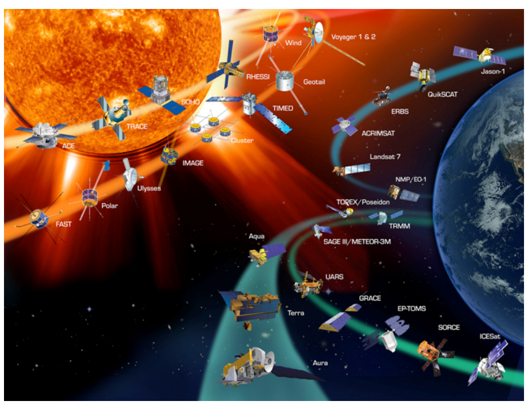
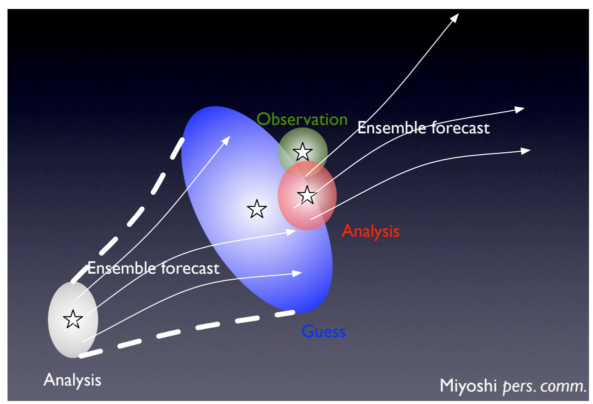
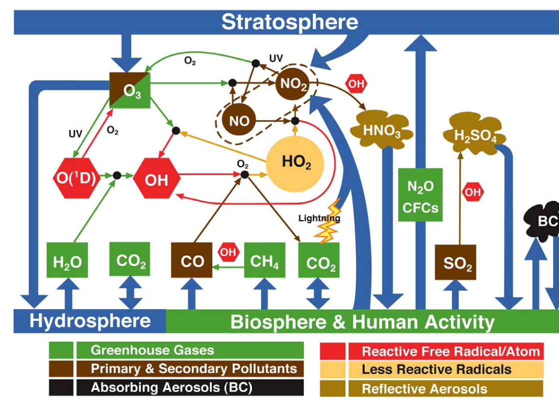
Satellite data assimilation of atmospheric composition







Kazuyuki Miyazaki

Japan Agency for Marine-Earth Science and Technology

Who am I?

Kazuyuki Miyazaki, Ph.D. (2006)

Research Scientist at JAMSTEC, now Visitor at IPRC

Research topics:

- **Stratospheric ozone, general circulation, chemical transport modeling,** *with Prof. Iwasaki (Tohoku Univ.) and Dr. Shibata (MRI-JMA)*

- **Transport and mixing in the UTLS,** *with Prof. Sato and Prof. Takahashi (Univ. Tokyo)* under KANTO project

- **Chemical/carbon satellite data assimilation,** *with Dr. Eskes (KNMI), Prof. Boersma (Eindhoven Univ.) and Prof. Sudo (Nagoya Univ.)*

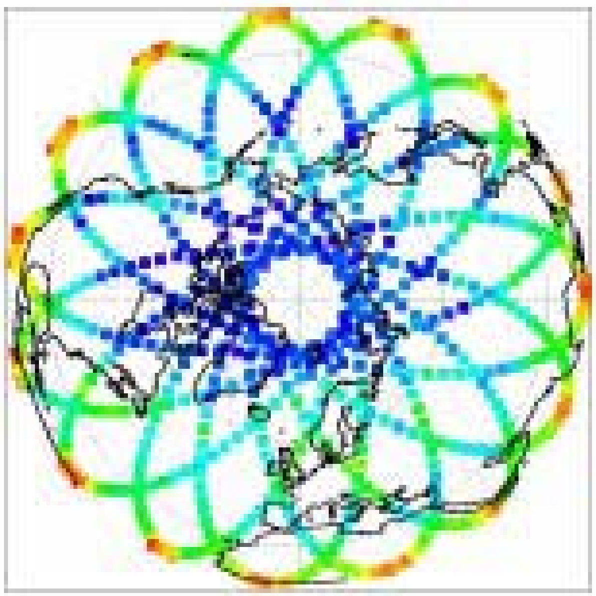
Outline

- Basics on Data Assimilation
- Chemical Data Assimilation
    - Stratospheric O_3
    - Aerosols
    - Carbon cycle
    - Tropospheric chemistry
    - ? TTL studies ?

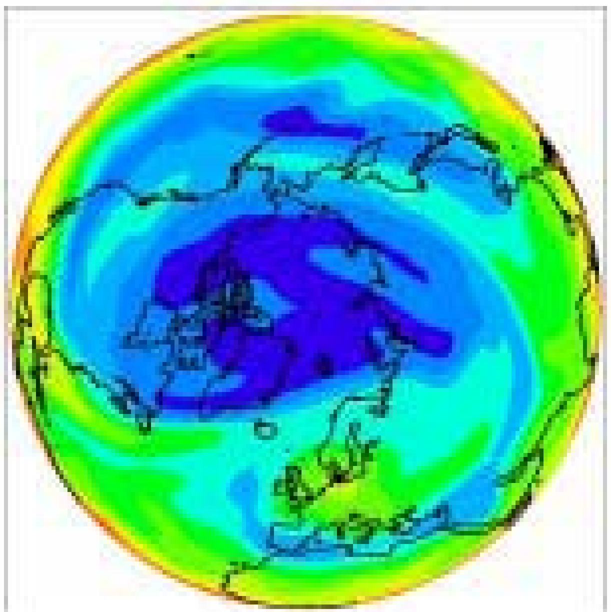
Data Assimilation Basics

Objective of Data Assimilation

is to produce a regular, physically consistent 4D 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.



(Struthers et al., 2002)



UARS MLS ozone data at 10 hPa on 1st February 1997.

Ozone analyses at 10 hPa at 12 UTC on 1st February 1997.

Objective of Data Assimilation

is to produce a regular, physically consistent 4D 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.

Data assimilation
extracts the signal from noisy observations (filtering),
interpolates in space and time (interpolation), and
reconstructs state variables that are not sampled by the observation network (completion).

(Daley, 1997)

Data Assimilation Inputs

Two sources of information are used in the analysis

- observations (y)
- background (x^b) = *first guess*

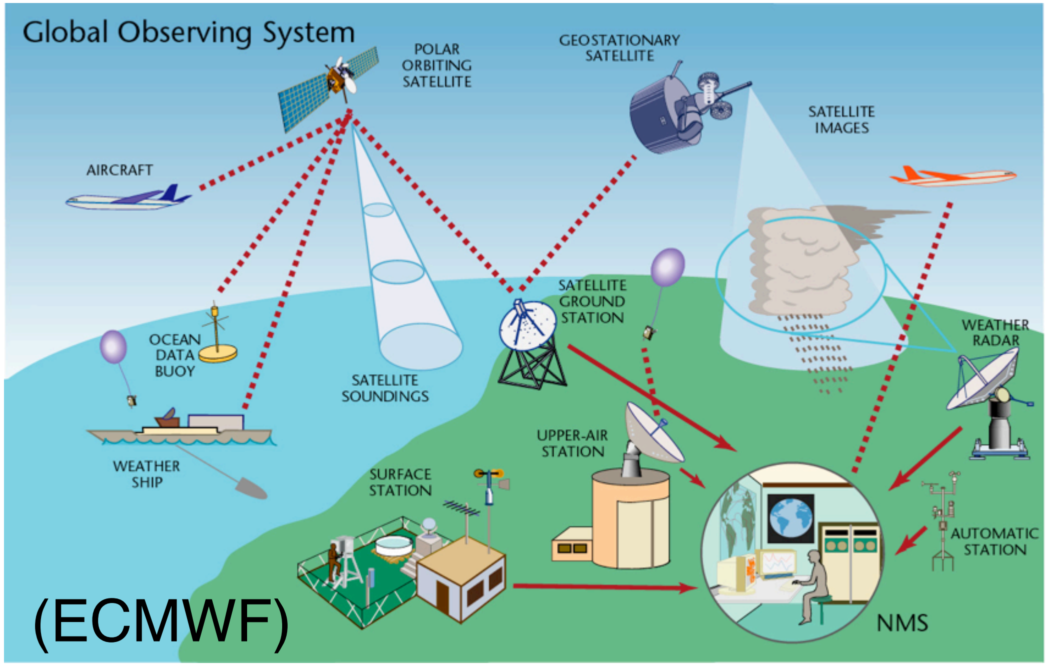
In order to maintain statistical optimality, the error source statistics need to be specified,

- the observation error covariance matrix (R)
- the background error covariance matrix (B)

The Output

a maximum likelihood estimate of atmospheric state (=*analysis*)

What is Data Assimilation for



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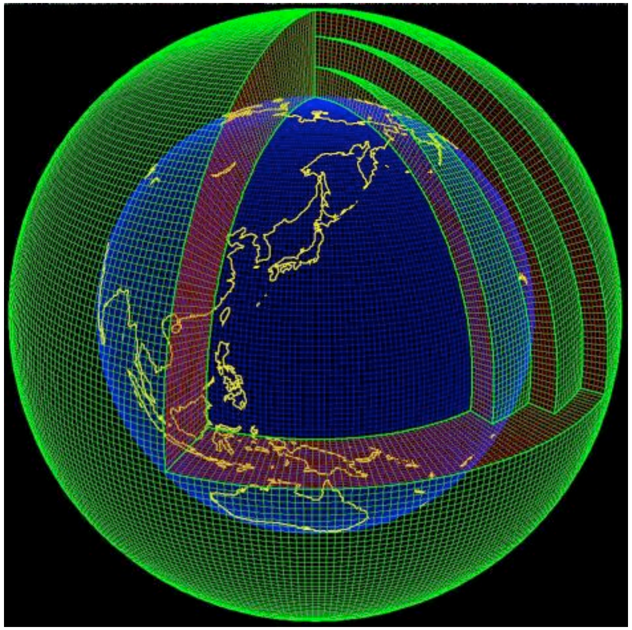


- Initial state estimation for weather forecasting
- Producing reanalysis data
- Observing system design, monitoring and assessment
- Better understanding (model errors, data errors, physical process interactions, parameters, etc)

(Nodet, 2012)

Data Assimilation Techniques

real time assimilation | retrospective analysis

complexity

non-linear methods

Kalman smoother

(4D-Var or) 4D-PSAS with model error

fixed-lag Kalman smoother

EKF

intermittent 4D-Var or 4D-PSAS

long 4D-Var or 4D-PSAS

3D-Var or 3D-PSAS

Optimal Interpolation (OI)

Cressman

Successive Corrections

nudging

Interpolation of observations

(ECMWF tech. note)

ECMWF atmospheric reanalysis projects

3D-OI 3D-VAR 4D-VAR 4D-VAR in ensemble context

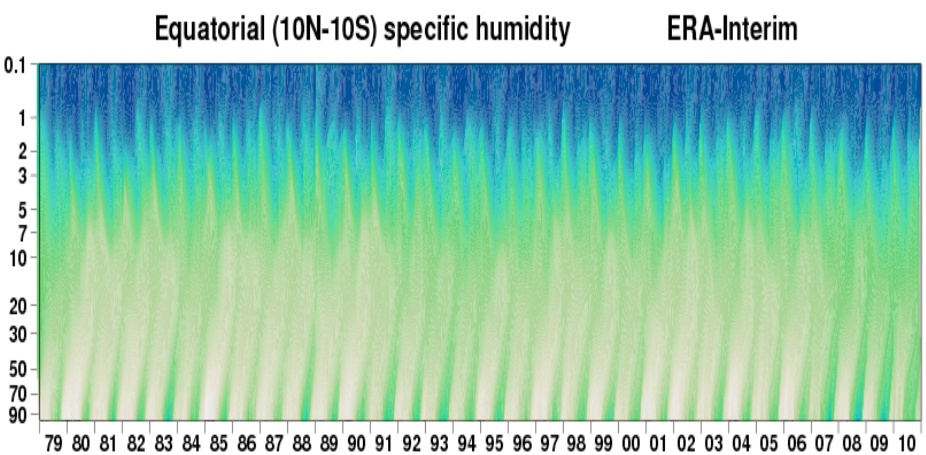
FGGE → ERA-15 → ERA-40 → ERA-Interim → ERA-CLIM

