

GEOS-5 Nature Runs and Observation Simulations for the Atmospheric Composition Geostationary Constellation

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Michael Long, Lu Hu, Daniel Jacob (Harvard University) and the GEOS-Chem Development Team

Shobha Kondragunta and Pubu Ciren (NOAA /NESDIS/STARR)

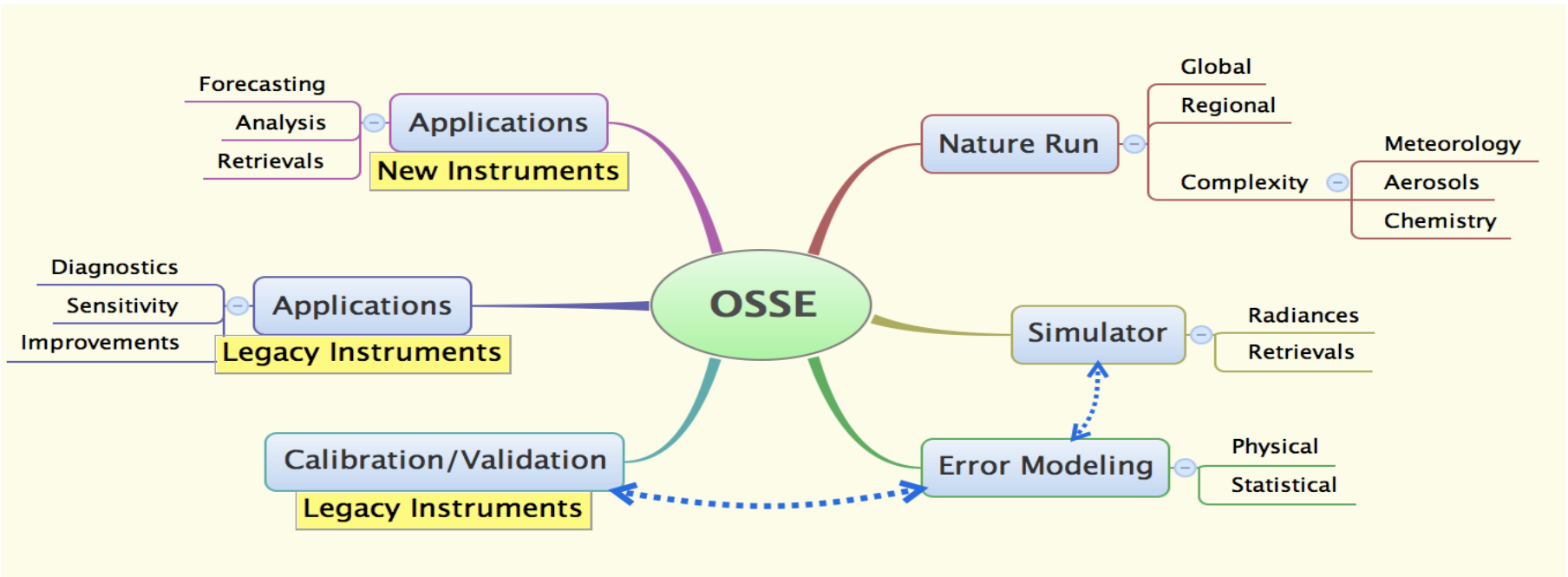
13th Meeting of the
Atmospheric Composition Virtual Constellation
Paris, France, June 27-29, 2017

Outline



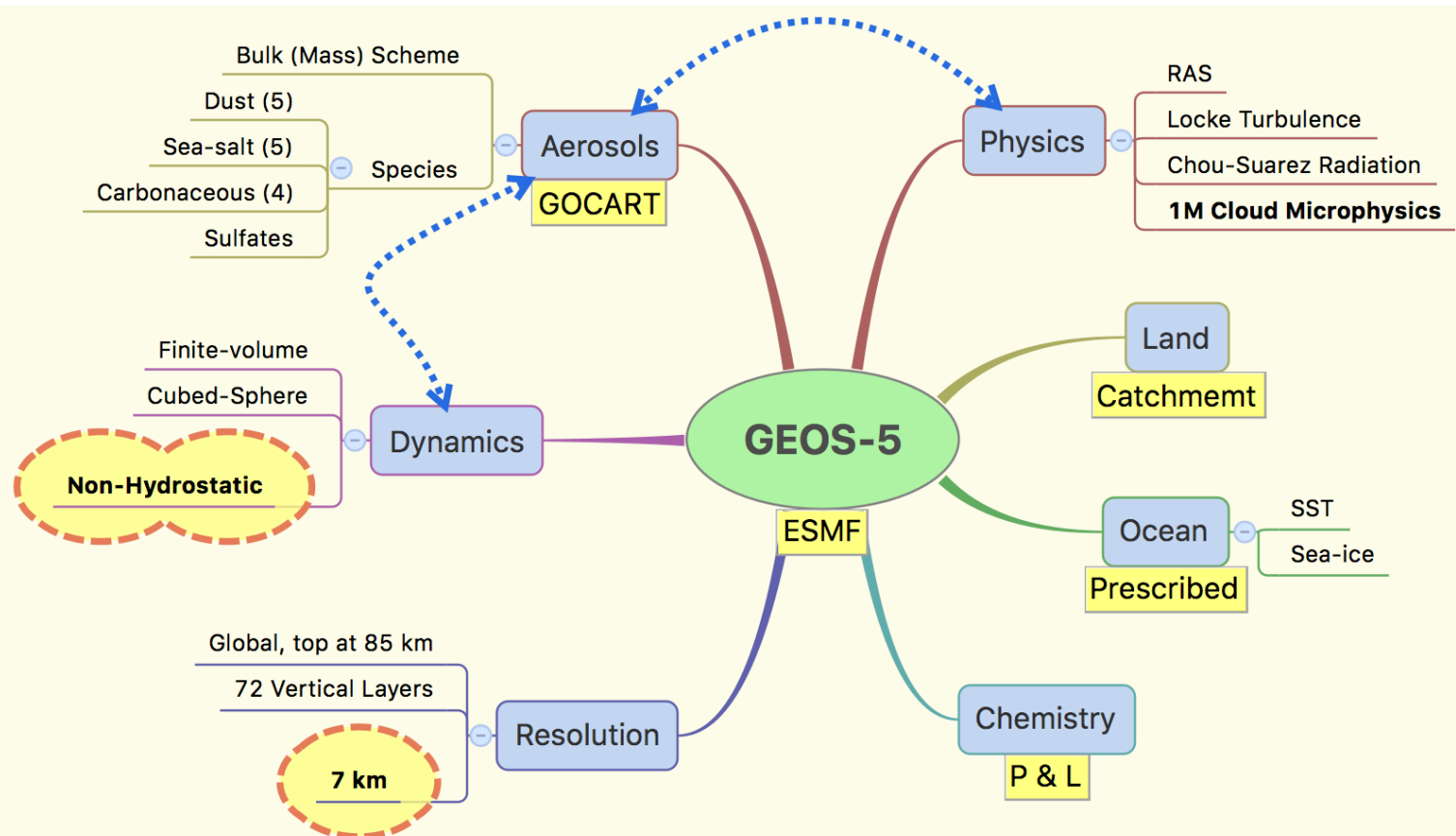
- GEOS-5 Nature Runs
 - 7 km GEOS-5 Nature Run (G5NR)
 - 12 km GEOS-5 Nature Run with Full Chemistry
- Observation simulators for Geo constellation
 - Instruments: TEMPO, GEMS, SENTINEL-4, GOES-R
 - Vector RT optimizations
 - Retrieval simulators: UV & GOES-R synergism

Elements of an OSSE System



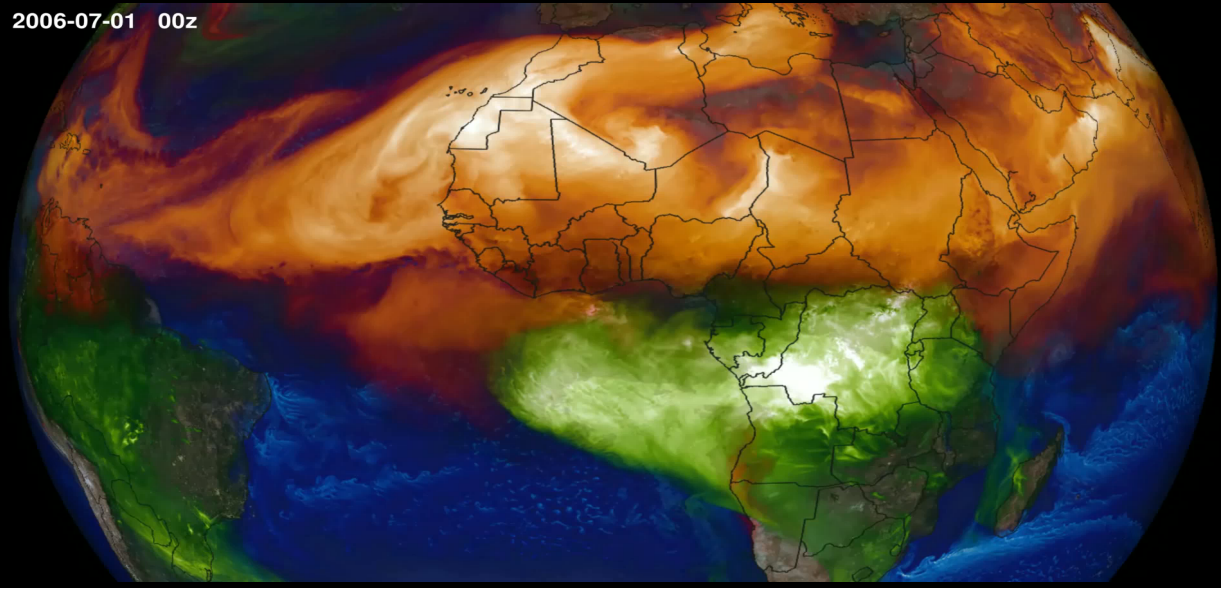
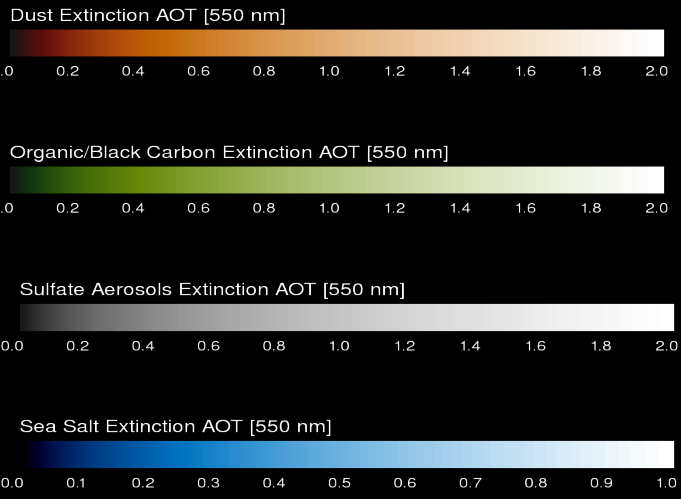
Nature Runs

G5NR Configuration



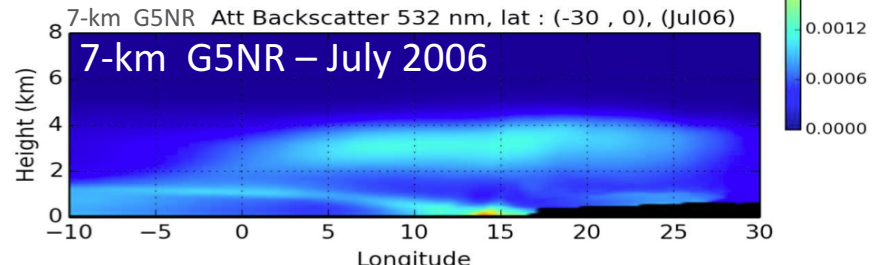
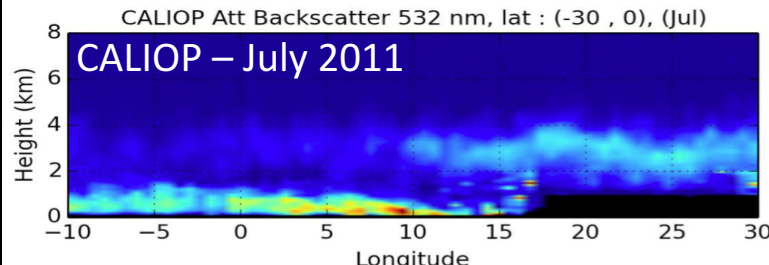
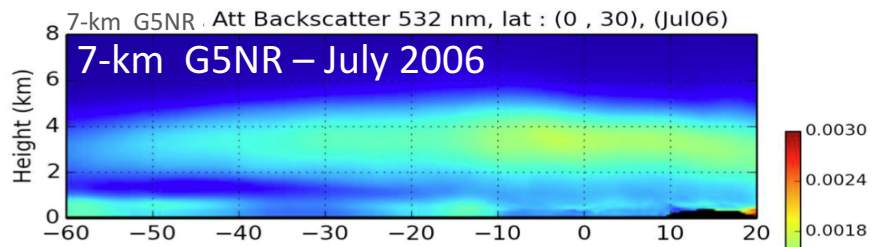
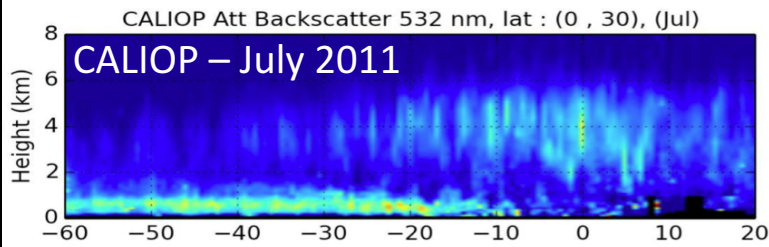
Aerosols

2006-07-01 00z



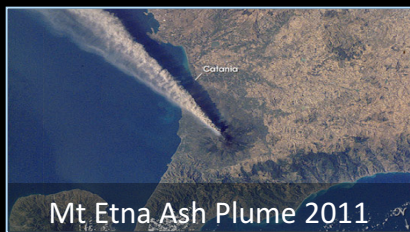
North African Dust

South African Fires

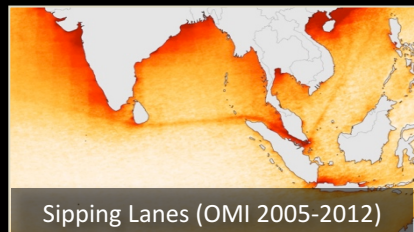




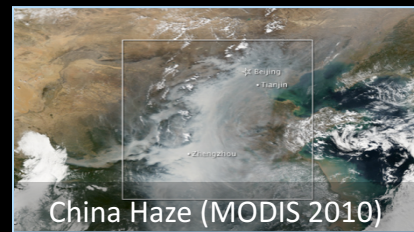
Sulfate and Sulfur Dioxide



Mt. Etna Ash Plume 2011



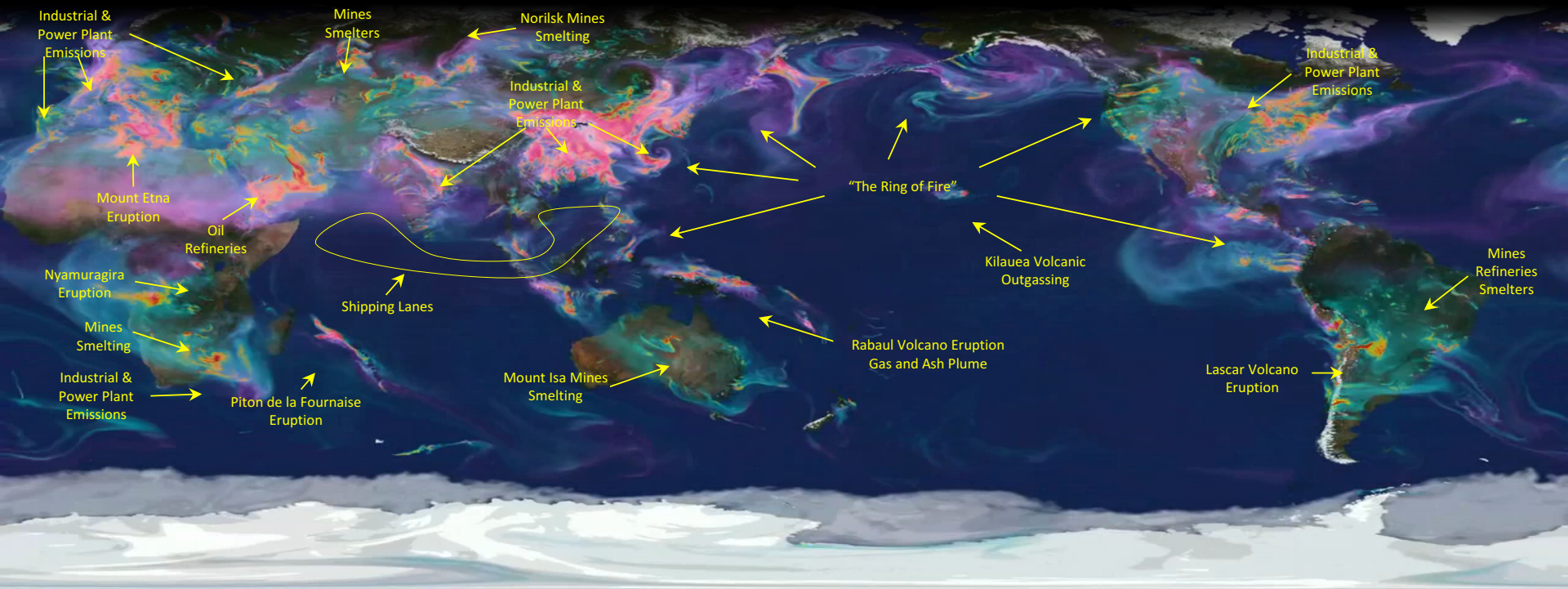
Shipping Lanes (OMI 2005-2012)



China Haze (MODIS 2010)

