# Chemical Data Assimilation - The Need for Closer Integration of Measurements and Models

Greg Carmichael, Dept. Chemical & Biochemical Engineering
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University of Iowa


*This picture, adapted from Katsushika Hokusai's masterpiece "The Great Wave off Kanagawa," artistically displays the spirit of supercomputing. Complex phenomena, such as waves on the surface of a fluid, are modeled by covering space with a grid and then solving the laws of physics at discrete points on that grid. The finer the grid, the closer the numerical simulation is to the actual solutions of the mathematical laws of nature that govern the physical world.*

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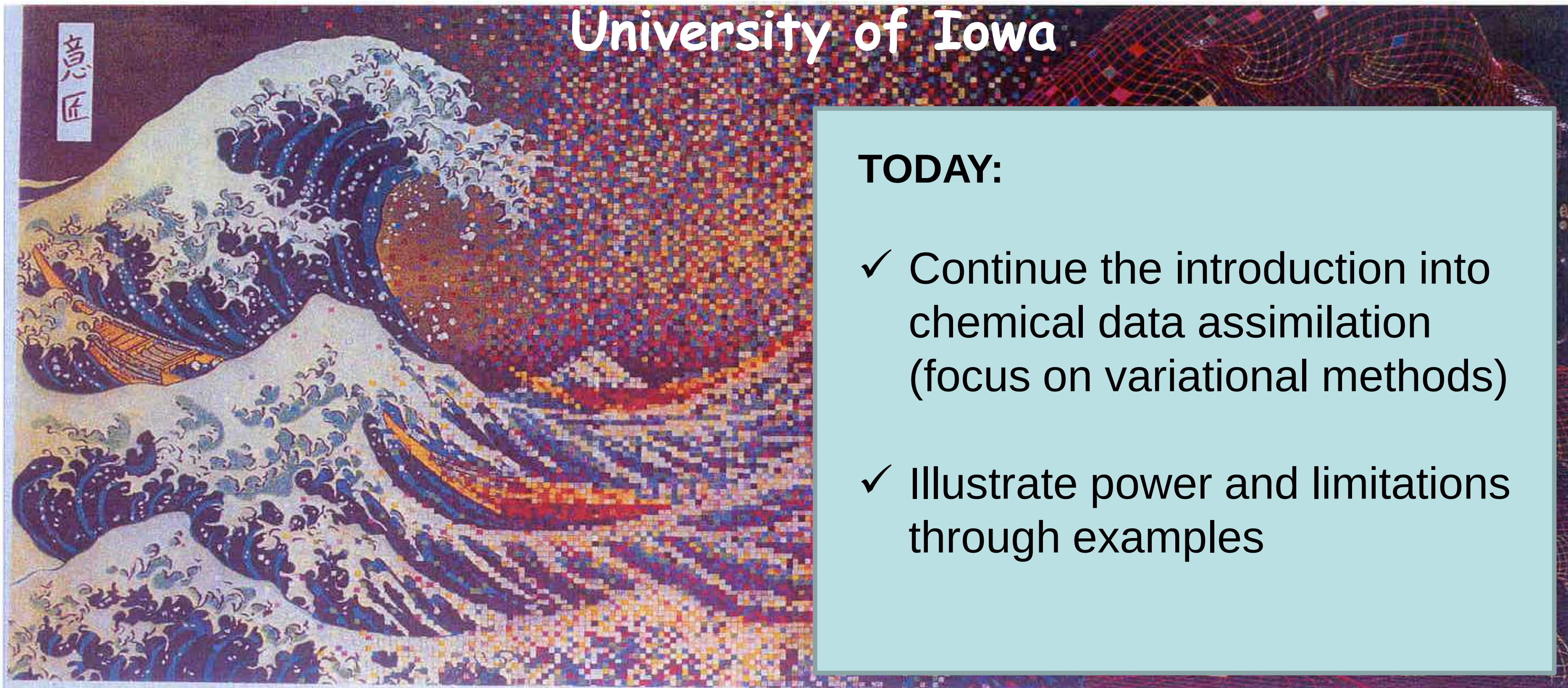

**TODAY:**

- ✓ Continue the introduction into chemical data assimilation (focus on variational methods)
- ✓ Illustrate power and limitations through examples

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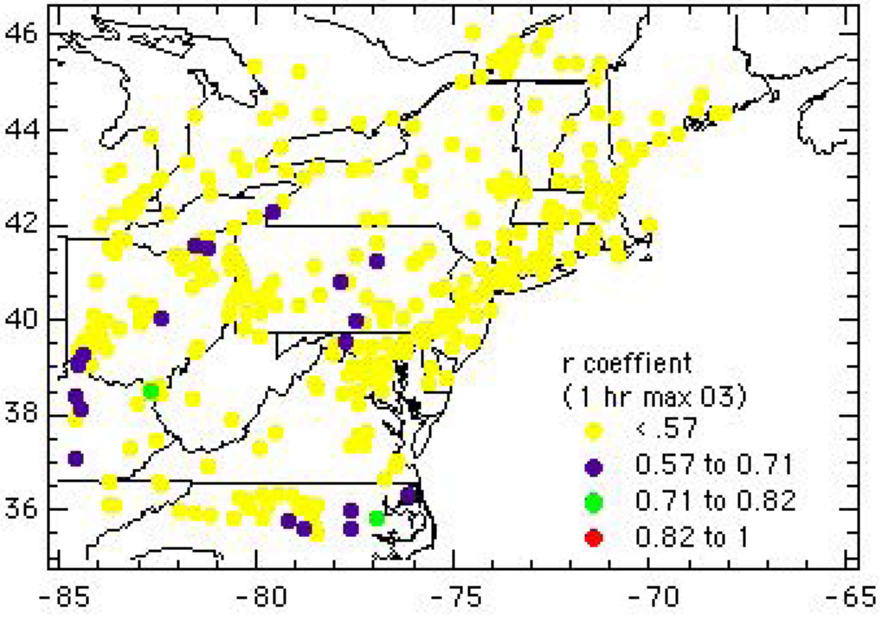
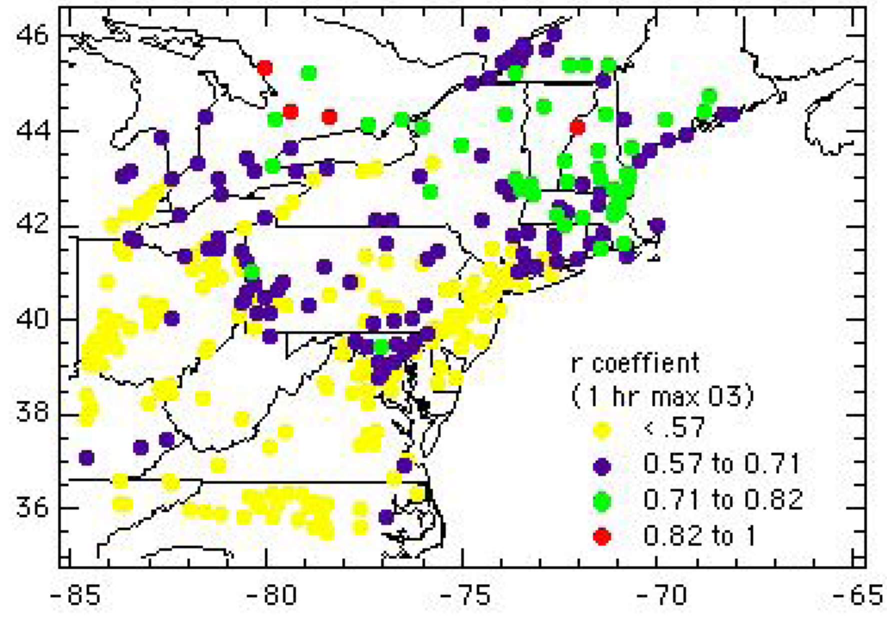
# Forecast Skill (Persistence vs Model)

Persistence

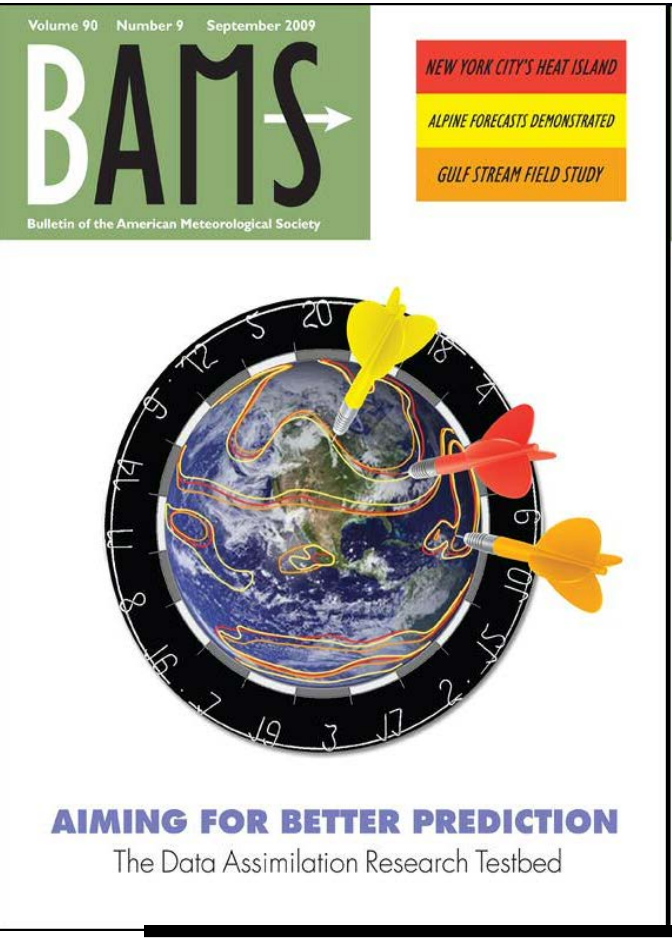


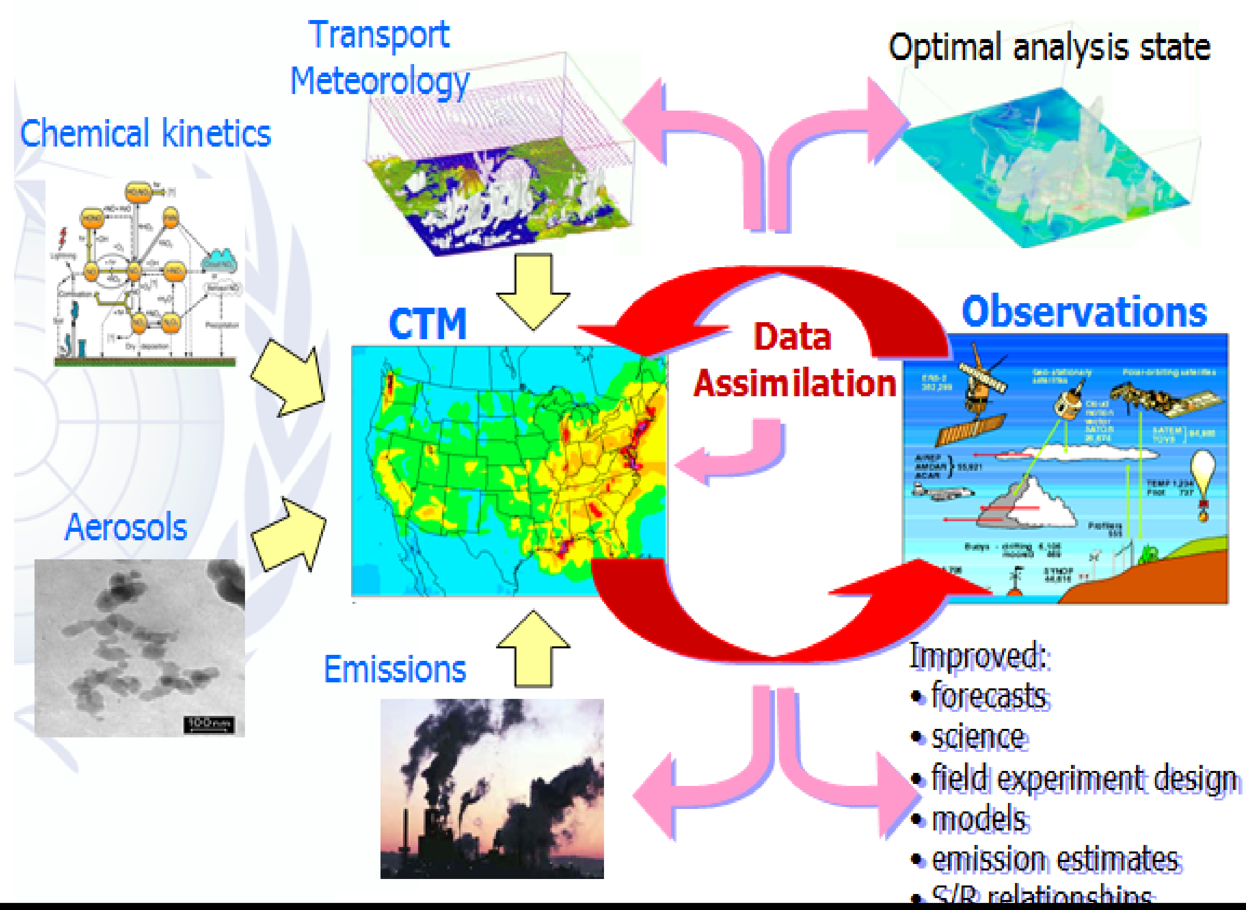

STEM-2K3




Ozone - summer

# Challenge: Improving Predictions through Closer Integration of Observations and Models



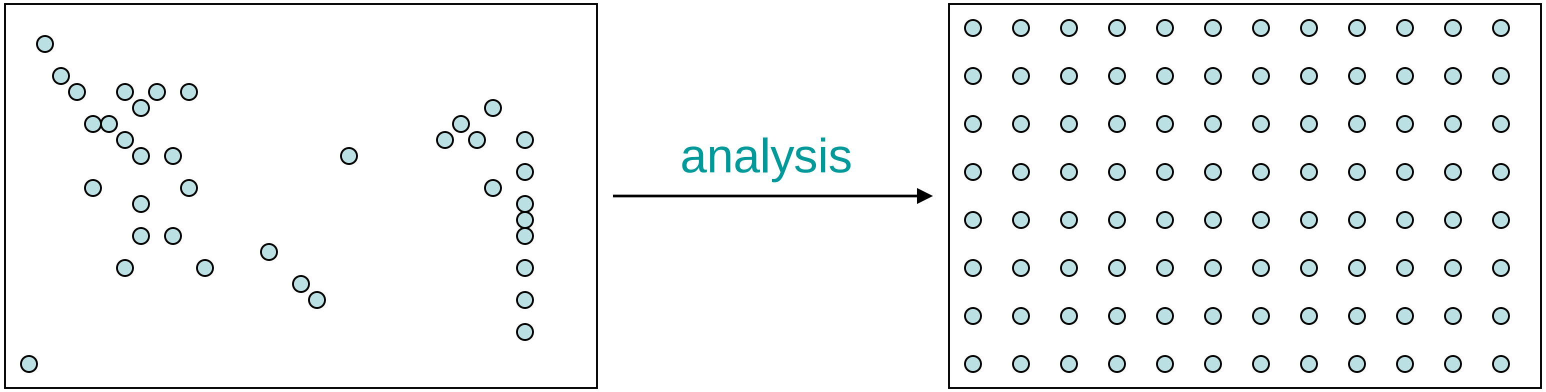




***+ Need to Integrated Air Quality & Met. Model assimilation systems***

***+ New requirements for NRT data, observing systems, and assimilation systems for chemical applications!!***

# Atmospheric Data Analysis

Goal: To produce a regular, physically consistent, four-dimensional representation of the state of the atmosphere from a heterogeneous array of in-situ and remote instruments which sample imperfectly and irregularly in space and time. (Daley, 1991)



# Why do data assimilation?

1. To obtain an initial state for launching forecasts
2. To make consistent estimates of the atmospheric state for diagnostic studies.
   - reanalyses
3. To challenge models with data and vice versa

# Data assimilation: Model + Observation

*To understand and/or forecast air pollution, we need*

- Measurements, samplings of the ‘reality’
- Chemical Transport Models (CTMs), describing the physical and chemical processes
- Data assimilation techniques, optimally integrate models and observations
  - Background (a priori) error statistics
  - Observation error statistics
  - Model error information

# Challenges in chemical data assimilation

- A large amount of variables (~300 concentrations of various species at each grid points)
  - Memory shortage (check-pointing required)
- Various chemical reactions (>200) coupled together (lifetimes of species vary from seconds to months)
  - Stiff differential equations
- Chemical observations are very limited, compared to meteorological data
  - Information should be maximally used, with least approximation
- Strongly source driven and they are highly uncertain
  - Inventories often out-dated, and uncertainty not well-quantified, effect of initial conditions can quickly decrease

# Data assimilation methods

- "Simple" data assimilation methods
  - Optimal Interpolation (OI)
  - 3-Dimensional Variational data assimilation (3D-Var)
  - Kriging
- Advanced data assimilation methods
  - 4-Dimensional Variational data assimilation (4D-Var)
  - Kalman Filter (KF) - Many variations, e.g. Ensemble Kalman Filter (EnFK)
  - Hybrid Methods

# Optimal Interpolation (OI) Algorithm

- **Assimilation: A methodology to optimize state and evolution of the system using model predictions with observational constraints**

- **Collins et al. (2001)**

$$\tau'_m = \tau_m + K\left(\tau_o - H\tau_m\right)$$

$$K = BH^T\left(HBH^T + O\right)^{-1}$$

$$O = \left(f_o\tau_o + \varepsilon_o\right)^2 I$$

$$B_{ij} = \left(f_m\tau_m + \varepsilon_m\right)^2 \exp\left[-\frac{d_x^2 + d_y^2}{2l_{xy}^2}\right]$$

**•K – Kalman gain matrix**

**•H – Interpolator from model to observation space**

**•O/B Observed/Background error covariances**

**•f and ε - fractional error and RMS uncertainty**

**•$L_{xy}$ horizontal correlation length scale for errors in model fields**

**•$d_x$ and $d_y$ grid cell spacing**

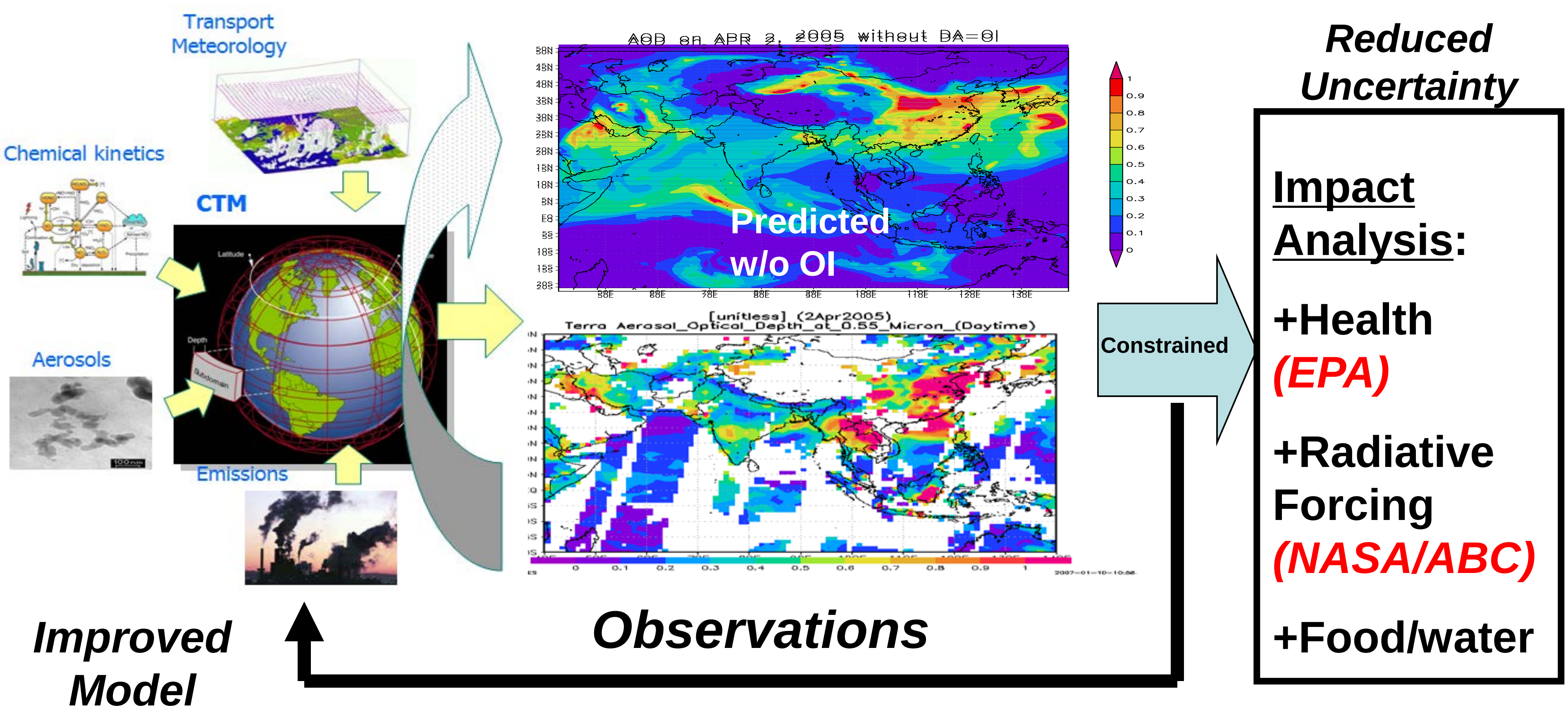
Collins, W. D., P. J. Rasch, B. E. Eaton, B. V. Khattatov, J.-F. Lamarque and C. S. Zender (2001). "Simulating aerosols using a chemical transport model with assimilation of satellite aerosol retrievals: Methodology for INDOEX." Journal of Geophysical Research, [Atmospheres] **106**(D7): 7313-7336.