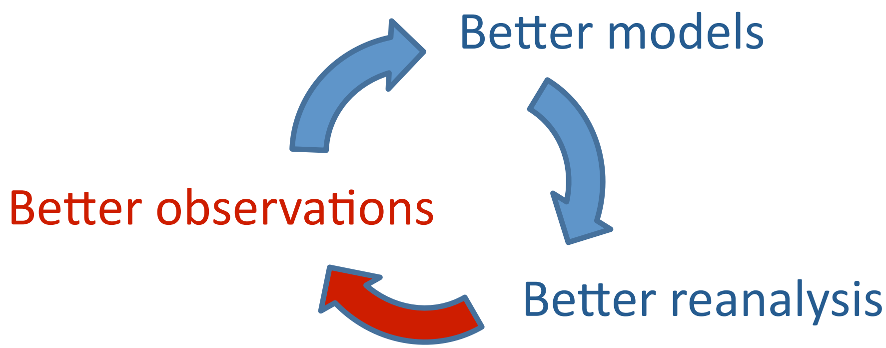
- **ERA-40** (1957-2002):

  Very large user base; science and downstream applications
- **ERA-Interim** (from 1979 onward):

  Near-real time updates; better trends; better data services
- **ERA-CLIM**: An EU project to prepare the next generation reanalysis

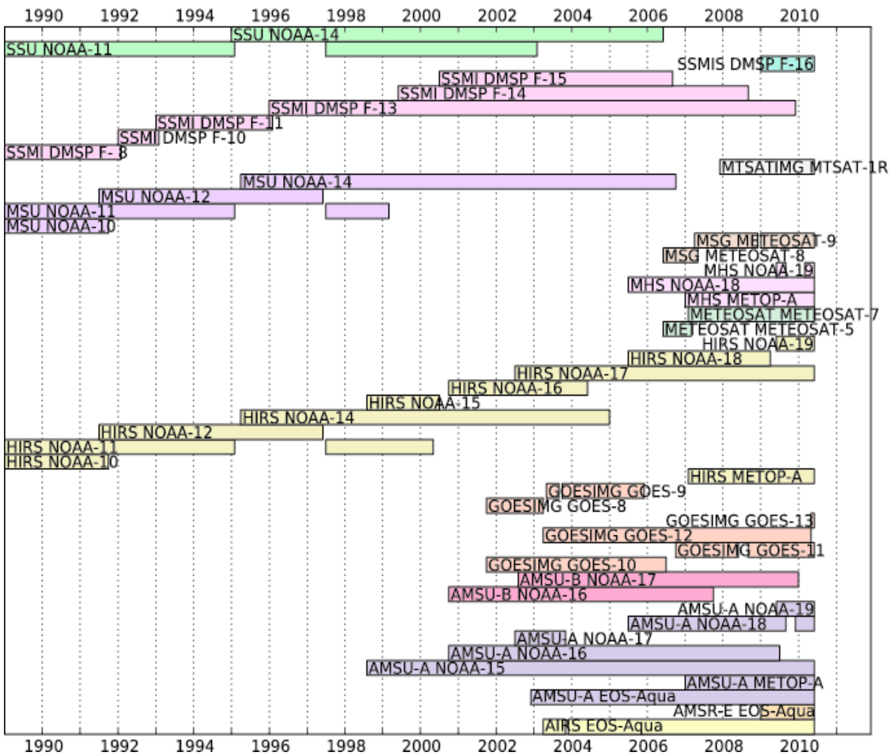
  Longer period; higher resolution; better input data; $\boxed{\text{uncertainty information}}$



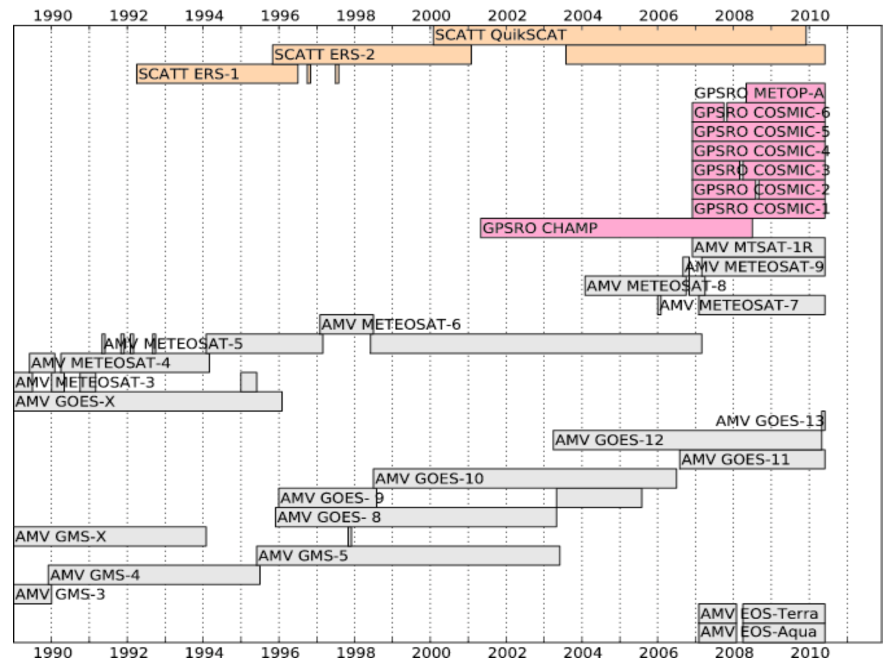


Observations used in ERA-Interim: Instruments

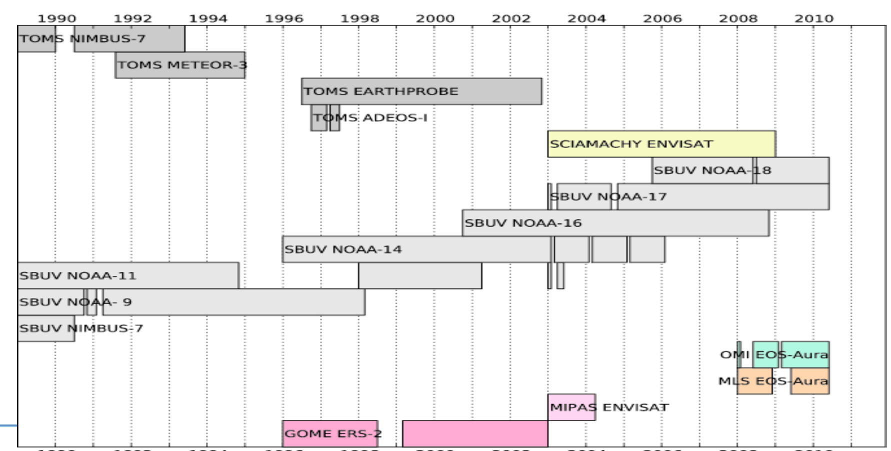
Radiances from satellites



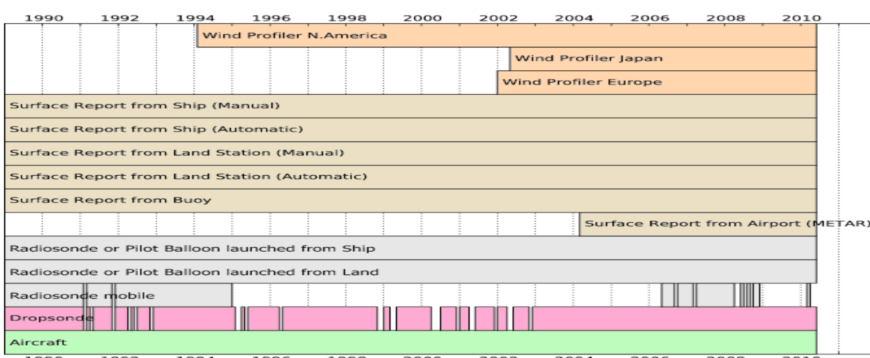
Backscatter, GPSRO, AMVs from satellites



Ozone from satellites



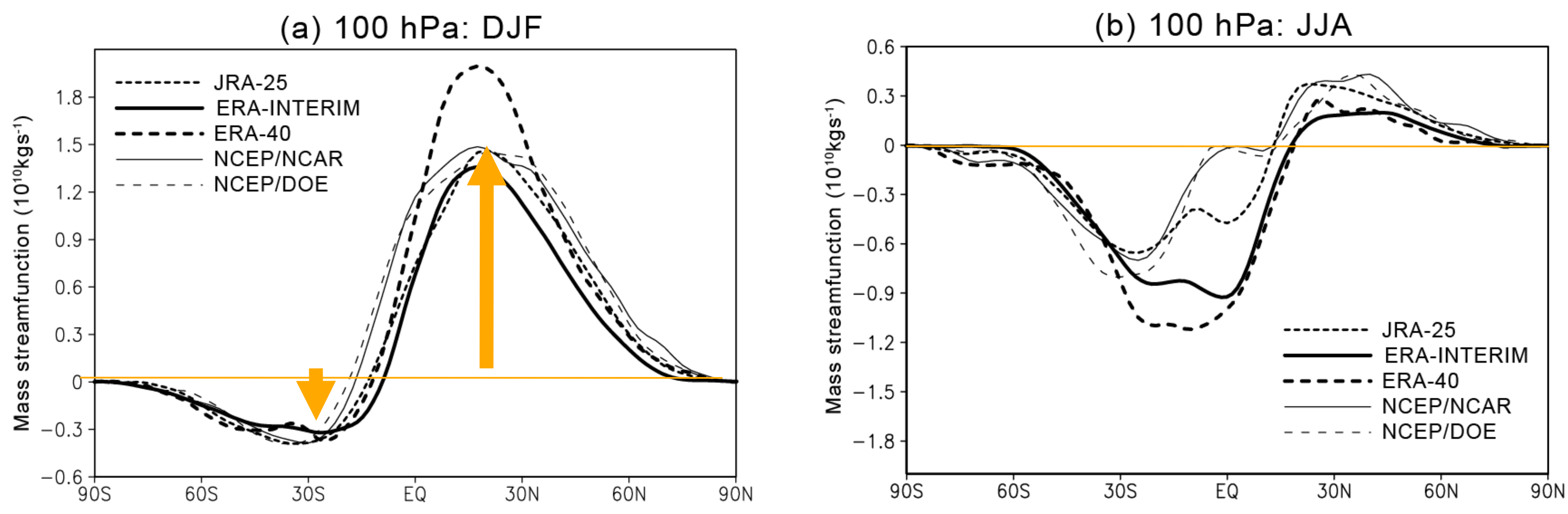
Sondes, profilers, stations, ships, buoys, aircraft



Comparisons of BD circulation among reanalyses

NCEP/NCAR	1979-2001	3Dvar
NCEP/DOE	1979-2001	3Dvar
ERA-40	1979-2001	3Dvar
ERA-INTERIM	1989-2001	4Dvar
JRA-25	1979-2001	3Dvar

(Iwasaki, Hamada, Miyazaki., 2009)



Mass Streamfunctions at 100 hPa

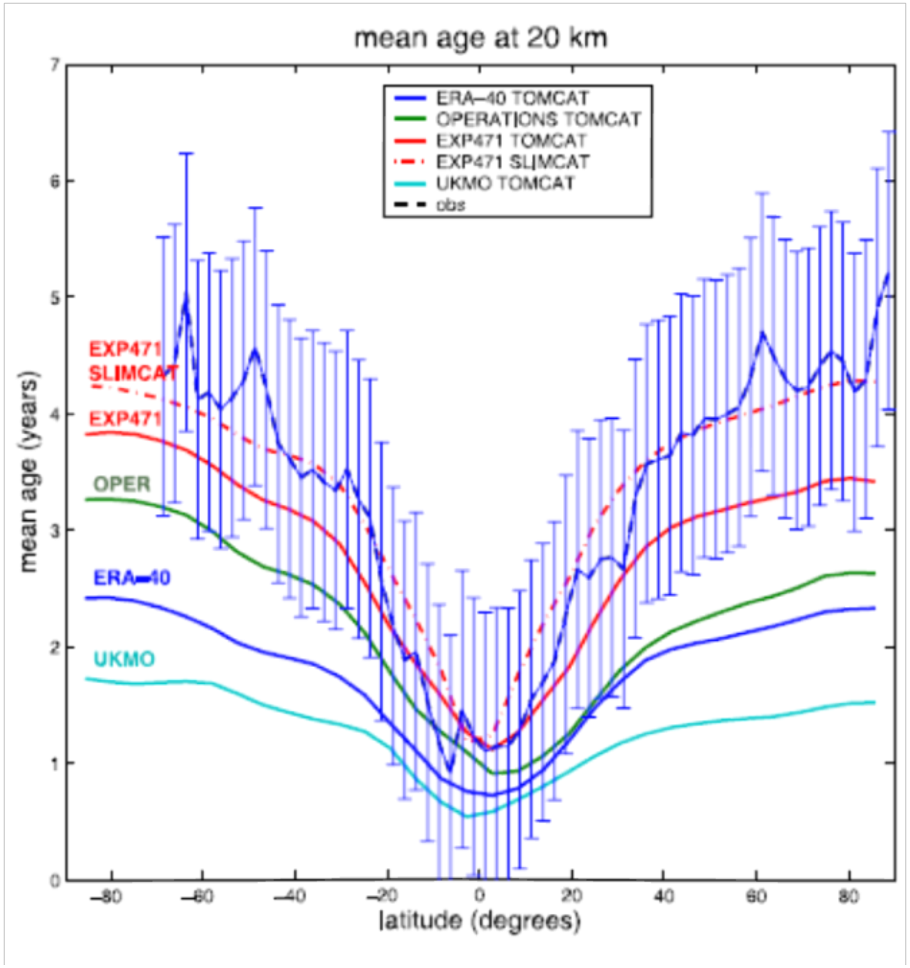
(Northward Mass Flux above 100 hPa)

ERA-40 has the strongest B-D circulation

Large contradictions are found in the tropics in JJA.