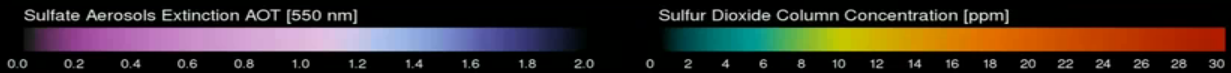


N Atlantic Aerosols (SeaWiFS)

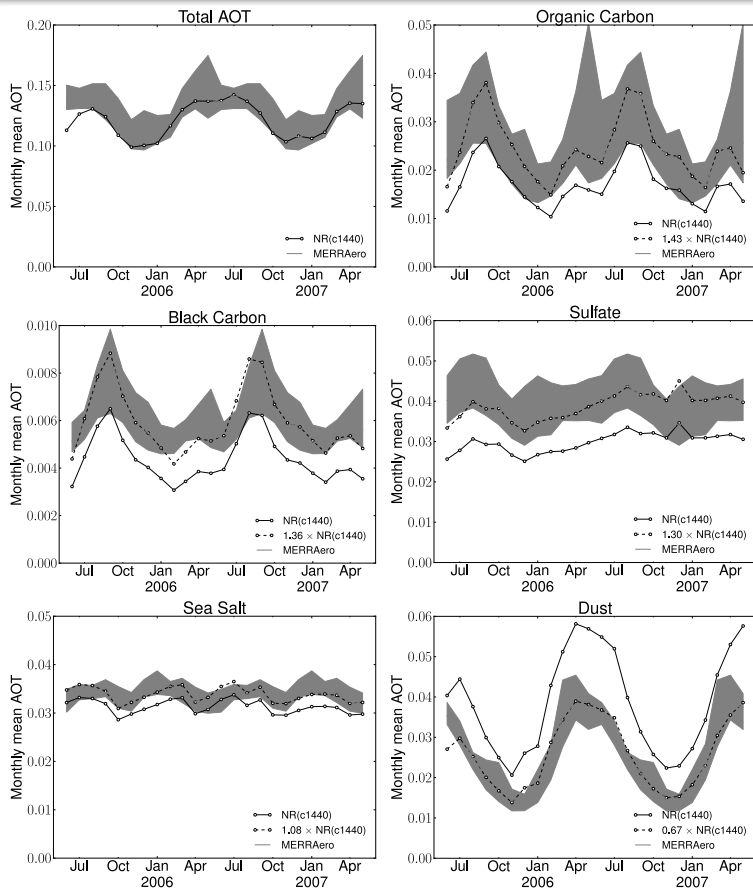


2006 / 08 / 01

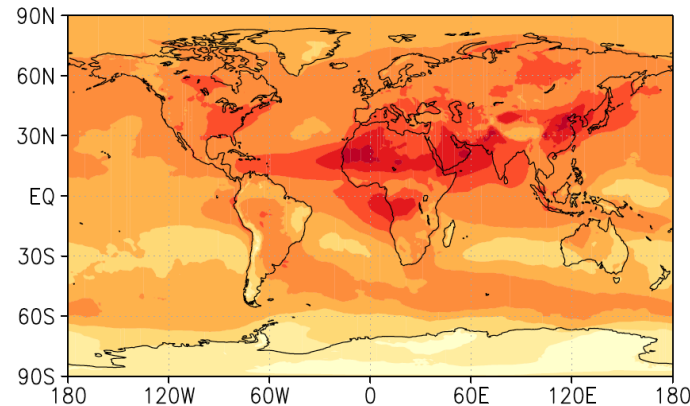
Global Modeling and Assimilation Office



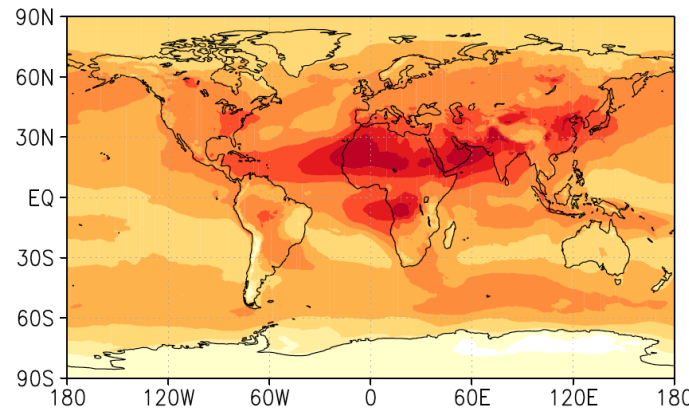
G5NR Aerosol Validation



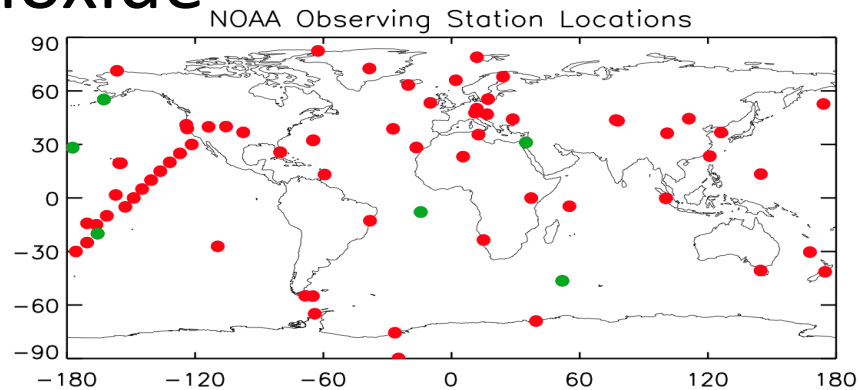
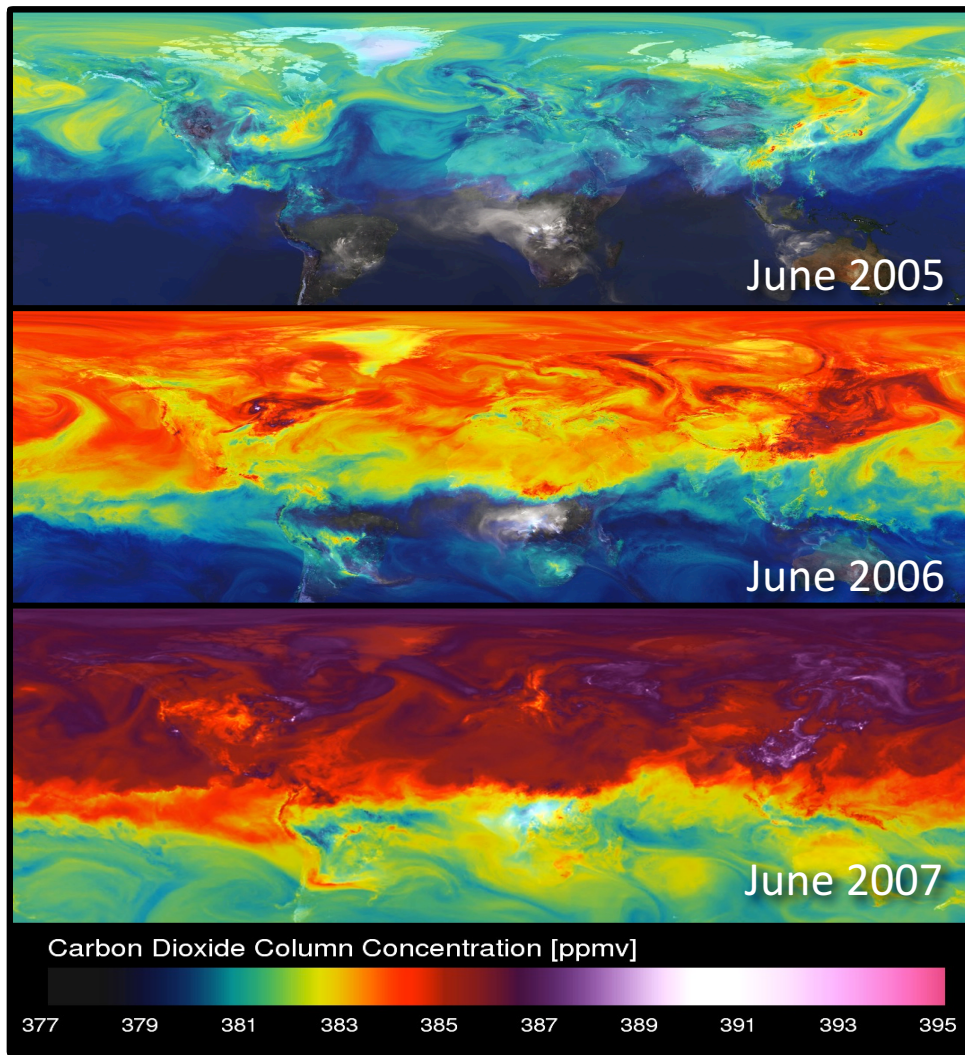
MERRAero – AOT, JJA



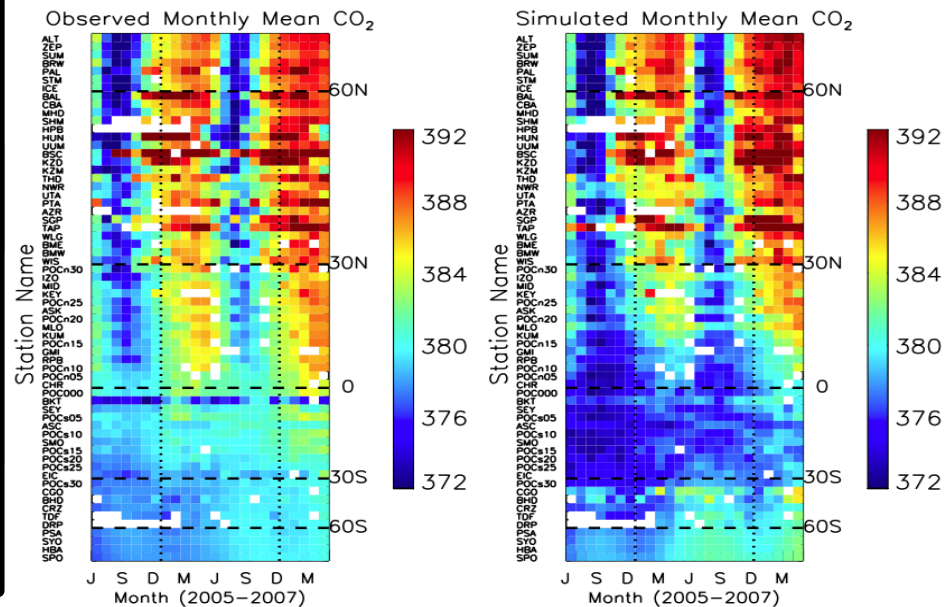
Nature Run – AOT, JJA



Carbon Dioxide



Monthly mean CO_2 (ppmv) at NOAA surface sites (above) for the 2005-2007 period

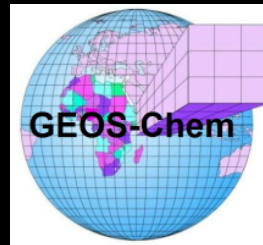


G5NR Summary

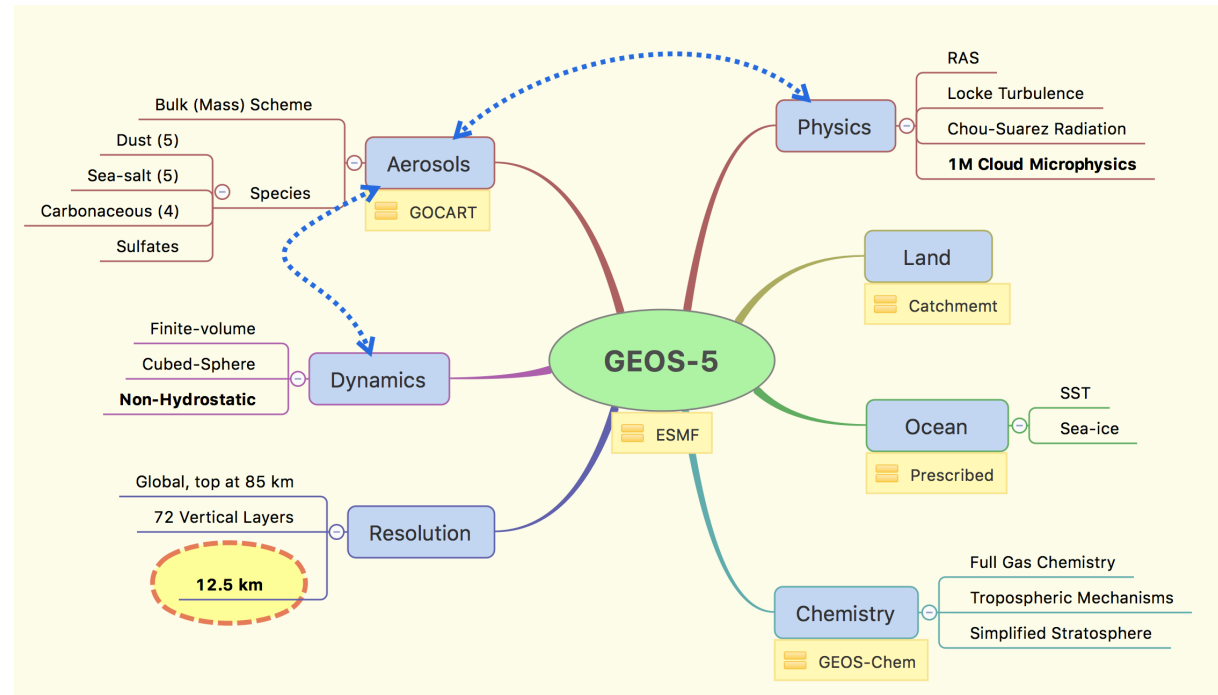
- **Clouds and Radiation / Precipitation**
 - Generally good
 - Too cloudy (drizzly) in subsidence regions
 - Tendency to produce double ITCZ
- **Waves and Cyclones**
 - Weak MJO (but several waves of eastward propagation observed)
 - Excellent tropical cyclone activity, structure and intensity
 - Northern hemisphere DJF extratropical activity slightly over active
 - Realistic mesoscale structure and regional impacts
- **Aerosols and Carbon Species**
 - Local fidelity of emissions and global transport
 - Representative climatology and seasonal trends

G5NR-Chem

GEOS-5 Nature Run with Full Gas Chemistry



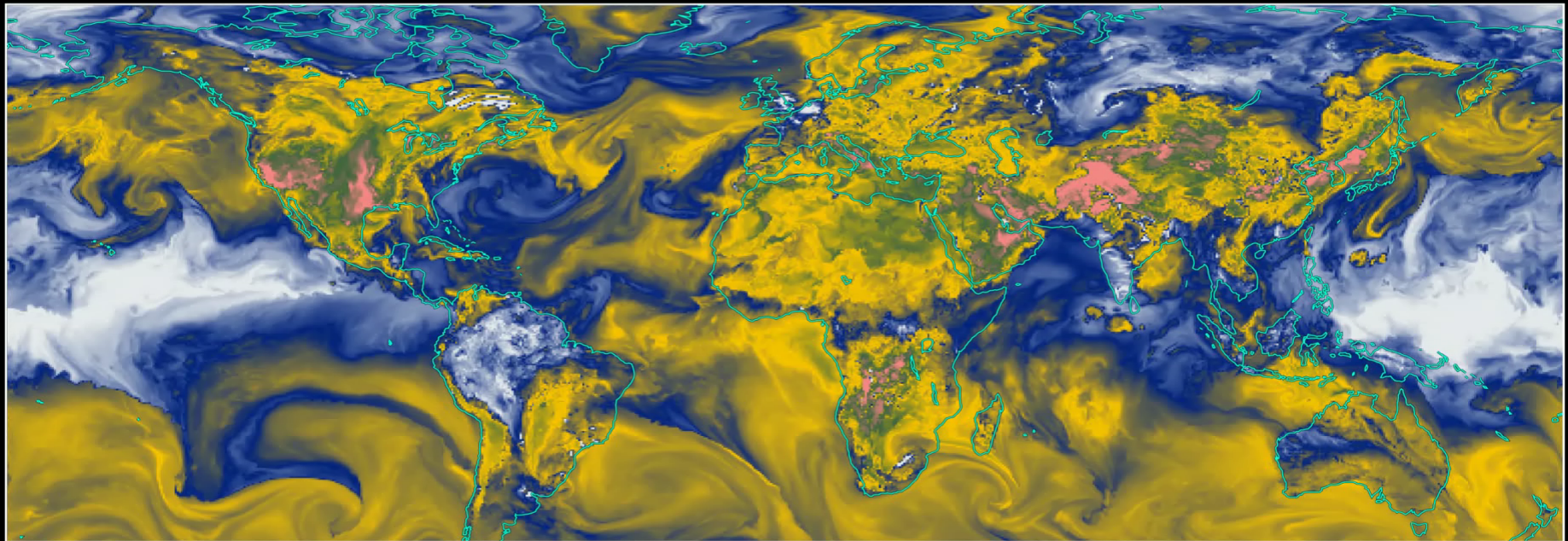
- Period: July 2013-June 2014, May-June 2016
- Validation: **SEAC4RS**, **KORUS-AQ**
- Chemical mechanisms from GEOS-Chem, simplified stratosphere
- Meteorology constrained by MERRA-2 downscaling
- Hourly output of 3D *retrievable gases*
- Documentation in prep:
 - File Spec
 - Model Configuration
 - Evaluation Tech Memo