# Models Constrained With Observations Play Increasing Important Roles In Research and Application

**Assimilation method:** optimal interpolation *(Adhikary et al., 2008, 2009)* **(AOD is not unique; aerosol, size, composition, RH etc.)**

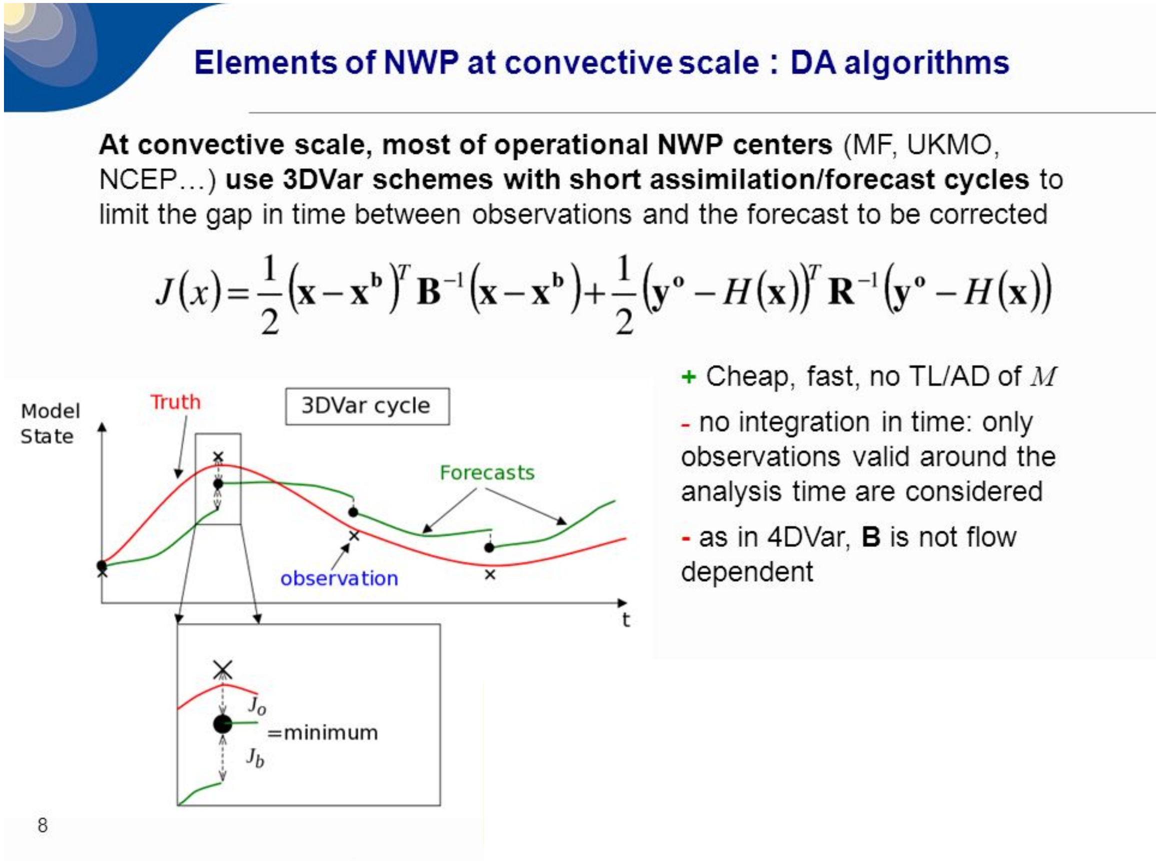
**Data used** in assimilation: MODIS, Deep Blue (5.1 L3), and MISR (CGAS L3); Total AOD, fine mode, AAOD

**Validation** against observations: AOD from AERONET using 2 different retrievals (V2 L2); $PM_{10}$ and $SO_4$ from EANET



# GSI AOD assimilation

- Gridpoint Statistical Interpolation (GSI) (3dVAR) can perform simultaneous DA of different datasets (e.g. ground PM2.5 and AOD, different AOD retrievals, and number) for WRF-Chem model.



# Four-dimensional Variational (4D-Var) Chemical Data Assimilation (Using STEM)

# Chemical Transport Model

- 3D atmospheric transport-chemistry model (STEM-III)

$$\frac{\partial c_i}{\partial t} = -u \cdot \nabla c_i + \frac{1}{\rho} \nabla \cdot (\rho K \nabla c_i) + f_i(c) + E_i$$

where chemical reactions are modeled by nonlinear stiff terms

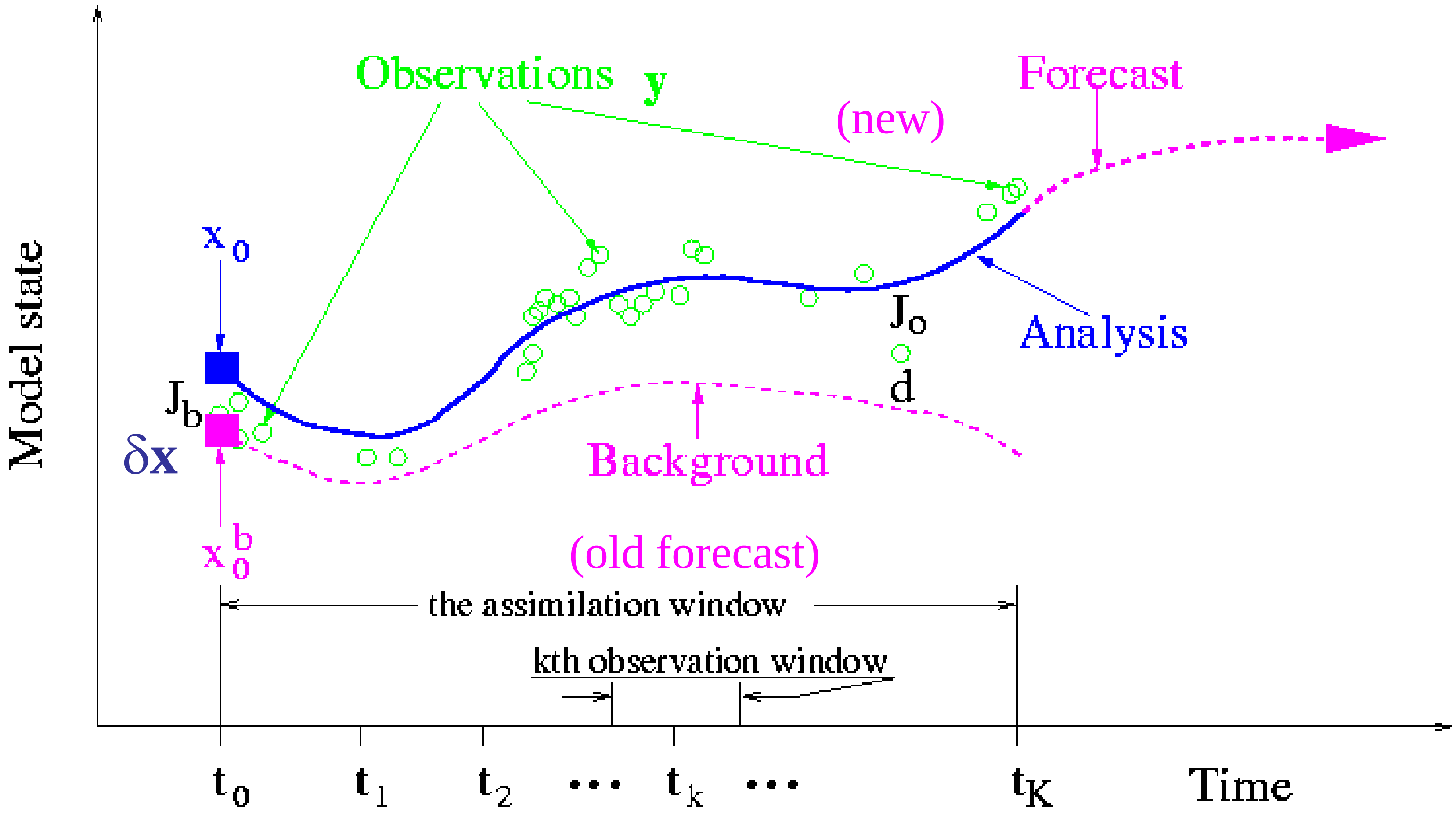
$$f_i(c) = P_i(c) - D_i(c) c_i$$

Control variables can be initial conditions, parameters, emissions, boundary conditions

- Use operator splitting to solve CTM

$$\mathrm{M}_{[t,t+\Delta t]} = T_X^{\Delta t/2} \cdot T_Y^{\Delta t/2} \cdot T_Z^{\Delta t/2} \cdot C^{\Delta t} \cdot T_Z^{\Delta t/2} \cdot T_Y^{\Delta t/2} \cdot T_X^{\Delta t/2}$$

# Data assimilation



# Basic idea of 4D-Var

- Define a cost functional

$$J(c^0) = \frac{1}{2}\left(c^0 - c^{\mathrm{b}}\right)^T B^{-1}\left(c^0 - c^{\mathrm{b}}\right) + \frac{1}{2}\sum_{k=0}^{N}\left(c^k - c^{k,\mathrm{obs}}\right)^T R_k^{-1}\left(c^k - c^{k,\mathrm{obs}}\right)$$

which measures the distance between model output and observations, as well as the deviation of the solution from the background state

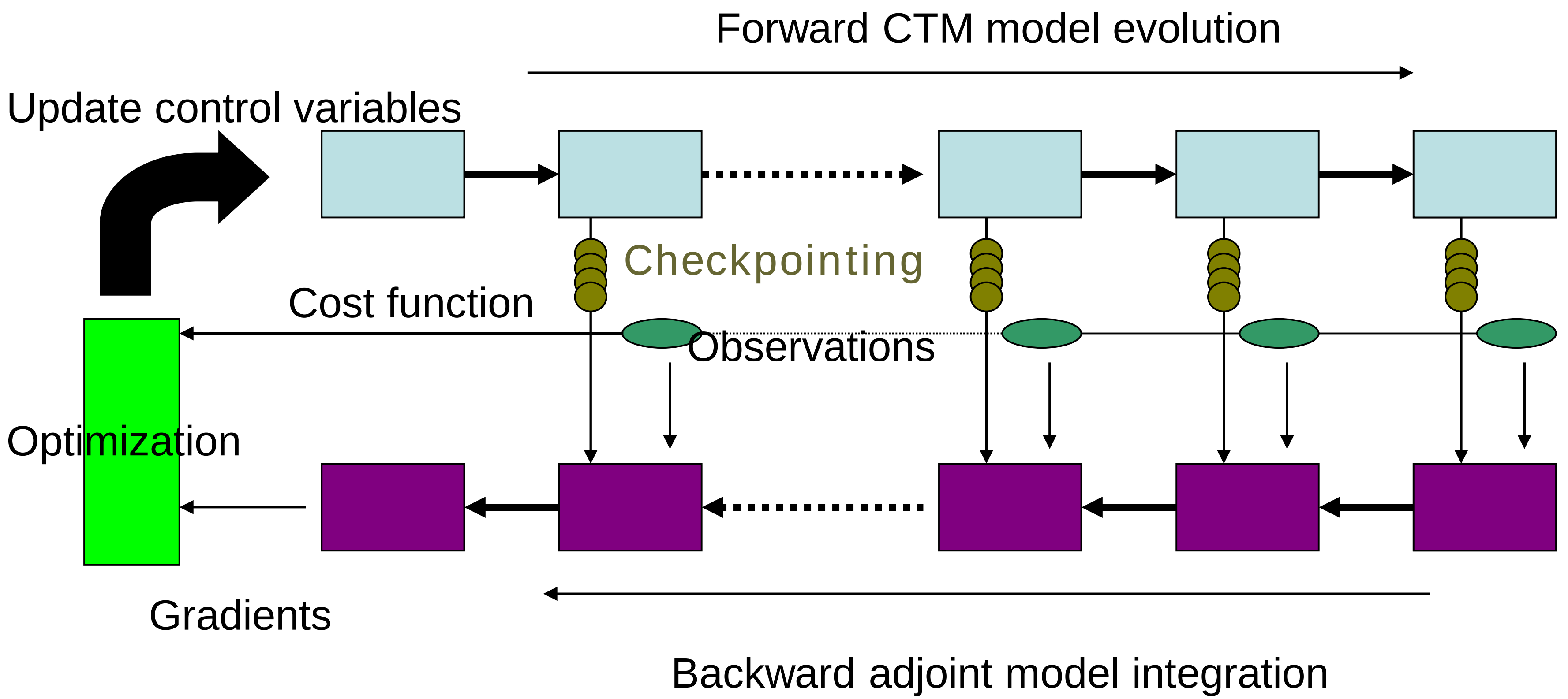
- Derive adjoint of tangent linear model

$$\frac{\partial \lambda_i}{\partial t} + \nabla \cdot (u\lambda_i) = -\nabla \cdot \left(\rho K \nabla \frac{\lambda_i}{\rho}\right) - \left(F^T(\rho c)\lambda\right)_i - \varphi_i$$

Where φis the forcing term, which is chosen so that the adjoint variables are the sensitivities of the cost functional with respect to state variables (concentrations), i.e. $\lambda_i = \dfrac{\partial J}{\partial c_i}$

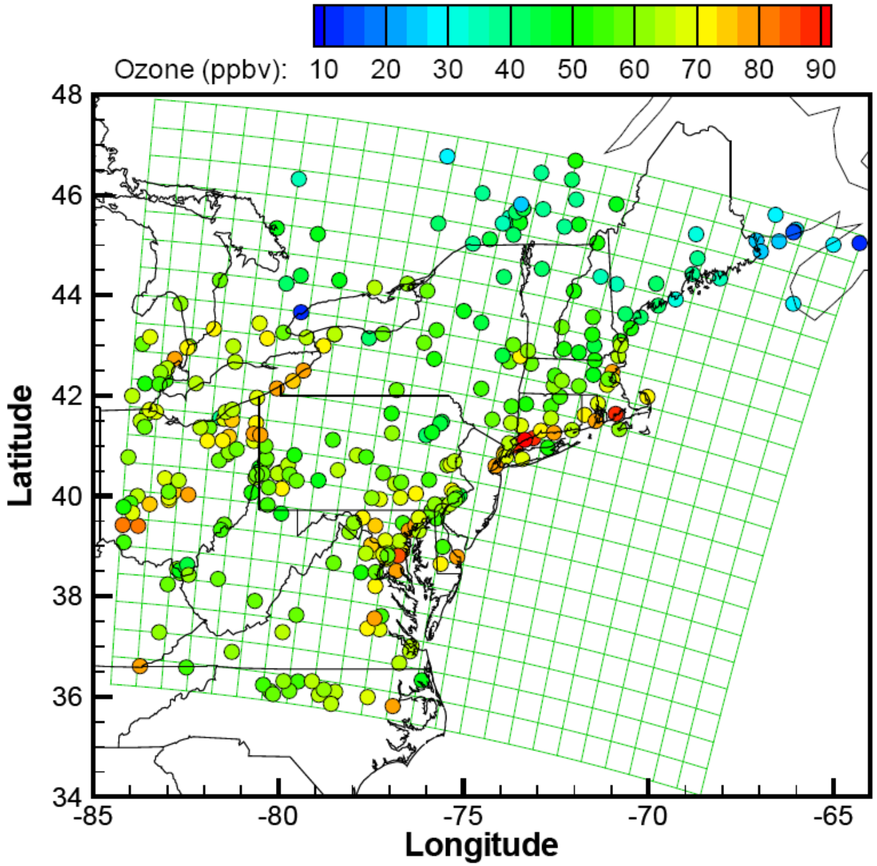
- Use adjoint variables for sensitivity analysis, as well as data assimilation

# 4D-Var application with CTMs



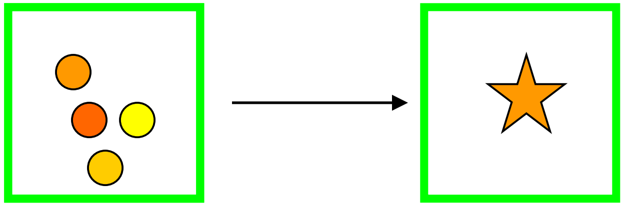
# Observational error

$$J = \frac{1}{2}\left[c_0 - c_b\right]^T B^{-1}\left[c_0 - c_b\right] + \frac{1}{2}\left[y - h(c)\right]^T O^{-1}\left[y - h(c)\right]$$




## Observational Error:

- Representative error
- Measurement error



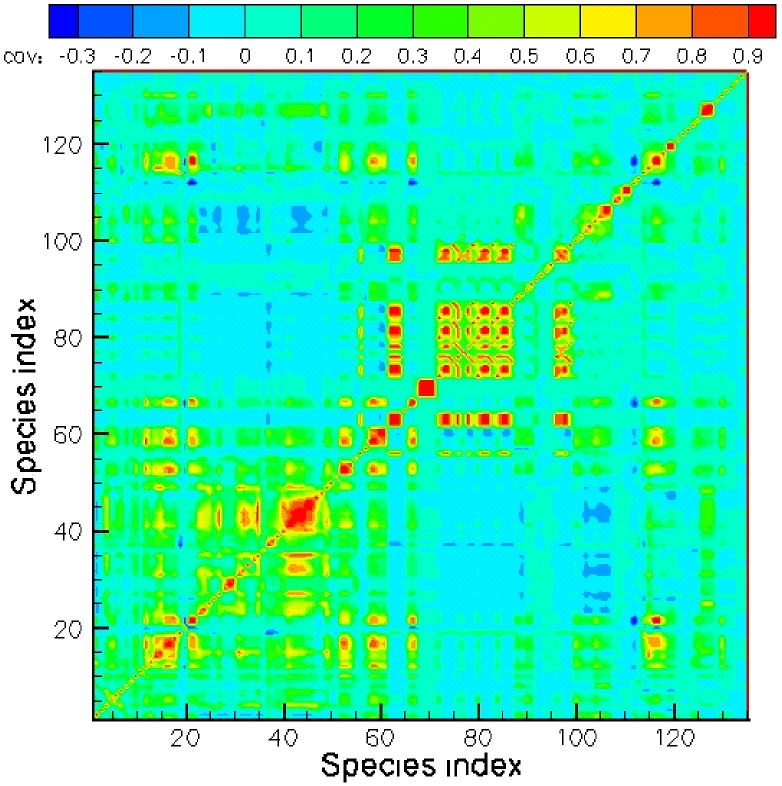
## Observation Inputs

- Averaging inside 4-D grid cells
- Uniform error (8 ppbv)

# Model Background Errors NMC method

- Substitute model background errors with the differences between 24hr, 48 hr, 72 hr forecasts verifying at the same time
- Calculate the model background error statistics in three directions separately

$$CORR(O_3, CO) = \frac{\overline{\epsilon_{O_3} \cdot \epsilon_{CO}}}{\sqrt{\overline{\epsilon_{O_3} \cdot \epsilon_{O_3}}} \cdot \sqrt{\overline{\epsilon_{CO} \cdot \epsilon_{CO}}}}$$

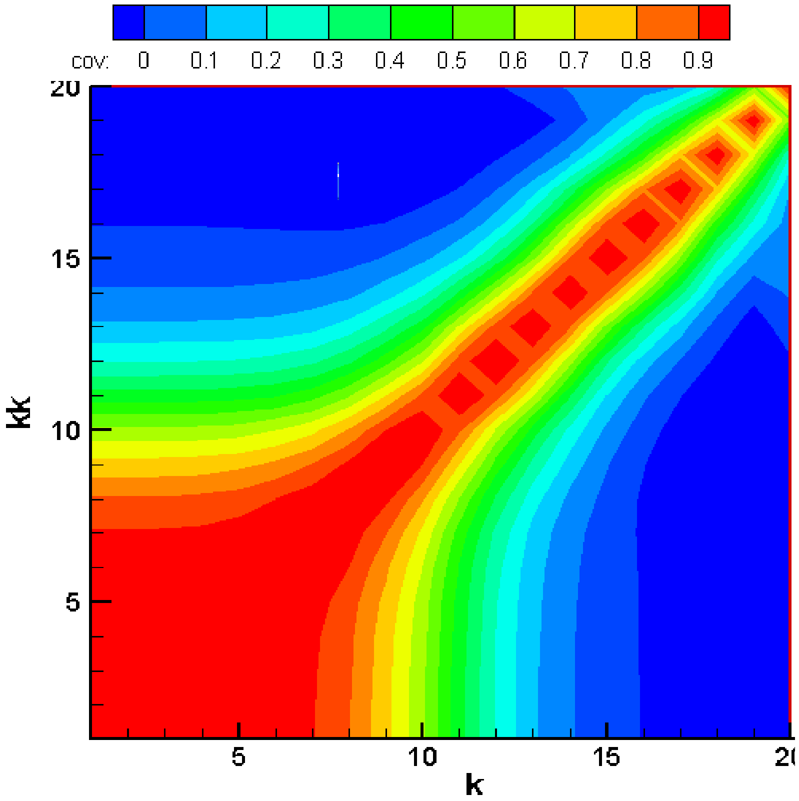


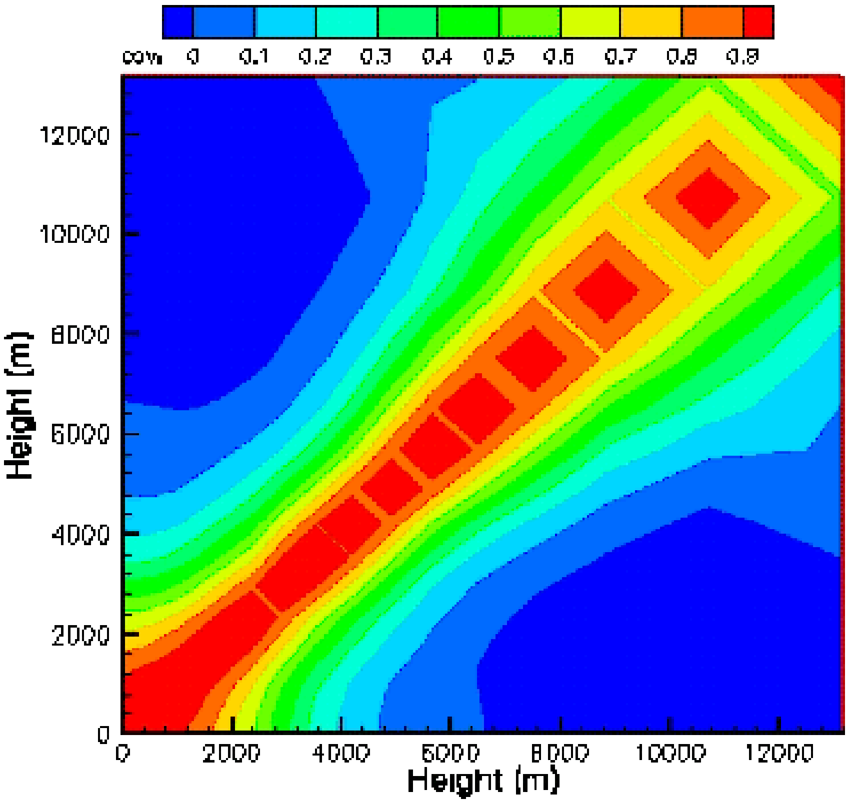

- Equivalent sample number: 811,890

# NMC method results

$$CORR(K,KK) = \frac{\overline{\epsilon_K \cdot \epsilon_{KK}}}{\sqrt{\overline{\epsilon_K \cdot \epsilon_K}} \cdot \sqrt{\overline{\epsilon_{KK} \cdot \epsilon_{KK}}}}$$