....due to many factors affecting dynamical and thermodynamical consistency

Improvements in the age-of-air calculation



(Monge-Sanz et al., 2007)

EXP471 uses an improved model with balance operator for omega-equation

To improve transport calculation, we should use

1. Forecast than analysis (Meijer et al., 2004)

2. <u>4D-VAR than 3D-VAR analysis</u> (Scheele et al., 2005)

3. 3-h interval data than 6-h (Bregman et al., 2006)

4. Time-averaged data than snapshot (Pawson et al., 2007)

- **1 & 2: Dynamical consistency, balanced circulation field**
- **4: Reduce transport error mainly caused by gravity waves**

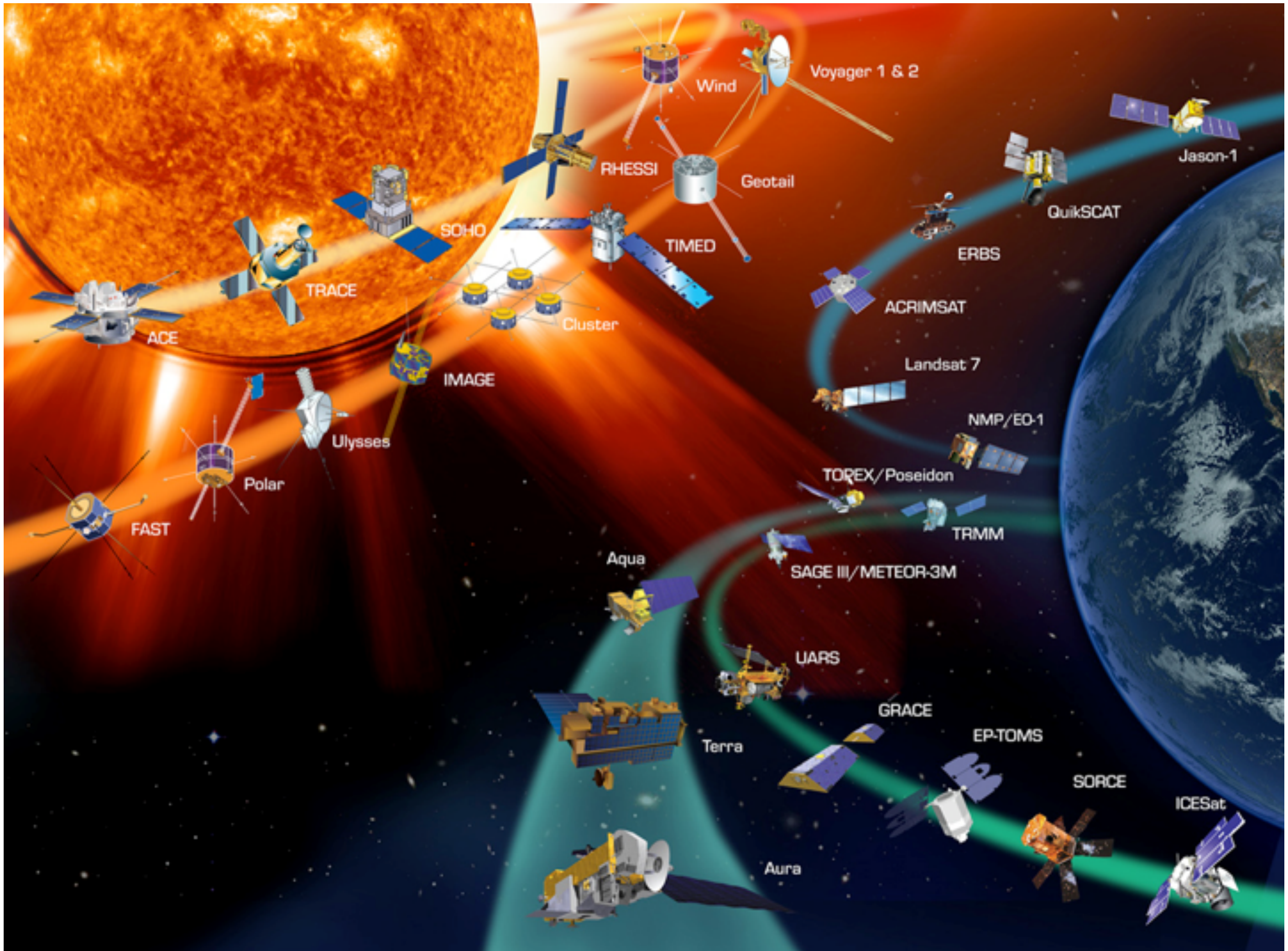
Best choice: 3-day forecast with 4-D VAR analysis

Chemical Data Assimilation

Stratospheric ozone
Tropospheric chemistry
Aerosols
Carbon Cycle

CTM simulation: large uncertainties in chemical/transport processes and boundary conditions (e.g., ozone precursor emissions)

Satellite instruments can provide strong constraints on chemical system



(NASA/Harvard univ.)

needs for advanced chemical data assimilation system to combine various obs info

Chemical Data Assimilation

- make best use of all available (satellite) data, from heterogeneous sensors, scattered in space and time
- ensure chemical and dynamical consistency
- extend analysis on non-observed species

Applications

- Weather/UV forecasting: better calculation of the radiative transfer
- Air quality/ozone hole monitoring
- Chemical reanalysis (i.e., climate simulation input)

(from Dr Elbern's lecture note.)

Satellite Data Assimilation

The observation operator should contain the averaging kernel and the a priori information of each retrieval to avoid the influence of the smoothing error and the retrieval error arising from the a priori profile.

The model fields in the observation space

$$y^b = H(x) = x_a + \mathbf{A}(S(x) - x_a).$$

- The averaging kernel matrix (A) represents the sensitivity of the retrieved parameters to the true state.

- The observation operator (H) converts the model profiles to the profile that would be retrieved from satellite measurements.

$$y^o - y^b = \mathbf{A}(x_{true} - S(x)) + \epsilon,$$

The model-satellite difference (the innovation) is not biased by the a priori profile.

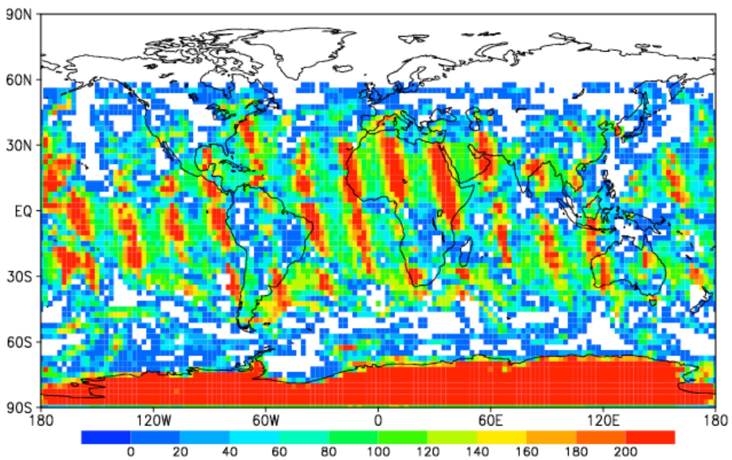
(Rodgers, 2000; Eskes and Boersma, 2003)

Super-observation approach

- fill spatiotemporal gaps between the model and retrievals
- produce more representative data
- reduce DA computational cost

$$\bar{x} = \frac{\sum_{i=1}^{m} w_i x_i}{\sum_{i=1}^{m} w_i}$$

$$\bar{y}_{measurement} = \frac{\sum_{i=1}^{m} w_i y_i}{\sum_{i=1}^{m} w_i} \sqrt{\frac{1-c}{m} + c}$$



Number of OMI data
for each super-obs pixel

Super-obs error =

measurement error + representativeness error

x : retrieved concentration

y : retrieval error

w : weight (coverage area for most cases)

m :number observation in a super-obs pixel

c : correlation among data

A Japanese chemical data assimilation project (2009-2012)

- We (MRI-JMA, NIES, JAMSTEC, Tohoku Univ.) have developed chemical data assimilation systems for monitoring atmospheric environment in East Asia and over the globe.
- The data assimilation systems developed by the four research institutes employed a same assimilation scheme (EnKF).

  → Impact of the model performance on data assimilation

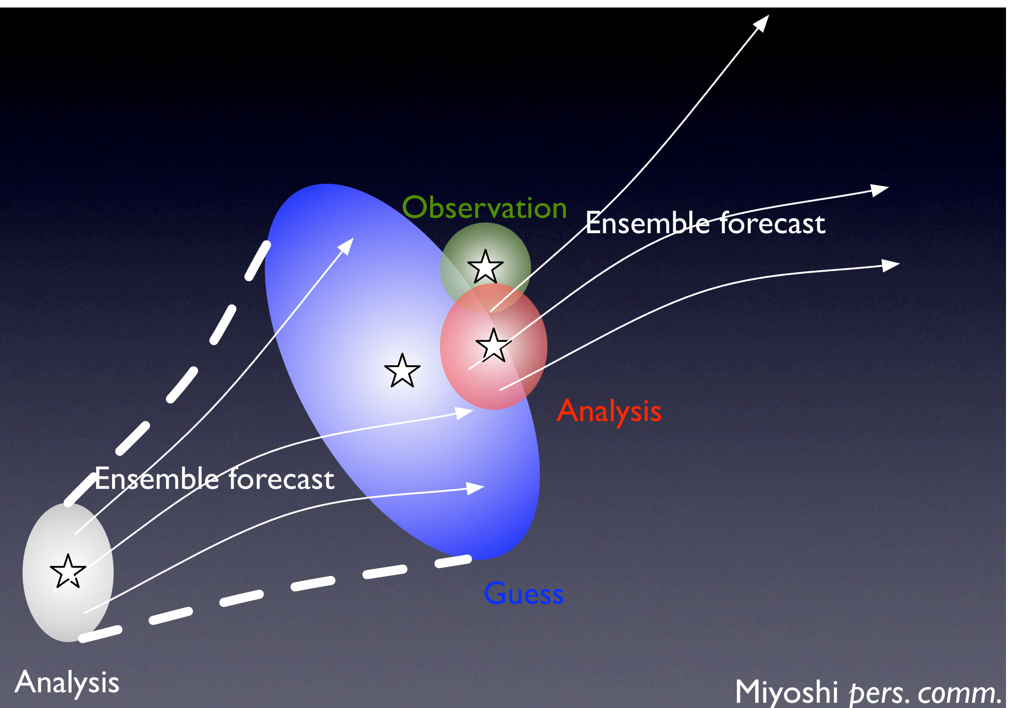
- The approach allows to simultaneously optimize forecast variables (i.e., concentrations) and parameters (i.e., emissions).

