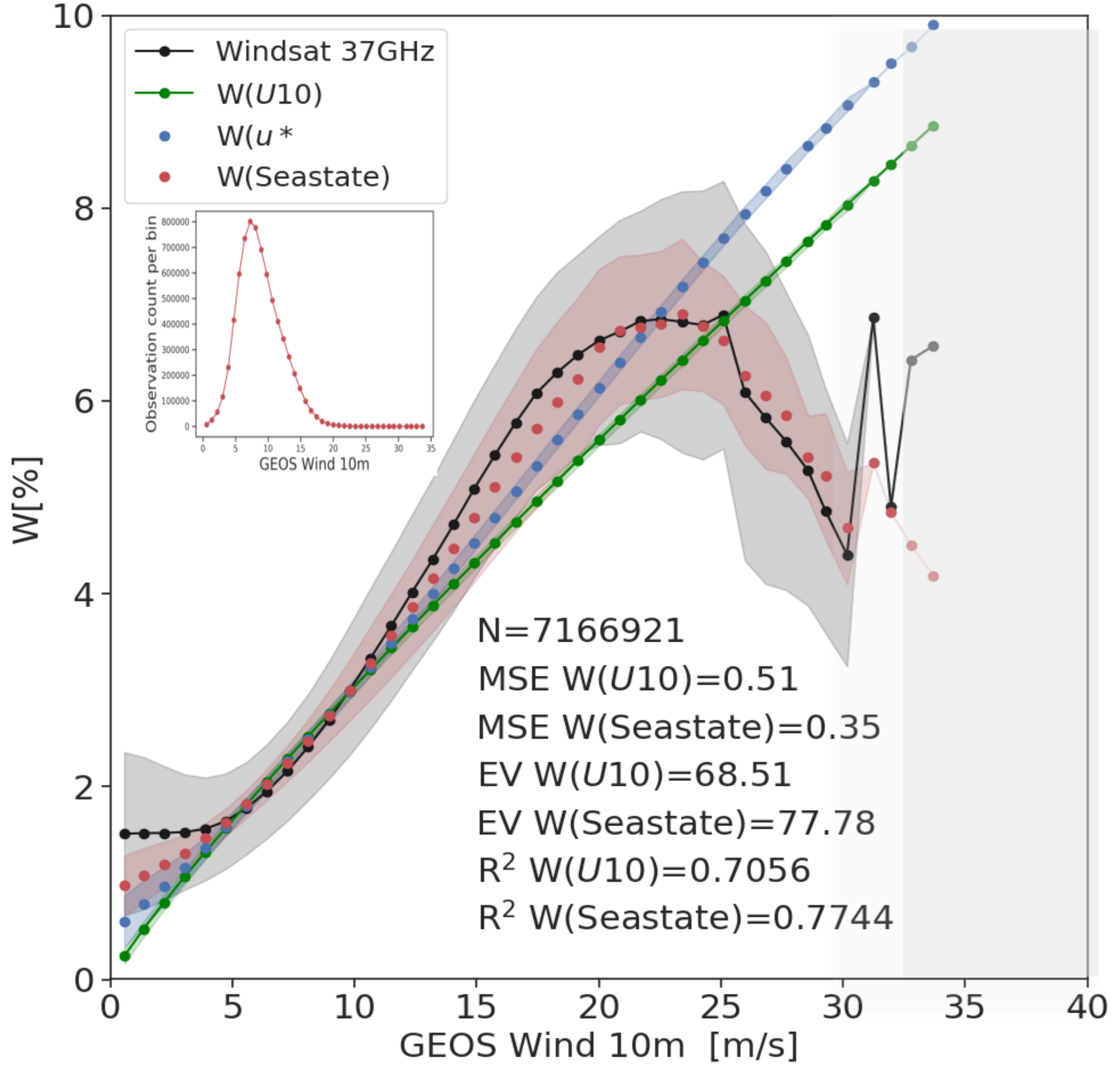
Steepness, Re, dissipation rate, peak, air-sea temperature difference, peak wave velocity

Test against independent Windsat W

A. Raman and A. Darmenov , in prep

Variability with wind speed

- Whitecap decreases for higher windspeed.
- In order to capture this behavior in models, additional terms based on wind stress were added to the Seastate W model for wind speed > 20 m/s.



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Aerosols as a part of the Earth System : What do we need from models and observations?