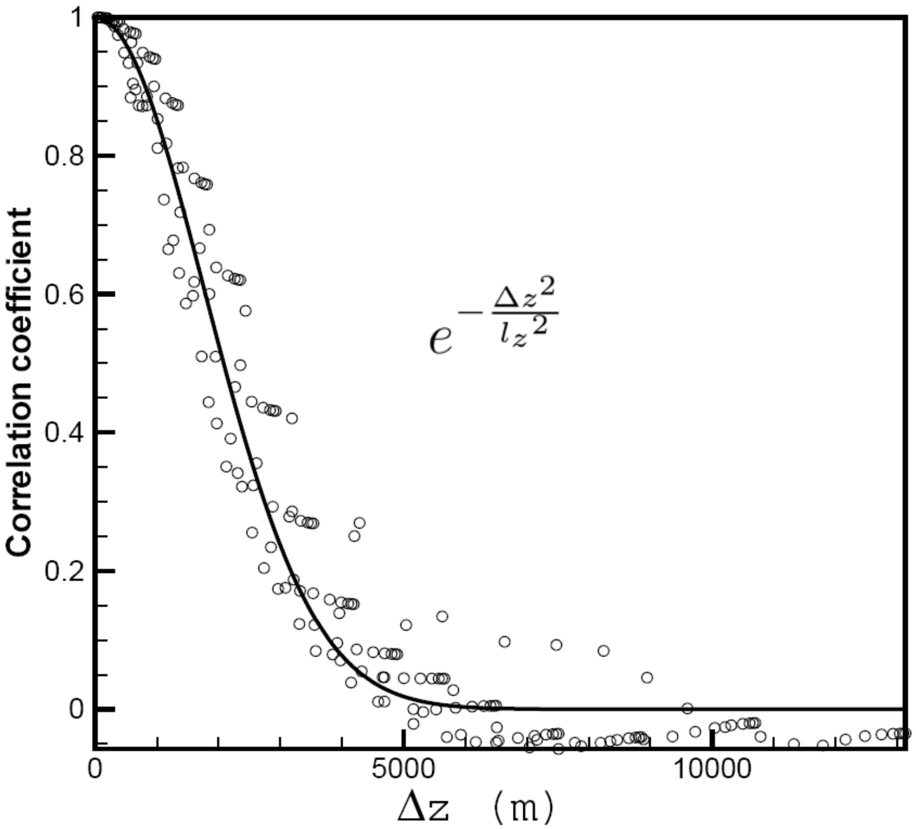
- Equivalent sample number: 360,840



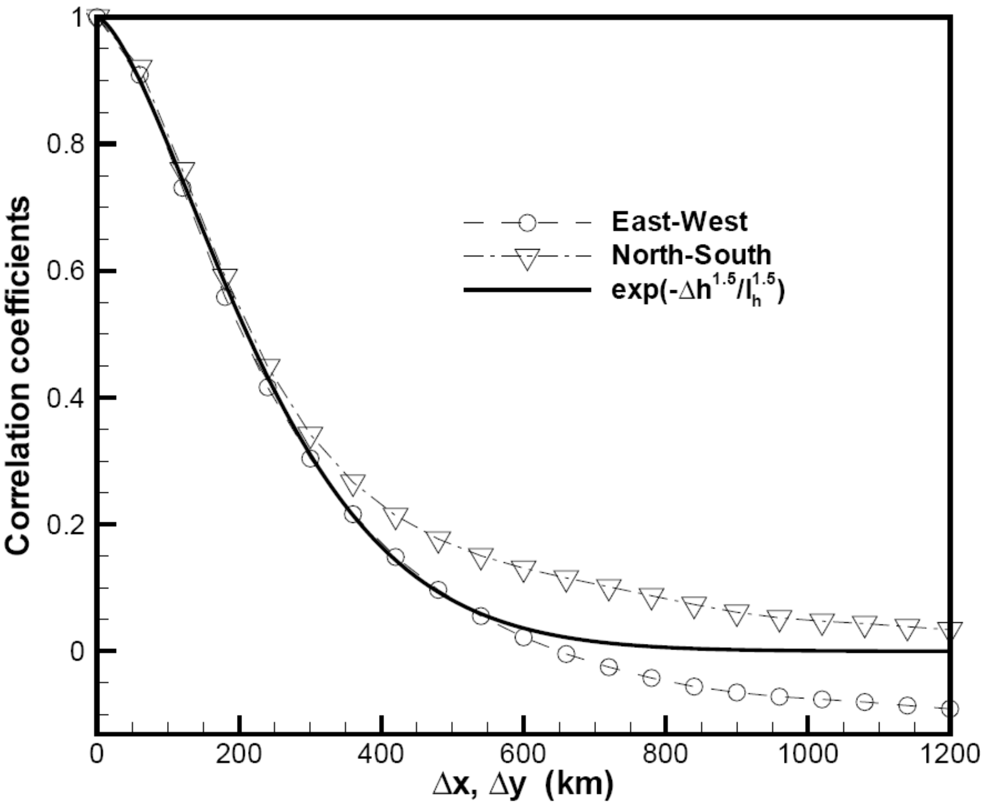



# NMC method results

Vertical correlation




Horizontal correlation



# Adjoints Provide a Powerful Tool for Sensitivity Analysis

The sensitivity can be obtained either via the direct chain rule (TLM/DDM) or via its transpose (ADJ)

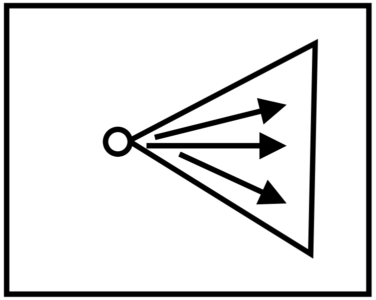
$$y^0(u), \quad u = \text{input}; \quad \psi\left(\mathbf{y}^N\right) = \text{output}$$

$$\Delta u \rightarrow \Delta y^0 \rightarrow \cdots \rightarrow \Delta y^N \rightarrow \Delta\psi\left(\mathbf{y}^N\right)$$

$$\frac{\partial \psi}{\partial u} = \frac{\partial \psi}{\partial \mathbf{y}^N}\left(\frac{\partial \mathbf{y}^N}{\partial \mathbf{y}^{N-1}} \cdots \frac{\partial \mathbf{y}^1}{\partial \mathbf{y}^0}\right)\frac{\partial \mathbf{y}^0}{\partial u}$$

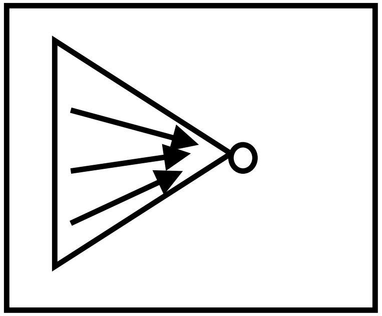
## TLM (DDM) = source-oriented approach

$$\frac{\partial \psi}{\partial u} = \frac{\partial \psi}{\partial \mathbf{y}^N} \cdot \frac{\partial \mathbf{y}^N}{\partial u}; \quad \frac{\partial \mathbf{y}^k}{\partial u} = \frac{\partial \mathbf{y}^k}{\partial \mathbf{y}^{k-1}} \cdot \frac{\partial \mathbf{y}^{k-1}}{\partial u}, \quad k = 1, \cdots, N$$



## ADJ = receptor-oriented approach

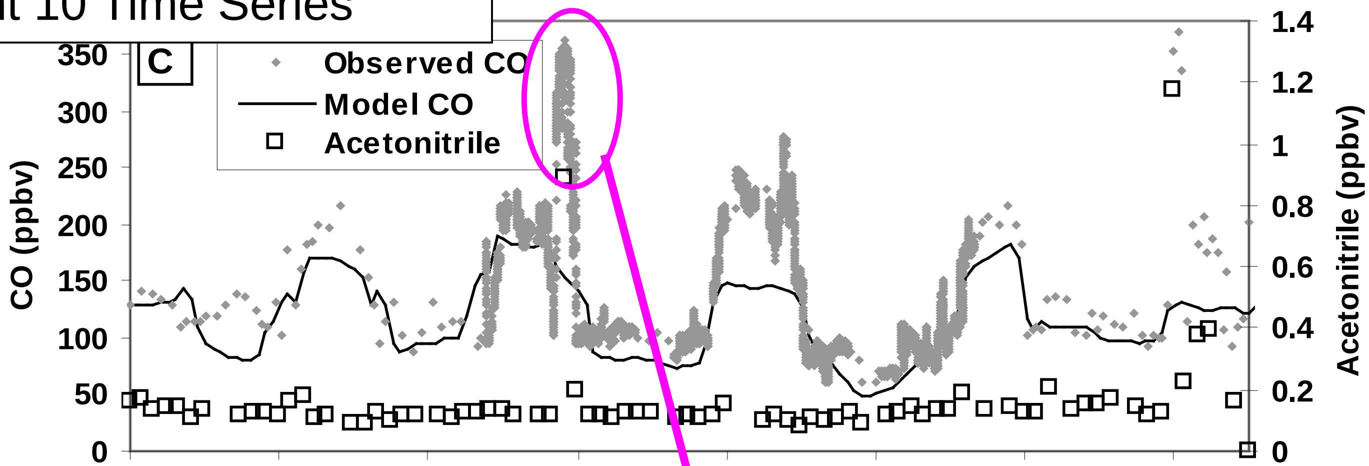
$$\frac{\partial \psi}{\partial u} = \frac{\partial \psi}{\partial \mathbf{y}^0} \cdot \frac{\partial \mathbf{y}^0}{\partial u}; \quad \left(\frac{\partial \psi}{\partial \mathbf{y}^{k-1}}\right)^T = \left(\frac{\partial \mathbf{y}^k}{\partial \mathbf{y}^{k-1}}\right)^T \cdot \left(\frac{\partial \psi}{\partial \mathbf{y}^k}\right)^T, \quad k = N, \cdots, 1$$



# The Adjoints Are Themselves Very Valuable

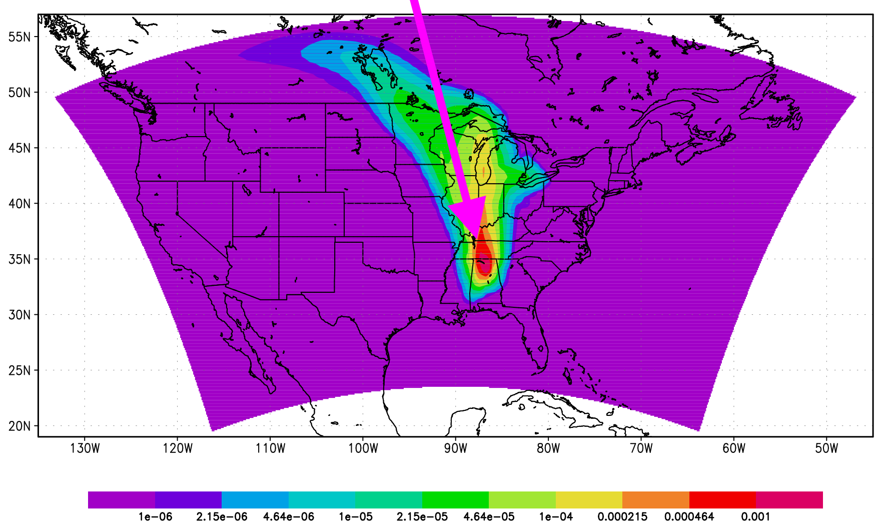
## CO as a tracer of fossil fuel $CO_2$…
## Caveat: Fire, chemistry, LPS (Campbel et al, In Press)

Flight 10 Time Series



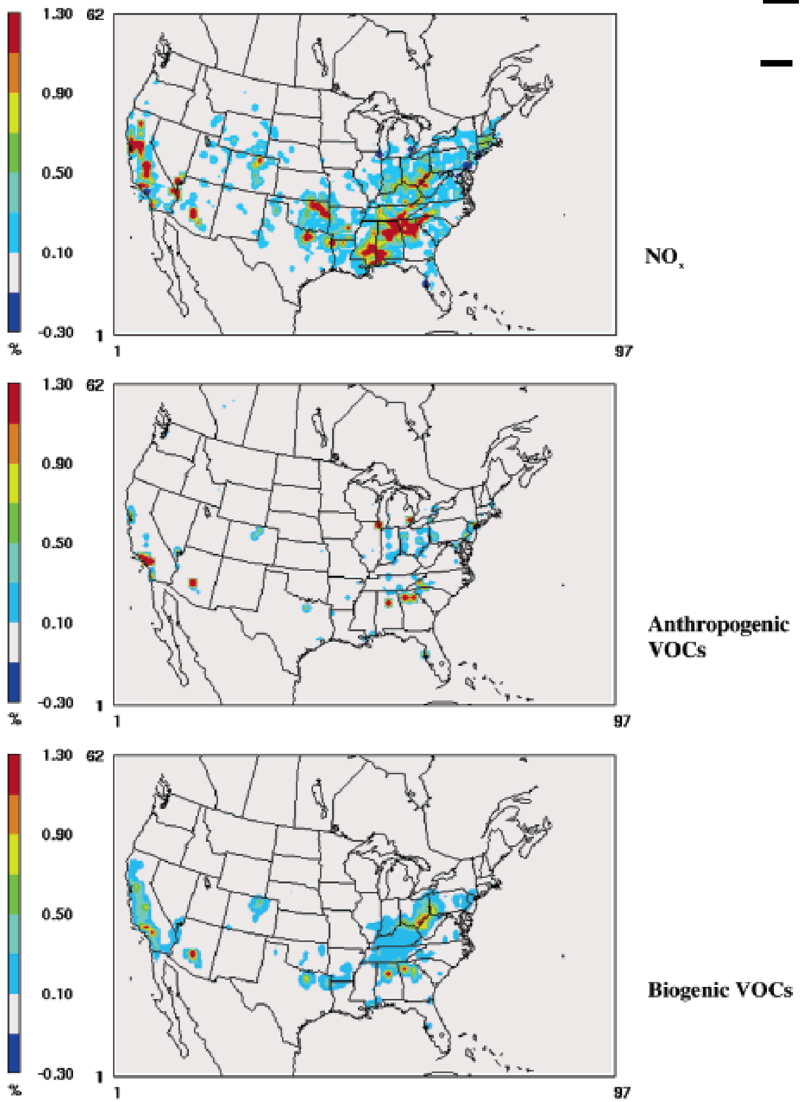

Adjoint Sensitivity

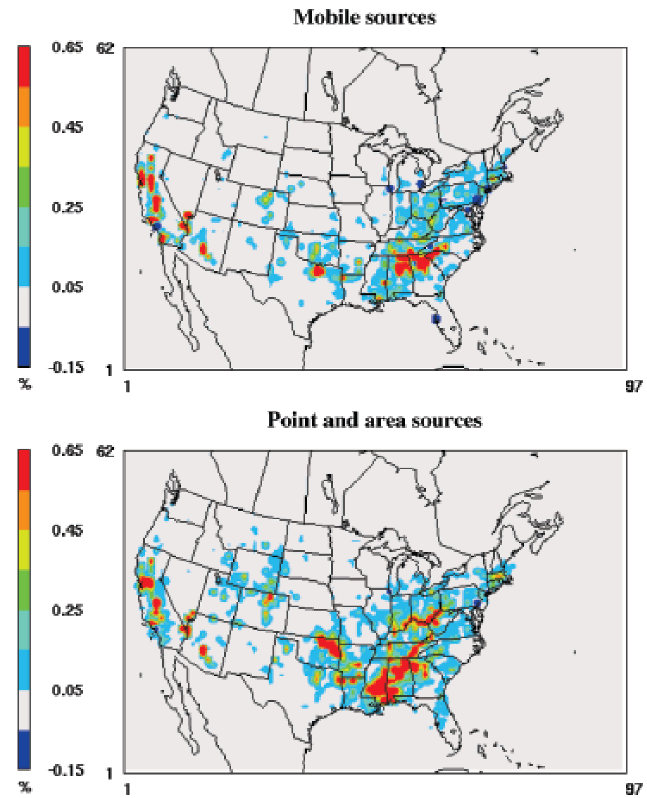
*Provide insights into the footprint of an observation*



*Sensitivity of ozone violations wrt emissions*

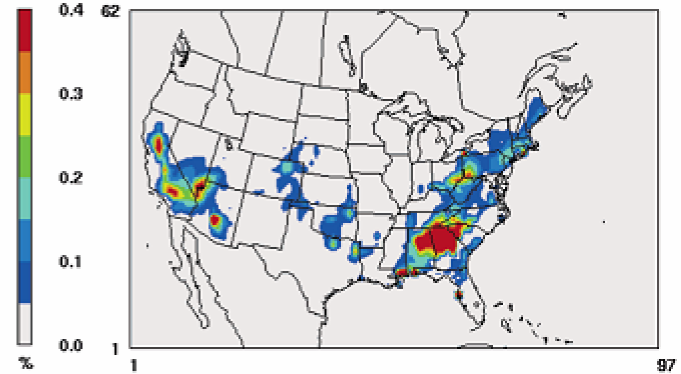
# Adjoint Analysis of the Contribution of Different Emissions to Ozone Violations – July & August 2004



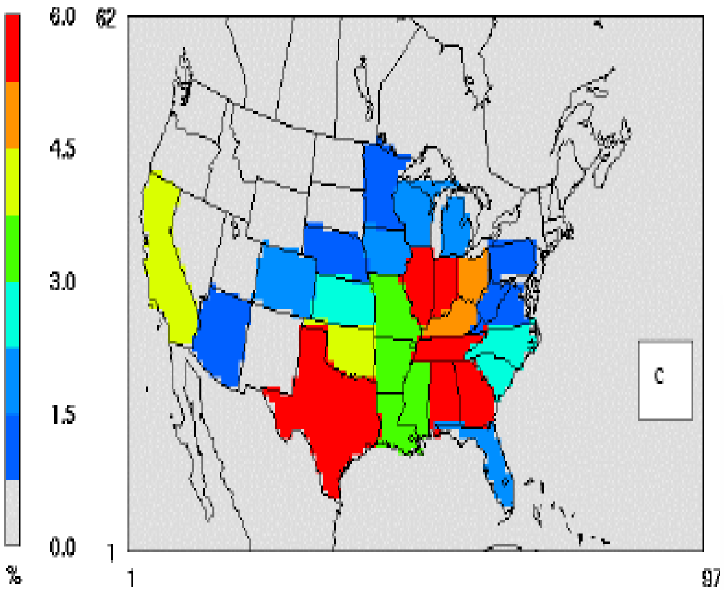

Hakami et al., ES&T 2006

# Analysis of the impact of assimilation of observations on the calculation of States contribution to ozone violations …

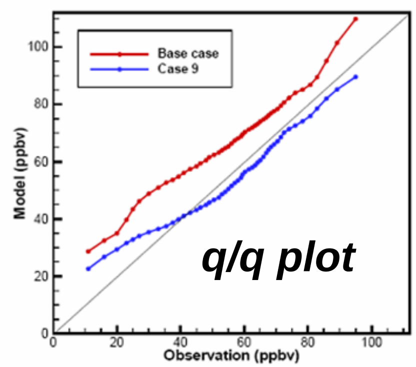


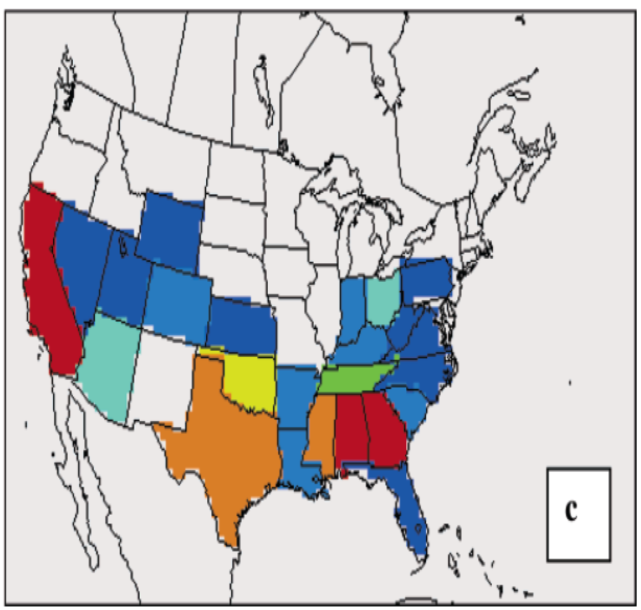

O3-violations

$\Delta$O3-viol./anthr-emissions




w/o assimilation

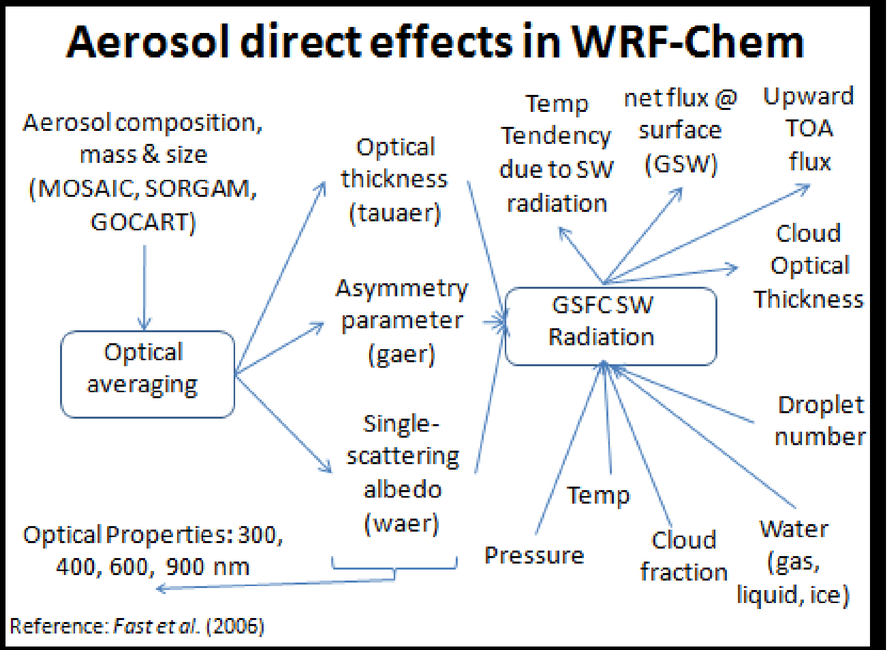


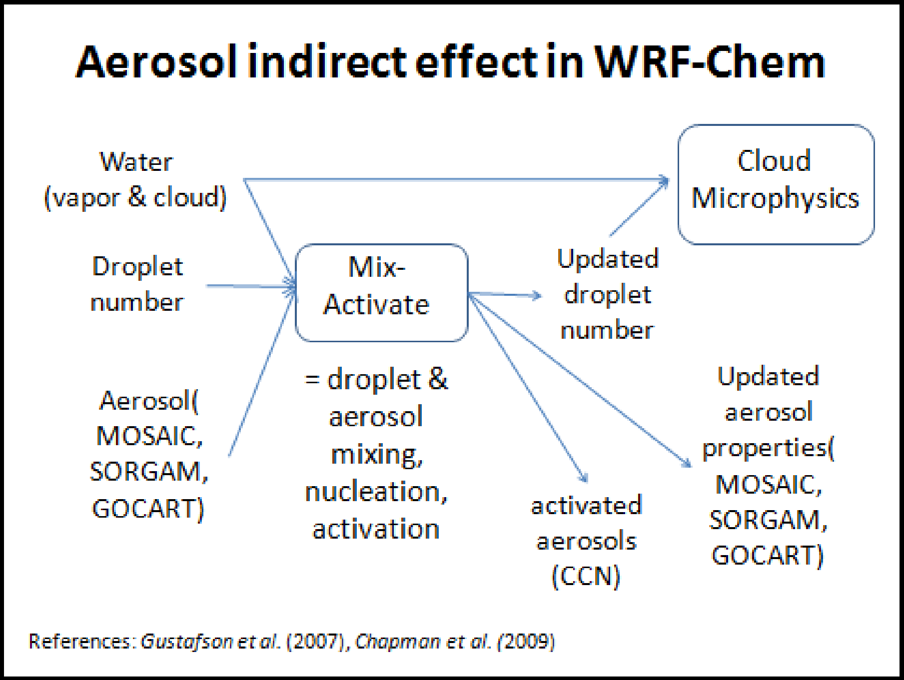




w assimilation

*Hakami et al.,ES&T 2006*

# Building Assimilation Systems for WRF-Chem




***We are developing the adjoint of the full WRF-Chem Model***

***Ref: Saide et al., 2013, Saide et al., PNAS 2012, GRL 2014, 2015a,b; Guerette and Henze GMD, 2015 for use in 3d (GSI) and 4dVar applications***