Ensemble Kalman Filter

	4D-Var	4D-EnKF
Background error statistics	Flow-dependent	Flow-dependent
Program code	Complicated	**Simple**
Adjoint matrix	Necessary	**Unnecessary**
Observation operator	Requires tangent linear & adjoint operators	**Requires only a forward transform operator**
Asynchronous observations	Handles at each observational time	Handles at each observational time
Analysis error covariance	Not provided	Explicitly provided

(Kalnay et al., 2007)

EnKF data assimilation: An ensemble Kalman filter (EnKF) is an advanced data assimilation technique in which the **forecast error covariance is advanced by the model itself** (i.e., flow-dependent forecast error covariance). The advanced approach allow us to **fully take advantage of CTMs.**



Background error covariance

$$\overline{\mathbf{x}^b} = \frac{1}{k}\sum_{i=1}^{k} \mathbf{x}_i^b \; ; \; \mathbf{X}_i^b = \mathbf{x}_i^b - \overline{\mathbf{x}^b}.$$

$$\mathbf{P}^b = \mathbf{X}^b (\mathbf{X}^b)^T.$$

Observation operator

$$\mathbf{y}_i^b = H\left(\mathbf{x}_i^b\right)$$

$$\mathbf{y}_i^b = H\left(\mathbf{x}_i^b\right) = \sum_{i=1}^{k} a_i \mathbf{x}_i^b,$$

Analysis error covariance

$$\tilde{\mathbf{P}}^a = \left[\frac{(k-1)\mathbf{I}}{1+\Delta} + \left(\mathbf{Y}^\mathbf{b}\right)^T \mathbf{R}^{-1}\mathbf{Y}^\mathbf{b}\right]^{-1},$$

$$\mathbf{T} = \left[(k-1)\tilde{\mathbf{P}}^a\right]^{1/2}$$

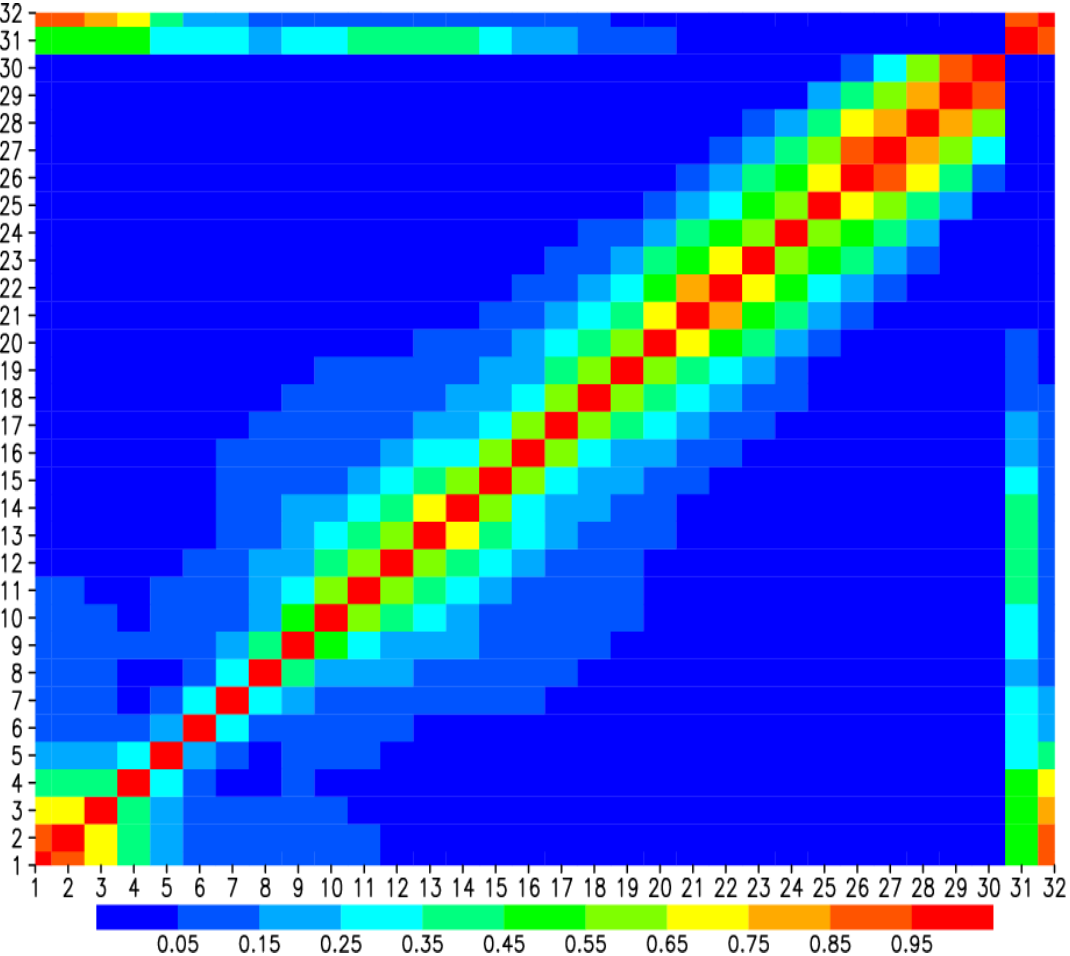
Analysis (incl. perturb.)update

$$\overline{\mathbf{x}}^a = \overline{\mathbf{x}}^b + \mathbf{X}^\mathbf{b}\tilde{\mathbf{P}}^a \left(\mathbf{Y}^\mathbf{b}\right)^T \mathbf{R}^{-1}\left(\mathbf{y}^o - \overline{\mathbf{y}^b}\right)$$

$$\mathbf{X}^a = \mathbf{X}^b \mathbf{T}$$

Simultaneous optimization of state and parameter in EnKF

Background error covariance (X_b)



1-30: NO_2 conc. at each model level,
31: Trop. NO_2 column, 32: NOx emission

The state vector augmentation technique allows us to simultaneously estimate the **model state (i.e., concentration)** and the **uncertain model parameter (i.e., emission)**.

Extended state vector

$$z = \begin{pmatrix} \boxed{\mathit{state}} \\ \boxed{\mathit{parameter}} \end{pmatrix}$$

(Miyazaki et al., 2012a)

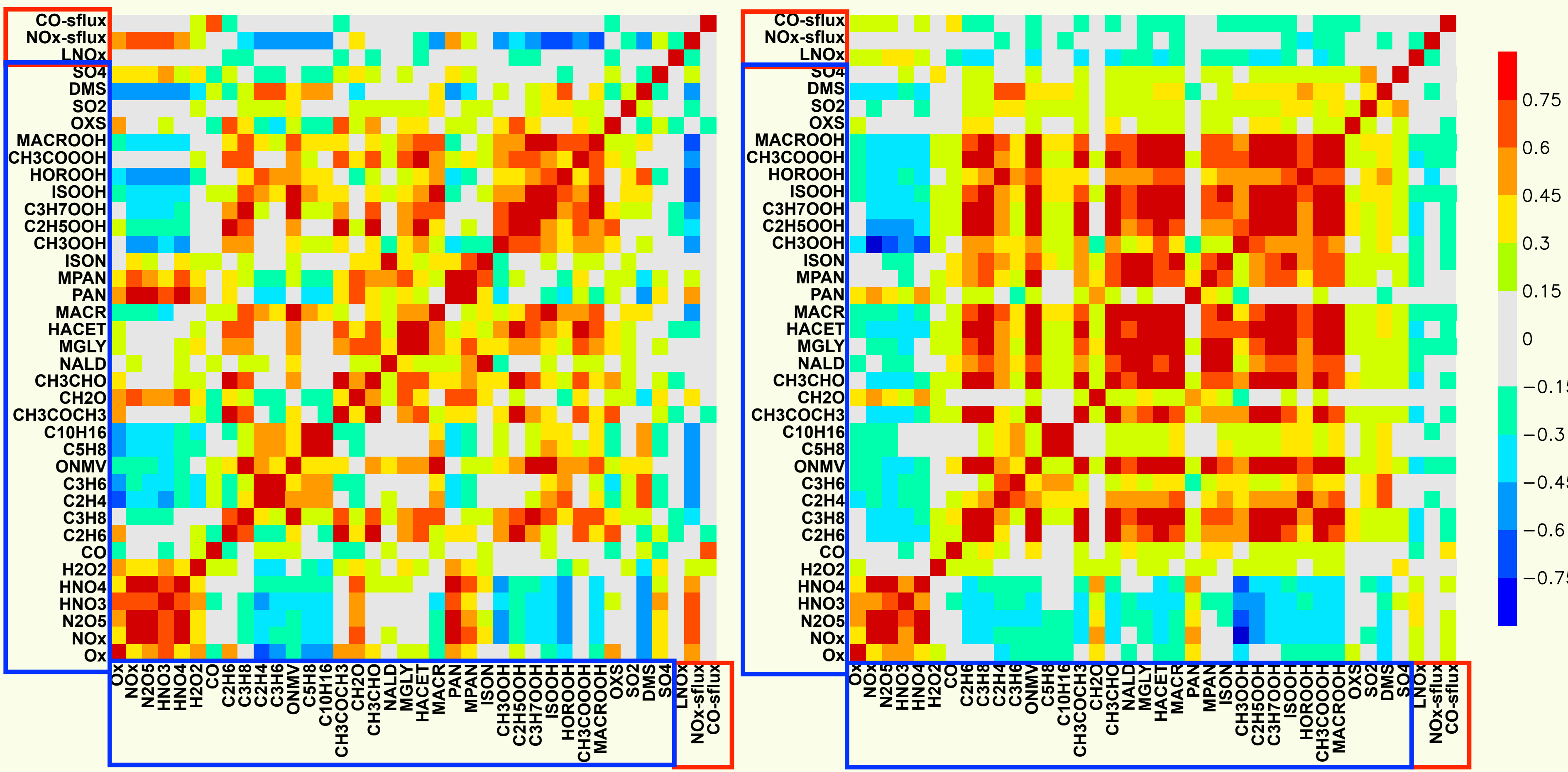
Emission estimation: A state vector which includes both the concentrations and the emissions makes it possible to find the optimal values for the emissions.

$$\mathbf{x}_i^b = \begin{bmatrix} \boxed{\mathbf{c}_i^b} \\ \mathbf{e}(\mathrm{NO_x})_i^b \\ \mathbf{e}(\mathrm{CO})_i^b \\ \mathbf{e}(\mathrm{LNO_x})_i^b \end{bmatrix}$$

Concentration

Emissions

Background error covariance structure in EnKF



(Miyazaki et al., 2012b)

1. Stratospheric ozone

(MLS, OMI)

2. Aerosols

(CALIPSO, ground-based lidar)

Japanese CTMs/CCMs

& 3D/4D-LETKF

?TTL water vapor?
still very challenging!

3. Surface CO2 flux

(GOSAT, CONTRAIL)

4. Air quality

(OMI, SCIAMACHY...)

1. Stratospheric ozone

Forecast models:

(1) **CCSR/NIES CCM** (Akiyoshi et al., 2009) T42L34 p-top=0.01 hPa	
(2) **MRI CCM2** (Shibata and Deushi, 2008, Deushi and Shibata 2011) T42L68 p-top=0.01 hPa	
(3) **CHASER** (Sudo et al., 2002) *not shown here* T42L32 p-top=3 hPa	

The multi-model comparison provides an opportunity to examine the effects of the model bias on the assimilation performance.

Assimilated data: **MLS O3 profile, OMI O3 column, JCDAS (met. data)**

Control variables: **O3, U, V, T**

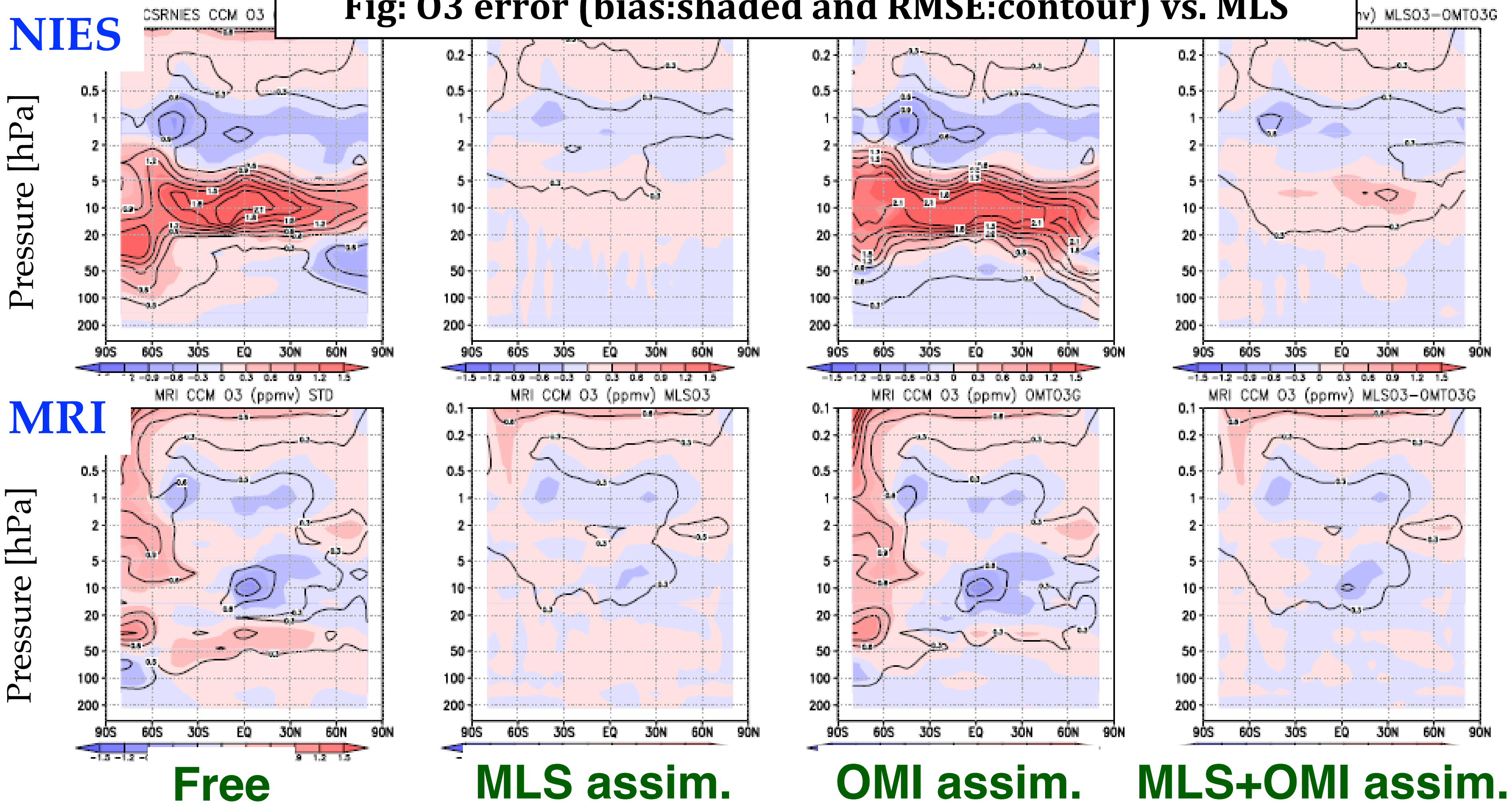
Assimilation setting: **3D analysis with 6-hourly cycle**

Ozone data assimilation

Improvements by MLS O3: throughout the stratosphere.
Improvements by OMI-TO3: only in the lower stratosphere.