- Observations of vertical profiles of aerosol concentrations and number distribution.
- Point by point data uncertainties from satellite retrievals.
- Ensemble Forecasting of aerosols
- Use of aerosol products from satellites to improve model parameterizations in addition to direct assimilation of AOD [e.g. R.Kahn , 2020]

Acknowledgements

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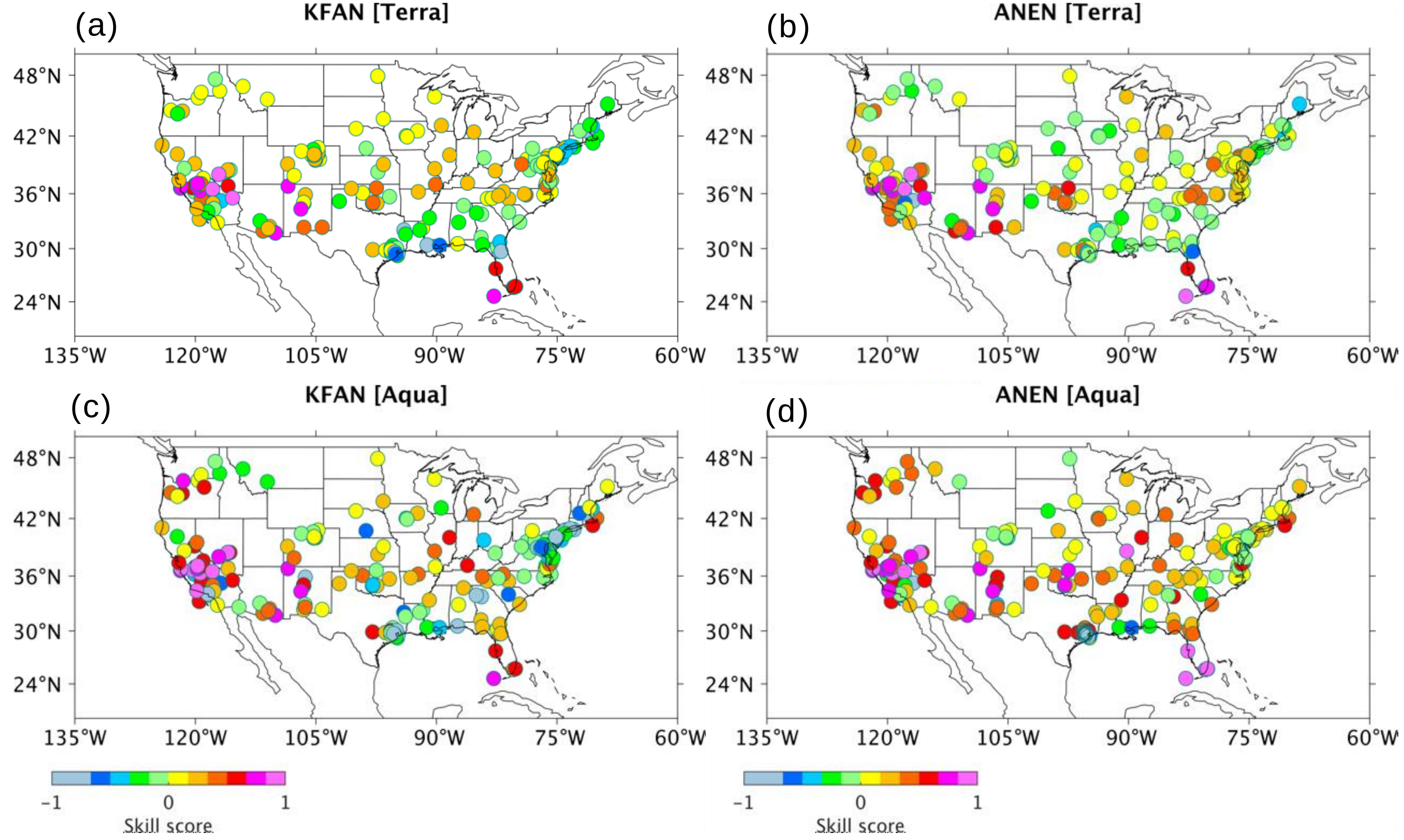
Thanks to Magadalena Anguelova, NRL for Windsat retrievals.

Thank you

Extra slides

Importance of meteorology for aerosol analogs



Skillscore for analog predictions of AOD for June-August, 2012. Skill score is calculated here using Mean Square Errors in comparison with MODIS Terra and Aqua retrievals. (a , b) KFAN and ANEN AOD estimated with reference to WRF-Chem AOD Mean Square Errors for Terra overpass. (c, d) similar to (a, b) for Aqua overpass.