# Building Assimilation Systems for WRF-Chem

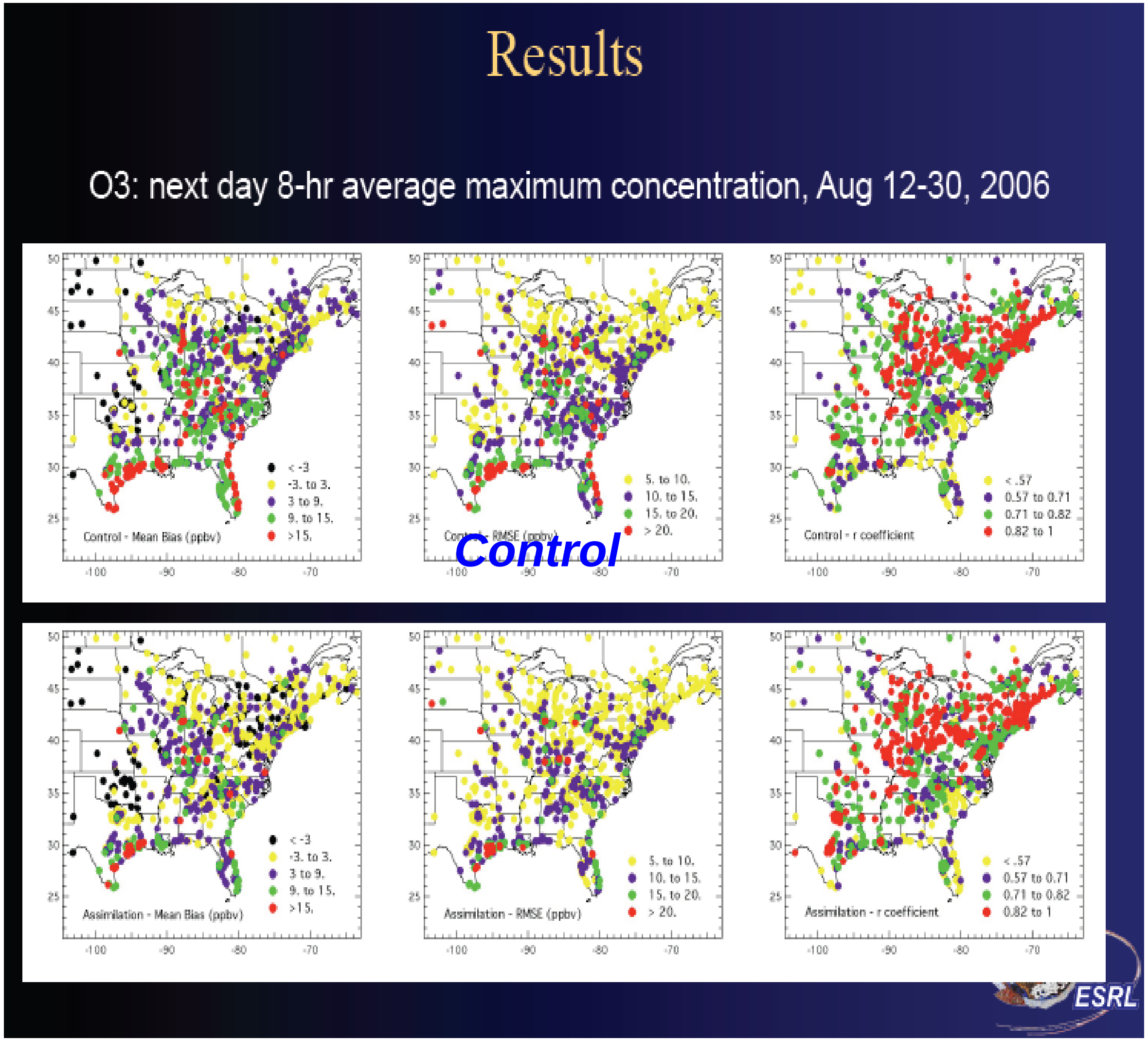
## WRFPLUS-Chem Current Capabilities

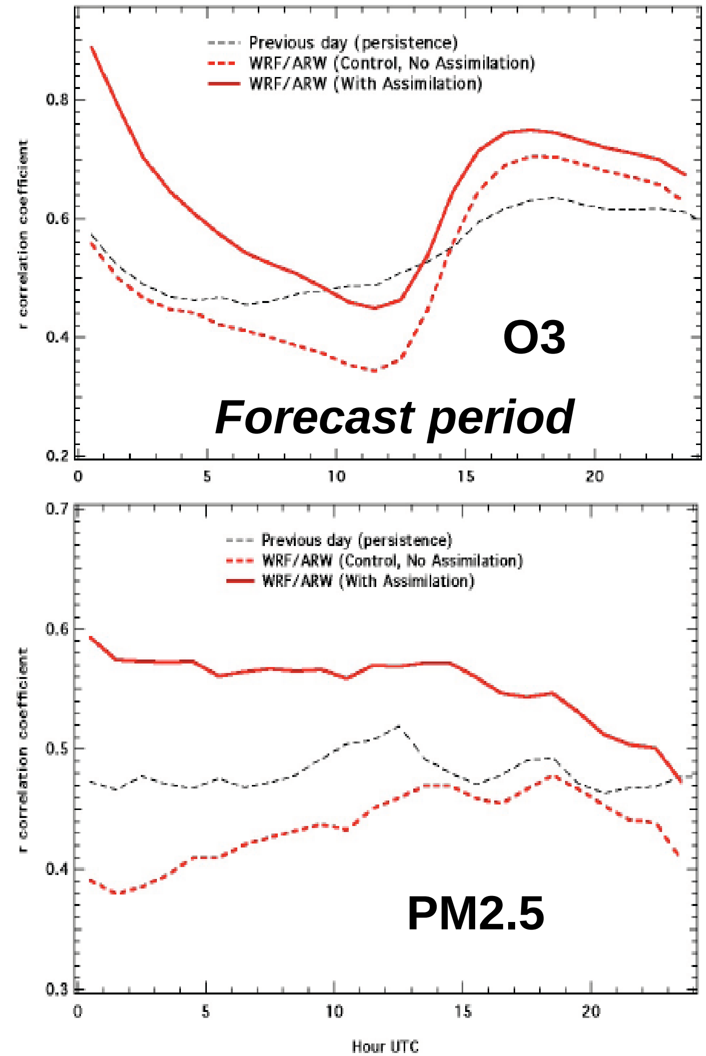
*Guerette and Henze GMD, 2015*

- AD and TL developed for:
  - Emissions (Anthropogenic and Biomass Burning for GOCART)
  - ACM2 PBL (Pleim et al. 2007) w/ integrated tracer transport (2013)
  - Pleim-Xiu and SFCLAY surface layer schemes
  - Pleim-Xiu and SLAB LSMs
  - Wesely Dry Deposition
  - Chem advection (similar to tracer advection by Xin Zhang in 2012)
  - GOCART Aerosols
    - BC aging
    - PM summation
    - Sulfate chemistry (pending testing)
- 2$^{nd}$-order checkpointing for long duration (>6 hr) AD/TL simulations
- New adjoint forcing scheme for in-situ chemical observations
- Standalone AD and TL:
  - Grell-Freitas Convection (2013) [chemical tracers in development]

*Ref: Saide et al., 2013, Saide et al., PNAS 2012, GRL 2014, 2015a,b; Guerette and Henze GMD, 2015 for use in 3d (GSI) and 4dVar applications*

# ARW-WRF/Chem and the Gridpoint Statistical Interpolation (GSI) Analysis System (3dVar)



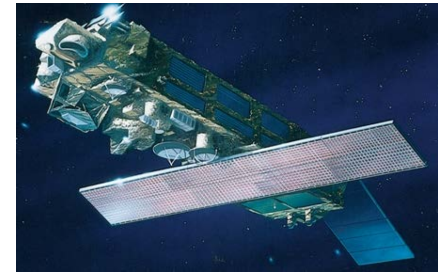

**Bias** **RMSE** **R**

Grell et al., 2009

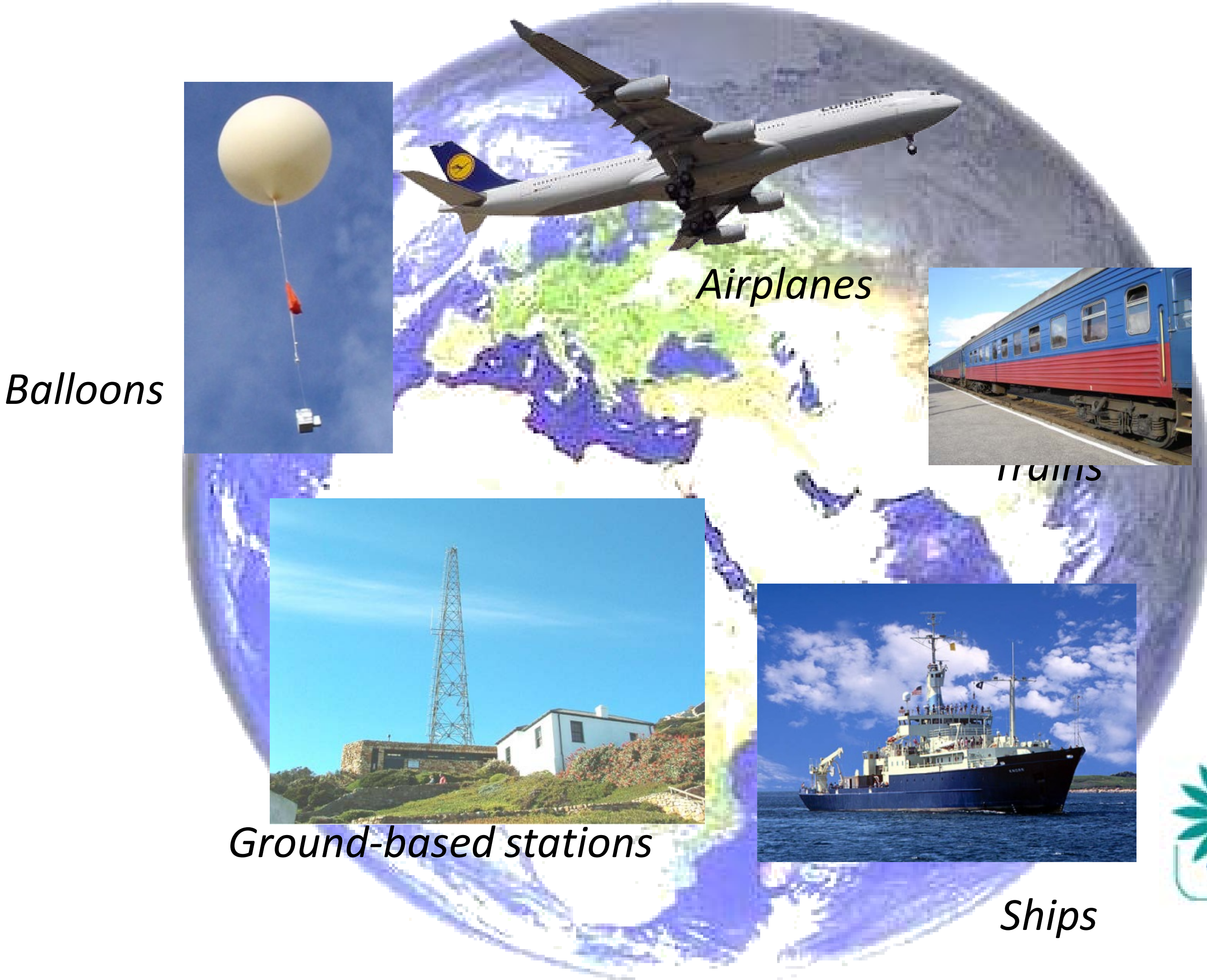
# Models Constrained with Observations Play increasing Important Roles in Research and Applications

- ✓ Need for ***More*** aerosol and atmospheric composition data for use in assimilation

# Good News: The global observing systems for atmospheric composition are growing



*Satellites*




GLOBAL ATMOSPHERE WATCH

ICOS integrated carbon observation system

IAGOS

ACTRIS

EEA

...

AERONET Aerosol Robotic Network

# Models Constrained with Observations Play increasing Important Roles in Research and Applications

- ✓ Need for ***More*** aerosol and atmospheric composition data for use in assimilation
- ✓ New observations streams are in the pipe-line …
- ✓ **Are our modeling & assimilation systems ready to use these data?**

# Application: Impacts of Geostationary AOD Assimilation

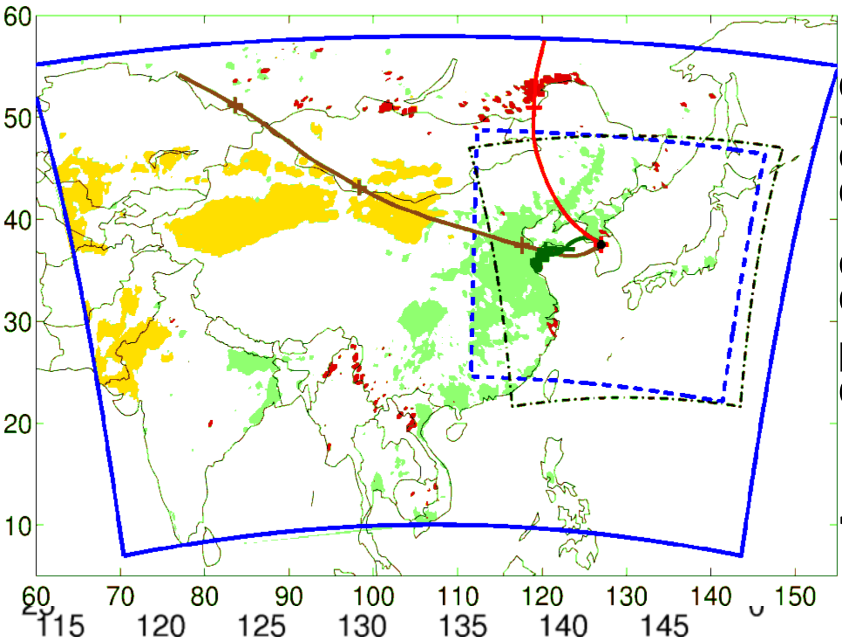
*(Are we "ready " to see an impact?)*

**Near future more assets , e.g., GEMS, TEMPO!**

- **Objective:** Assess performance of assimilating Geostationary GOCI AOD into a system already assimilating MODIS AOD

- **System:** WRF-Chem - GSI for MOSAIC sectional aerosol model (Saide et al., ACP 2013) allows assimilation of multiple data

- **Experiments:** GSI AOD assimilation every 3 hours, MODIS only, MODIS+GOCI. (*Only over-sea AOD used)*




Aug 27-29, 2012

***Saide et al., GRL, 2014***

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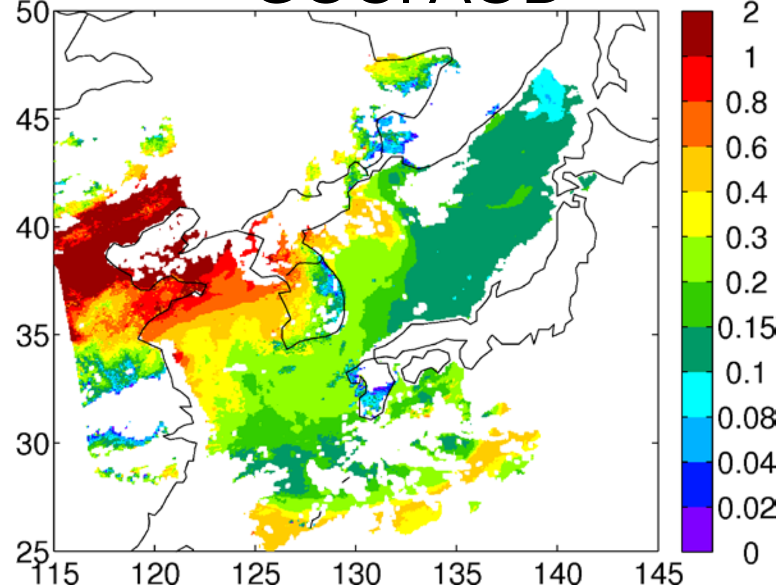
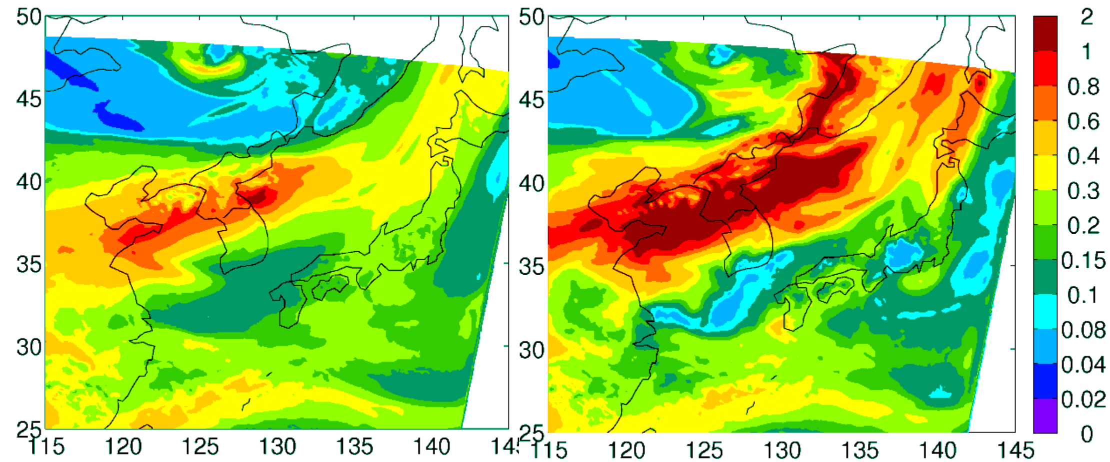
GOCI AOD




Aug 27-29, 2012

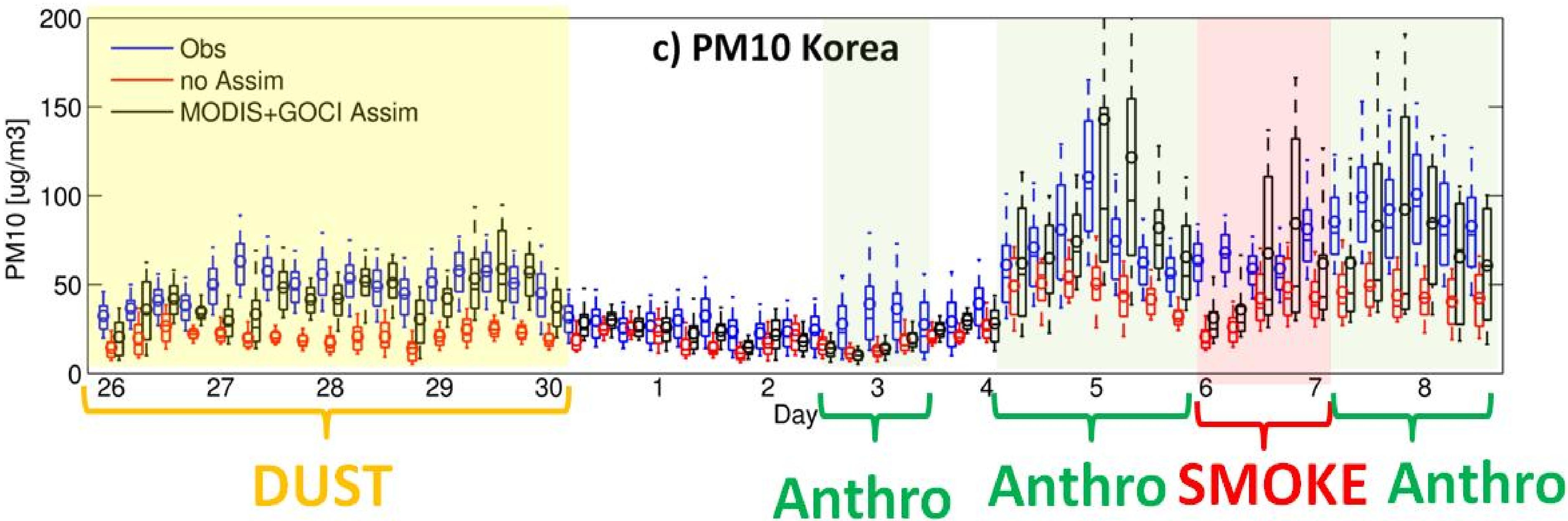


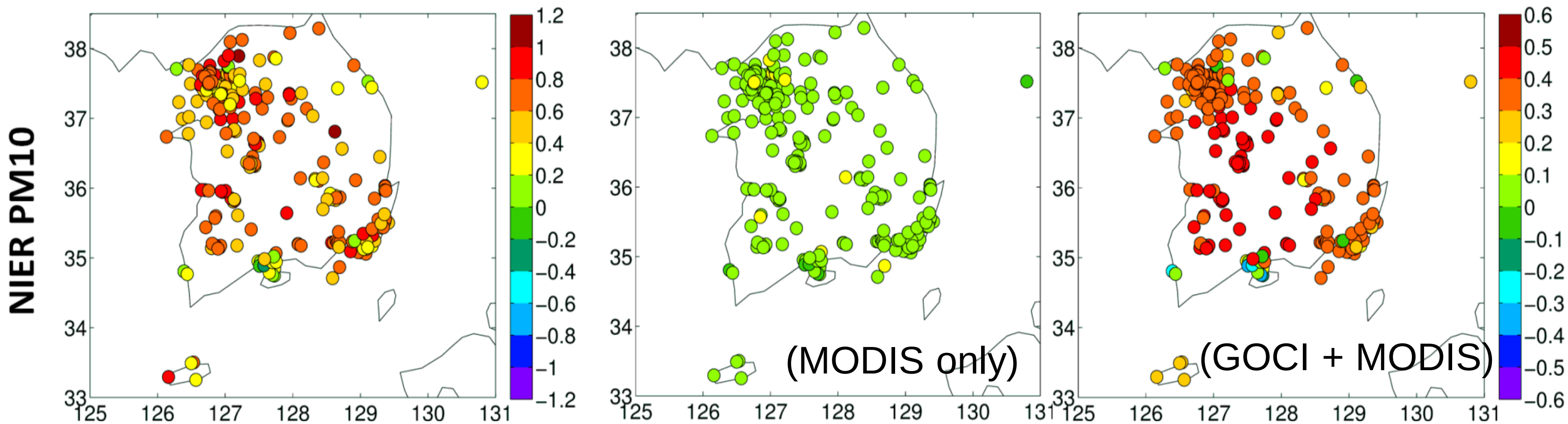

WRF-Chem NO Assim

WRF-Chem MODIS+GOCI Assim

***Saide et al., GRL, 2014***

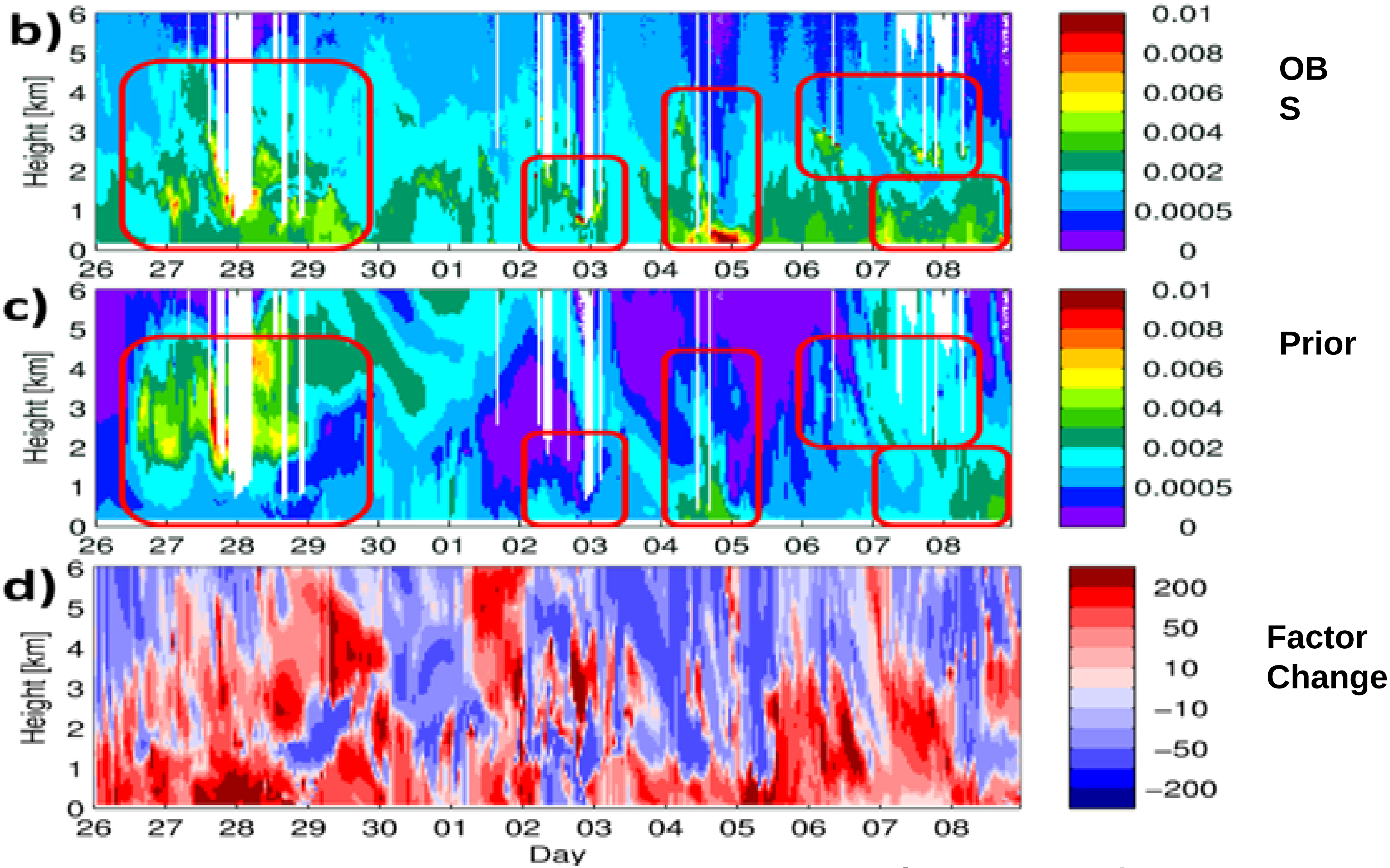
# Impact of GOCI on PM10



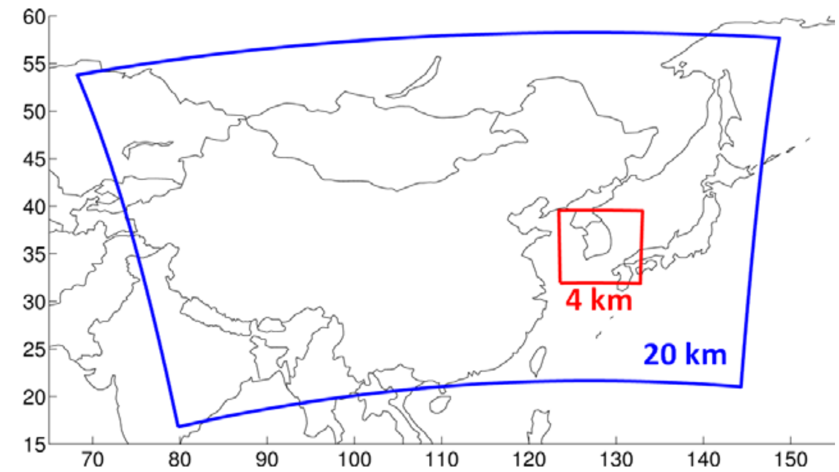

**Fractional Bias reduction**

# Assimilation Technique along with GOCI
# Assimilation Changes 4-d Fields --




LIDAR Back Scat., Seoul Nat. U.