(Nakamura, Miyazaki, et al., submitted)

Fig: O3 error (bias:shaded and RMSE:contour) vs. MLS

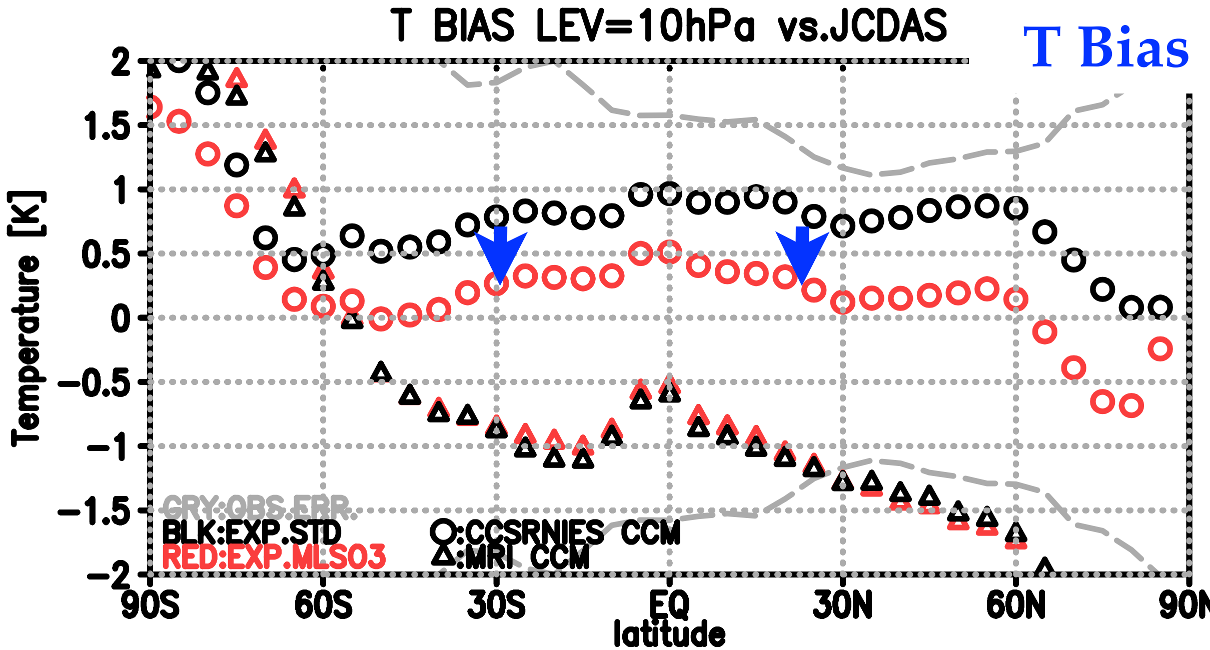


UVT assimilation

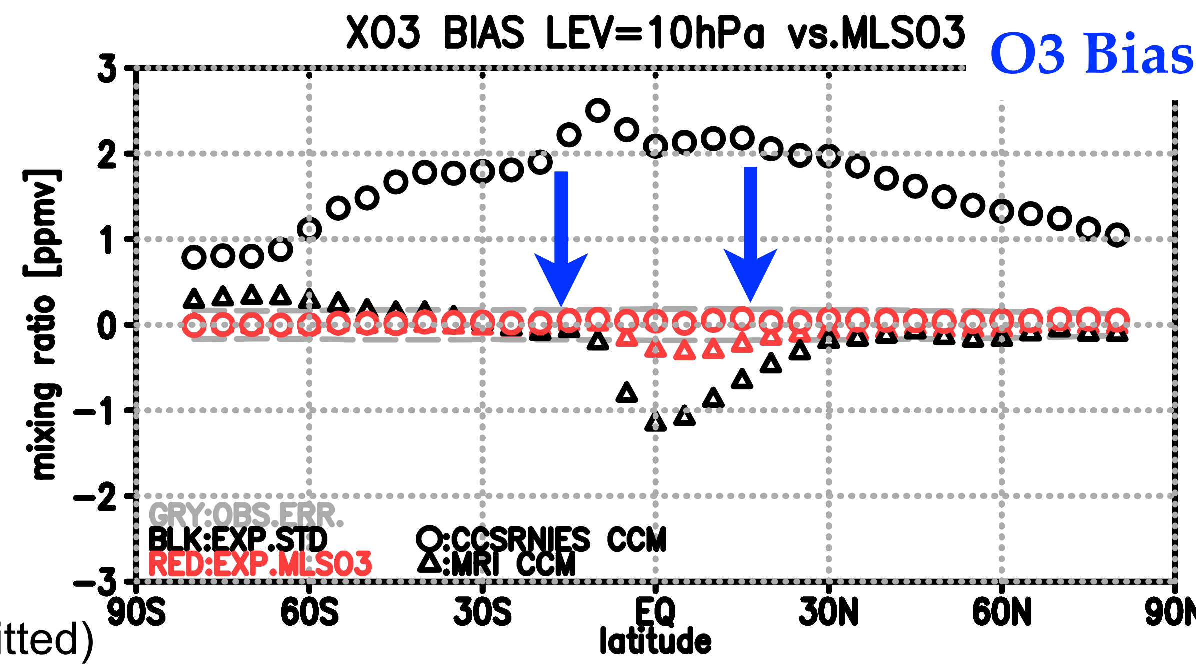
UVT+O_3 assimilation

T was assimilated in both the cases.

○: **NIES** △: **MRI**



- The temperature bias of the NIES model has been largely (about 50 %) removed by O_3 assimilation.



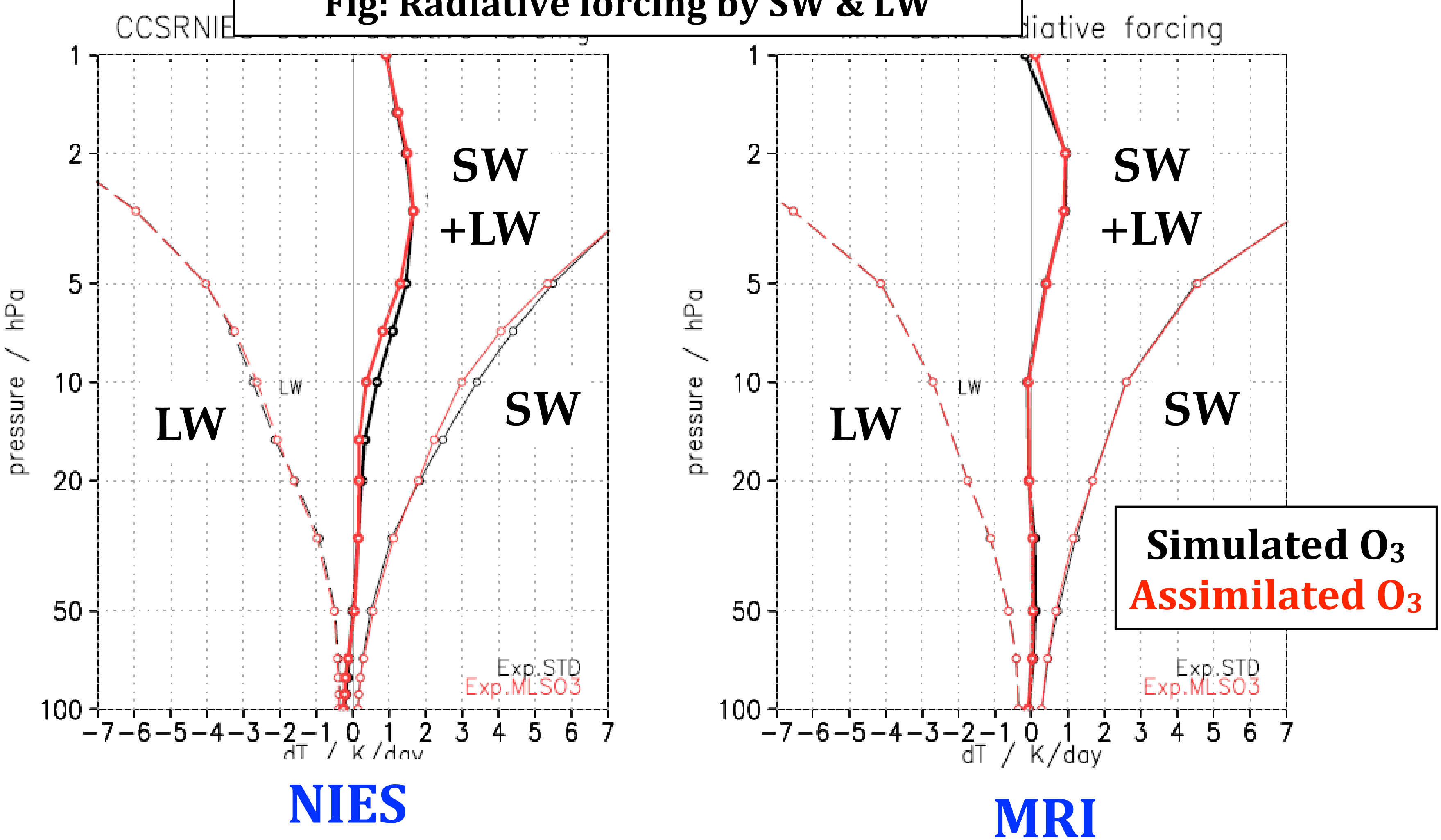
(Nakamura, Miyazaki, et al., submitted)

- **NIES:** O_3 assimilation → SW heating - 10 % → net radiative heating - 40%
  (→ might also influence chemical reaction (under investigation))

  chemistry-climate coupling data assimilation is important !

- **MRI:** dynamics or radiation calculation problem?

Fig: Radiative forcing by SW & LW



(Nakamura, Miyazaki, et al., submitted)

2. Aerosols

under development by JMA (T. Sekiyama)

- **Asian Dust**
  - seasonal phenomenon sporadically affecting East Asian countries during the springtime,
  - causes health and aviation problems,
  - originates in the deserts of Mongolia and China.