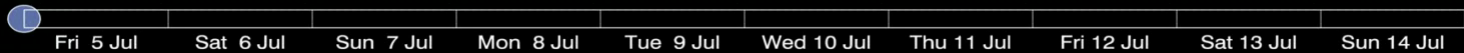
Surface Ozone



Surface Ozone



g5nr-chem-rc1-c720



Global Modeling and Assimilation Office
NASA Goddard Space Flight Center

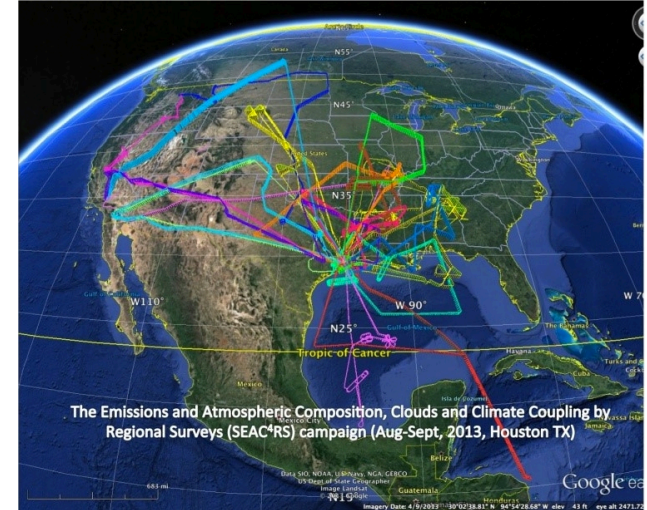


GEOS-5 GEOS-Chem
12.5 km x 12.5 km

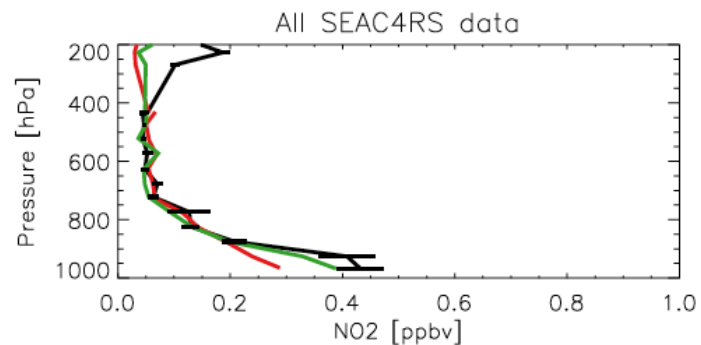
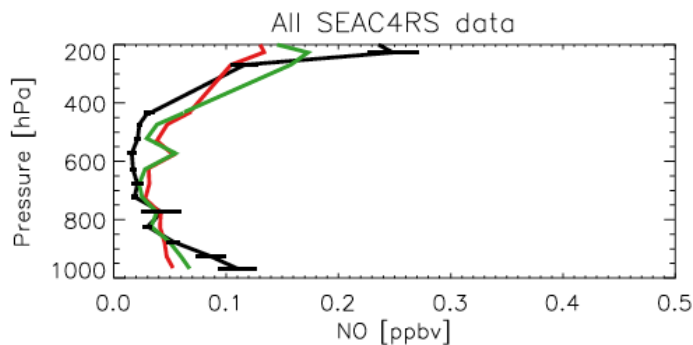
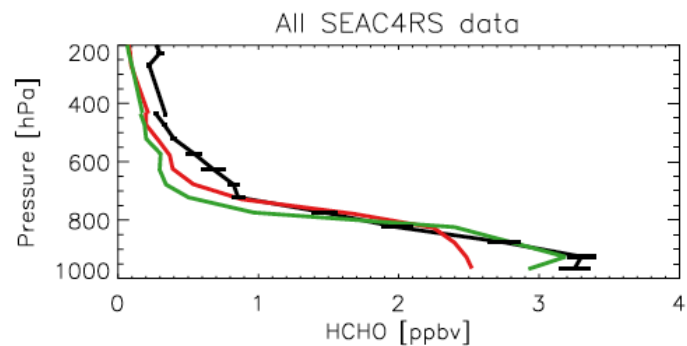
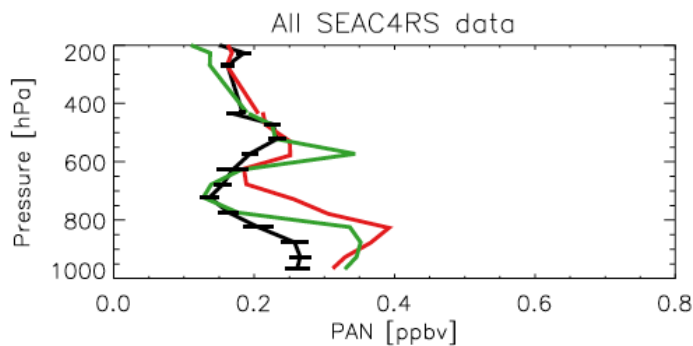
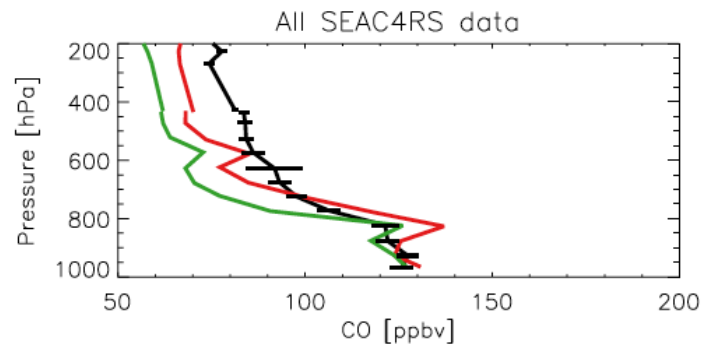
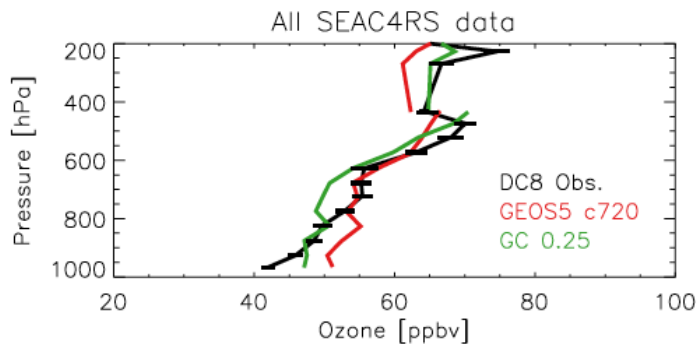
G5NR-Chem Validation during the SEAC⁴RS Field Campaign



- SEAC⁴RS field campaign over the U.S.
 - Detailed chemical species during August-September 2013
- The worldwide network of ozonesondes (WOUDC and NOAA ESRL-GMD)
 - Global ozone vertical distribution
- OMI satellite data
 - Global mid-tropospheric ozone distribution
- Benchmark against GEOS-Chem CTM
 - Emission
 - Chemical species



DC-8 Observations **G₅NR-Chem** **GEOS-ChemCTM ~25km**



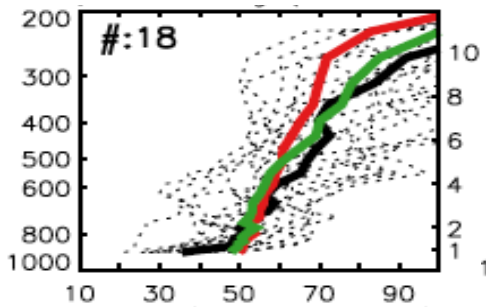
Comparison to Worldwide Network of Ozonesondes

Black: Ozonesonde

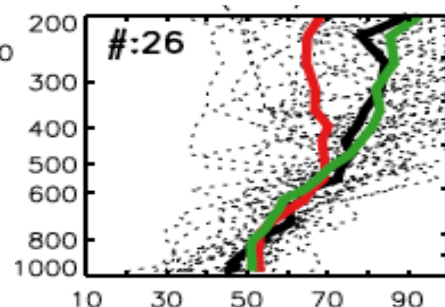
Red: GEOS5-Nature Run ~12km

Green: GEOS-Chem ~200km

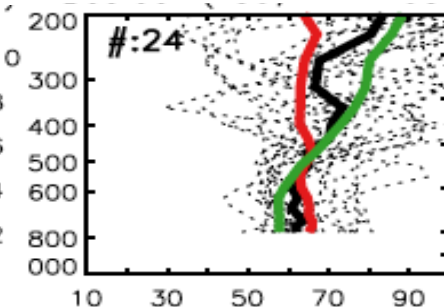
Hohenpeissenberg (47°N)



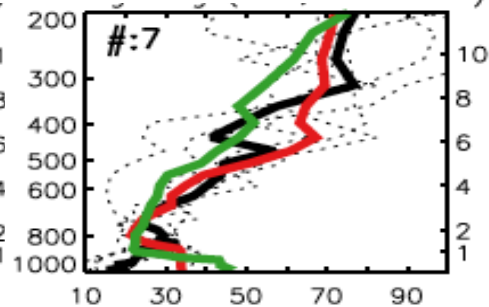
Huntsville (34°N)



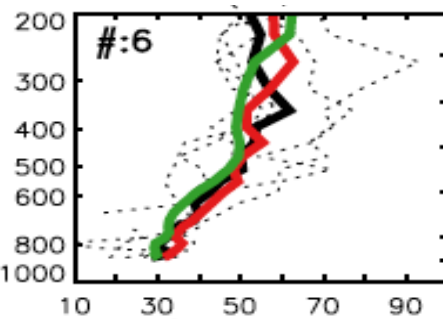
Boulder (39°N)



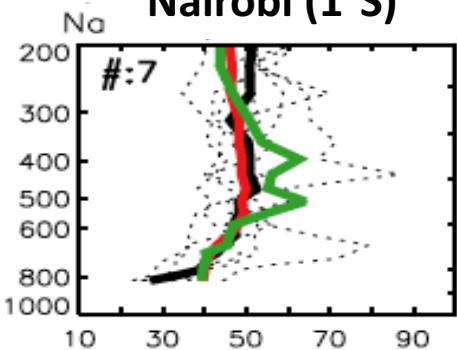
Hong Kong (22°N)



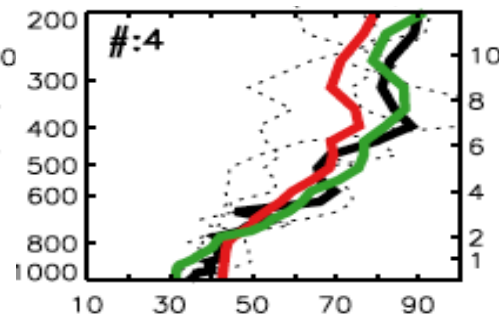
Costa Rica (9°N)



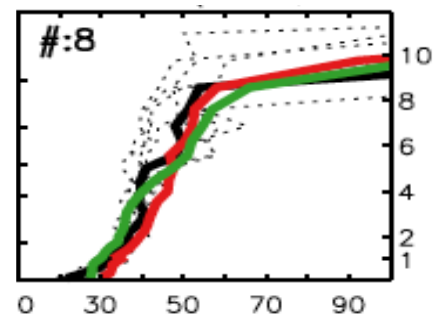
Nairobi (1°S)



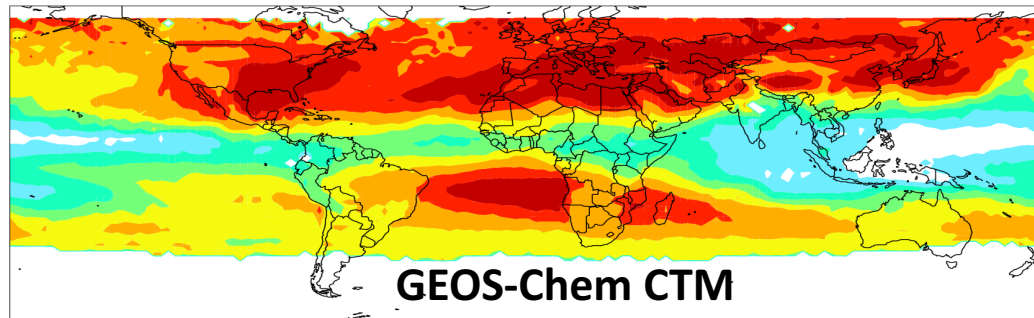
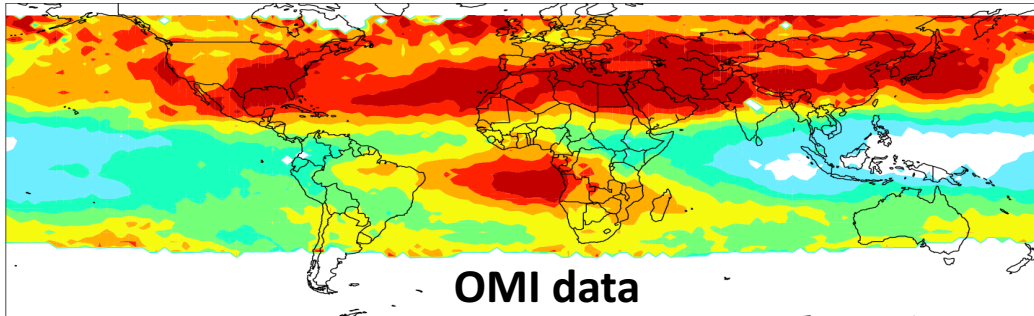
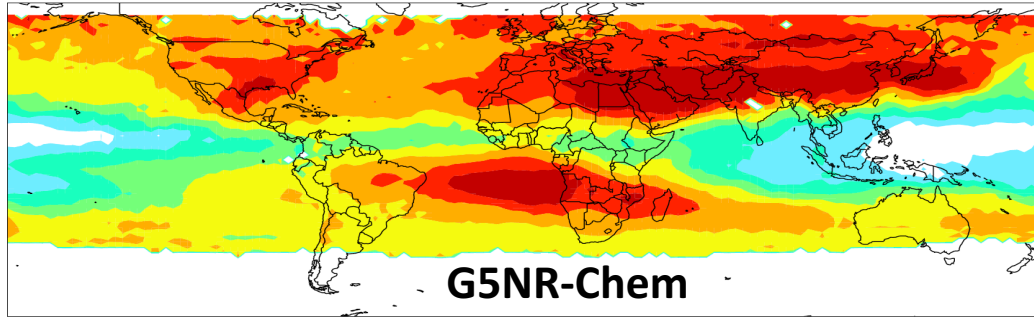
Reunion Island (21°S)



Broadmeadows (37°S)



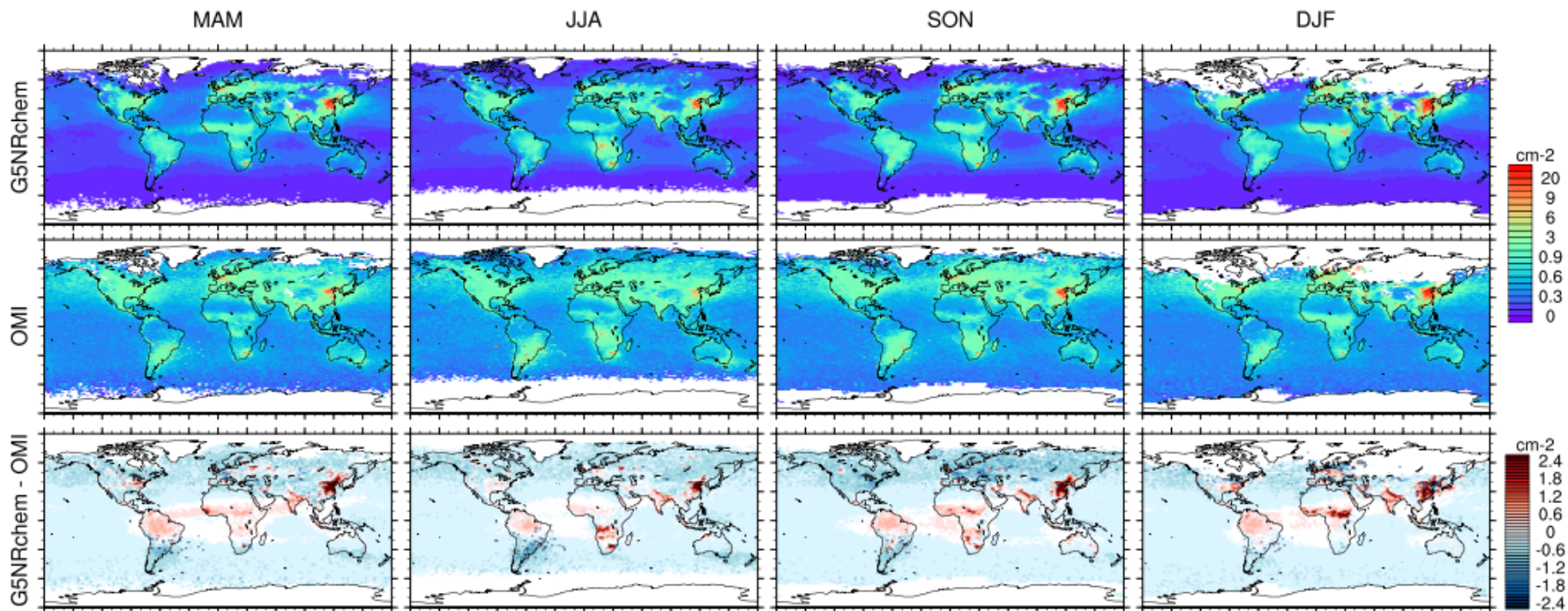
Global comparison to OMI ozone data at 700-400 hPa for August 2013



- OMI data have been
 - adjusted to a single fixed a priori
 - corrected for a global bias relative to ozonesondes
- Model data have been
 - sampled along the OMI tracks
 - smoothed by OMI averaging kernels

OMI ozone data from Xiong Liu (CFA, Harvard-Smithsonian)