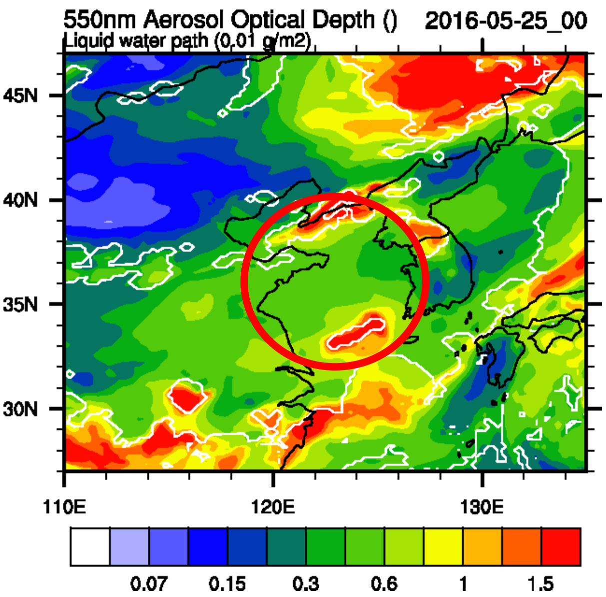
# KORUS-AQ forecasting system



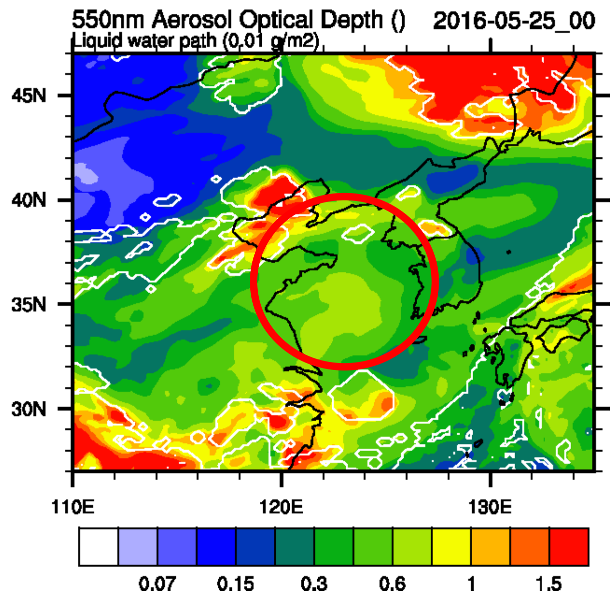

- WRF-Chem with MOSAIC aerosols and a Reduced Hydrocarbon chemistry (Pfister et al. JGR 2014), including simplified SOA formation (Hodzic and Jimenez, GMD 2011)
- GFS and MACC meteorological and chemical boundary conditions
- KORUS-AQ anthro (Jung-Hun Woo) and QFED fire emissions
- AOD data assimilation using GSI (Saide et al., ACP 2013). MODIS and GOCI data were assimilated simultaneously every three hours. **First NRT system assimilating GEO AOD**
- Four days of forecasts were available for the outer domain, 2 days for the inner domain

# Example of AOD assimilation impact during KORUS-AQ

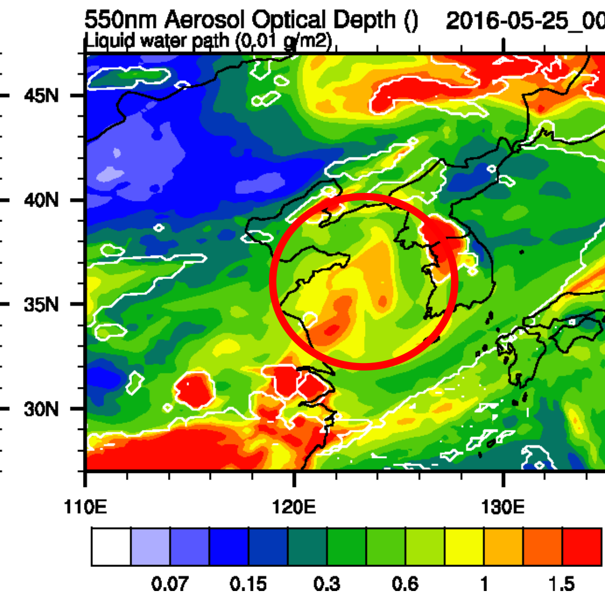
Day-3




Day-2

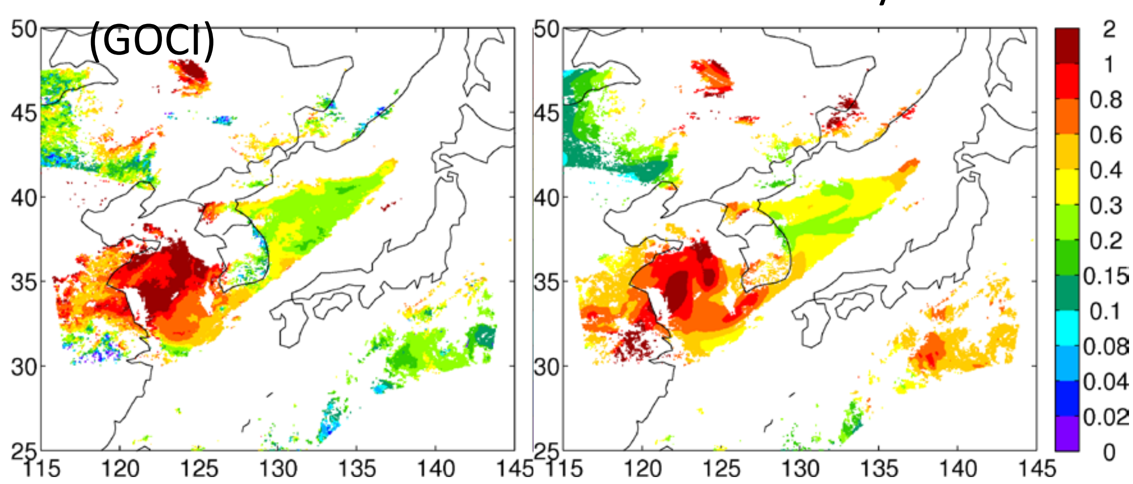



Day-1



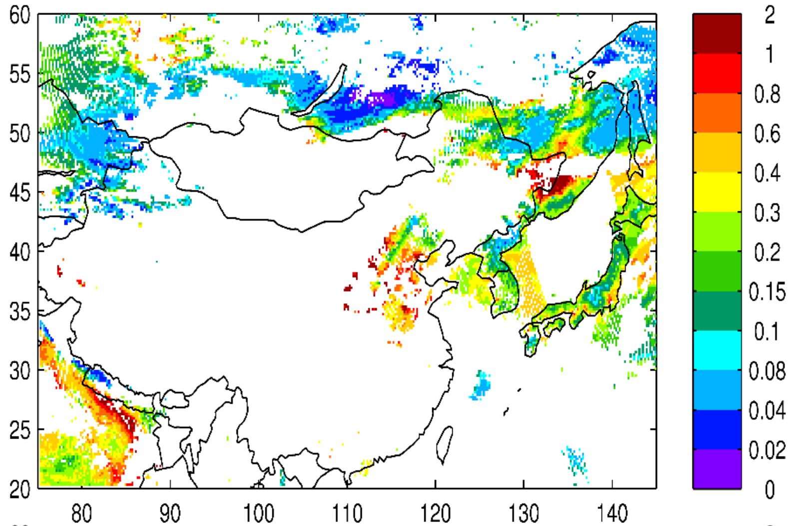

Observed AOD (GOCI)

WRF-Chem Day-1

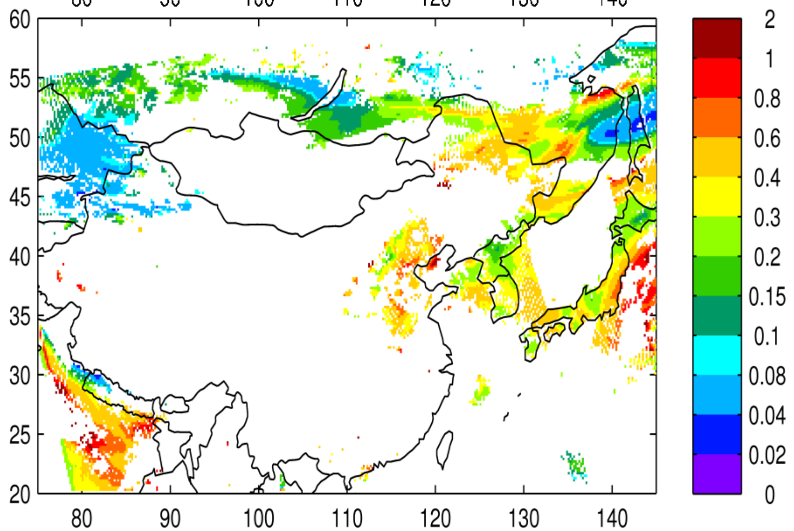


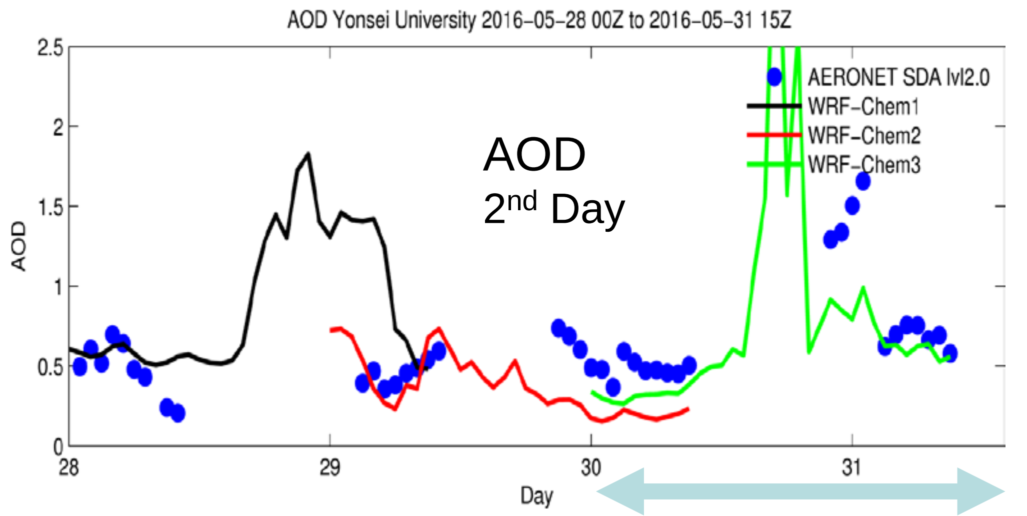
# WRF-Chem Forecast Evaluation vs MODIS and AERONET AOD