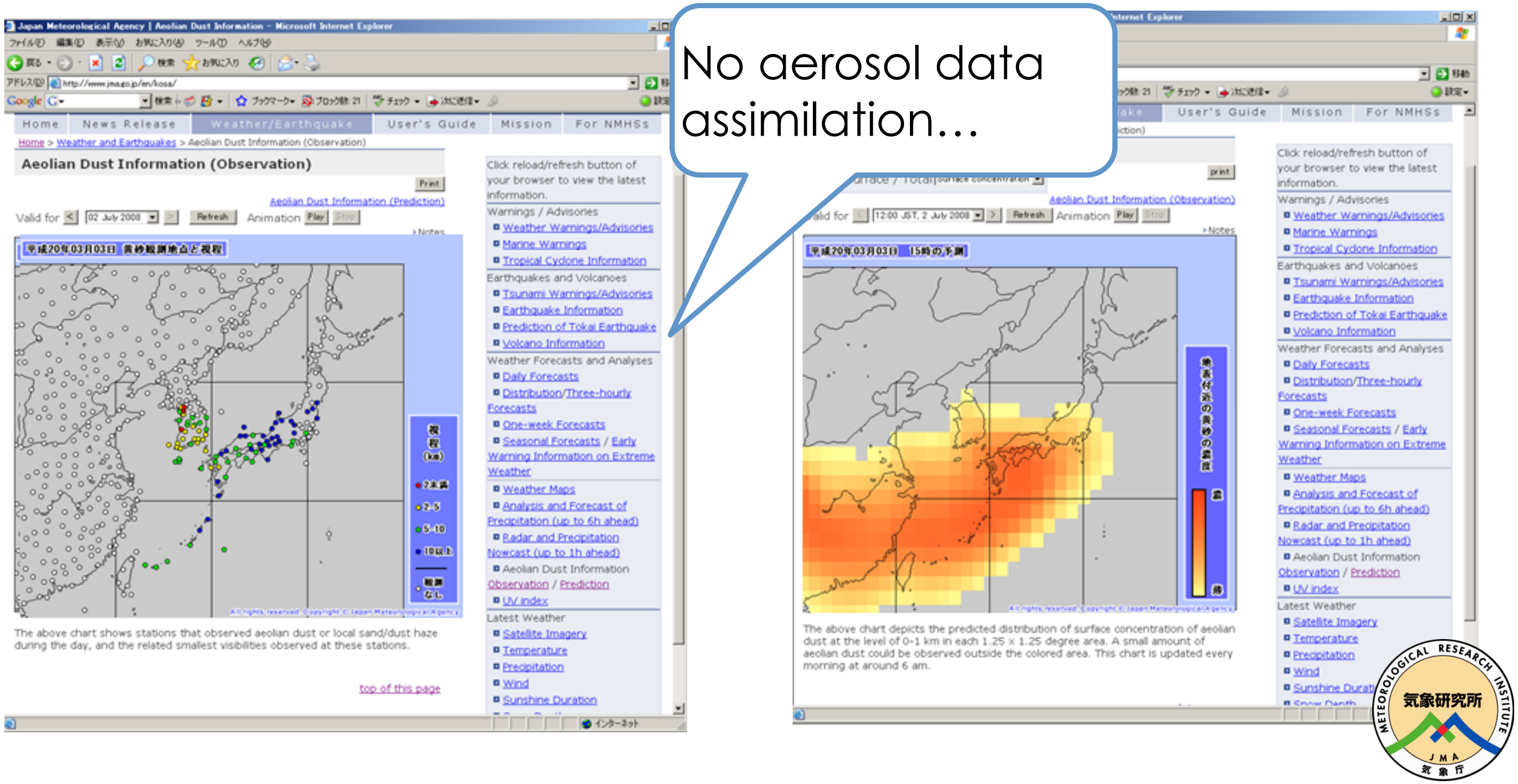
Forecast models: MASINGAR

Assimilated data: Satellite (CALIPSO/CALIOP) and ground-based lidar

Control variables: dust (partitioned into 10-size bins), dust flux, sea-salt, OC, BC, and sulfate aerosols

Assimilation setting: 4D analysis with 48-h time window

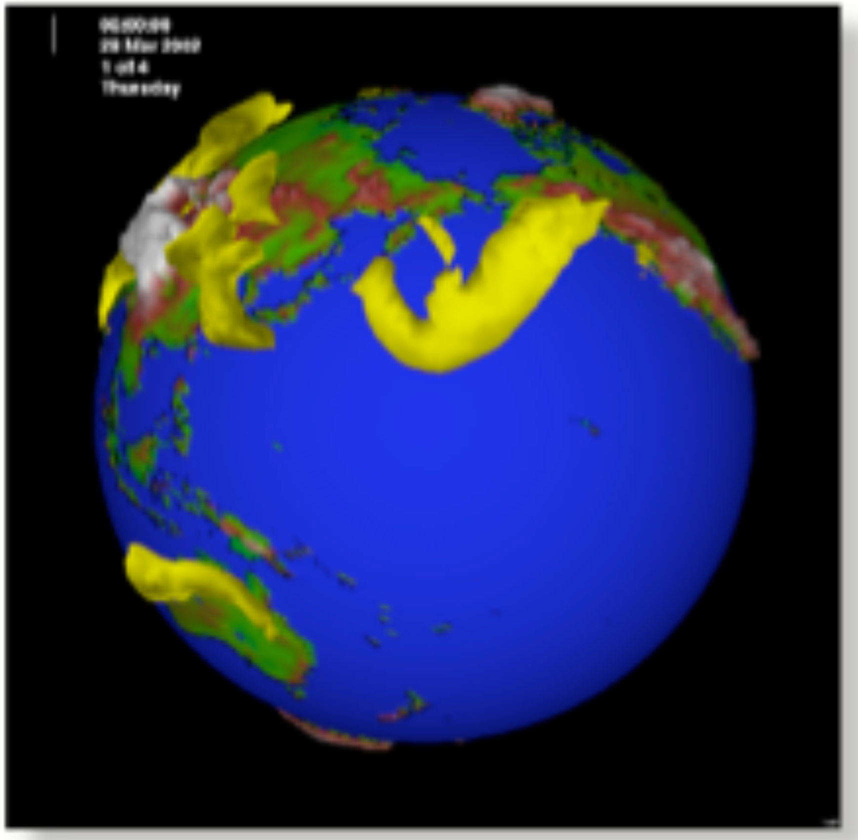
Operational dust prediction



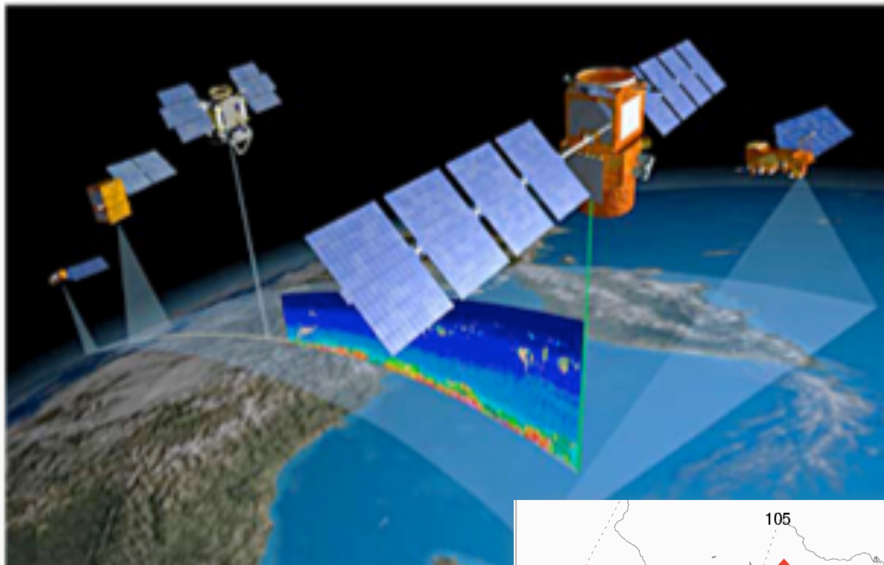
- JMA wants to utilize aerosol data assimilation for improving their operational dust prediction.
- If possible, they want to use the aerosol analysis for their NWP and climate simulations.

EnKF for aerosol analysis

- The Model of Aerosol Species in the Global Atmosphere (**MASINGAR**) of MRI/JMA simulates…
- **dust** (partitioned into 10-size bins), sea-salt, OC, BC, and **sulfate** aerosols



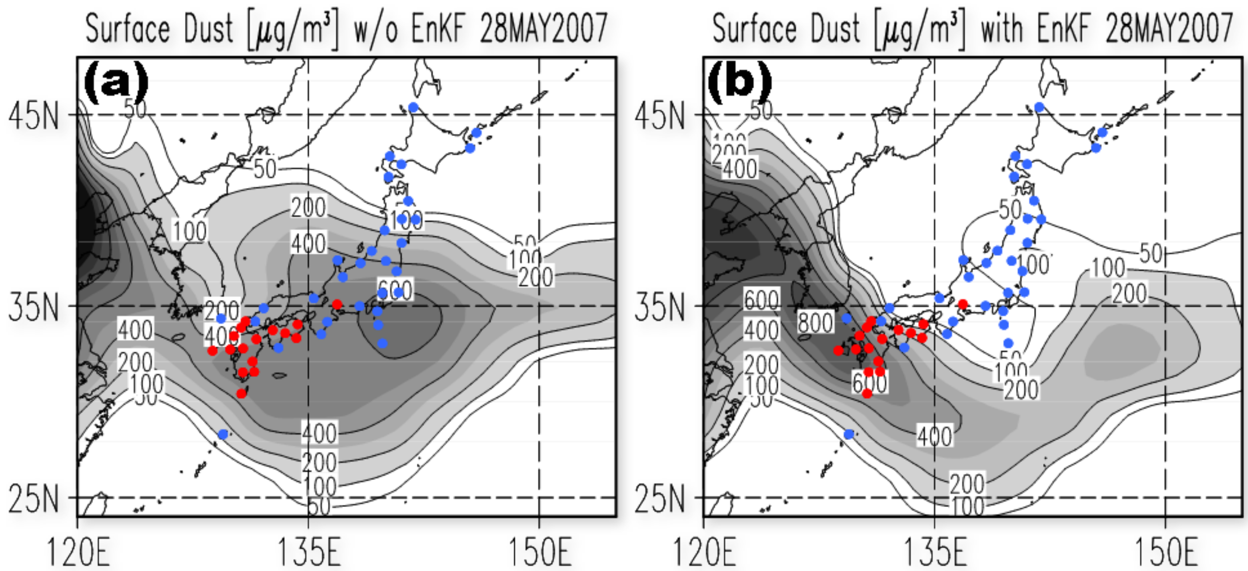
EnKF for aerosol analysis



Satellite Lidar observation (CALIPSO/CALIOP):
NASA launched the polar-orbit satellite in 2006.

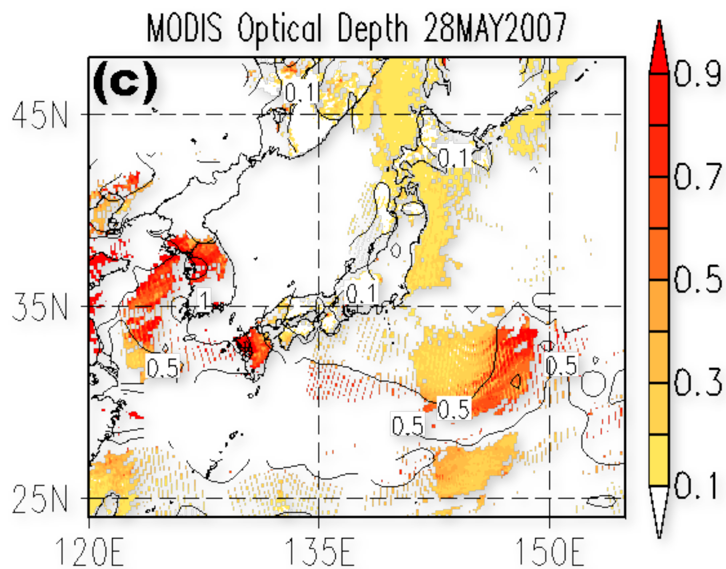
Ground-based lidar network (NIES AD-Net):
NIES Japan is operating more than 20 lidar stations in East Asia.

EnKF for aerosol analysis



Contours and gray shades are **surface dust concentrations**.

(a) Free model-run result without data assimilation.
(b) CALIPSO data assimilation result.



Sekiyama et al., ACP (2010)

Red and blue circles are weather stations.

Red ones observed aeolian dust.

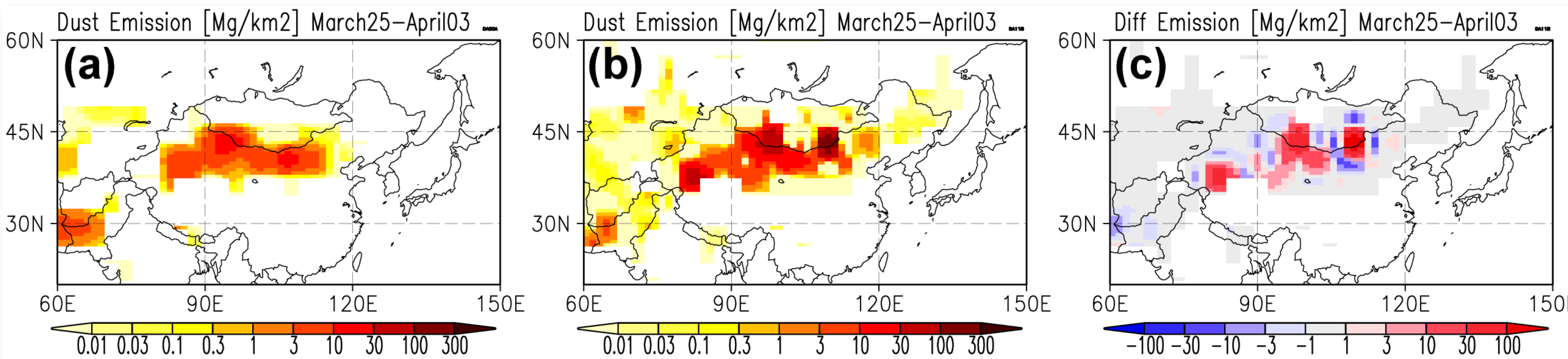
Blue ones did not observe any dust events.