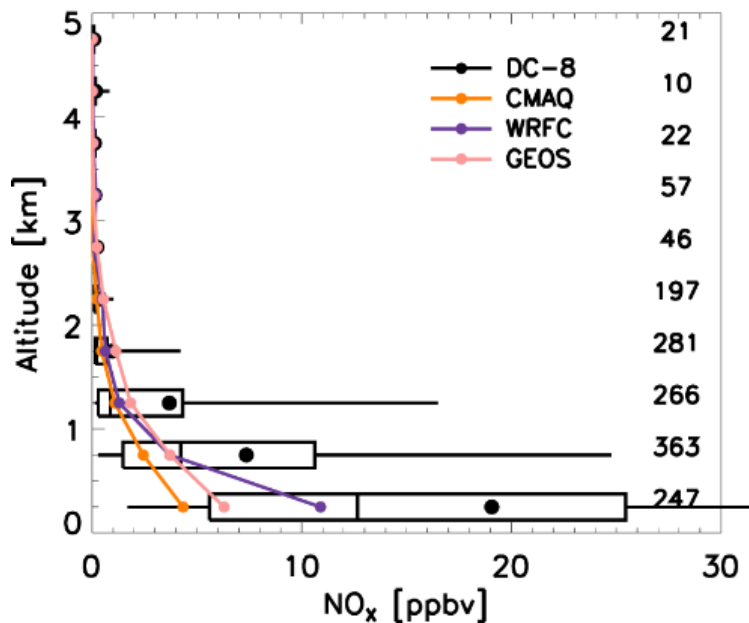
OMI NO₂ Comparison: 2013



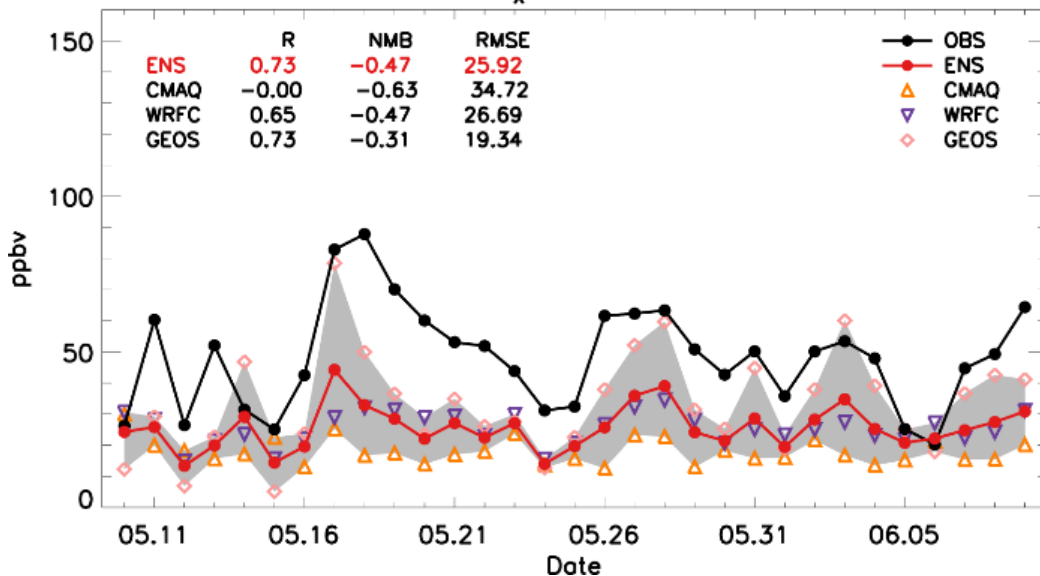


Preliminary Finding: The magnitudes of **NO_x** emissions and key reactive VOCs (e.g. toluene) are underestimated in the current inventory for SMA

Vertical Profile over SMA



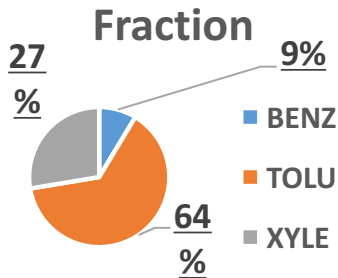
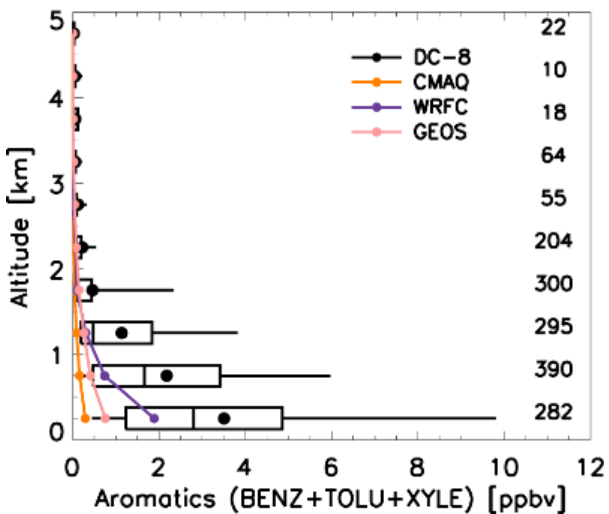
Surface NO_x at OLYMPIC PARK



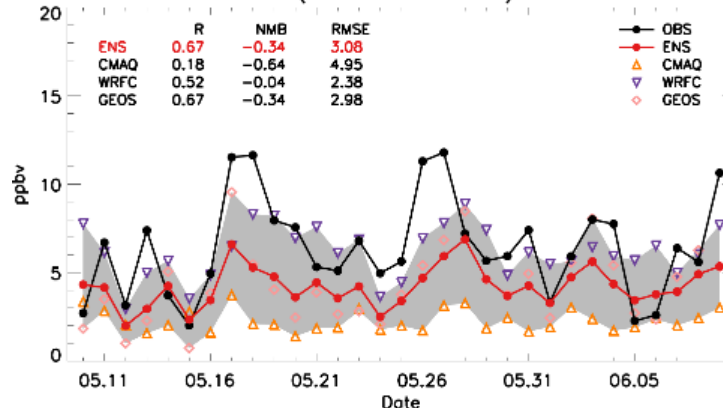


Preliminary Finding: The magnitudes of NO_x emissions and key reactive VOCs (e.g. toluene) are underestimated in the current inventory for SMA

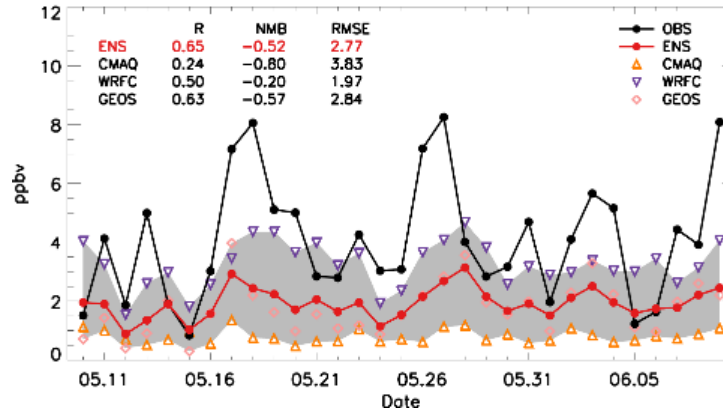
Vertical Profile over SMA



Surface Aromatics (BENZ+TOLU+XYLE) at OLYMPIC PARK



Surface Toluene at OLYMPIC PARK



G5NR-Chem Summary



- G5NR-Chem is broadly consistent with SEAC⁴RS field observations, ozonesondes, and OMI satellite data
- Compared to the GEOS-Chem CTM, G5NR-Chem tends to show better CO simulation in the free troposphere
- Unlike the GEOS-Chem CTM, G5NR-Chem tends to underestimate free tropospheric ozone in the mid-latitudes
 - likely reflecting differences in parameterization of lightning NO_x locations
- Validation for the full year in progress

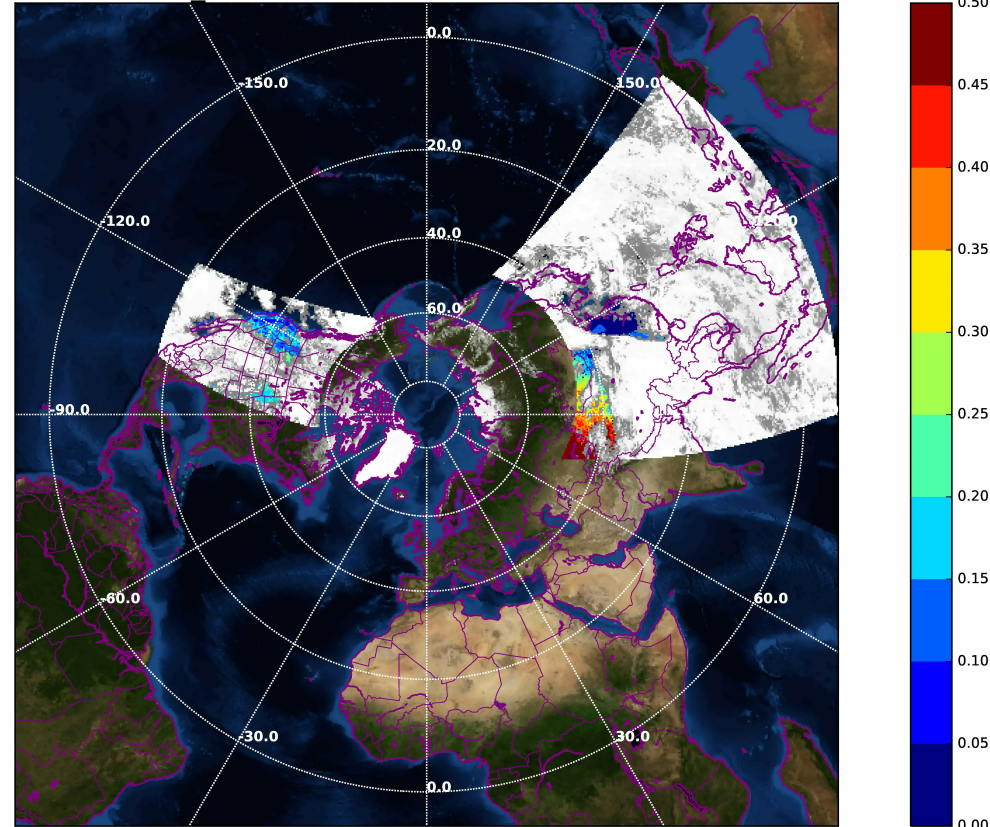
Observation Simulators

Geostationary Constellation: TEMPO+GOES-R, GEMS and SENTINEL-4

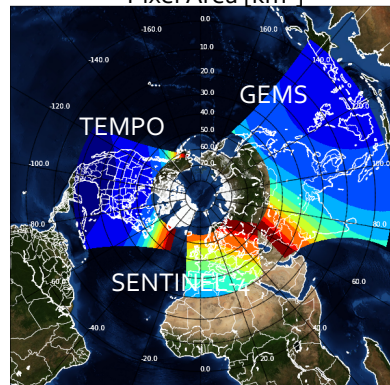


- TOA Reflectance for 6 aerosol relevant channels
- 354, 388, 412, 470, 550, and 670 nm
- Radiative Transfer Model: VLIDORT
- Surface
- MAIAC BRDF Kernels
- Atmosphere
 - GEOS-5 Nature Run with GOCART aerosols

TOA REFLECTANCE 20060727 00z 550nm



Pixel Area [km²]

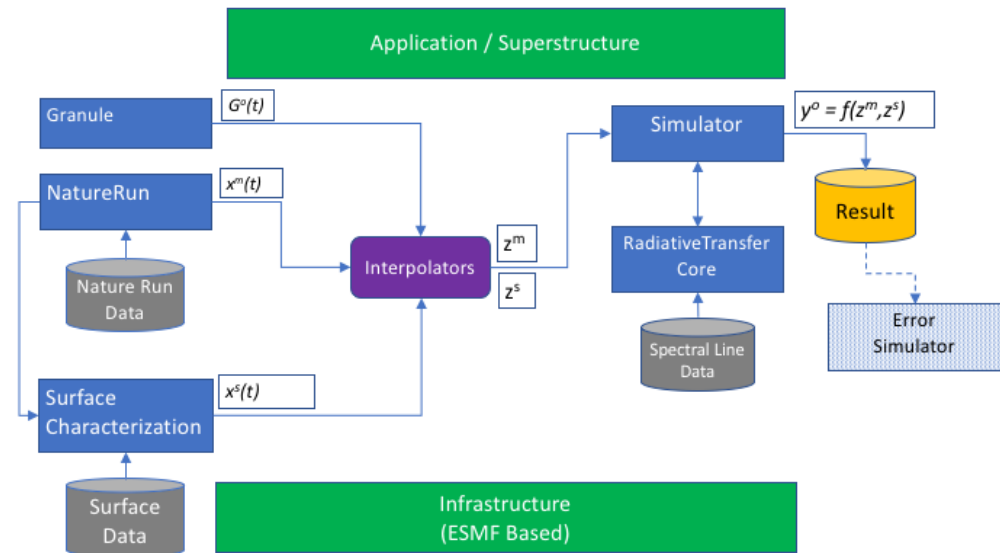


Download TEMPO,
GEMS, SENTINEL-4, and
GOES-R synthetic data
from
[http://g5nr.nccs.nasa.gov/
data/OBS](http://g5nr.nccs.nasa.gov/data/OBS)

FORSE



- Framework for Observation of Radiances: Simulation and Experimentation
- Collaboration between Goddard, JPL and UW/CIMSS, NOAA
- Focus on Aerosols, Cloud, Trace Gases
- Target: future hyperspectral atmospheric composition sensors: UV, VIS, NIR, TIR



TEMPO/GOES-R Synergism

Thanks to: Shobha Kondagrunta & Pubu Ciren (NOAA/NESDIS/STAR)

TEMPO Aerosol Retrievals

TEMPO

- ❖ No cloud camera
- ❖ No short-wave Infrared channel (2.1 μm)
 - Cannot adapt MODIS aerosol algorithms
- ❖ Science team plan is to adapt OMI aerosol algorithm

TEMPO/GOES-R Synergy

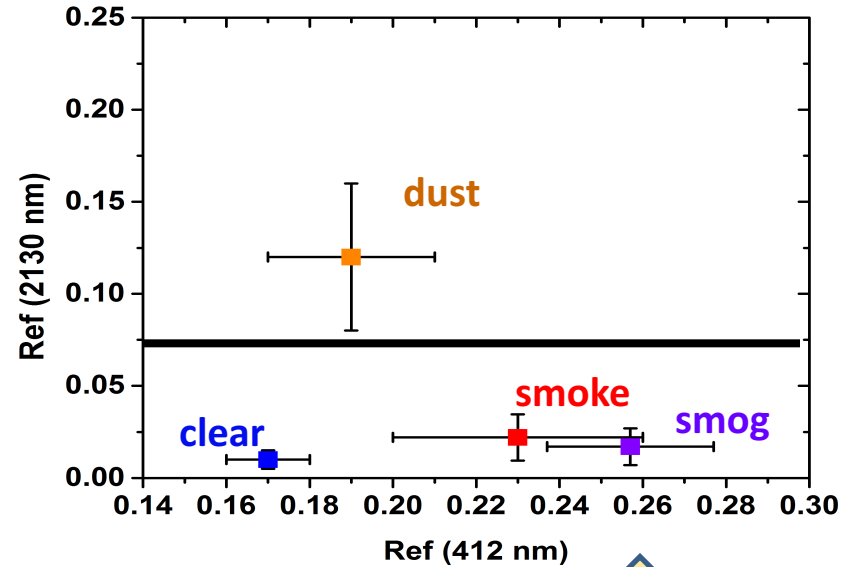
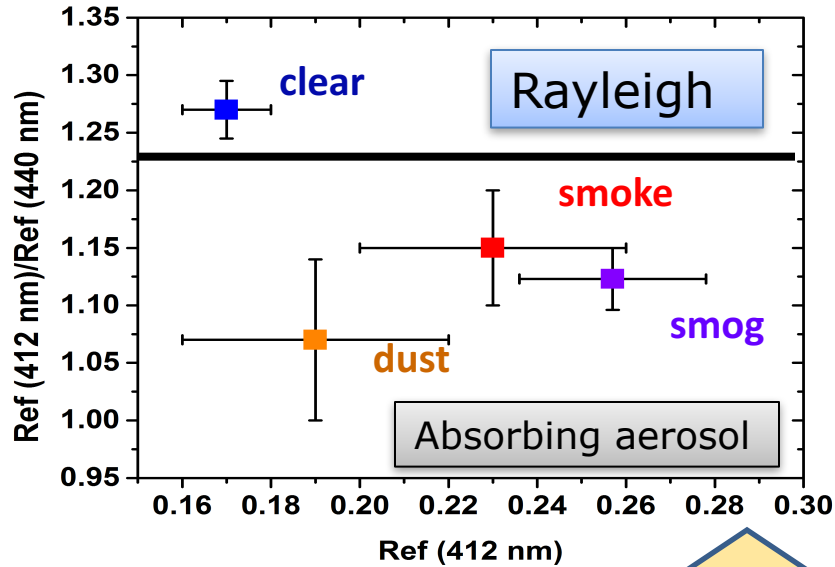
- ❖ Can GOES-R ABI cloud mask be used by TEMPO?
 - Remapped to TEMPO grid
- ❖ Can GOES-R ABI 2.25 μm be combined with TEMPO visible bands?
 - Derive AOD using MODIS aerosol algorithms (MAIAC or dark target)
 - Use AOD in OMI aerosol algorithm to get aerosol height

In this study we tested a simple aerosol detection algorithm (developed for SNPP VIIRS) to test the TEMPO/GOES-R synergy

TEMPO/GOES-R Synergy Experiments

- **G₅NR generated synthetic radiances for about 22 cases**
 - Hourly, 7-km nature run for; smoke cases for July 27 and August 7, 2006 used in this study
 - Simulated radiances for GOES-R and TEMPO footprints using VLIDORT
 - Aerosol optical properties from OPAC data base
- **JPSS Enterprise Processing System (EPS) *Aerosol Detection* algorithm was applied to the synthetic radiances**
 - EPS aerosol detection algorithm detects the presence of absorbing aerosols, by using the fact that absorbing aerosol reduces the contrast between two neighboring wavelengths in deep-blue region, due to their strong wavelength-dependent absorption.
 - EPS aerosol detection algorithm further separates smoke from dust by using the observations at short-wave IR, such as 2.25 μ m.