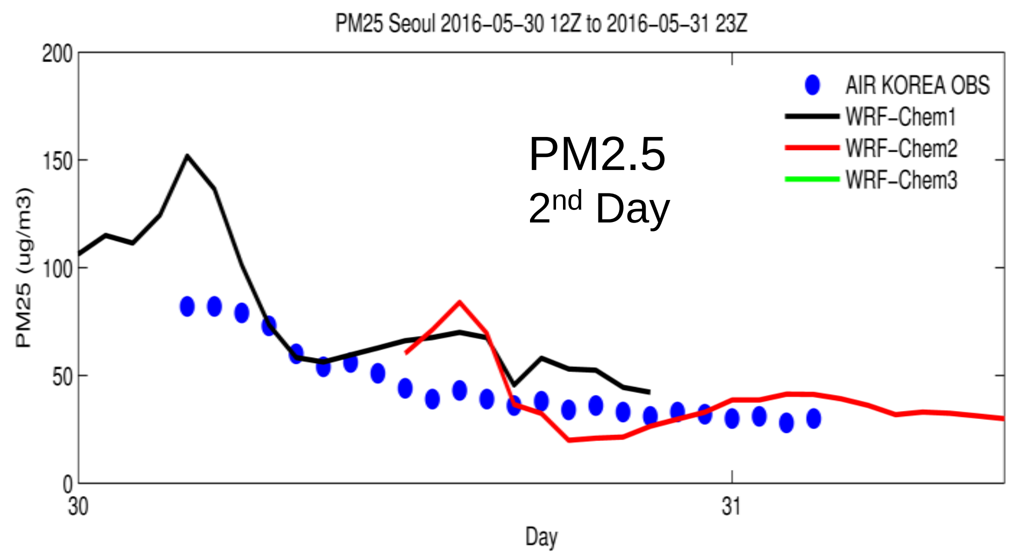
Terra/Aqua NNR




WRF-Chem

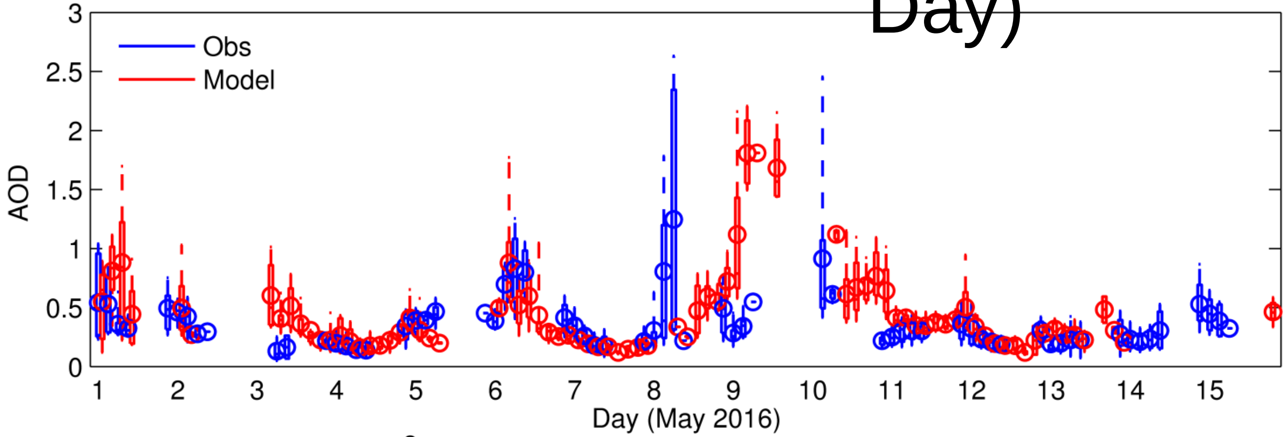


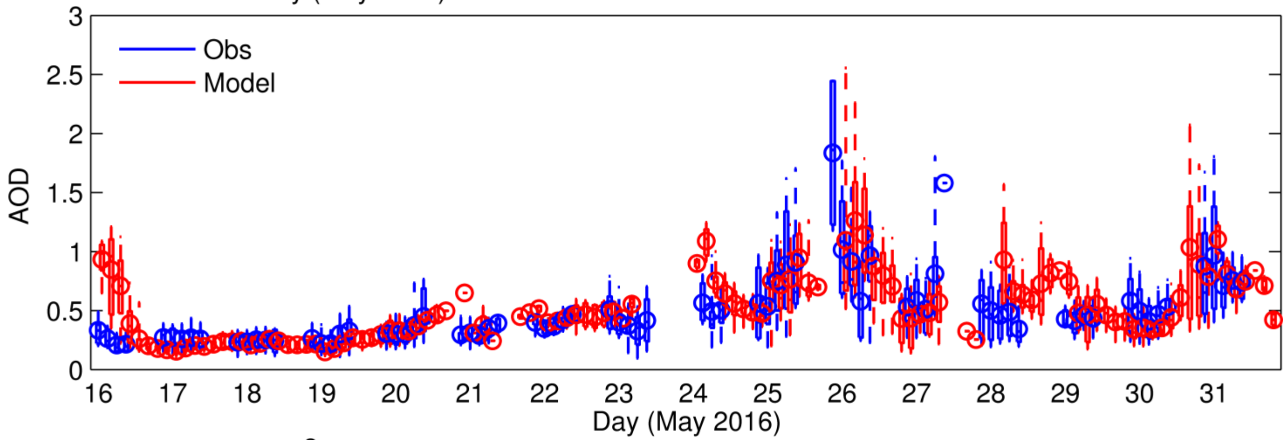



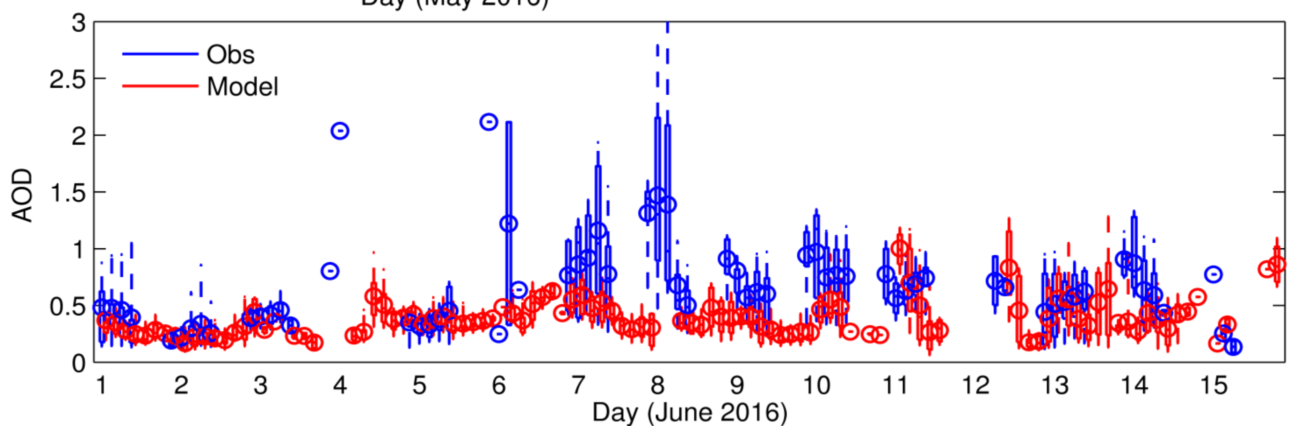



# Impact of Assimilation on AOD Forecasts (2$^{nd}$ Day)

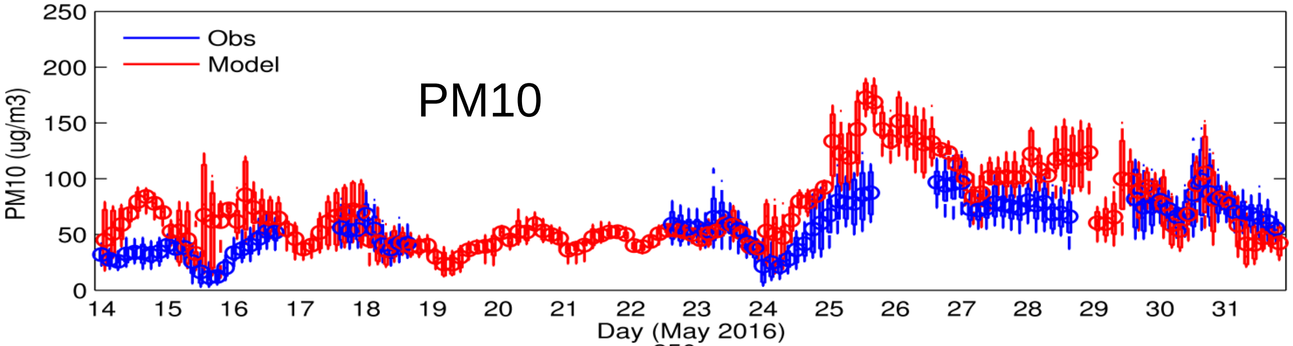
All sites in Korea

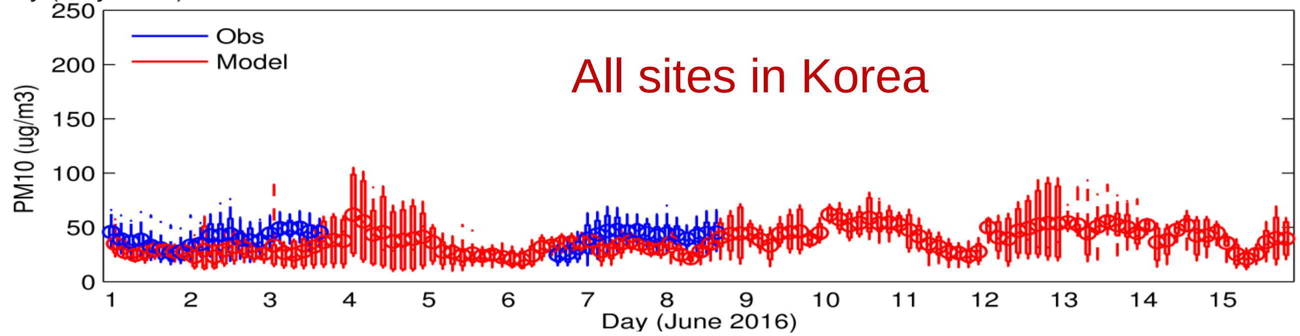


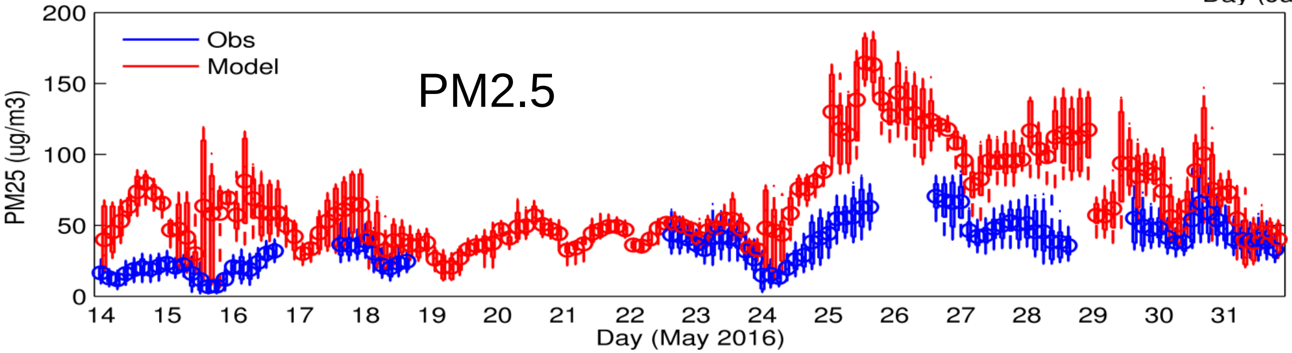



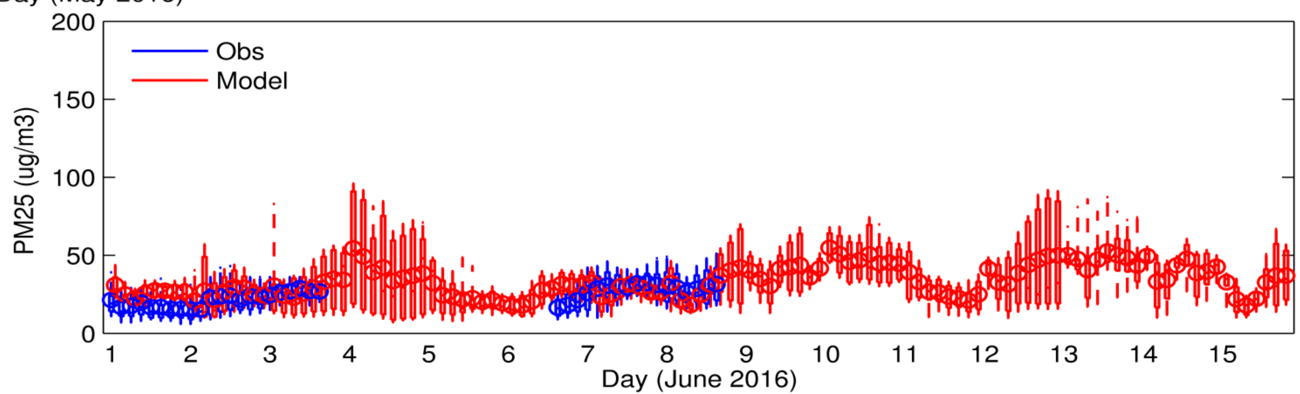



# Impact of Assimilation on PM Forecasts

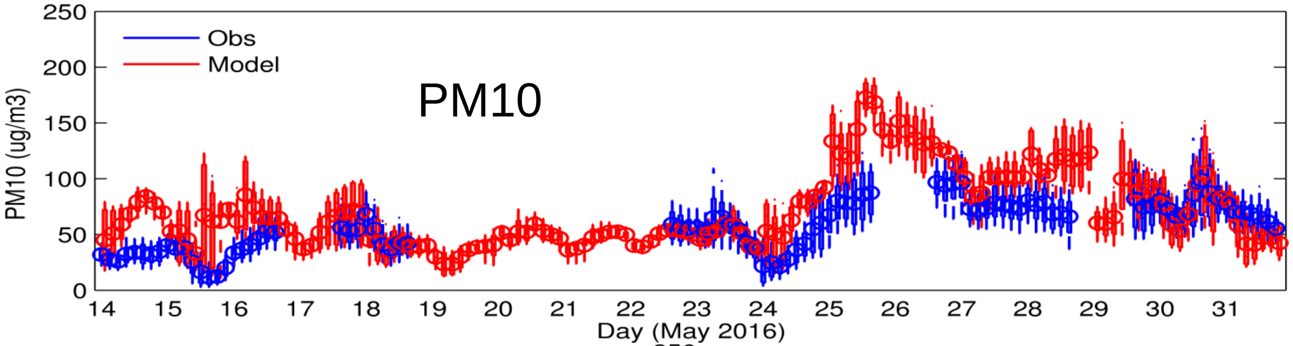


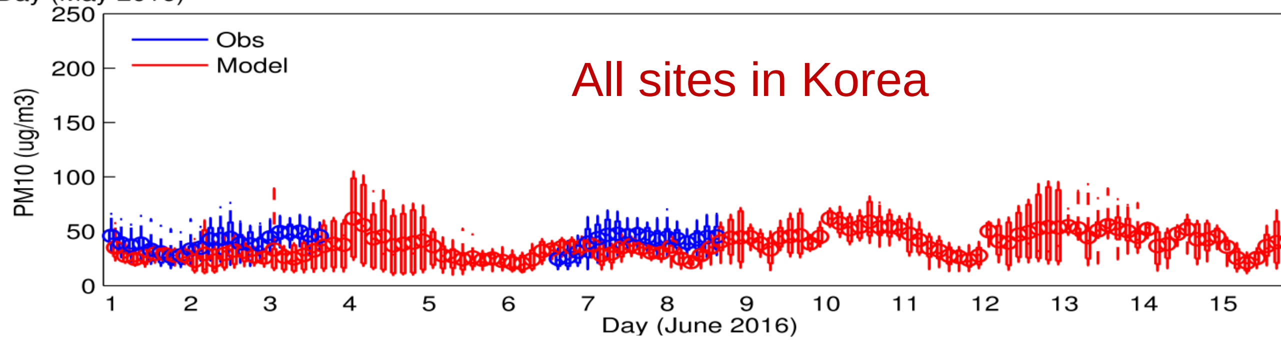



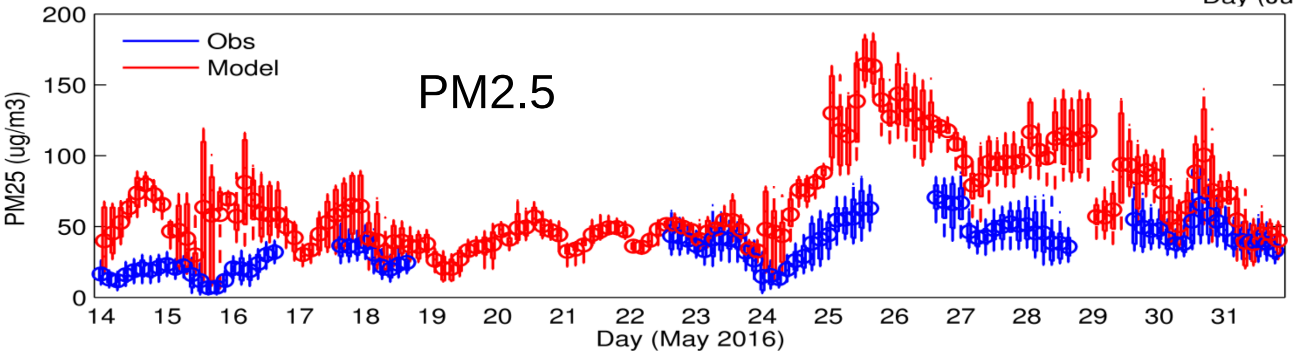



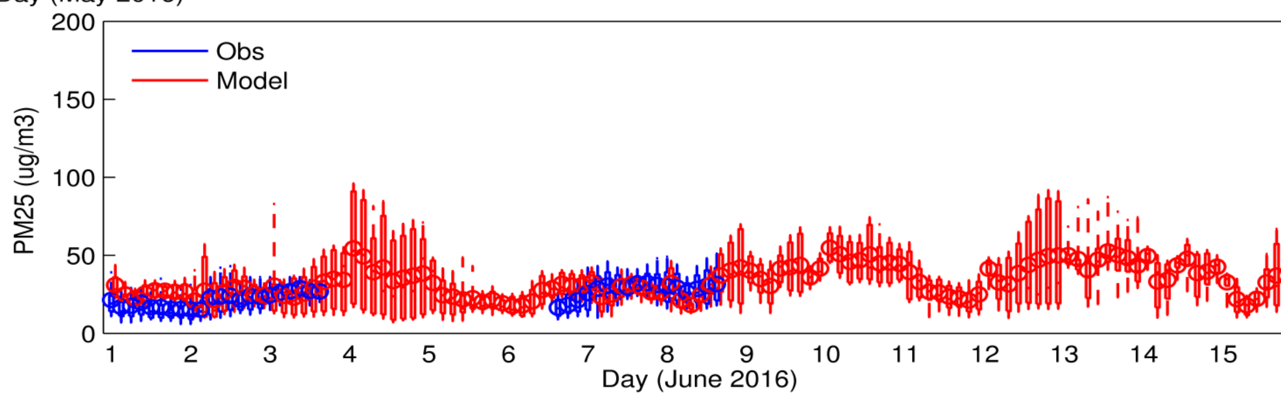



# Impact of Assimilation on PM Forecasts



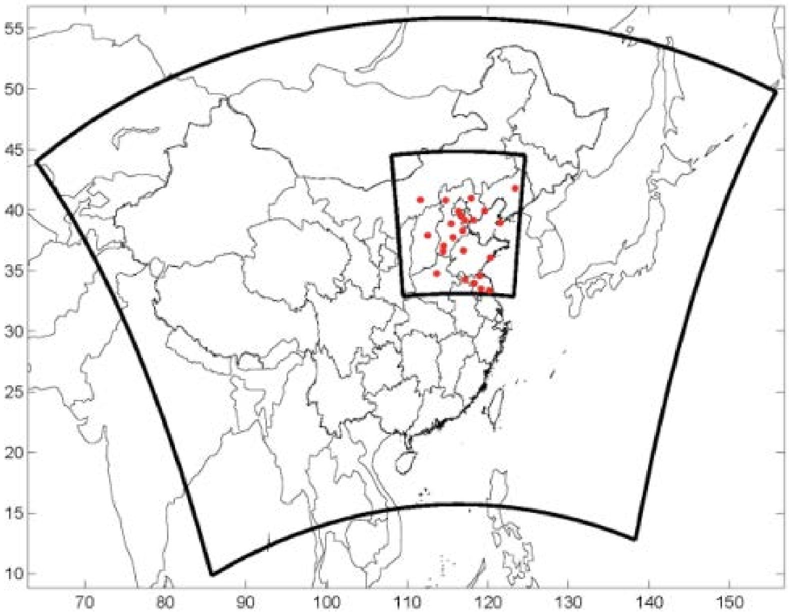



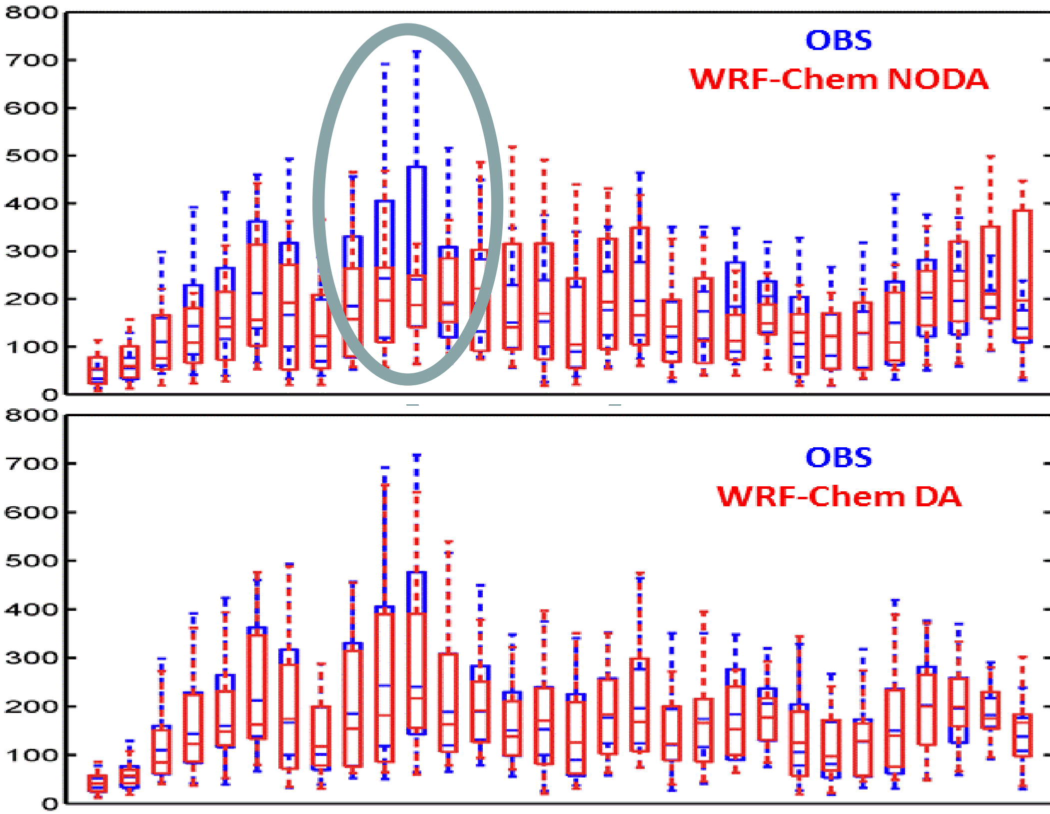

*Further work needed to improve linkages between AOD and PM2.5*

# Technique already Extended to include Assimilation of Surface PM2.5 Observations




**PM2.5 Observations are growing rapidly**

## Haze JAN 2013




*Health impacts from winter haze; e.g., Gao et al., Science Tot. Env., (2015)*

# Application #3a. Adding More Information ***(AOD is not unique!)****- multiple wavelength AOD*

Fractional error reductions (FER)

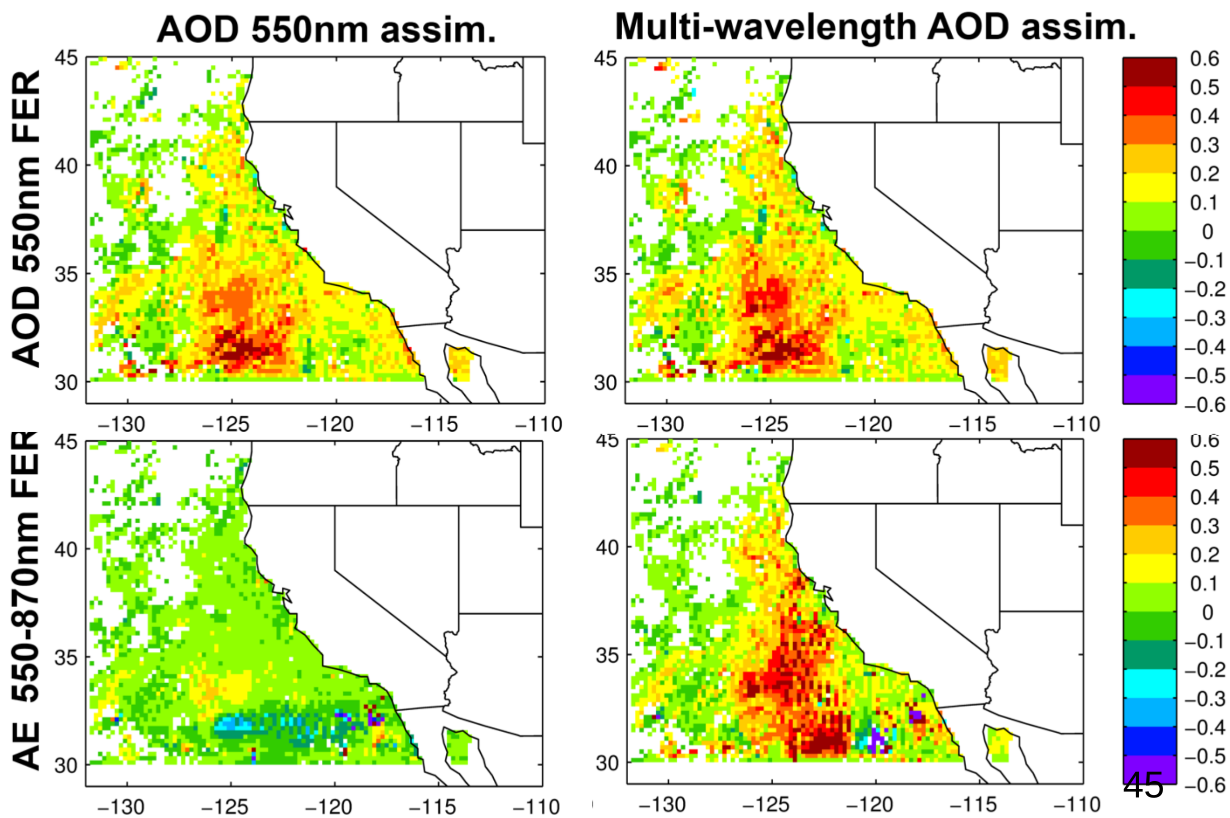
- Compute fractional error for guess and assimilation
- Take the difference
- **Positive values mean improvements**

$$\text{FE}=\frac{1}{N^*M}\sum_{i=1}^{N}\sum_{j=1}^{M}\left|2\frac{P_{ij}-O_{ij}}{P_{ij}+O_{ij}}\right|$$

Angstrom Exponent

$$\frac{\tau_\lambda}{\tau_{\lambda 0}}=\left(\frac{\lambda}{\lambda_0}\right)^{\boxed{-\alpha}}$$