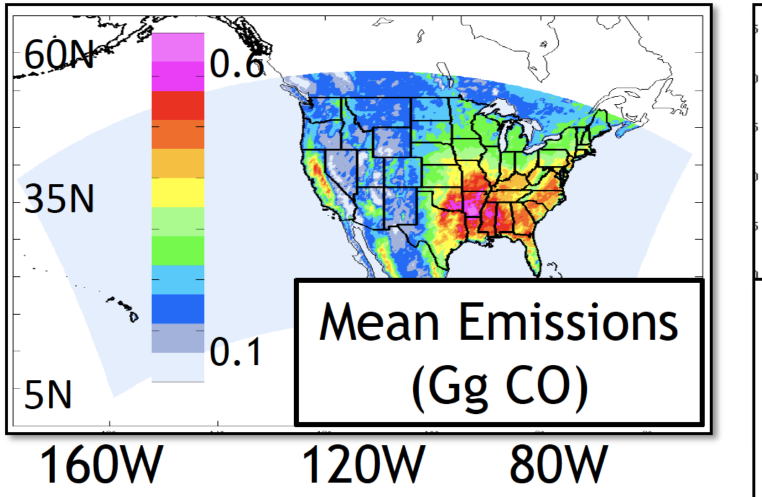
Negative skill scores in the East coast:

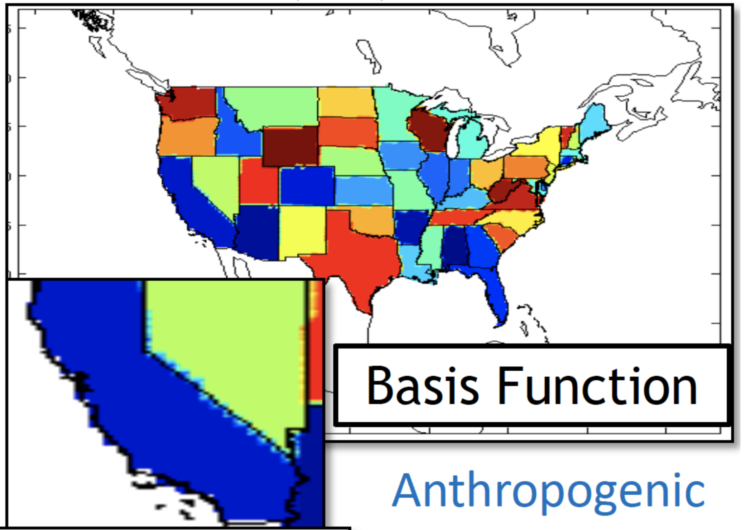
- Strong correlation with meteorology, in particular precipitable water

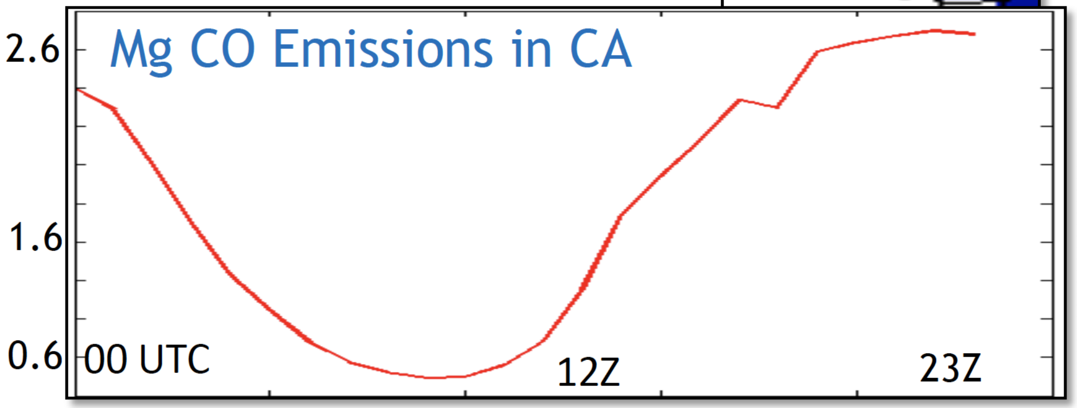
- Impact of wet scavenging processes.

Using $PM_{2.5}$/CO ratios in WRF-Chem to improve $PM_{2.5}$ concentrations

Bayesian Synthesis Inversion : Methodology illustration : Prior CO emissions (Xa)