Aerosol Detection Algorithm (1)



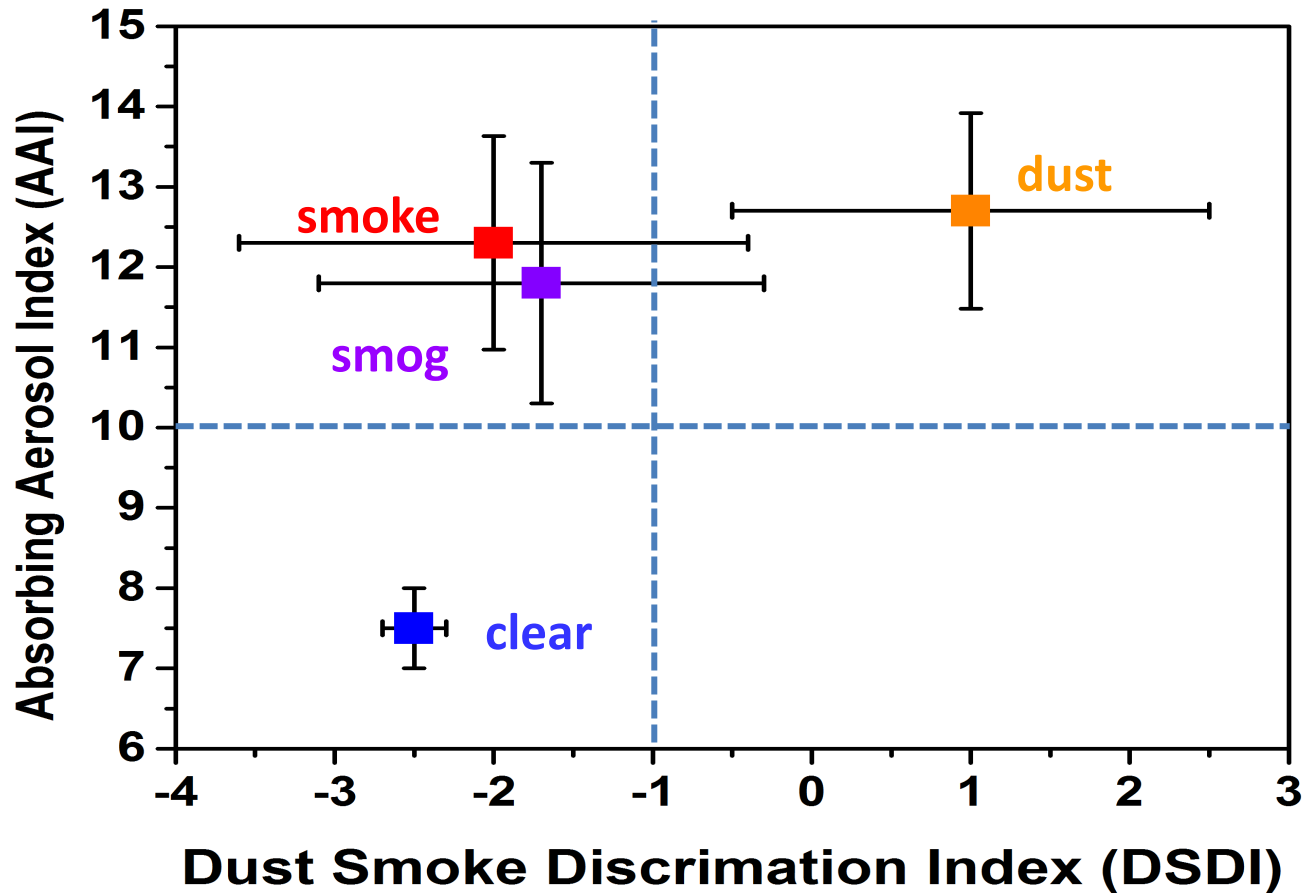
Absorbing Aerosol Index

$$AAI = -100[\log_{10}(R_{412}/R_{440}) - \log_{10}(R'_{412}/R'_{440})]$$

Dust Smoke Discrimination Index

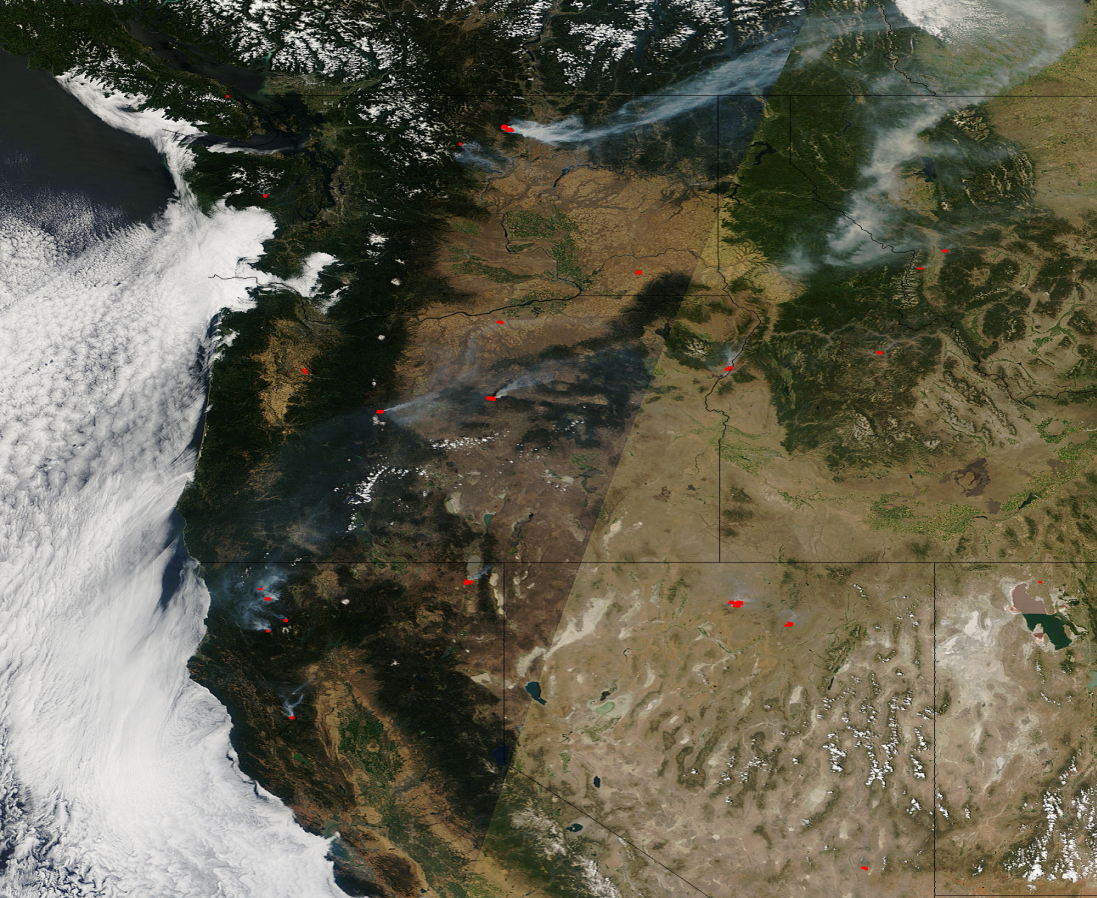
$$DSDI = -10[\log_{10}(R_{412}/R_{2250})]$$

Aerosol Detection Algorithm (2)

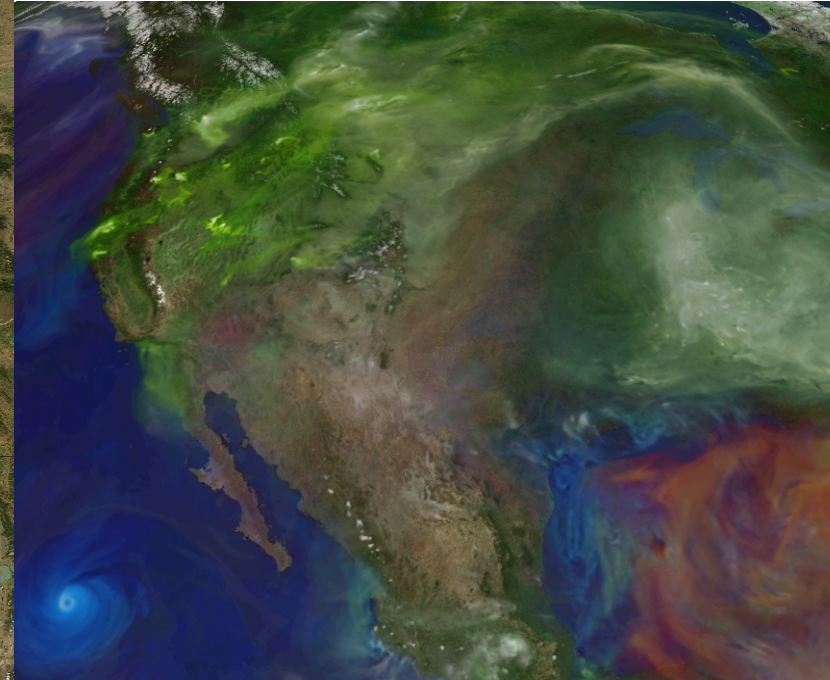


Case Study 1: July 27, 2006

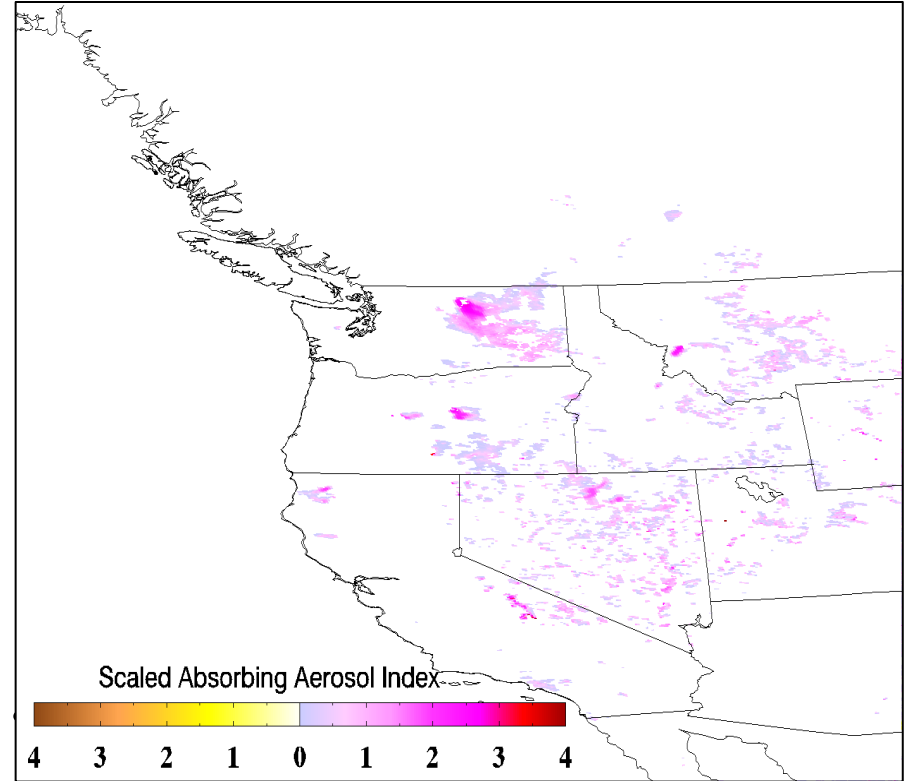
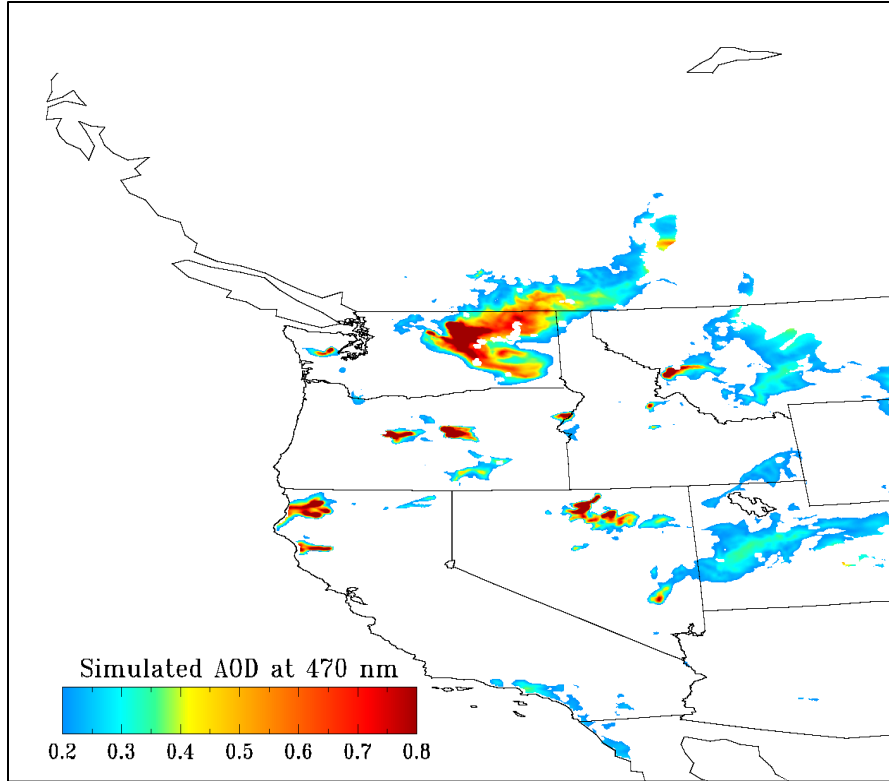
MODIS (Terra) RGB with hotspots



Aerosol Inputs to Nature Run



UTC: 14:00



Dust

Smoke

Key Findings

- ❑ Successful testing of VIIRS aerosol detection algorithm with GOES-R and TEMPO synthetic radiances
- ❑ Results indicate that with some loss of diurnal capability, aerosols can be detected and identified
- ❑ GOES-R ABI 2.25 μm channel is a viable complement to TEMPO's UV-VIS channels

Future Work

- ❑ Optimize aerosol detection retrieval and study a dust episode
- ❑ Apply VIIRS aerosol optical depth (AOD) algorithm

TEMPO UV Aerosol Retrieval

Thanks to: Santiago Gasso, Omar Torres, Pete Colarco

Carry out a full retrieval for one TEMPO scan using synthetic radiances generated by GEOS-5

- G5NR Radiances 354, 388 and CO
- TEMPO Viewing Geometry
- OMAERUV Surface albedo database