The shape of the high AOD detected by MODIS are consistent with the surface dust analysis.

EnKF for aerosol analysis

- Dust emission inverse analysis by EnKF

Model **Assimilation** **Increment**



A dust outbreak in March 2007

Sekiyama et al., SOLA (2011)

The dust concentrations in the downwind region are evidently improved when this dust emission analysis is installed to the model simulation.

JMA's plan for aerosol prediction

- **The EnKF aerosol analyses as initial conditions of aerosol prediction.**
  (hopefully, in practical use by 2014...)
- Aerosol **reanalysis**:
  available for climate modeling?
- Aerosol **climatology** (detailed):
  available for NWP?
- Ideally, **weather-chemistry** coupled DA...

3. Surface CO_2 flux

- establish a 4D-EnKF data assimilation system to estimate global surface CO_2 fluxes from various data.
- evaluate the potential impacts of various data obtained from the surface network, satellite (GOSAT), and aircraft (CONTRAIL) measurements, using observational system simulation experiments (OSSEs).

Forecast models: MJ98-CDTM, FRCGC ACTM

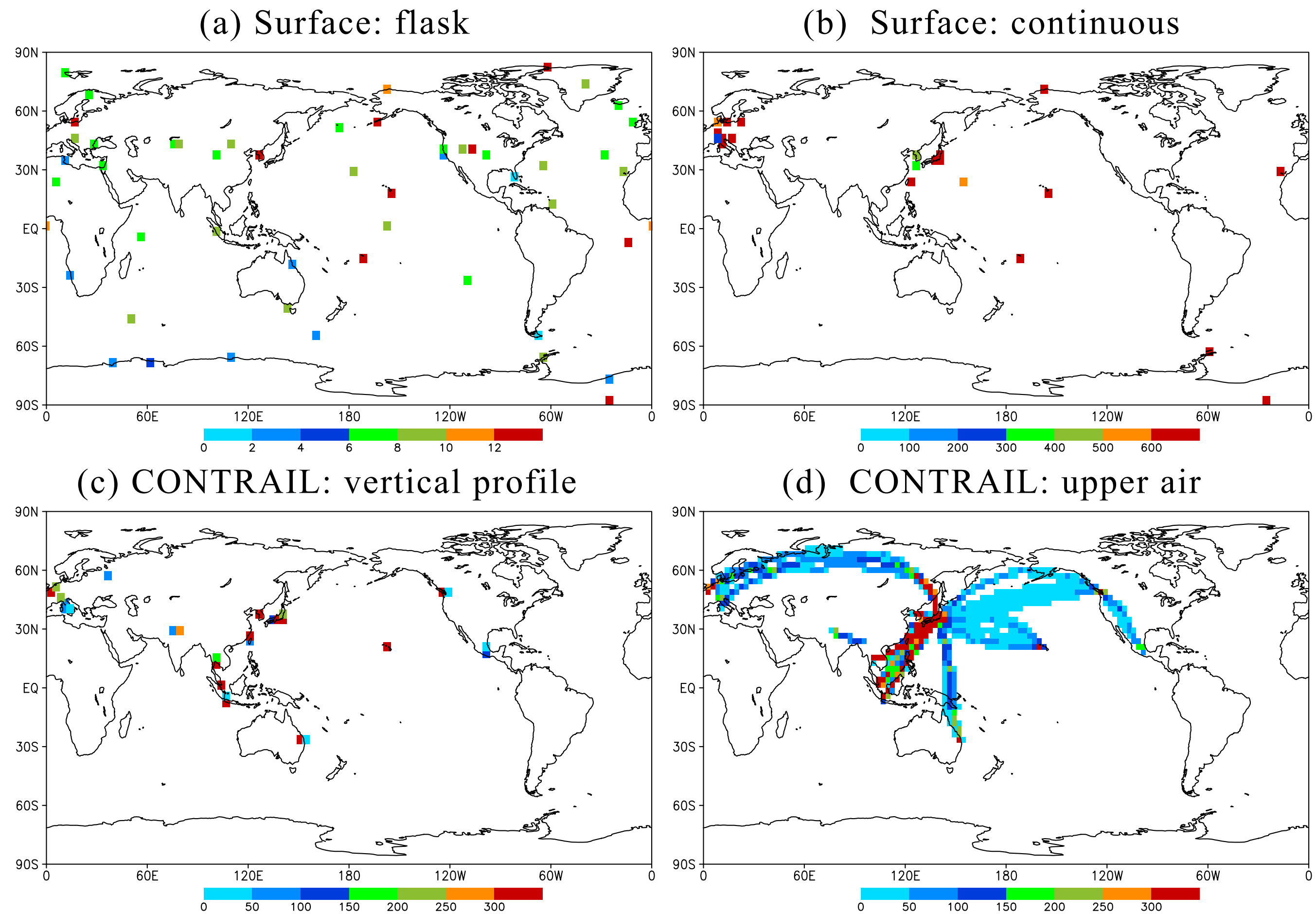
Assimilated data: Satellite (GOSAT), Aircraft (CONTRAIL), Ground-based network

Control variables: Surface CO_2 flux, Atmospheric CO_2 concentration

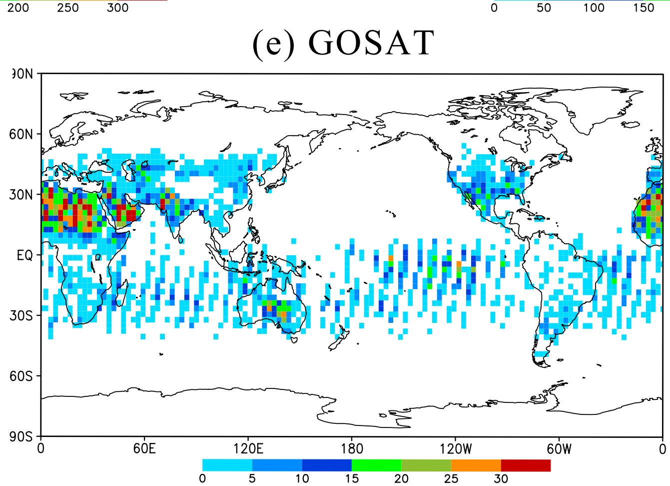
Assimilation setting: 4D analysis with 7-day time window

(Miyazaki, 2009, Miyazaki et al., 2011)

Observation System Simulation Experiments (OSSEs)



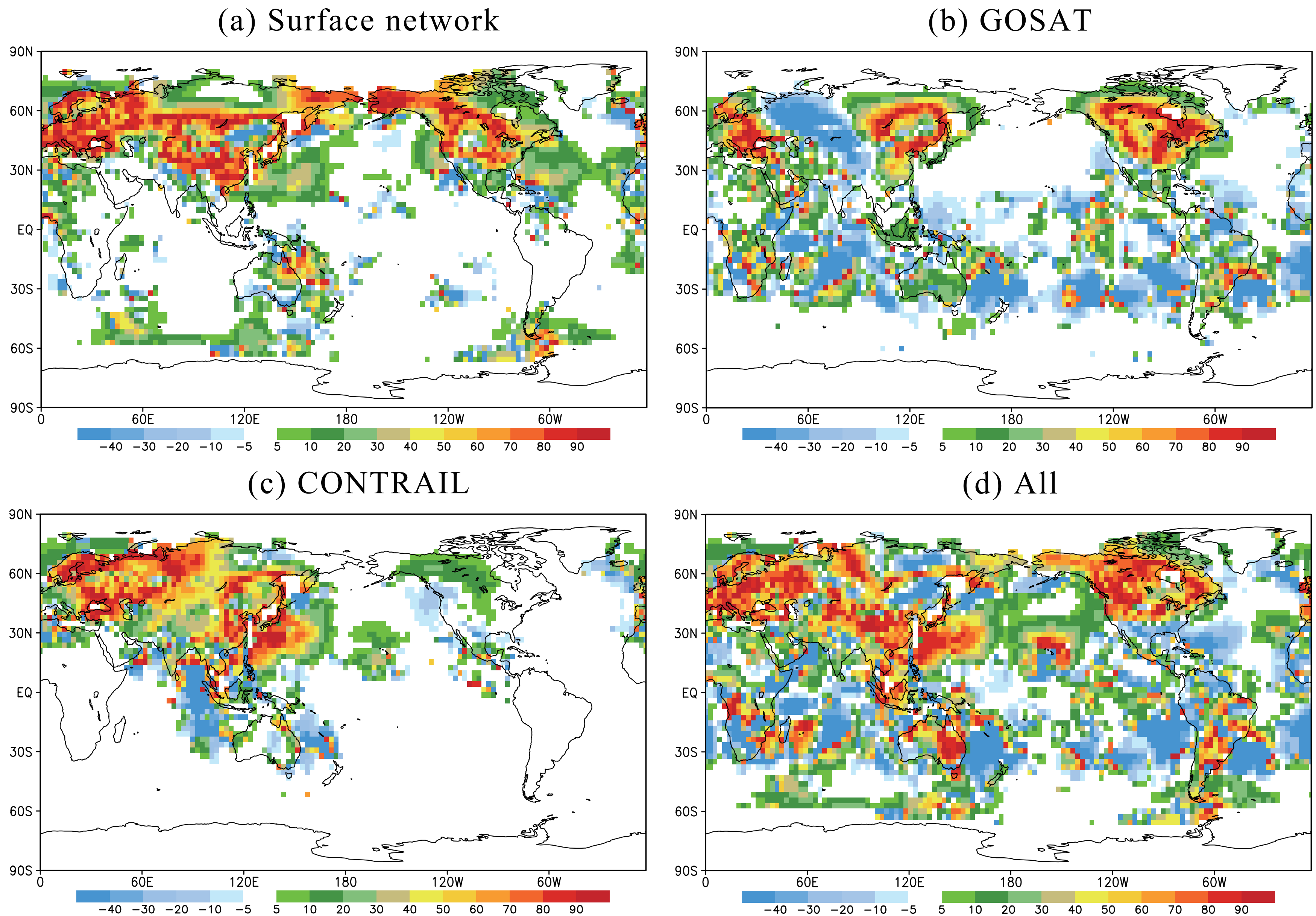
(Number of obs)



- **demonstrate the performance of the DA scheme with known errors**
- **tell us how much error reductions can be expected by each dataset**