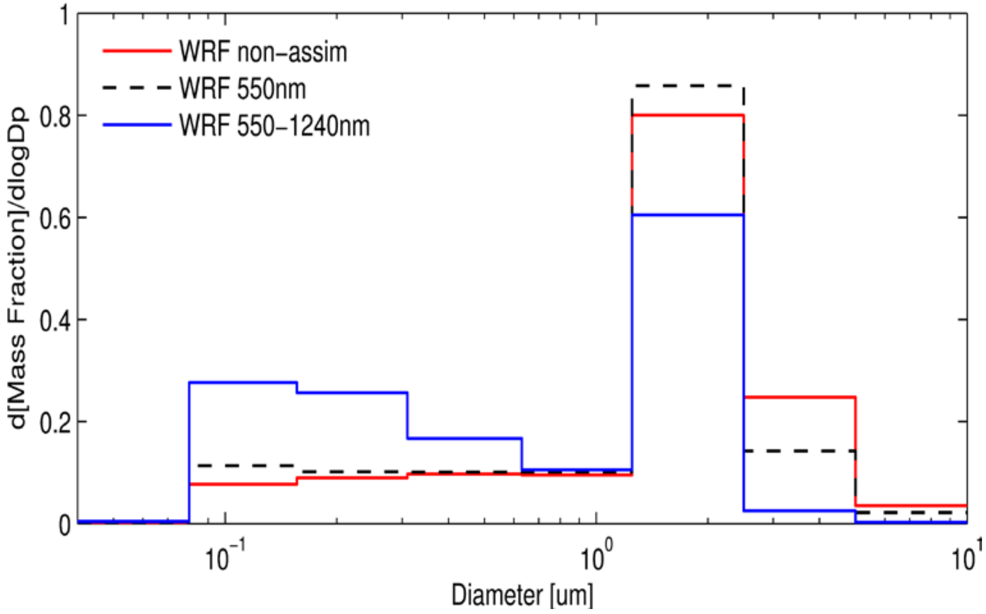
AOD Wavelength

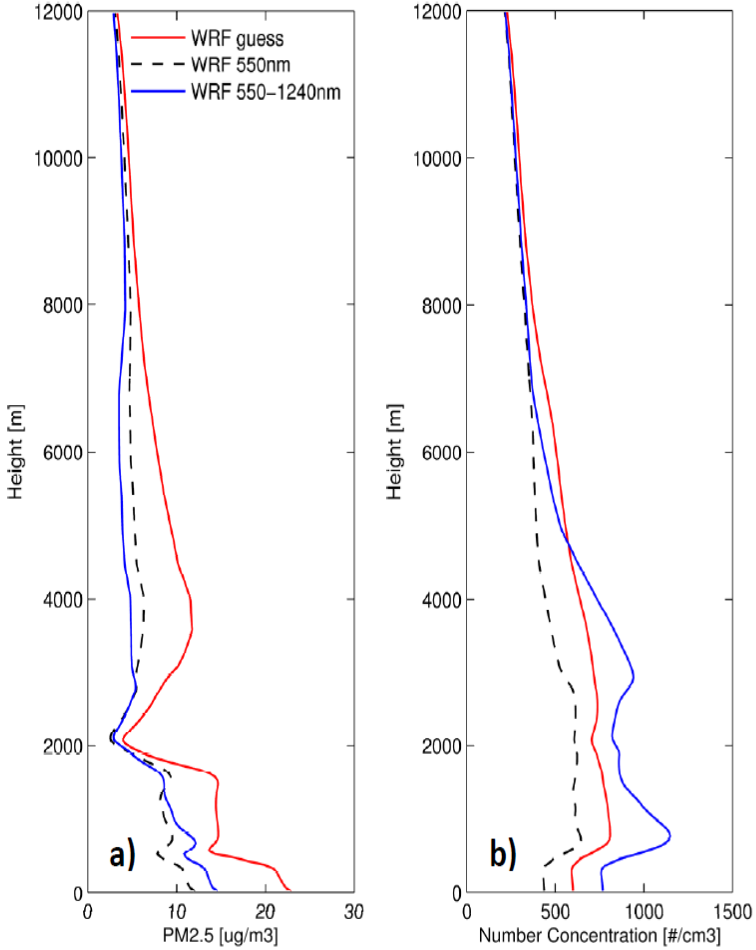



Ref: Saide et al ACP 2013

# Multiple wavelength assimilation impact aerosol size distributions

**Vertical profile May 6th 21Z over the ocean**



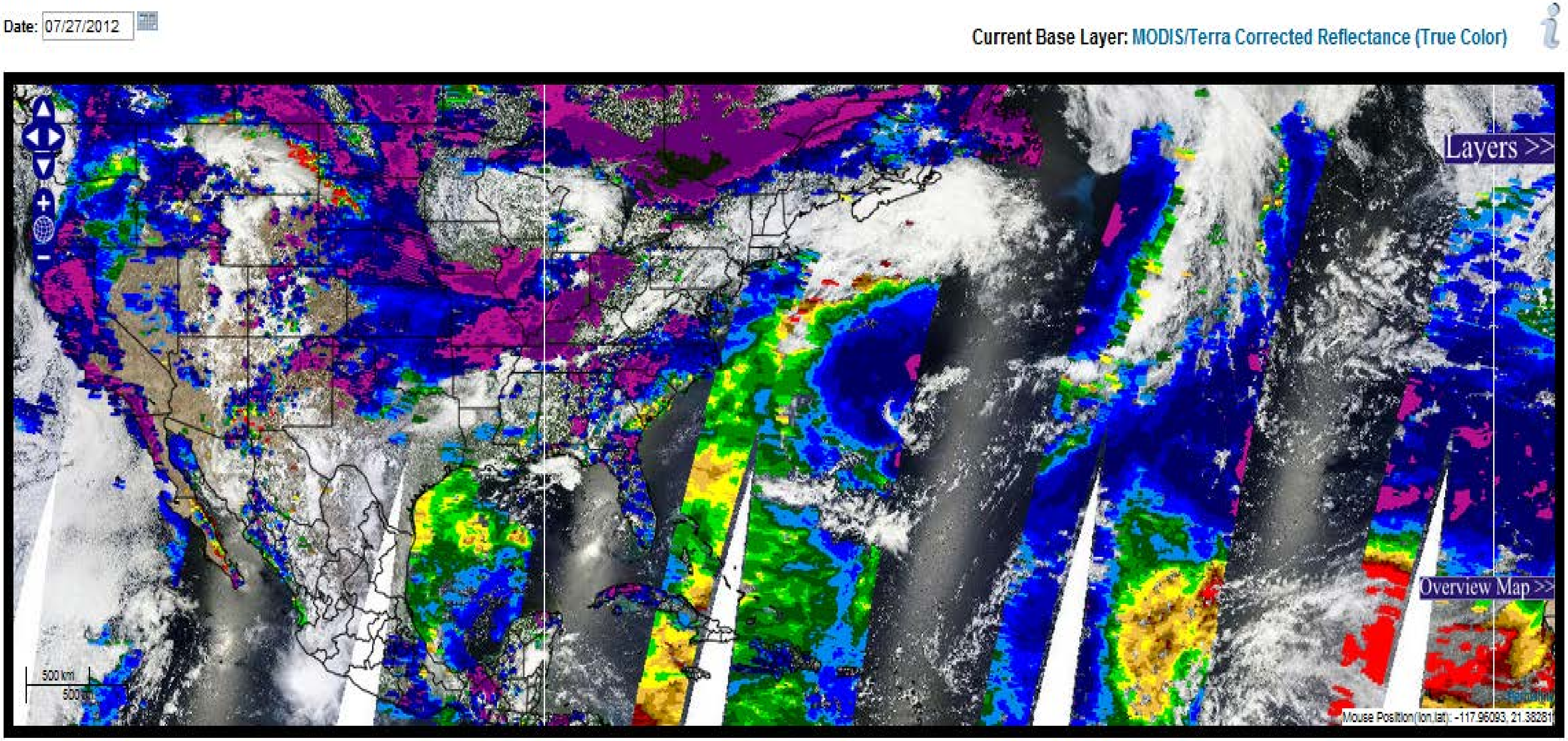




Shift in size distribution

Ref: Saide et al ACP 2013

# Application #3b. Adding More Information – *problem with clouds*

## Challenge in the Use of AOD in AQ Forecasting/Reanalysis



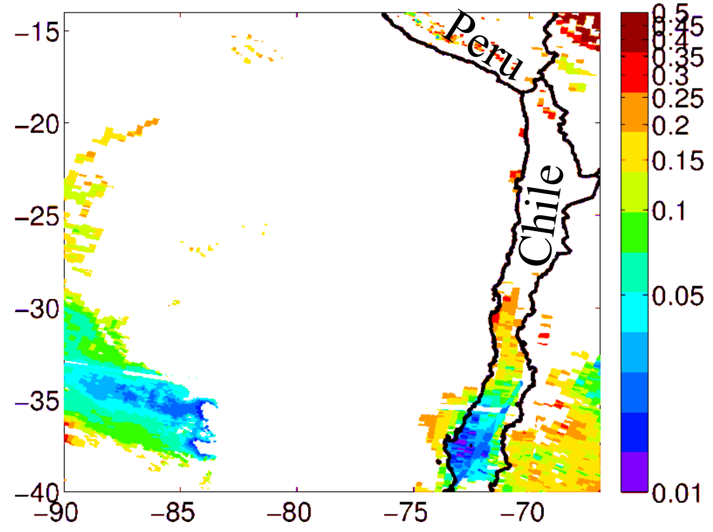
# Challenge

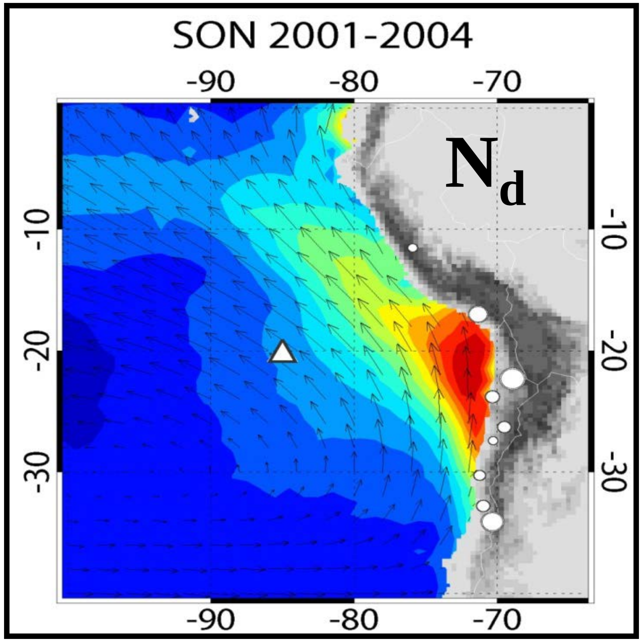
**In cloudy regions there is little AOD information – also it provides limited info on size/composition**

**Idea:**

**Can we use the cloud retrievals to improve sub-cloud aerosol distributions?**

MODIS Terra AOD off Chile & Peru

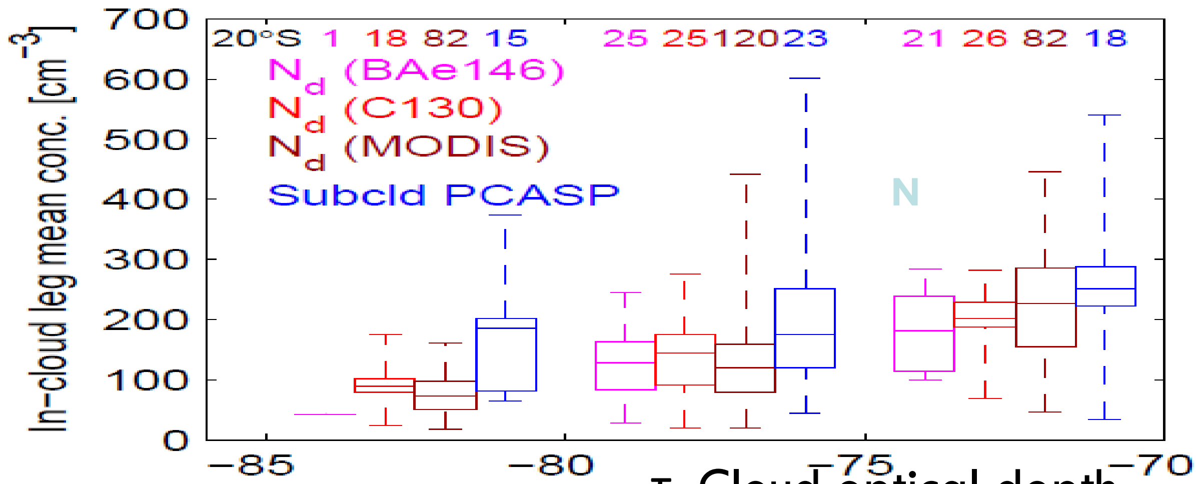


20° S VOCALS-REx stats

# Idea use cloud drop information

- **SEP marine Sc $N_d$ satellite retrievals show evidence of aerosol load and agree with observations**
- **Aerosol indirect effects simulated with some skill in WRF-Chem**
- **Hypothesis: variational assimilation with $N_d$ retrievals can improve below-cloud aerosols in models** ***(see aerosols through clouds)***




$$N_d = K \tau^{1/2} r_e^{-5/2}$$

τ: Cloud optical depth

$r_e$: Cloud effective radius

$N_d$: Cloud droplet #

N: Aerosol #conc.

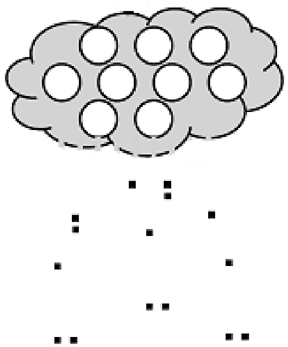
Refs: Saide et al. (2012), Bretherton et al.(2010), Painemal and Zuidema (2011)

# Aerosol data assimilation using cloud satellite retrievals



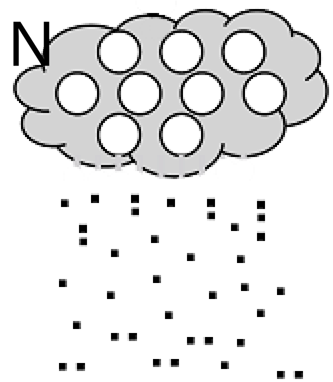
$N_d$ changes during the forecast due to activati

Model N & $N_d$

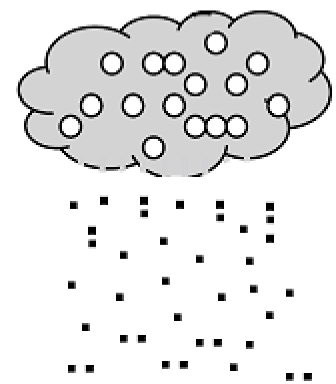


Below cloud aerosols

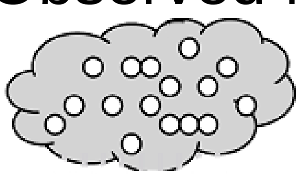
Assimilated N



Forecast N & $N_d$ after assim



Observed $N_d$



?

- Log 3DVAR
- Adjoint of WRF Aerosol Activation
- Changes N and

N: Aerosol Number

$N_d$: Cloud droplet number

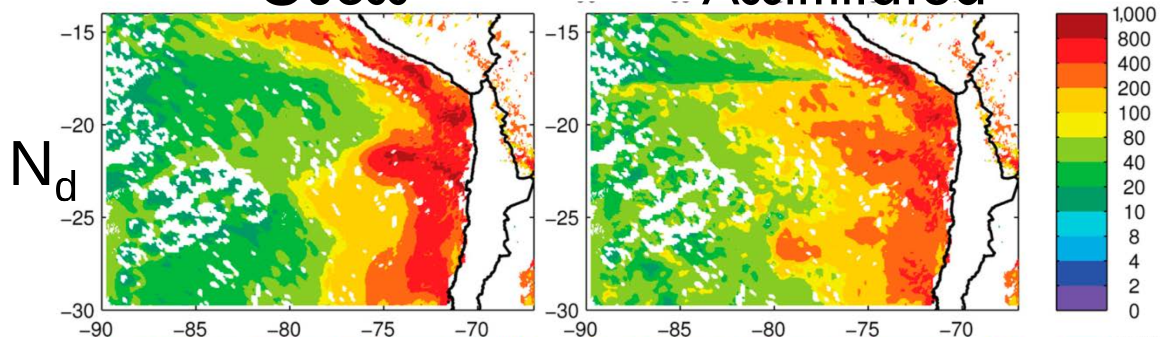
Ref: Saide et al., PNAS 2012

# Assimilation results: + & - biases reduced

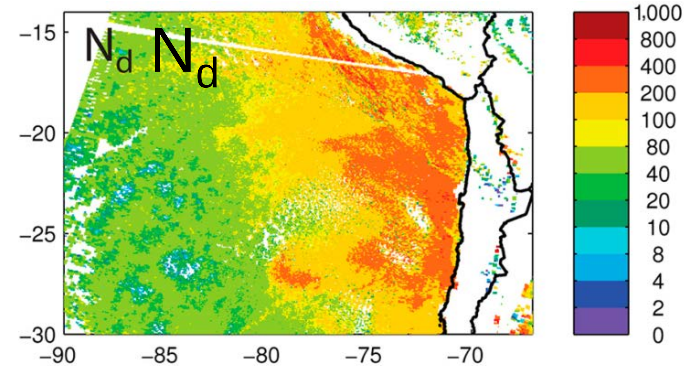
- Assimilate MODIS Terra $N_d$
- Aerosol mass and number are changed

WRF-Chem Guess

WRF-Chem Assimilated




MODIS Obs

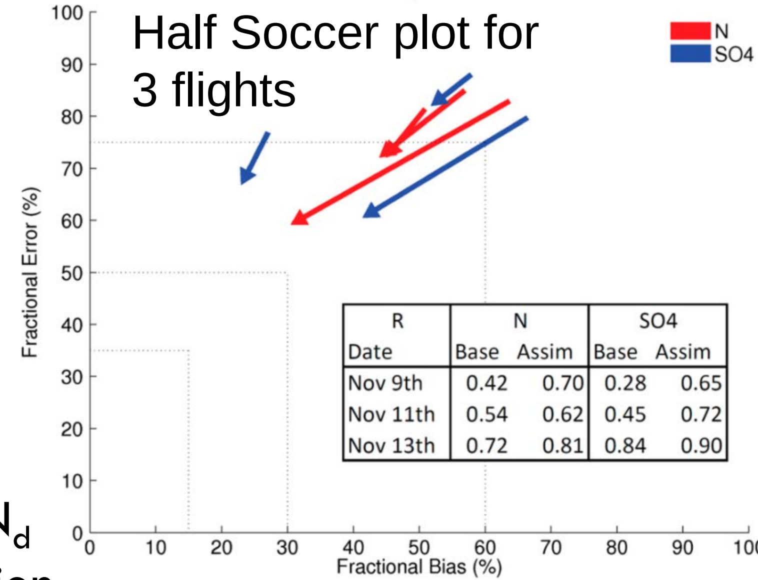



Ref: Saide et al., PNAS 2012

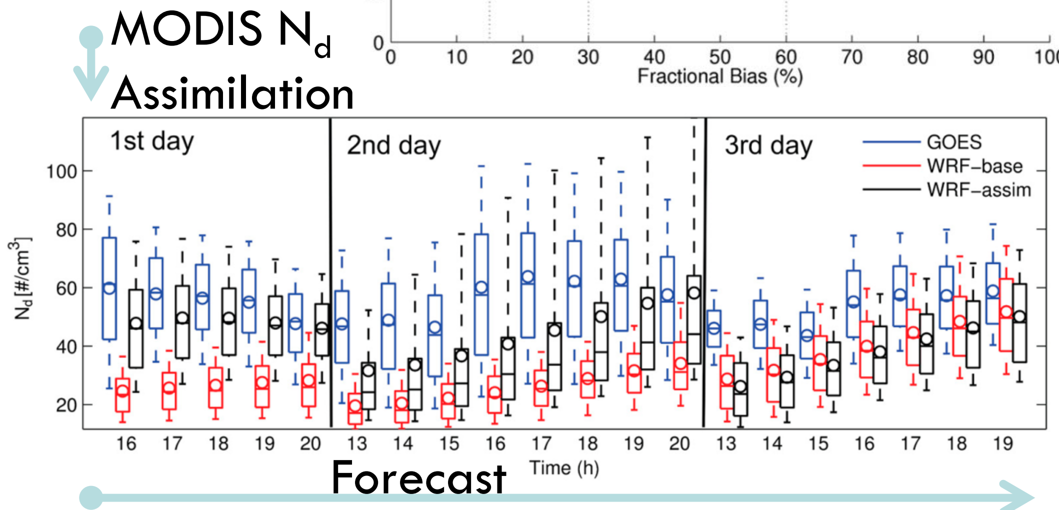
# Daytime $N_d$ after assimilation vs GOES and in-situ aerosol

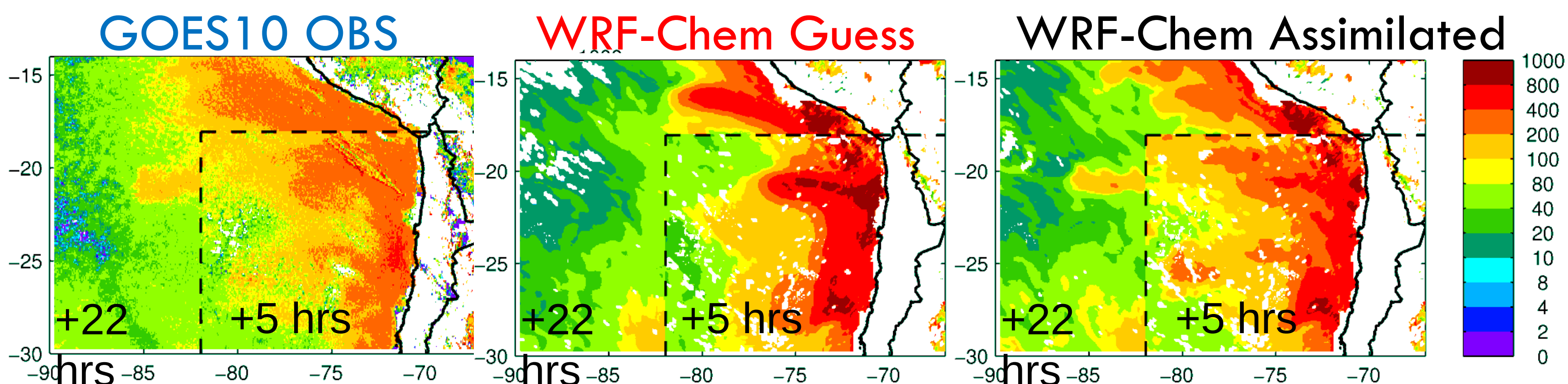
52

- Large improvements during the first 2 days for all domain
- GOES Assimilation improves agreement with VOCALS-Rex C130 aerosol number and mass observations

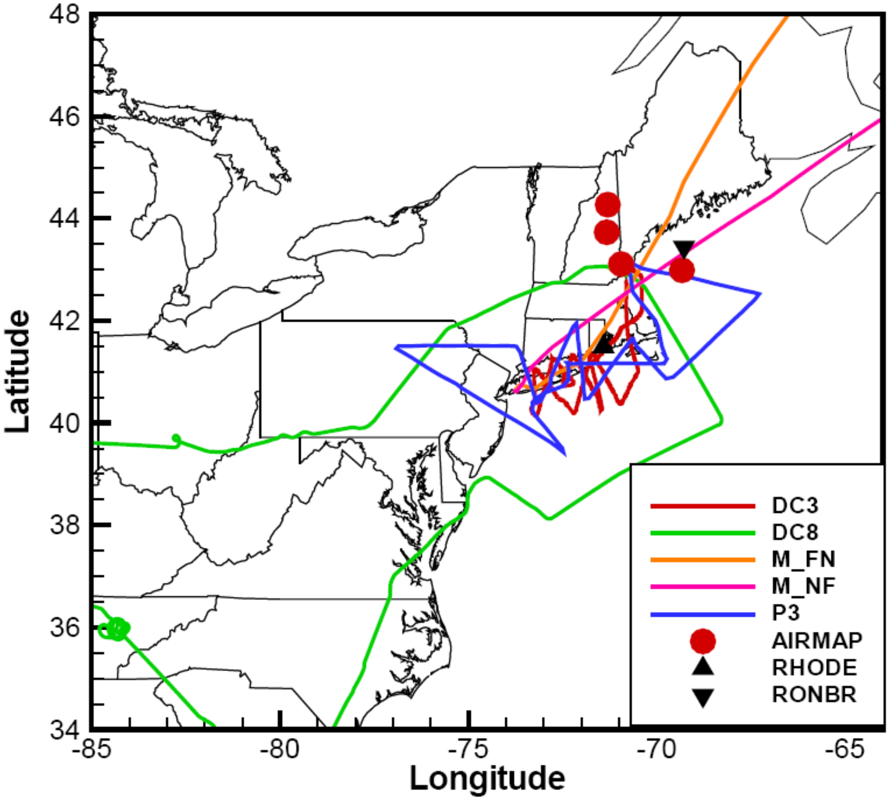



| R | N | | SO4 | |
|---|---|---|---|---|
| Date | Base | Assim | Base | Assim |
| Nov 9th | 0.42 | 0.70 | 0.28 | 0.65 |
| Nov 11th | 0.54 | 0.62 | 0.45 | 0.72 |
| Nov 13th | 0.72 | 0.81 | 0.84 | 0.90 |



# Assimilation of ICARTT Ozone Observations -- Assessing Information Content (4dVar)



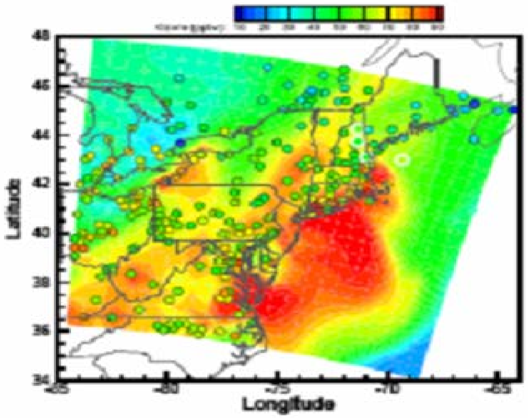

| Observations | Description |
|---|---|
| AIRNOW | EPA surface stations, hourly averaged data used |
| DC3 | Vertical profile of ozone mixing ratio from lidar |
| MOZ-FN | MOZAIC, Frankfurt-New York flight |
| MOZ-NF | MOZAIC, New York-Frankfurt flight |
| P3 | NOAA P3-B measurement |
| AIRMAP | UV SPECTROSCOPY measurement at 4 sites |
| DC8-In | NASA In Situ Ozone via Nitric Oxide Chemiluminescence |
| DC8-Li | DC-8 Composite Tropospheric Ozone Cross-Sections |
| RHODE | Ozonesonde/Radiosonde data from Narragansett, RI |
| RONBR | Ozonesonde/Radiosonde data from the R/V Ronald H. Brown |

# Assimilation Produces An Optimal State Space

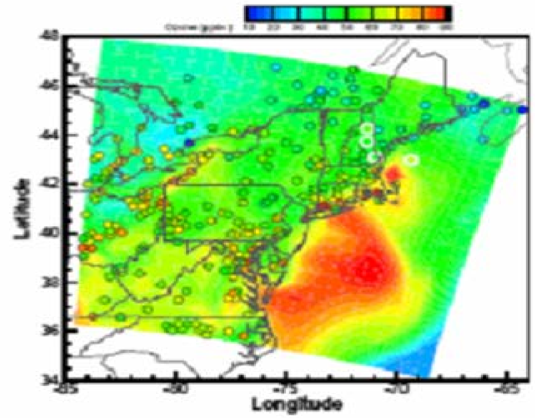
***the importance of measurements above the surface!***

**w/o assimilation** **with assimilation**

**Ozone predictions**




A



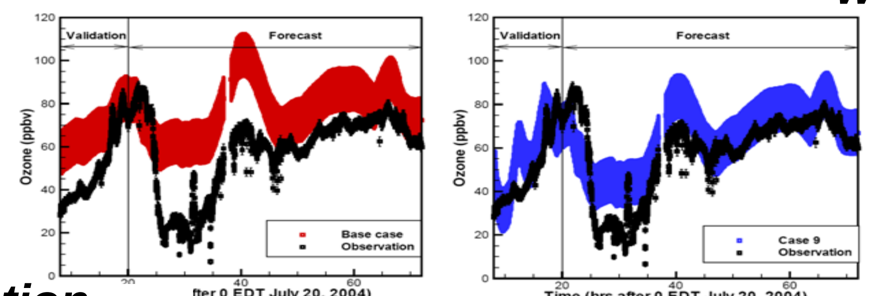

B

*Example July 20, 2004*

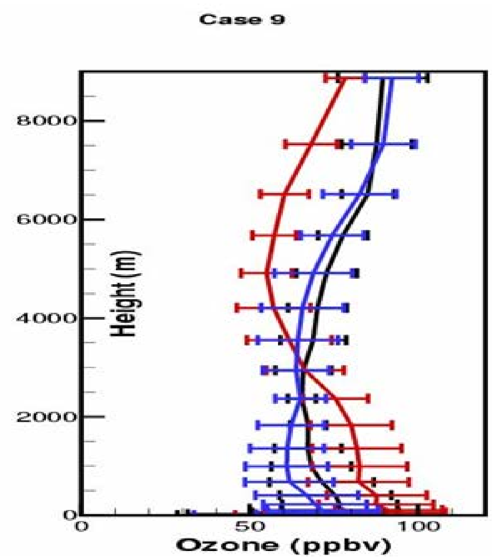
Verification: Ron Brown Observations
Independent Data