Radiances,
Geometry, CO

- OMI aerosol algorithm
OMAERUV 1.6.2

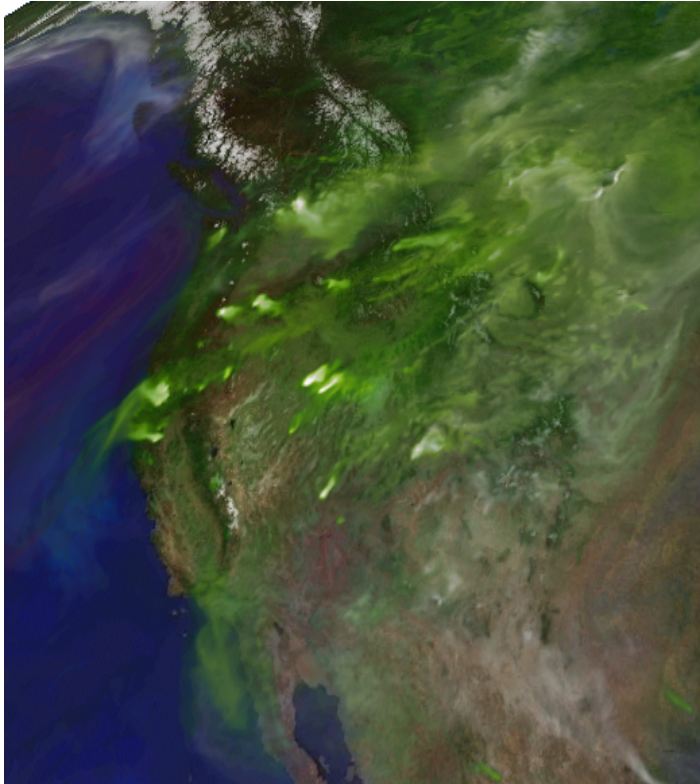
Ground Truth
AOD388
SSA388

Retrieved
AOD388
SSA388

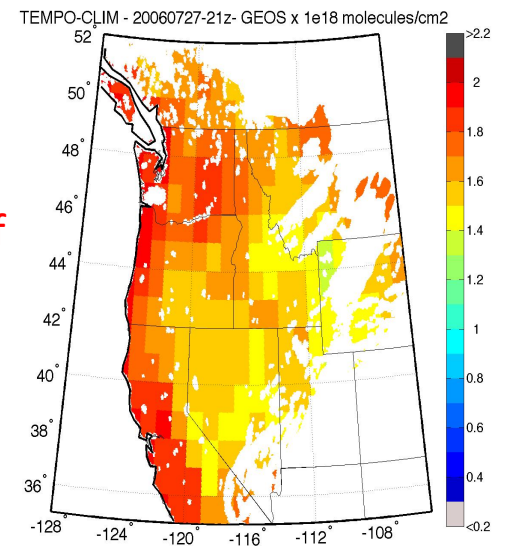
Compare
GEOS-5 vs OMAERUV
AOD and SSA

GEOS-5 scene: Smoke in the West US

Fires for July/27/2007 – 21UTC

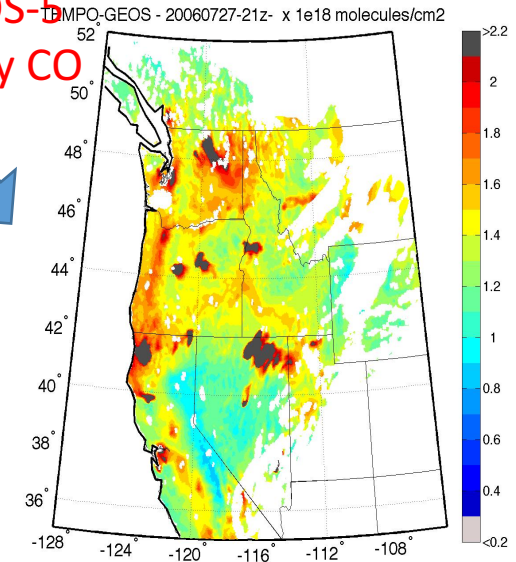


OMI Monthly
Climatology of
CO



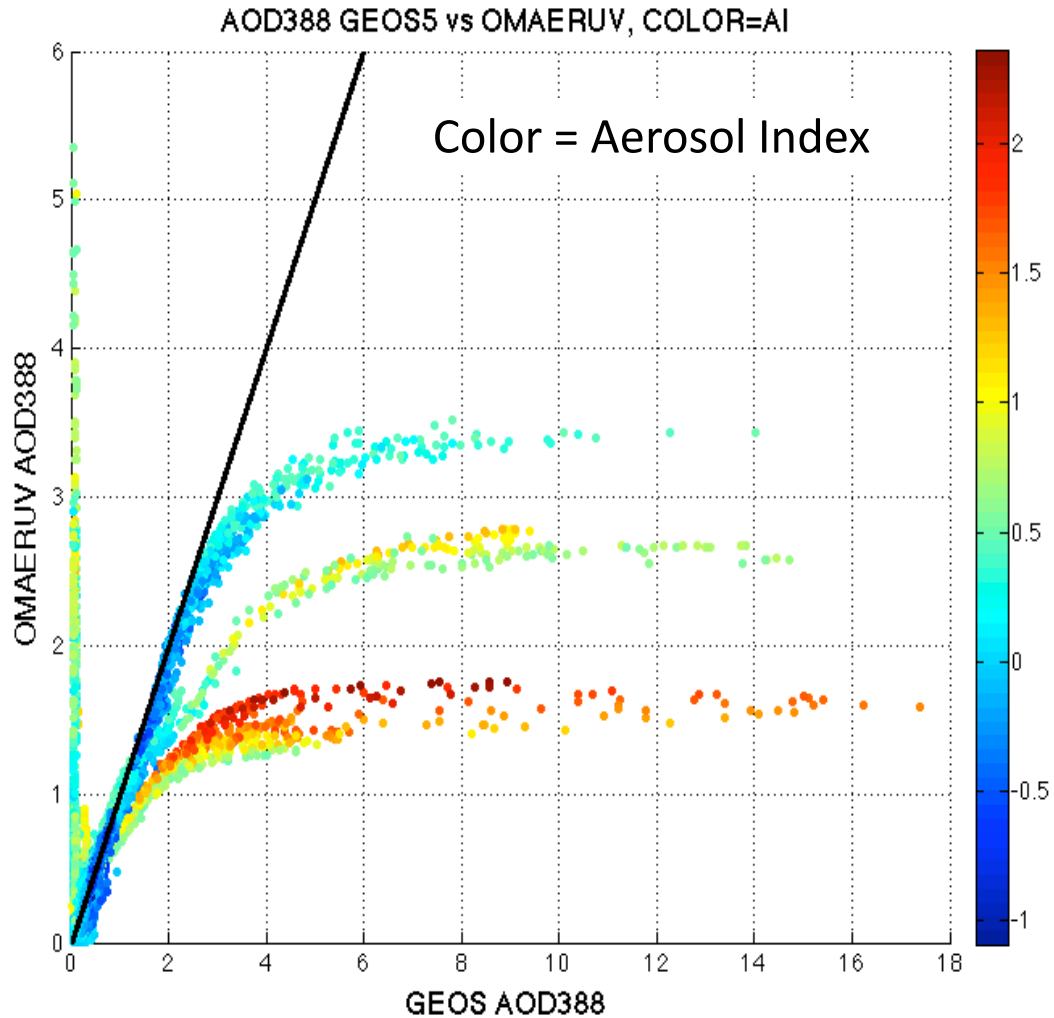
Right from the initial comparisons it became apparent that the OMI algorithm needed a better proxy for smoke. The OMI CO climatology was not adequate.

GEOS-5
Daily CO



In the subsequent comparisons all OMI retrievals ingested the CO from GEOS-5.

G5NR vs OAMERUV AOD388



- Saturation of OMAERUV retrievals
- Some GEOS-5 AODs seem too high

G5NR vs OAMERUV AOD388

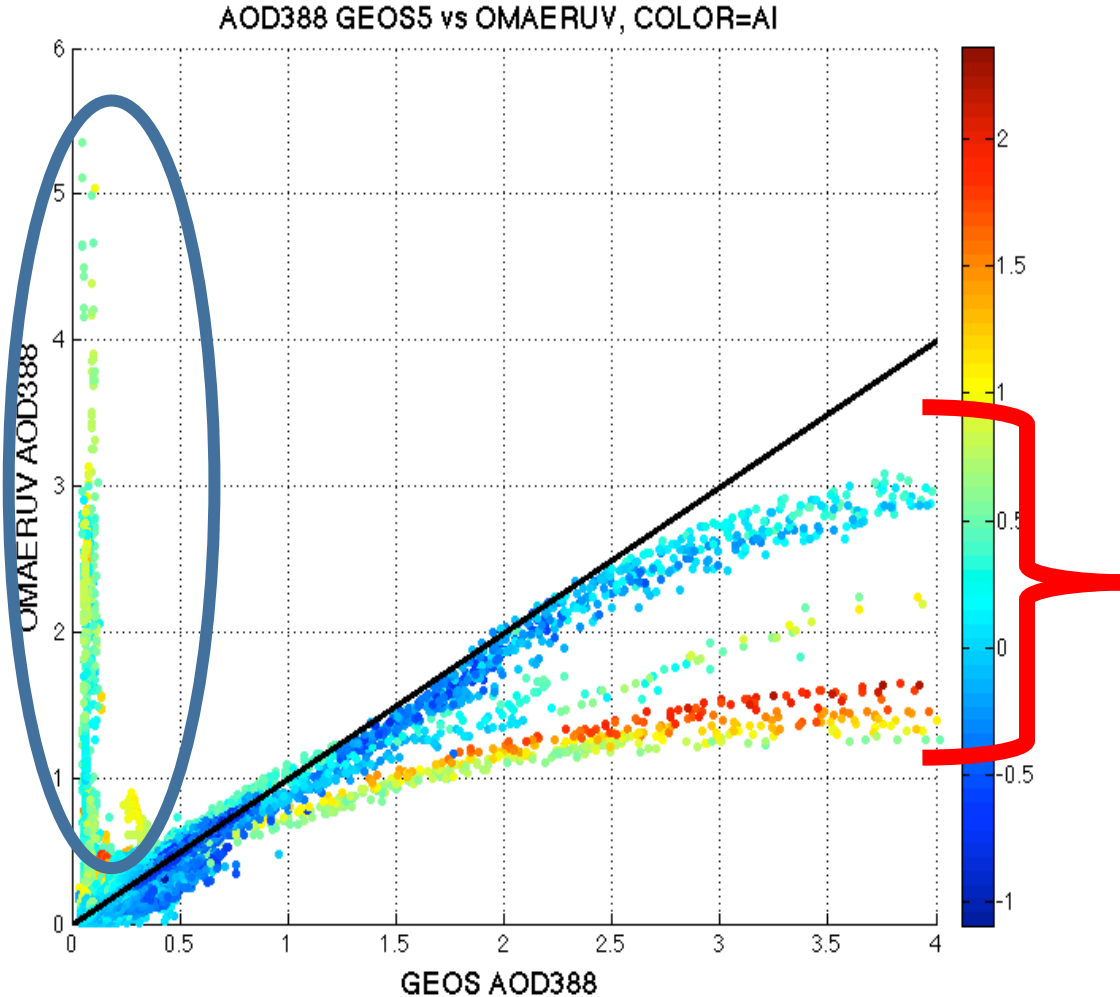
Why?

Cloud contamination?

There are no clouds in the GEOS-5 simulation

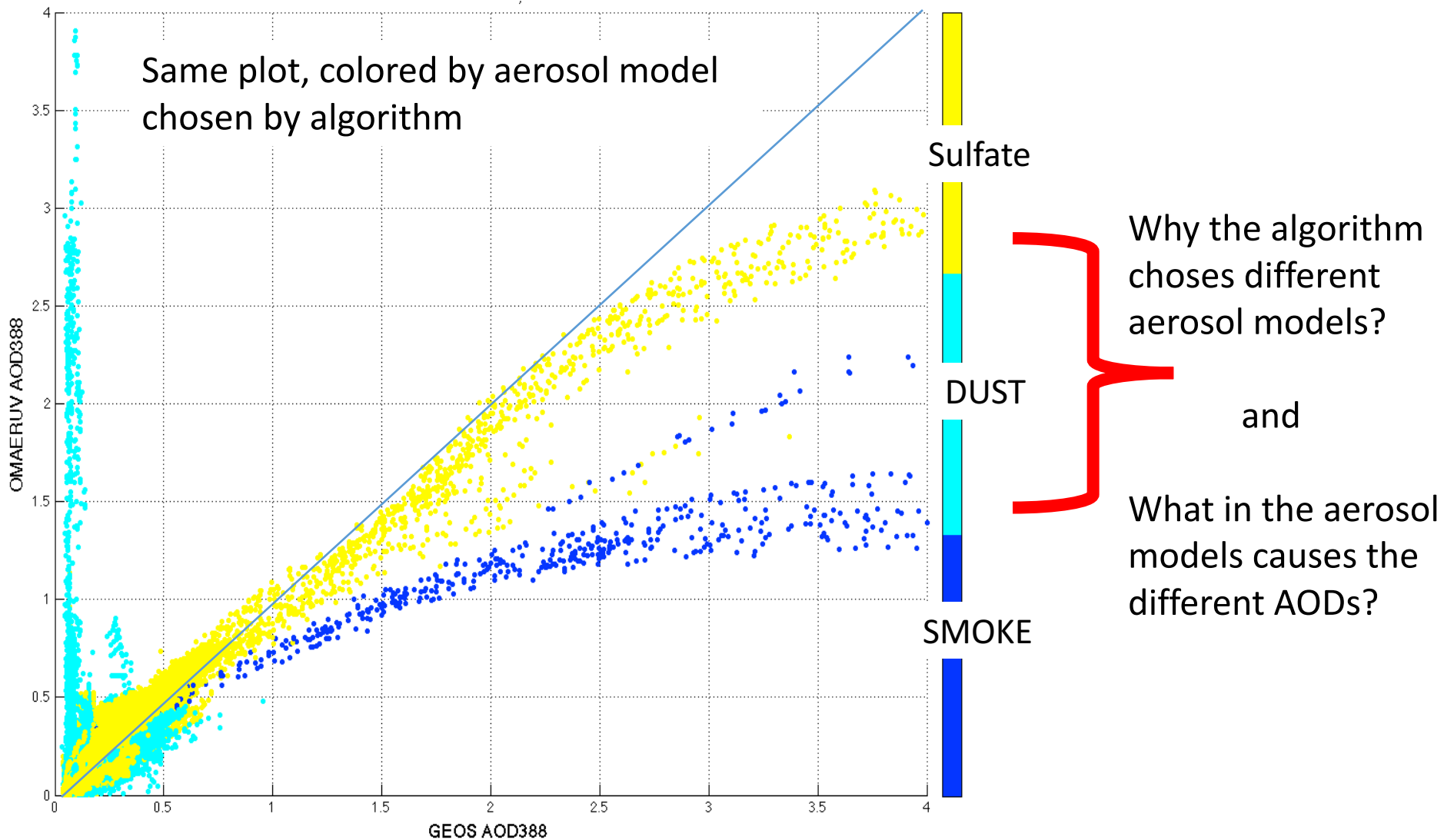
Surface?

Both GEOS5 and OMAERUV use the same database

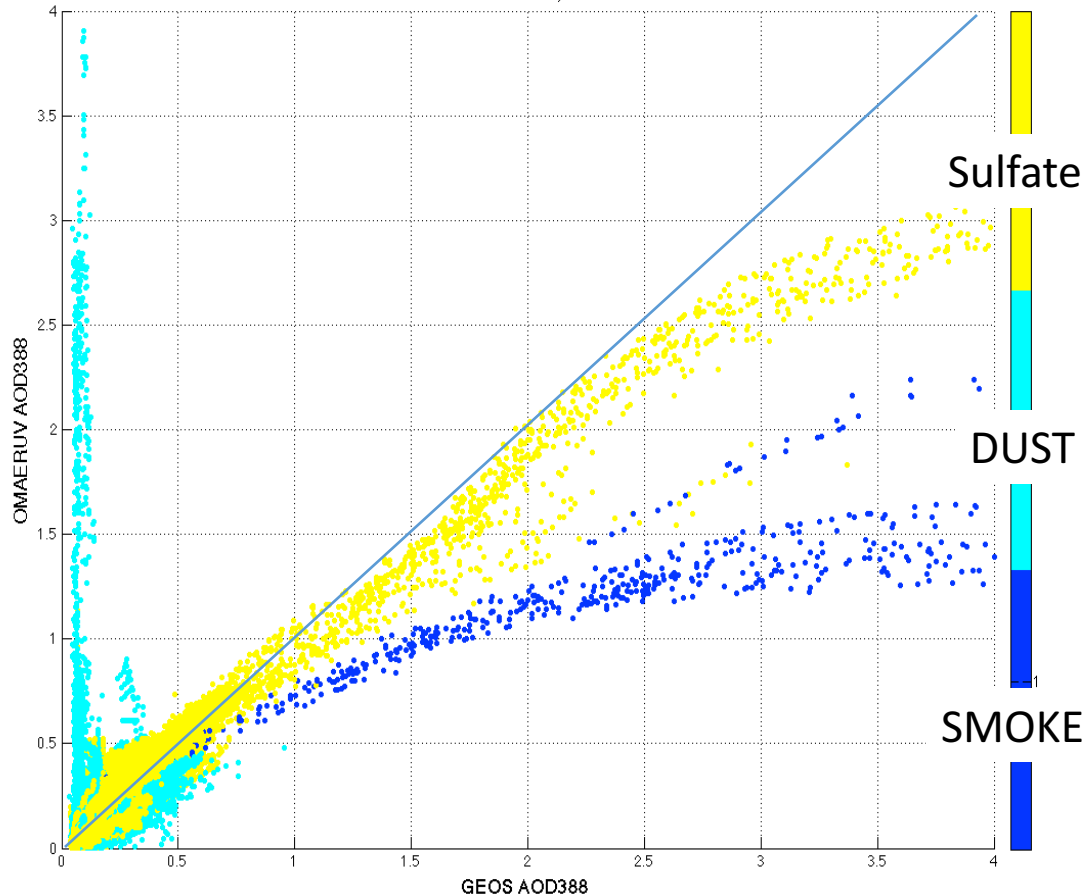


Why?

Let's focus on the source of the differences at higher AODs

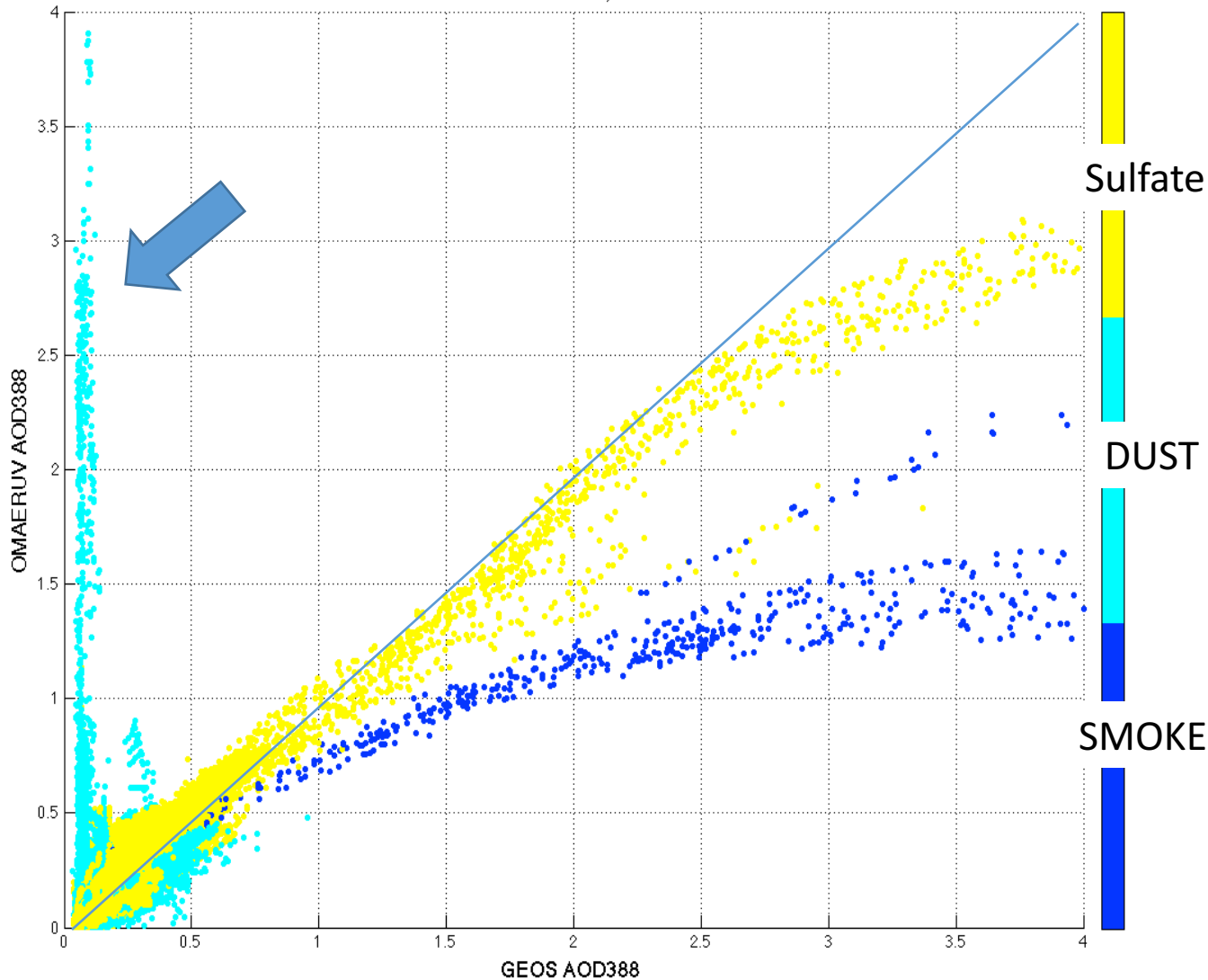


So, why OMI SULFATE AODs agree better with GEOS-5?



- OMI SULFATE models have less absorption and low AAE than its SMOKE models.
- OMI SULFATE models resemble more the optical properties of GEOS-5 models.