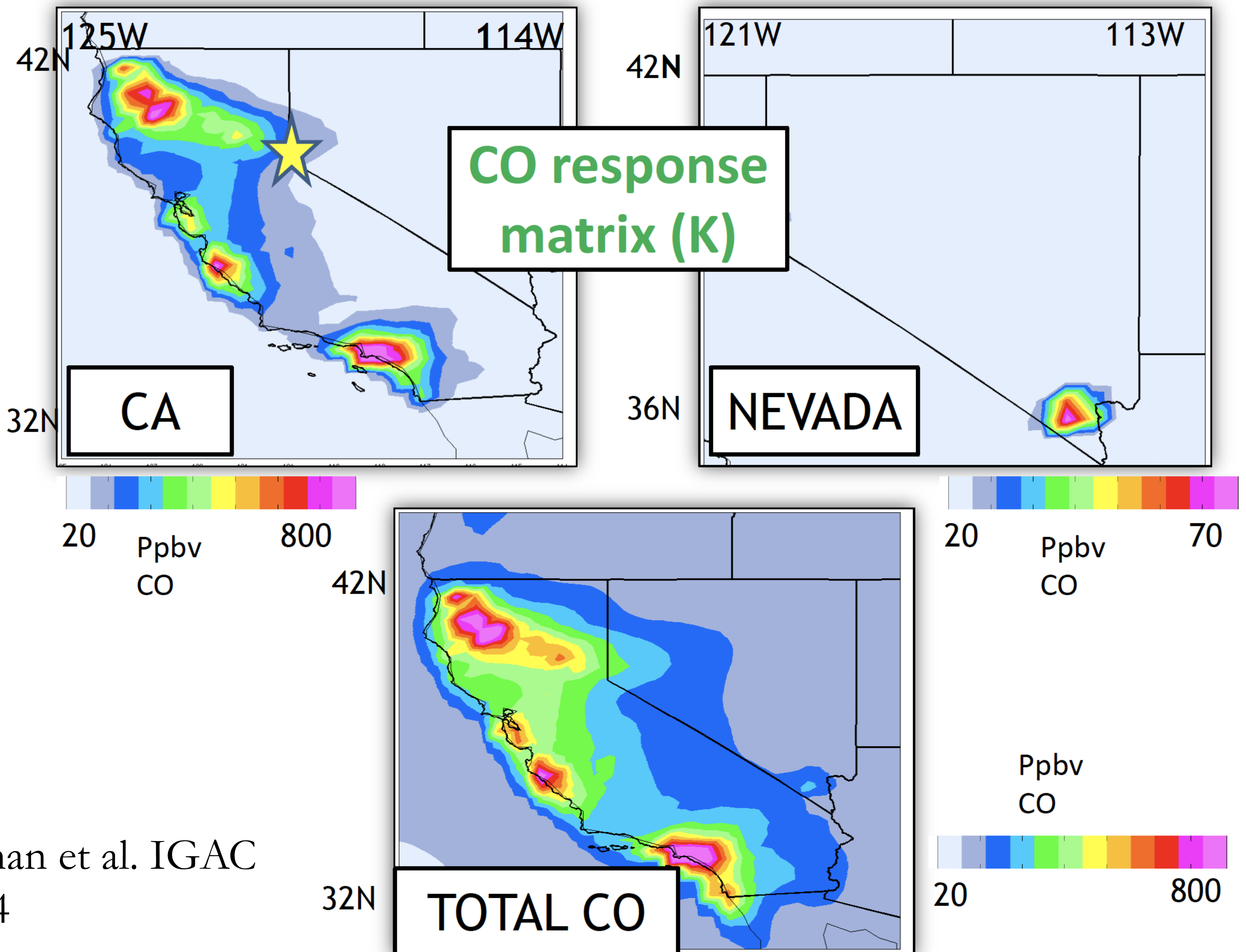




Anthropogenic emissions : NEI 2005

Fire : FINN

Biogenic : Megan



A. Raman et al. IGAC 2014

Optimizing PM given CO observations

- Information from the observed relationship between CO and PM
- Modeled responses K from a set of source basis functions
- An estimate of the change in emissions from a source inversion of CO.

$$\boldsymbol{p(PM|EPA\,CO)} \propto \boldsymbol{p(PM|CO)} \times \boldsymbol{p(CO|CO_{emis})} \times \boldsymbol{p(CO_{emis}|EPA\,CO)}$$

Mean and covariance of the estimate are given by

$$\hat{X} = X_a + \boldsymbol{Sa}\,(\boldsymbol{K})^{\boldsymbol{T}}\,[(\boldsymbol{K})\,\boldsymbol{S_a}(\boldsymbol{K})^{\boldsymbol{T}} + \boldsymbol{S_e}]^{-1}\,[\boldsymbol{Y} - (\boldsymbol{K})\boldsymbol{X_a}]$$

$$\hat{\boldsymbol{S}} = \left[(\boldsymbol{K})^{\boldsymbol{T}}\boldsymbol{S_e^{-1}}(\boldsymbol{K}) + \boldsymbol{S_a^{-1}}\right]^{-1}$$

Where Sa is the prior error covariance and Se is the observational error covariance.

Results

- Reductions in prior emissions in the New England mostly due to anthropogenic emissions.
- Huge increase in posterior emissions in Western US caused by biomass burning.