***with***

***w/o assimilation***




*Predicted uncertainties estimated from background (B) error estimates*




D

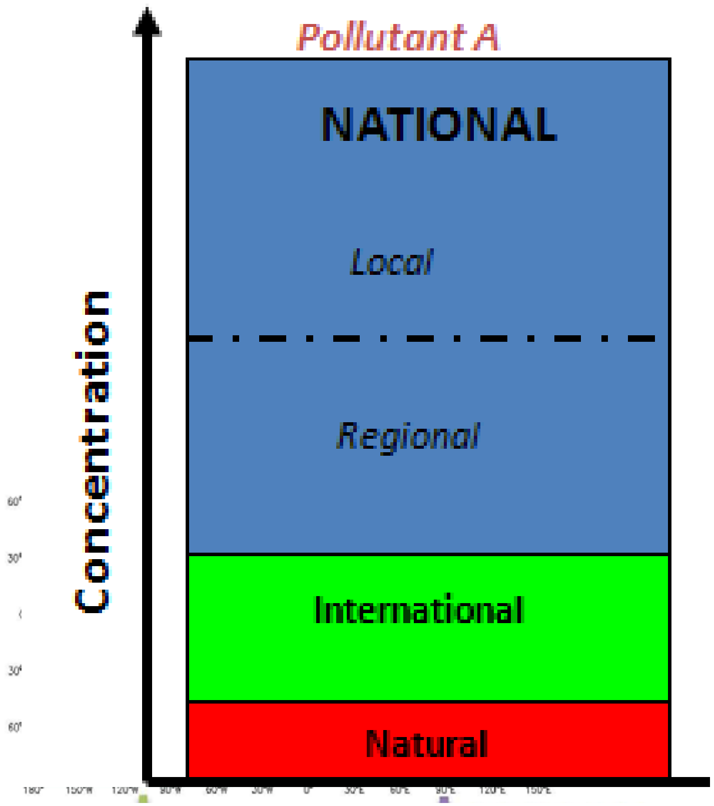
***Information below 4 km most important***

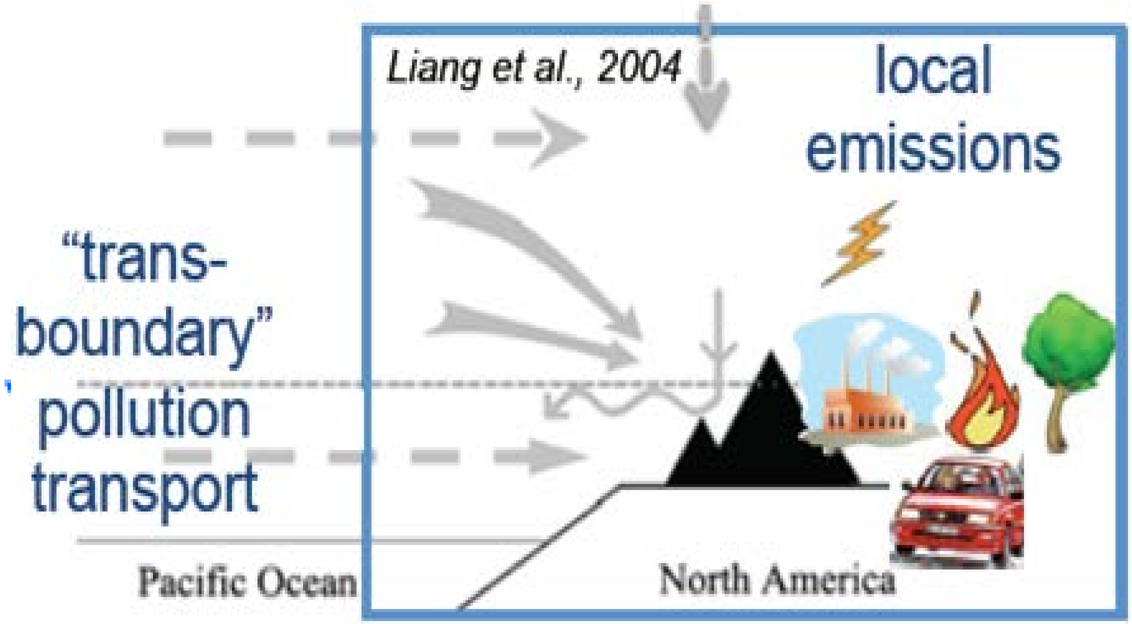
**Region-mean profile**

***Chai et al., JGR 2007***

**Framework** To improve modeled ozone contributions from non-local and local sources :

Using multi-model experiment and multi-scale chemical data assimilation of Aura observations, we aim at improving the estimated impacts on ozone in California from trans-boundary pollutants and US ozone precursors (NOx & isoprene) emissions




***Huang et al., JGR, 2015***

**Framework:** To improve modeled ozone contributions from non-local and local sources

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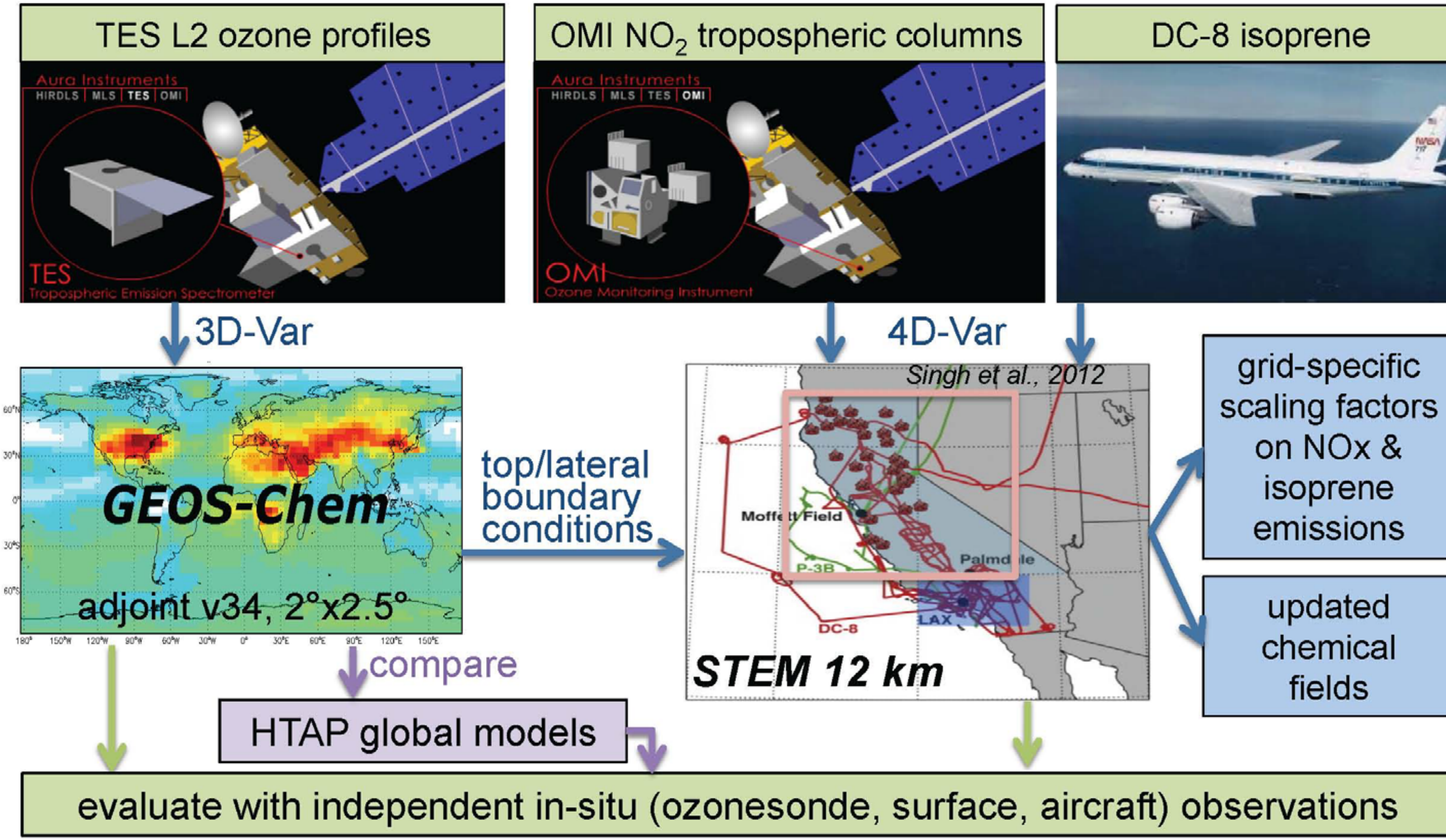
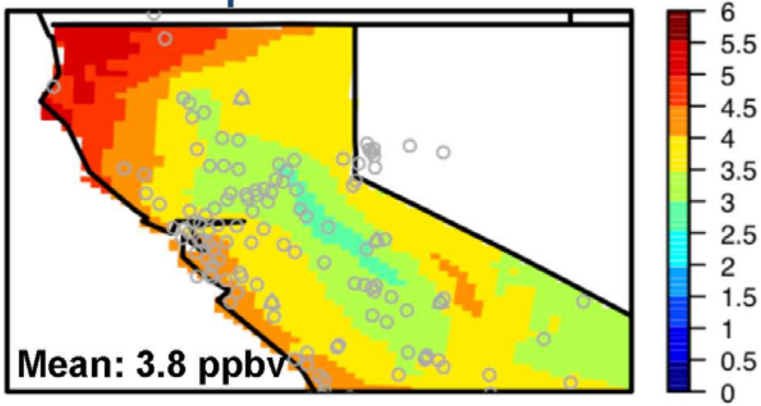


# Impact of the multi-scale assimilation on STEM ozone: We repartitioned ozone source contributions from local and non-local sources

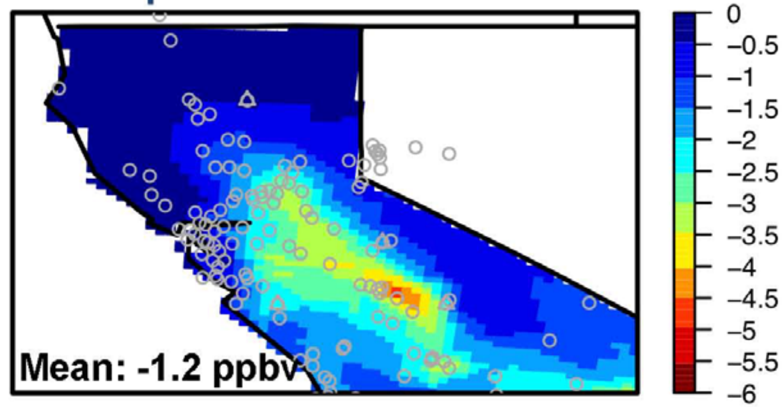
*Period-mean near-surface daytime (<2 km a.g.l., 8am-7pm) ozone in STEM, after-before assimilation*

## w/ updated BC



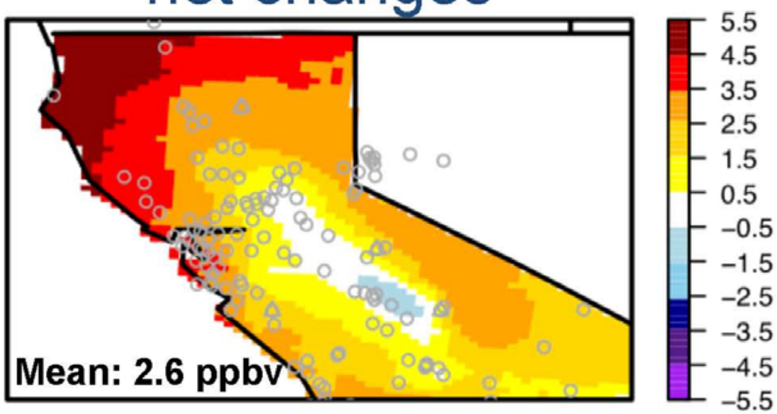

Contributions from "transported background" increased by **2-6 ppbv**.

## w/ updated emissions




Contributions from US NOx & isoprene emissions dropped by ~**0-6 ppbv**.

## net changes

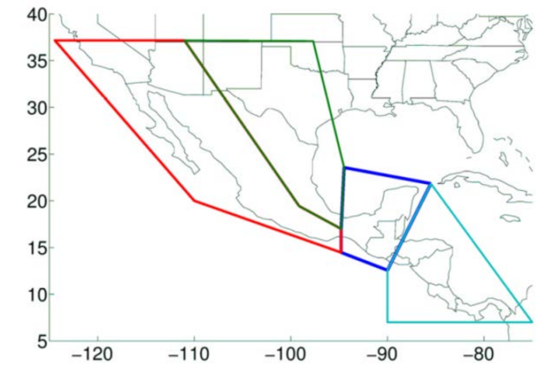


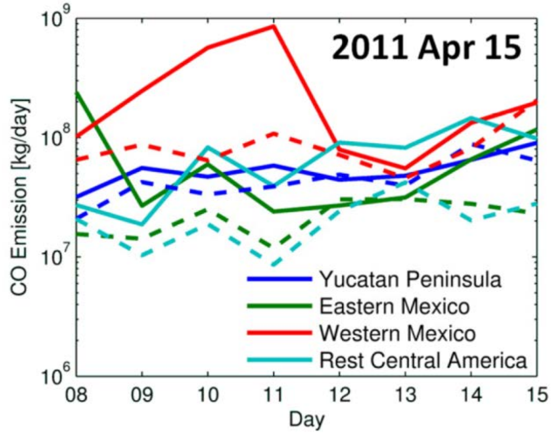

- Background ozone enhanced by ~4 ppbv (~8%)
- Monitoring sites unable to capture some strong changes made by the assimilation

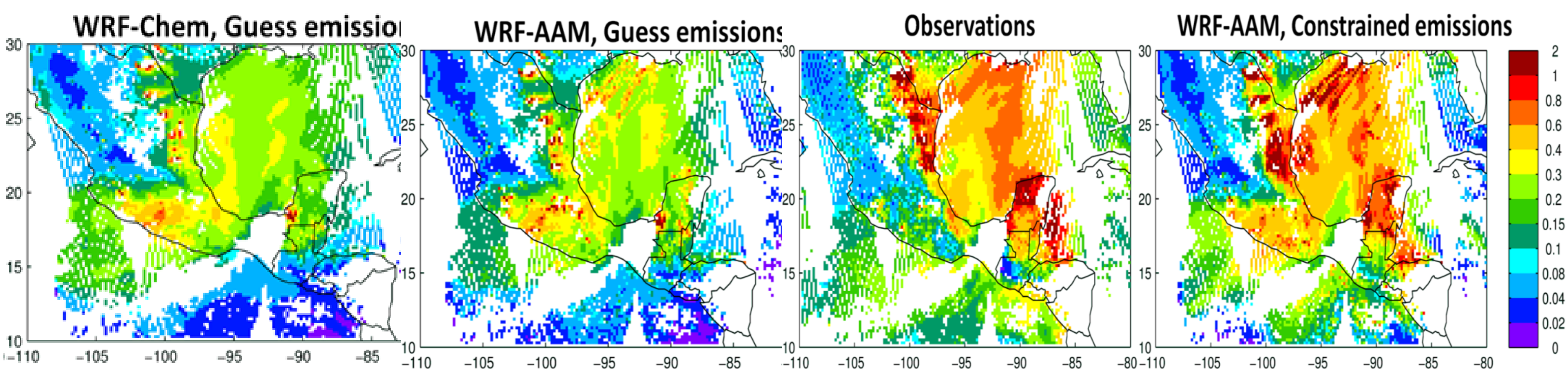
- High terrain regions: more sensitive to extra-regional sources
- Central Valley: more sensitive to local NOx and isoprene emissions

# Constraining biomass burning emissions for improved prediction skill and assessing smoke-weather interactions

- WRF with aerosol-aware microphysics (AAM) (Thompson and Eidhammer, 2014) and WRF-Chem emissions.
- Inversion based on Saide et al. (GRL 2015b) using WRF tracers (no adjoint, no ensembles)
- Plans for using it operationally for the NASA ORACLES and NOAA FIREX field experiments
- Run 2 forecasts needed by the inversion method (with and without feedbacks) so that aerosol feedbacks impacts are also forecasted





# **Opportunity:** Assimilation of Key Meteorological Parameters Improve AQ Prediction Skill

## Design Period Simulations – Satellite Inputs

**Retrospective – Data Assimilated for all Integration Period**

*Example: impact of met parameters*

Geostationary Satellite Observations –
- Insolation
- Skin temperatures
- Cloud Properties

MODIS
- Surface emissivity
- Surface albedo
- Skin temperatures

Satellite derived properties for photolysis rates

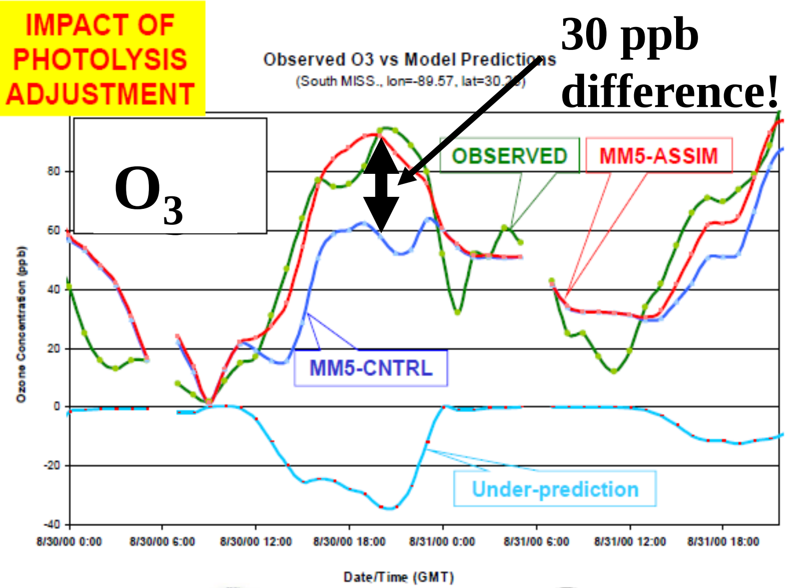
**Physical Model**

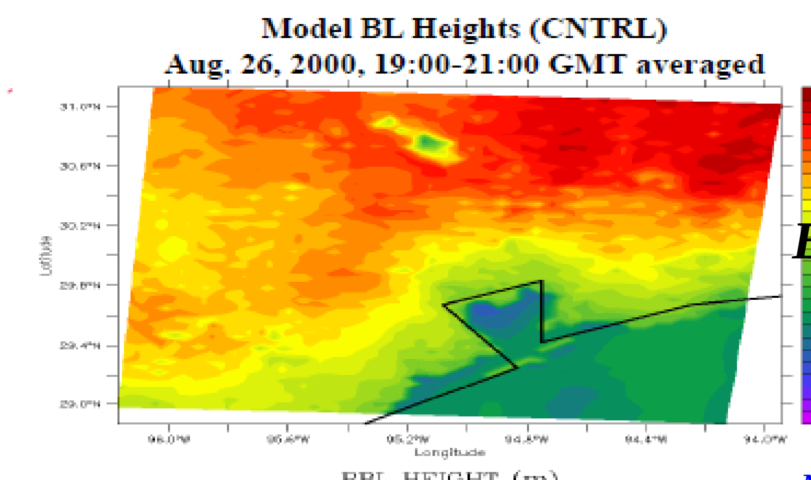
Recreates Physical Atmosphere

→

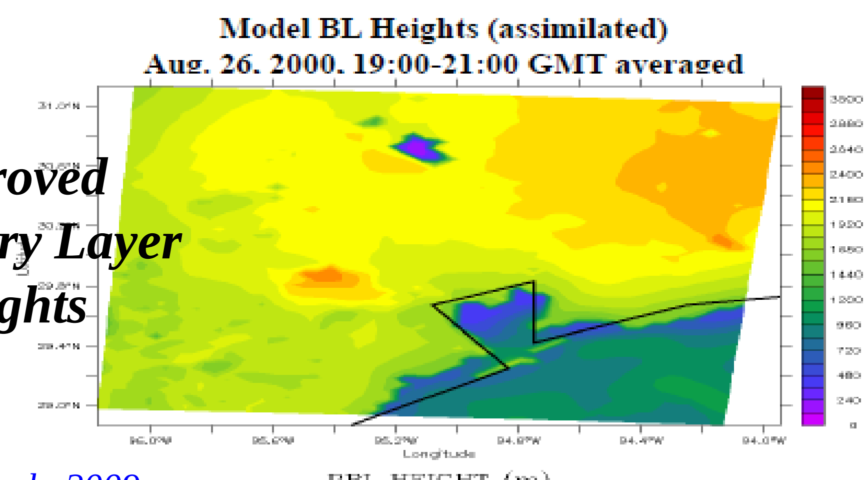
**Chemical Model**

Recreates Chemical Atmosphere




***Improved Boundary Layer Heights***



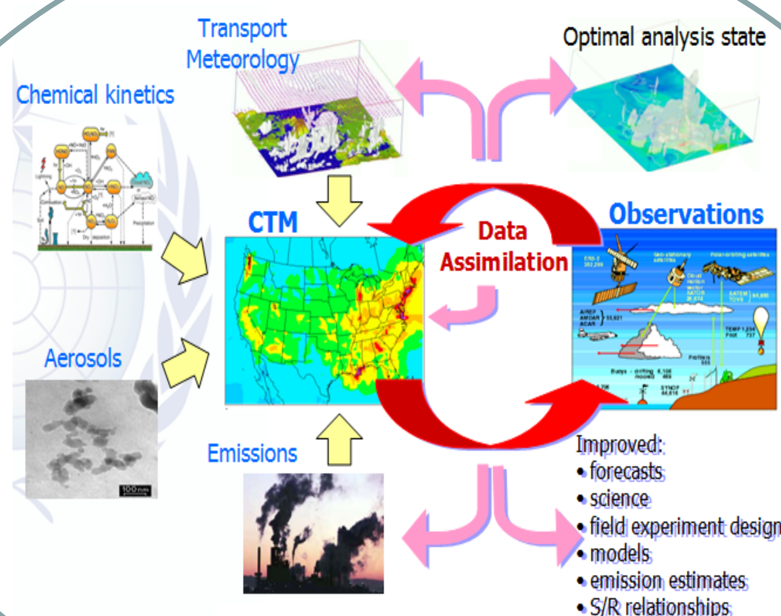

*McNider et al., 2009*

# The Growing Interest in Improving Air Quality Predictions/Services and the Role of Atmospheric Composition in Weather and Climate Applications Offer Great Opportunities for Our Community

Improved Forward Models & Assm. Sys.

Evolving Obs Systems

Continuous Research




**Improved Predictions** ***Requires***

Improved Emissions

Enhanced Data Management & Discovery Systems