Let focus in the cases with LOW GEOS-5 AODs...



- Only in dust!
- Only in cases of low aerosol loading
- The source of this discrepancy is traced to the processing of the surface albedo database

TEMPO UV Aerosols: Summary



- This retrieval OSSE exercise exposes the challenges of under-determined UV aerosol algorithms
 - Are NR/retrieval inconsistencies representative of such discrepancies in reality?
- OMI-like aerosol retrievals for TEMPO will need additional information to differentiate smoke from dust

Summary



NATURE RUNS

- The Current GEOS-5 Nature Run (G5NR) includes
 - Meteorology
 - Aerosols
 - Carbon Species
- A new nature run including full gas chemistry based on Harvard's GEOS-Chem mechanisms has been produced

OSSE APPLICATIONS

- Synthetic UV-VIS radiances have been simulated for a constellation of GEO satellites:
 - TEMPO, GEMS, GOES-R, SENTINEL-4
 - Working WITH JPL on efficient RT approaches for full spectra (2000 channels, PCA)
- Other AC OSSE activities:
 - GEO-CAPE aerosol retrievals
 - Lidar/polarimeter joint retrievals
 - Aerosol above cloud algorithms
 - Aerosol emission inversions

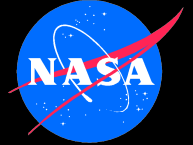
Data Availability



- G5NR Portal:
 - https://gmao.gsfc.nasa.gov/global_mesoscale/7km-G5NR/
- G5NR-Chem Data:
 - <https://portal.nccs.nasa.gov/datashare/G5NR-Chem/Heracles/12.5km/DATA/>
- G5NR-Chem OPeNDAP:
 - <https://opendap.nccs.nasa.gov/dods/OSSE/G5NR-Chem/Heracles/12.5km>

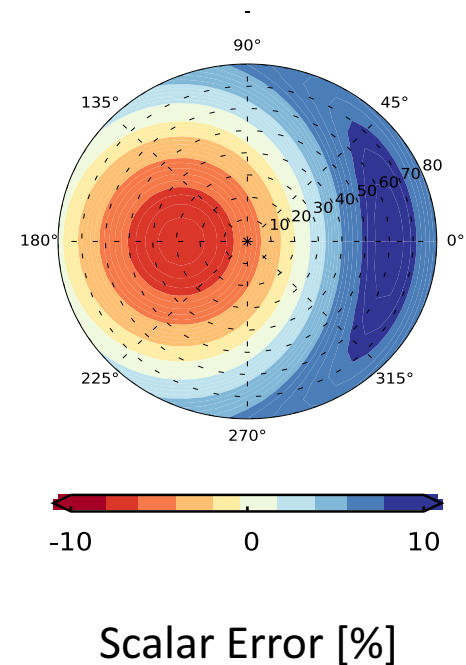
Backup Slides

Computational Challenges

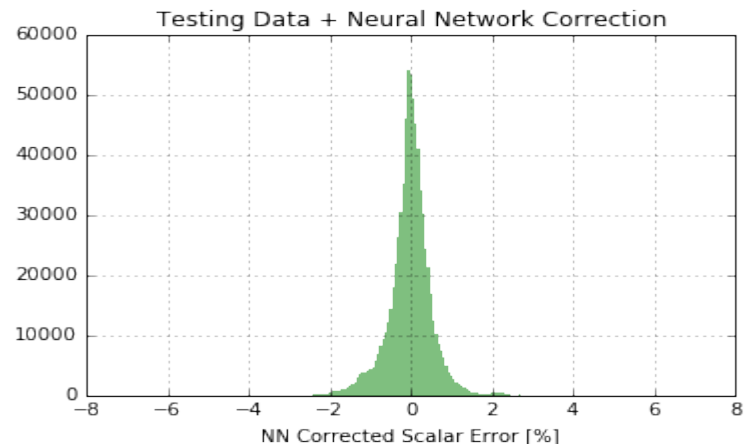
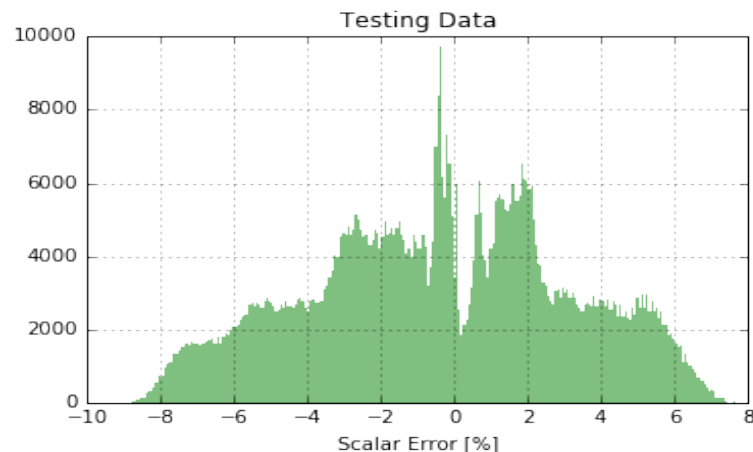
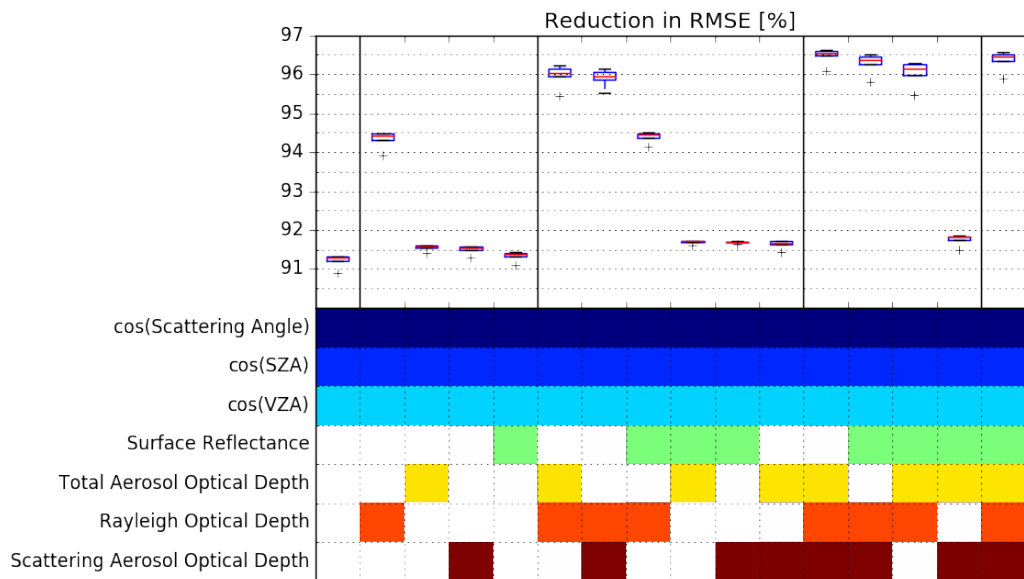


- ❑ Radiative transfer calculations for high spatial resolution, hyper-spectral sensors is extremely expensive
- ❑ *Vector* calculations that are critical in the UV are 6-8 times more expensive than *scalar* calculations

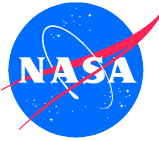
Rayleigh Slab [400 nm]



Neural Net Correction [354 nm]



O.S.S.E.



- Observing System
- Simulation
- Experiment

Model-based OSSE

A framework for numerical experimentation in which *observables* are simulated from fields generated by an earth system model, including a *parameterized* description of the *observational error* characteristics.

Simulations are performed in support of an experimental goal.

The Validation Imperative



- As with any simulation, OSSE results apply to new instruments only to the degree they have been validated with existing legacy instruments.
- OSSE credibility is first determined by carefully comparing a variety of statistics that can be computed in both the real and OSSE simulated contexts.

OSSEs need to be validated as a System.

Observation Error *at Instrument Footprint*



Measurement equation:

$$y = f(z^t) + \epsilon$$

where

- y measurement
- z^t true state at instrument footprint
- f observation operator
- ϵ observation error w.r.t. z^t (detector noise)

Radiance Error Modeling



Radiance errors (detector noise) ϵ are defined as

$$y = f(z^t, b^t) + \epsilon$$

where

- y radiance measurement
- f forward function (radiative transfer function)
- z^t true state ($z^t = Hw^t$)
- b^t true forward model parameters
(e.g., spectral line data, calibration parameters)
- ϵ detector noise + error of representativeness

The real physics of the radiative transfer is often too complex or its details unknown. In practice, a **forward model** (F) is used

$$f(z^t, b^t, b'^t) = F(z^t, b^t) + \delta f(z^t, b^t, b'^t)$$

Retrieval Error Analysis



Ignoring the transfer function bias for the **prior states**, the retrieval error reads:

$$\begin{aligned}\epsilon^r &\equiv z - Hw^t \\ &= (I - A)\epsilon^p + D_y F_b \epsilon_b + D_y \delta f + D_y \epsilon\end{aligned}$$

where $\epsilon^p = z^p - z^t = H(w^p - w^t)$, etc., and

A	averaging kernel ($= D_y F_z$)
$(I - A)\epsilon^p$	smoothing error (prior error)
$D_y F_b \epsilon_b$	forward model parameter error
$D_y \delta f$	forward model error
$D_y \epsilon$	instrument + representativeness error

Error of Representativeness



Let x^t be the true state in model grid point space:

$$z^t = \mathcal{I}(x^t) + \epsilon'$$

where

\mathcal{I} remapping operator
 ϵ' representativeness error

In OSSE studies the **Nature Run** is assumed to provide the ground truth, but it does so in grid-point space: x^t

$$\begin{aligned} y &= f(\mathcal{I}(x^t) + \epsilon') + \epsilon \\ &= h(x^t) + \epsilon + F_z \epsilon' + .. \end{aligned}$$

It is critical to account for error of representativeness errors when simulating observables with a footprint much smaller than the Nature Run resolution.

Retrieval Error Modeling



- ▷ Retrievals are produced as result of a nonlinear estimation,

$$z = D(y, b, z^p) = D(F(z^t, b^t) + \delta f + \epsilon, b, z^p)$$

where z^p is a **background state** (prior) used in the retrieval.

- ▷ In order to obtain a basic understanding we linearize this equation around a known state, say the prior z^p

$$\begin{aligned} z - z^p &= [D(F(z^p, b), b, z^p) - z^p] \\ &\quad + D_y F_z (z^t - z^p) \\ &\quad + D_y F_b (b^t - b) \\ &\quad + D_y \epsilon \end{aligned}$$

where $T(z^p, b) = D(F(z^p, b), b, z^p)$ is the so-called **Transfer Function**.

- ▷ The term in **brackets** is the transfer function bias and should be small for any reasonable retrieval,

$$T(z^p, b) = D(F(z^p, b), b) \approx z^p$$

i.e., the retrieval should return the first guess when noiseless data consistent with it is input.

Retrieval Error Mechanisms



- ▶ **Averaging Kernel.** The retrieved state is a smoothed version of the true state with smoothing functions given by the rows of A

$$z = Az^t + (I - A)z^p + \dots$$

Those details of the true state which are smoothed out by the retrieval must be provided by the first guess z^p . Notice that A is state dependent.

- ▶ **Model parameter errors** are usually associated with biases. If retrieval is too sensitive to a parameter then it should be retrieved as well (state augmentation).
- ▶ **Model error.** Hard to evaluate. If correct physics is known then it can be modeled (e.g., approximations introduced for computational efficiency.)
- ▶ **Instrument error.** Usually the easiest to evaluate. It can have a strong dependence on the state through D_y , although the detector noise ϵ is usually assumed stationary and state independent in clear sky. Cloud clearing introduces additional complications. However, **error of representativeness** is often state dependent.

Simulating Retrievals



FROM RADIANCES

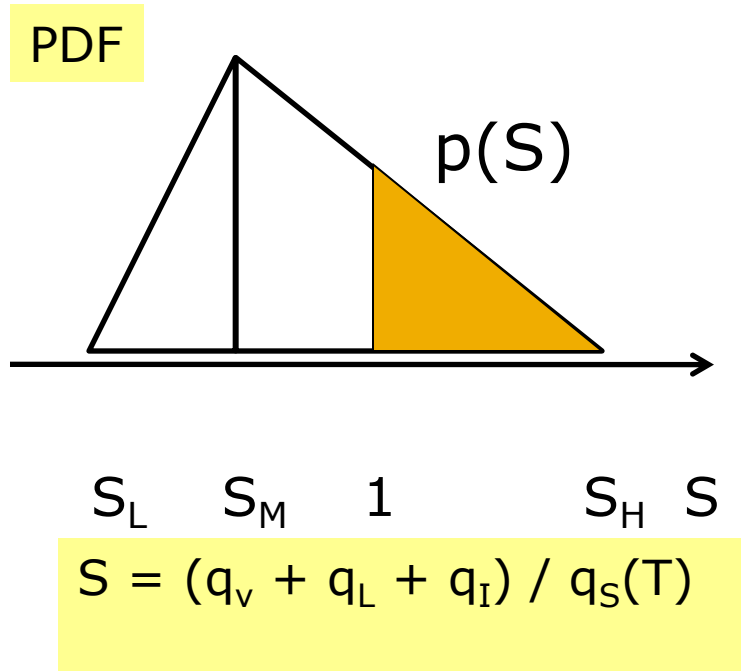
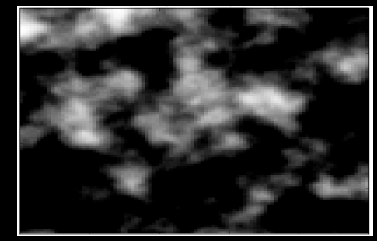
- Synthetic retrievals
 - Simulate radiances by radiative transfer
 - **Model radiance errors**
 - Apply retrieval code

BY MODEL SAMPLING

- Sample and perturb
 - Interpolate geophysical to obs location
 - **Model retrieval errors**
 - Done.

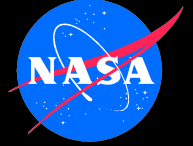
While interpolating a model simulated geophysical quantity to observation location is much more straightforward than performing a full RT calculation, modeling **retrieval errors** is far more complex than modeling **radiance errors**.

Clouds & Sub-grid Variability



- PDF-based cloud parameterizations provide very useful information about sub-grid variability
- Given a PDF of total water one can generate sub-columns consistent with that PDF
- Observation simulators can account for representativeness error by operating on these sub-columns

Hygroscopic Aerosols

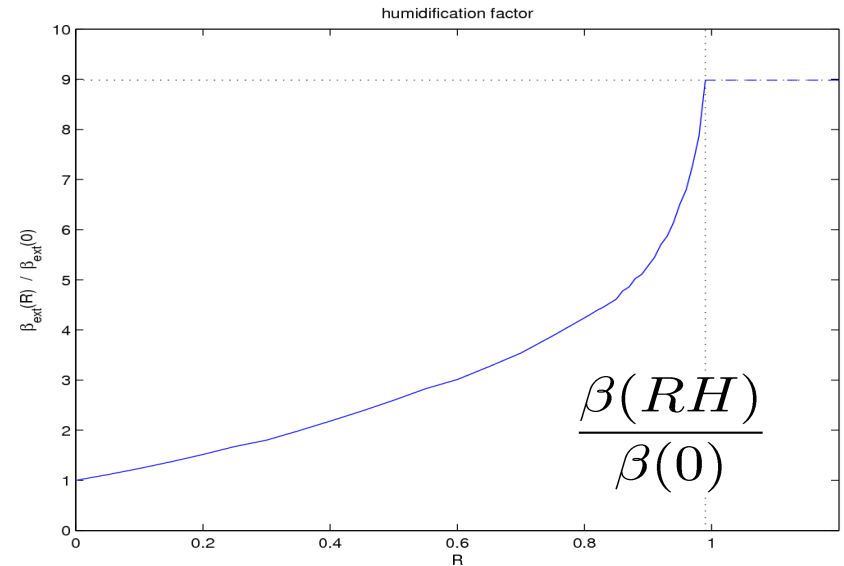


GOCART prognosticate aerosol dry mass mixing ratio q_{dry} , with humidification effects being included diagnostically prior to computing optical depth

$$\tau = \beta(RH; p) \cdot q_{\text{dry}} \cdot \rho_a \delta z$$

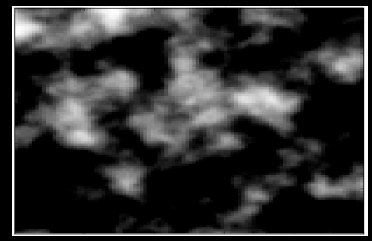
The normalized mass extinction efficiency

$$\hat{\beta} = \frac{\beta(RH)}{\beta(0)} \sim 1 - 10$$



$\hat{\beta}$ saturates at 99%

PDF-based Humidification



Recall that aerosol satellite retrievals are only available under *clear sky* conditions:

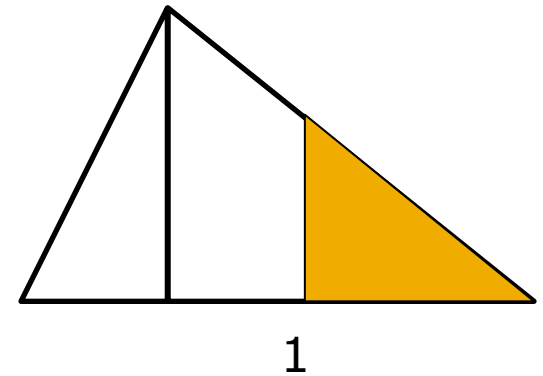
$$\tau_{\text{clear}} = \beta_{\text{clear}}(RH) \cdot q_{\text{dry}} \cdot \rho_a \delta z$$

PDF-based cloud schemes as in GEOS-5 can be used to estimate the mean humidification effect on a GCM gridbox

$$\begin{aligned} \langle \hat{\beta} \rangle &= \int_0^{\infty} p(S) \hat{\beta}(S) dS \\ &= \int_0^1 p(S) \hat{\beta}(S) dS + \int_1^{\infty} p(S) \hat{\beta}(S) dS \\ &= (1 - f) \cdot \langle \hat{\beta} \rangle_{\text{clear}} + f \cdot \langle \hat{\beta} \rangle_{\text{cloudy}} \end{aligned}$$

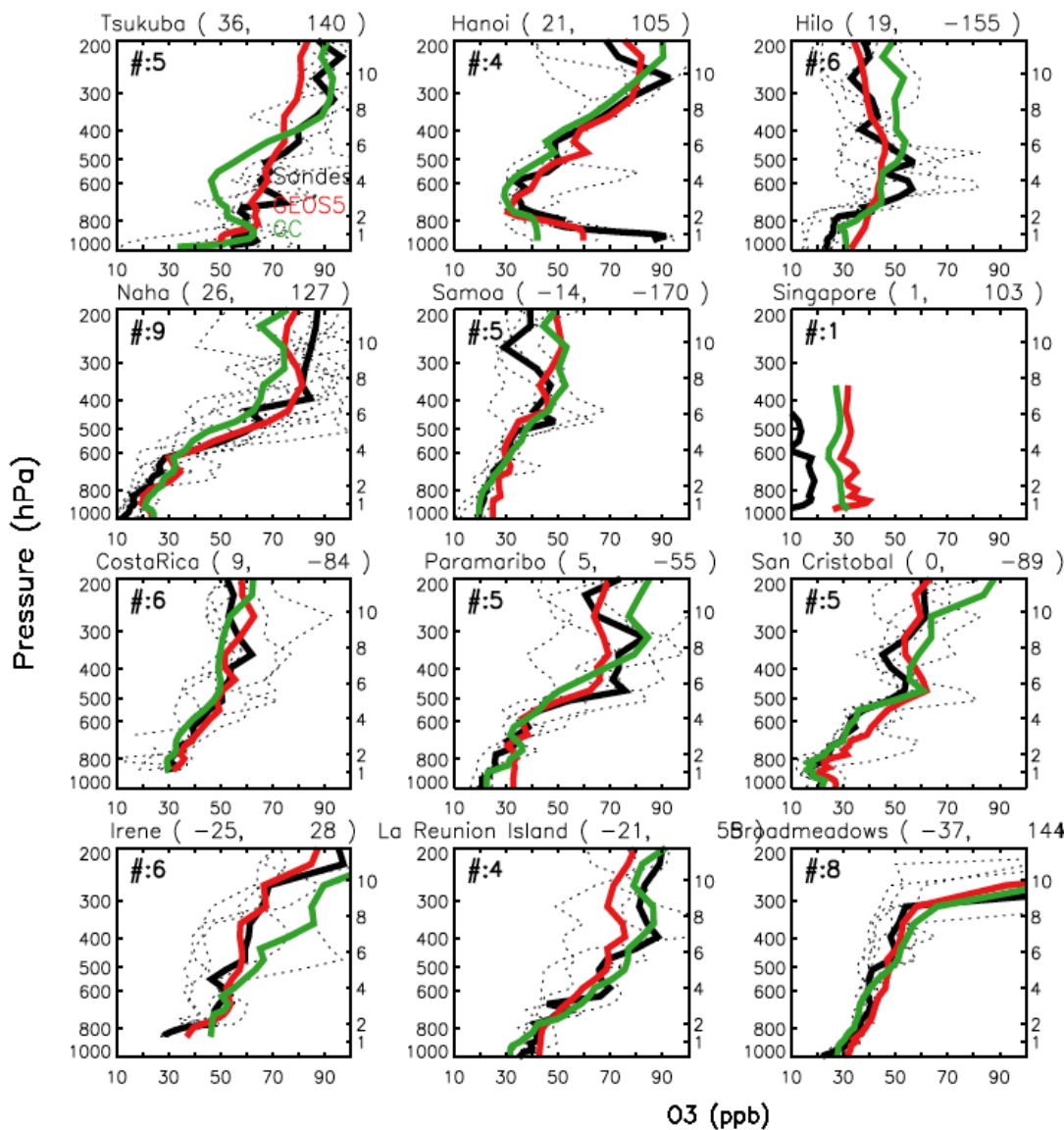
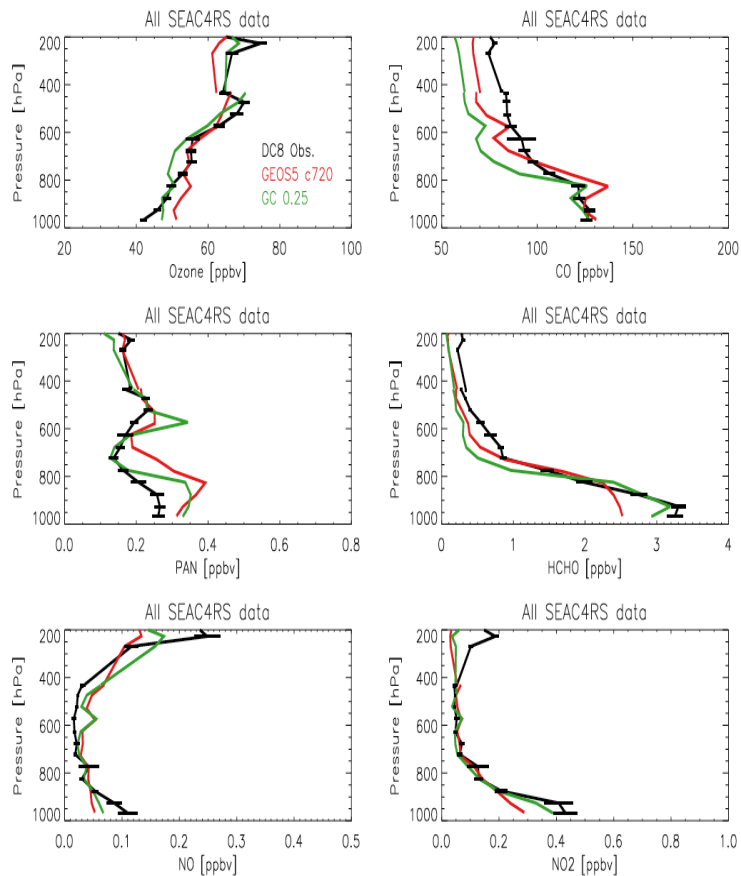
where the *cloud fraction* f is given by

$$f = \int_1^{\infty} p(S) ds$$



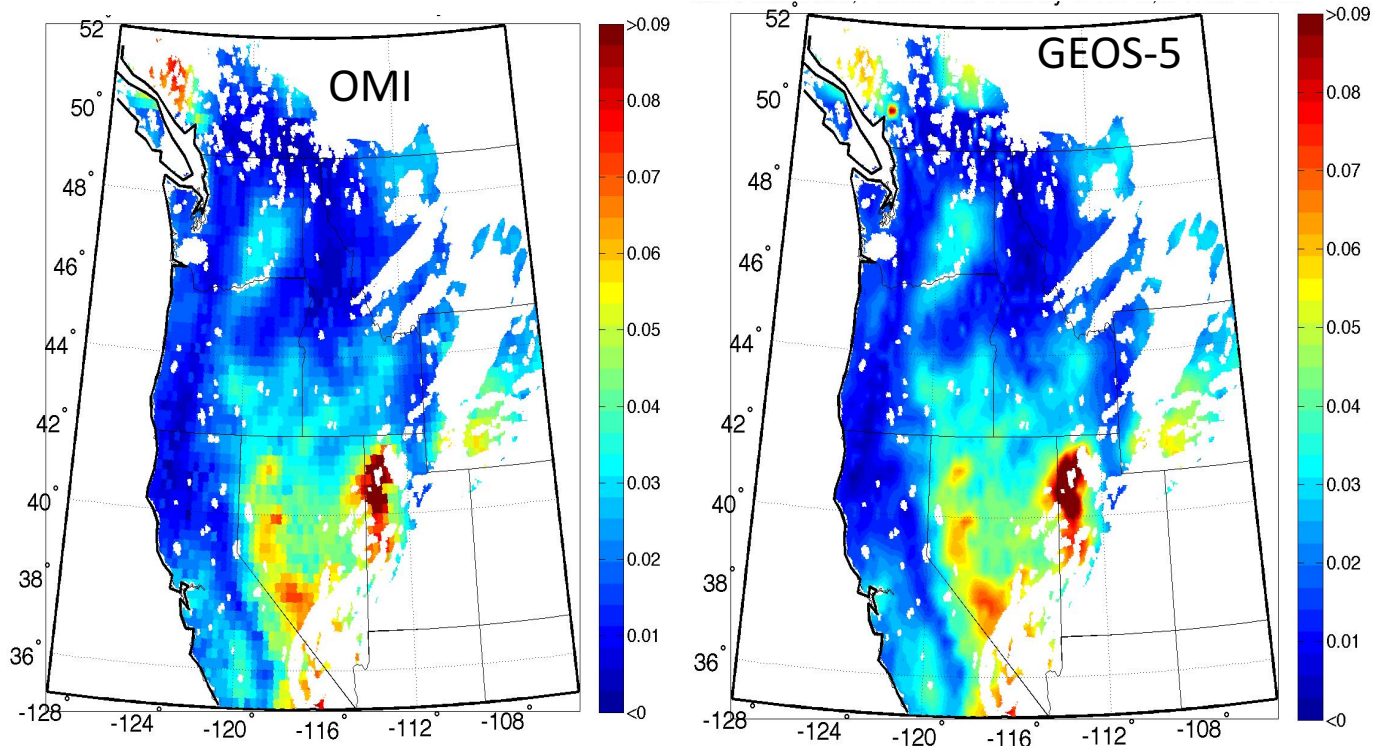
A PDF of water vapor + condensate is provided in each gridbox

G5NR-Chem Validation



Surface albedos in OMI and GEOS-5

Both OMI and GEOS-5 extract the surface albedo from the same common database. However, they look different

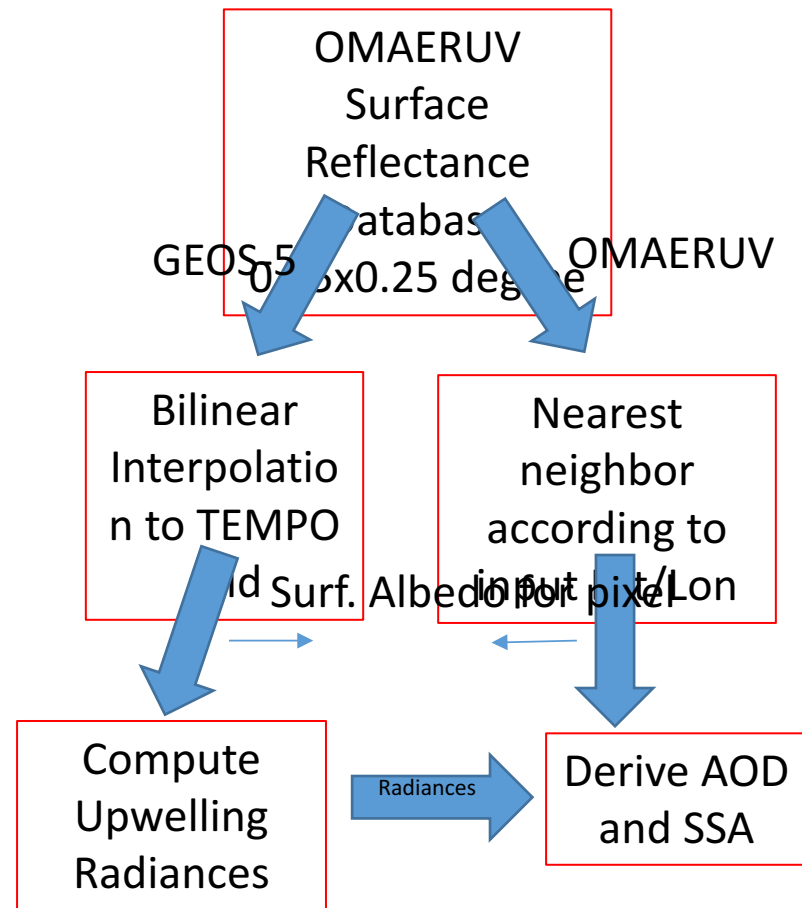
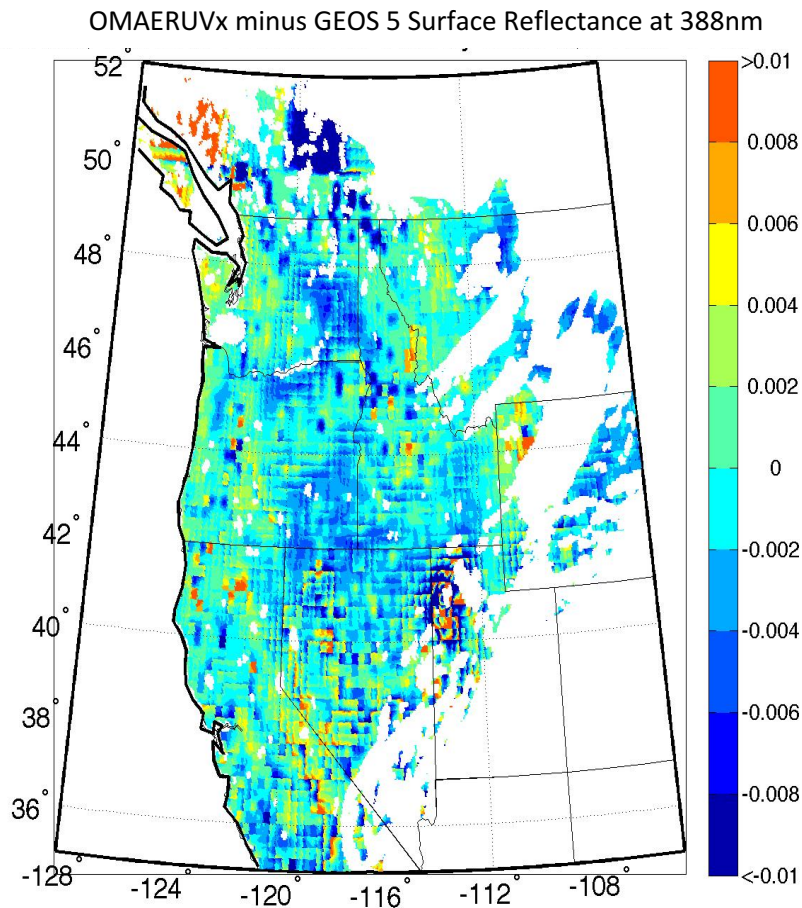


Output
Surface
Albedo used
in the
retrieval

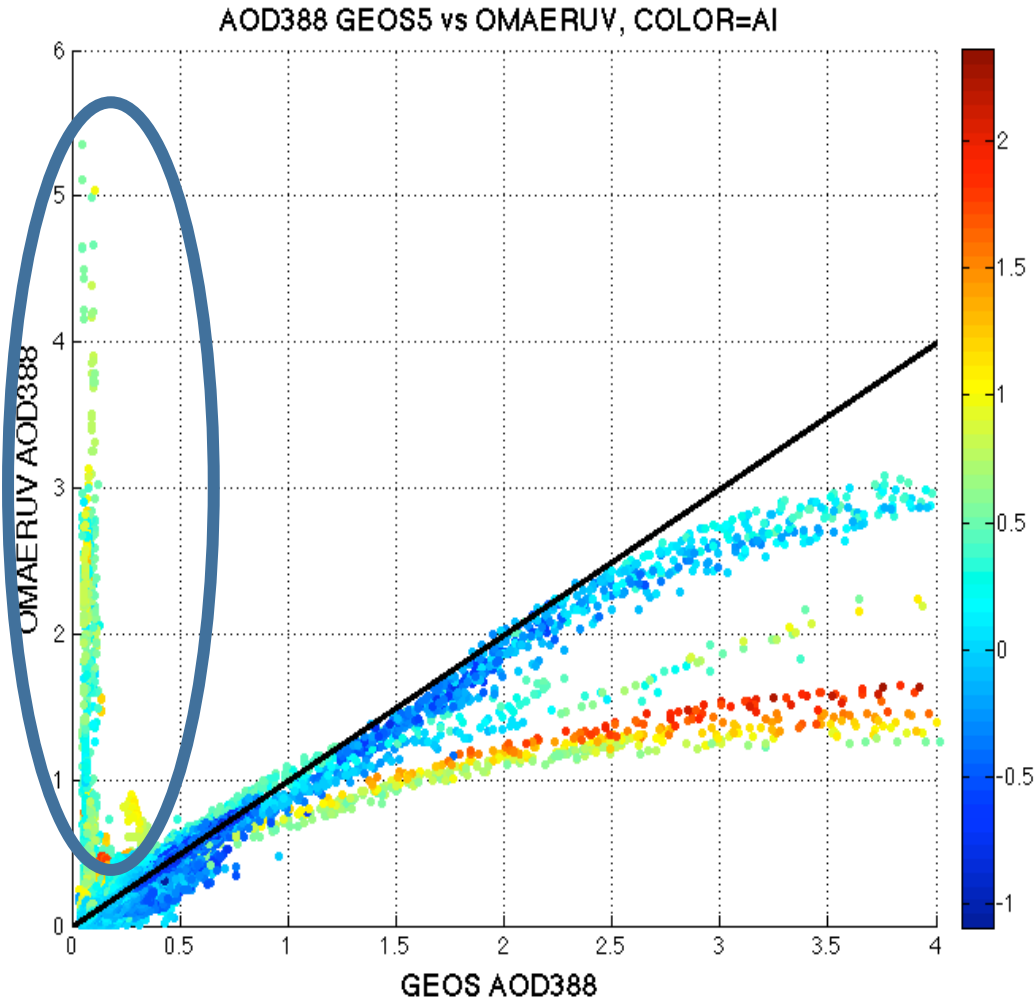
Albedo used
by GEOS5 to
compute the
TOA
radiances
provided to
OMI
algorithm

General Patterns are the same but both maps are not the same.

The difference in Surface albedos originates on the interpolation approaches



So , why the high AODs ?



- The GEOS-5 Radiances were generated with surface reflectances inconsistent with those used by OMI algorithm
- Before carrying out the aerosol retrievals, OMI algorithm subtracts the surface contribution from the total radiance.
- The small differences between the two surfaces become apparent at low aerosol loadings.