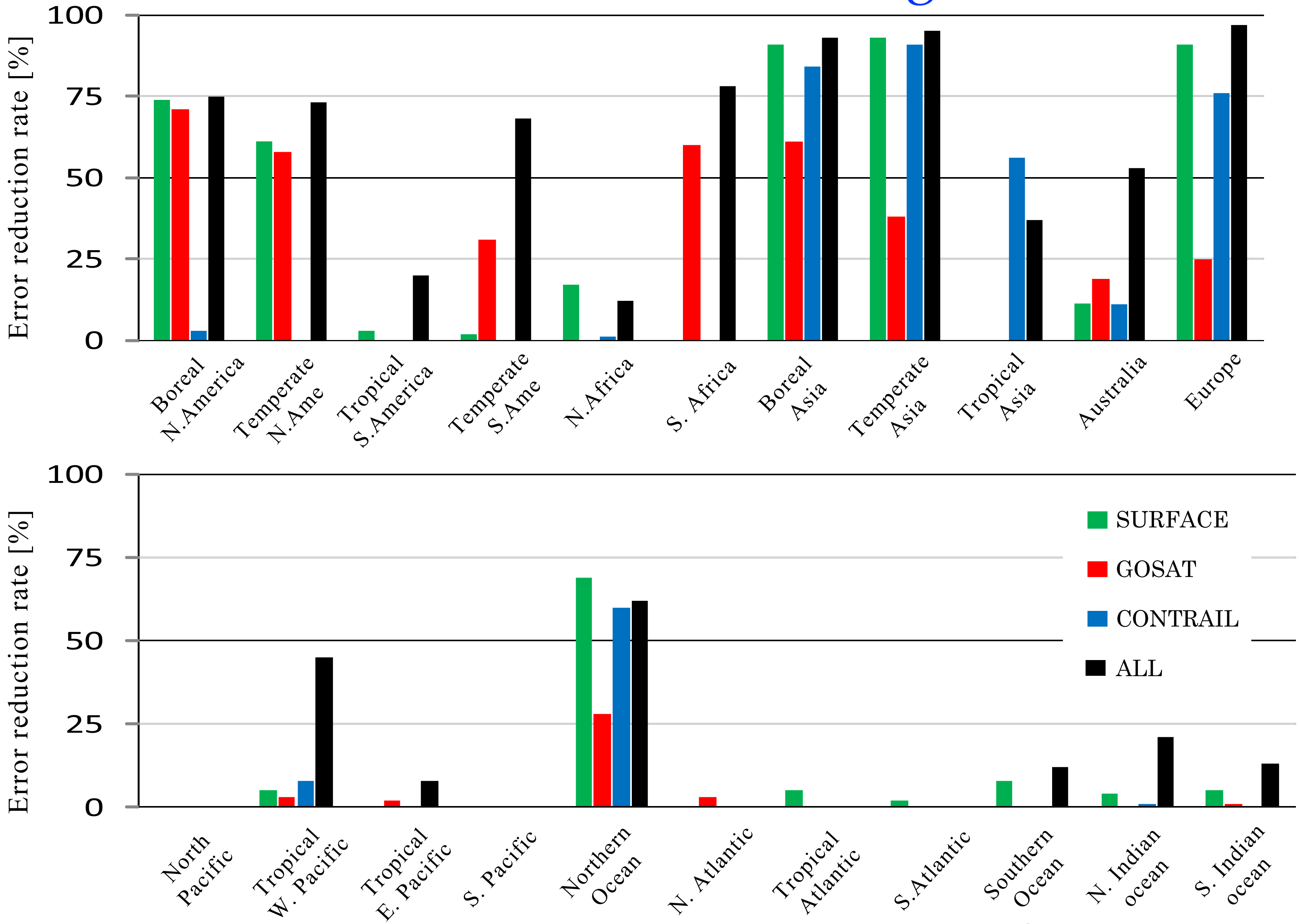
(Miyazaki et al., 2011)

Flux error reduction rate [%]: grid-scale



(Miyazaki et al., 2011)

Flux error reduction rate [%]: regional-fluxes

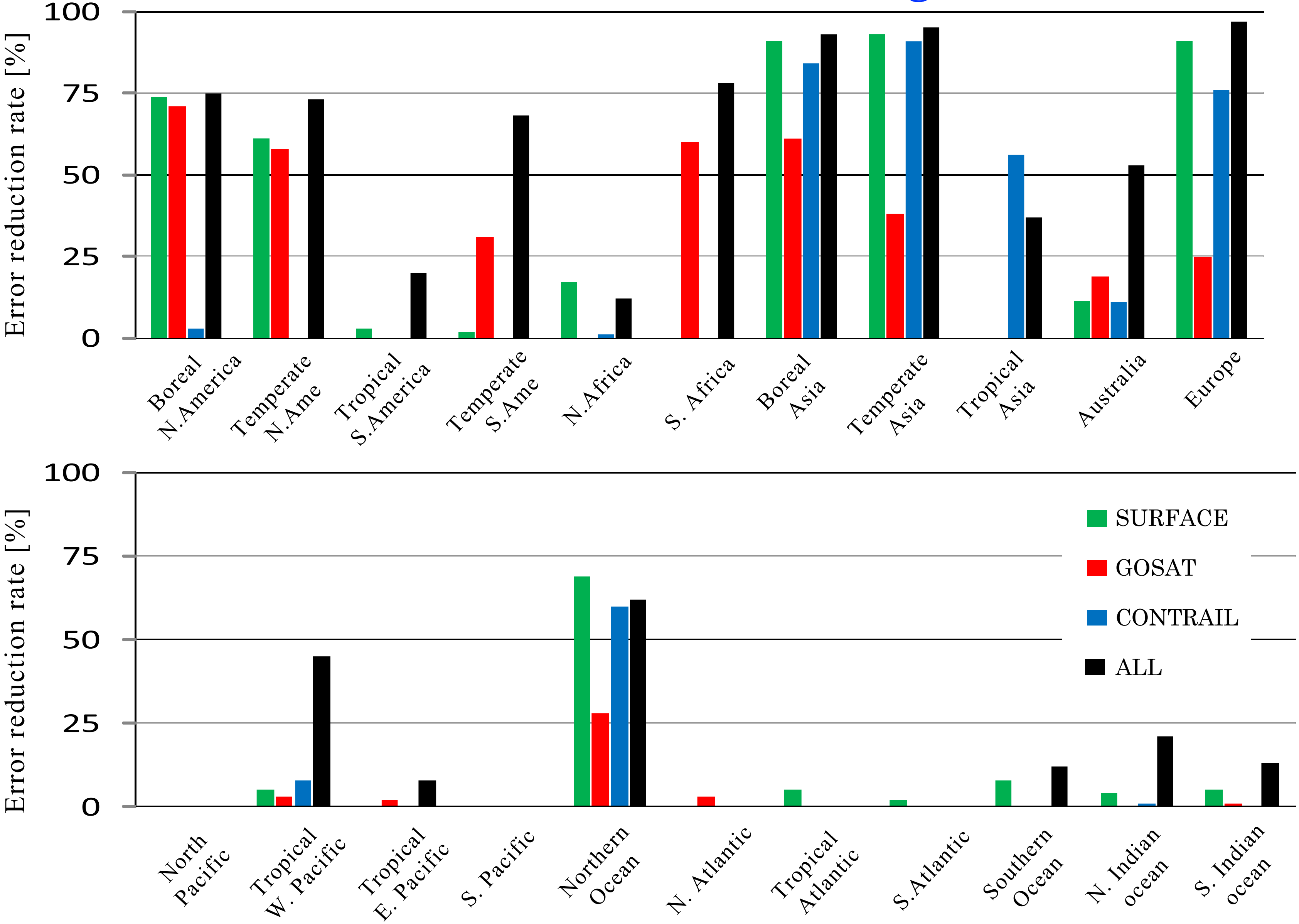


(Miyazaki et al., 2011)

CONTRAIL data: Europe and Asia.

GOSAT data: North and South America, South Africa, Asia, and Europe

Flux error reduction rate [%]: regional-fluxes



Additional constraints are required especially over North Africa, tropical South America, southern North America, and the oceans. **(Miyazaki et al., 2011)**

4. Air quality (tropospheric chemistry)

Forecast models:

(1) **CHASER** (Sudo et al., 2002) T42L32 p-top=3 hPa
(2) **MRI CCM** (Shibata and Deushi, 2008) T42L68 p-top=0.01 hPa

- **for monitoring Asian/global atmospheric environment**

Assimilated data: **OMI NO2, SCIAMACHY NO2, TES O3, etc...**

Control variables: **NOx emission, NO2, O3, HNO3, etc...**

Assimilation settings: **3D-analysis**

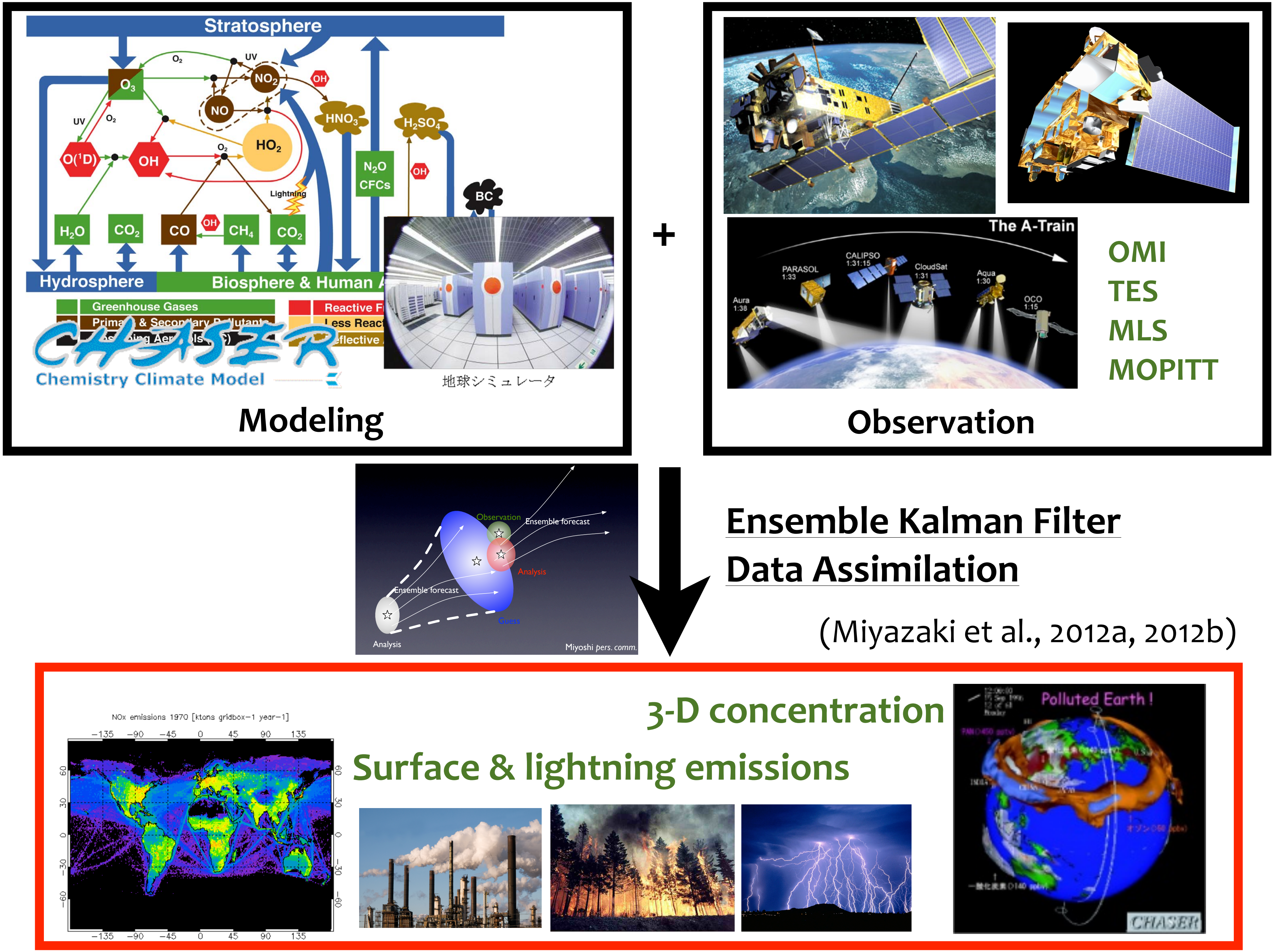
(Miyazaki et al., 2012a, 2012b)

Tropospheric chemical data assimilation

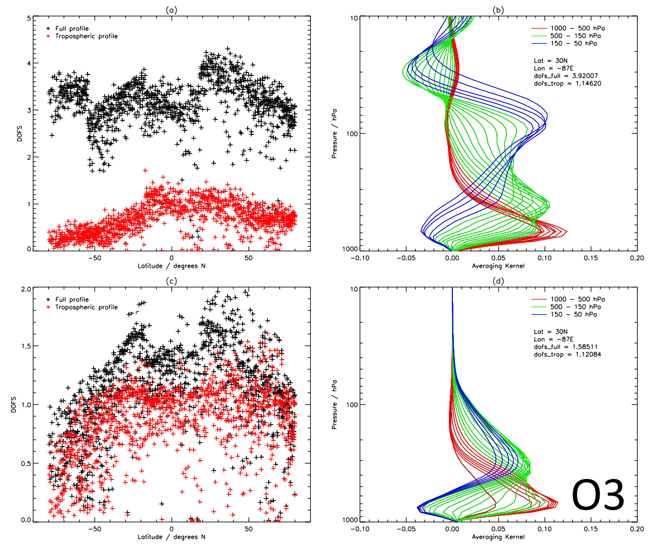
- ✓ **The use of data assimilation for atmospheric chemistry (e.g., MACC, NASA/DAO, JPL, BASCOE), especially for short-lived chemical species, is still challenging.**

- ✓ **The tropospheric chemical system is stiff. Small perturbations are damped out quickly in time. A large part of the chemical system is not sensitive to initial conditions, but is sensitive to the model parameters (e.g., emissions). → Simultaneous adjustment of model parameters (e.g., emissions) and concentrations is a powerful framework.**

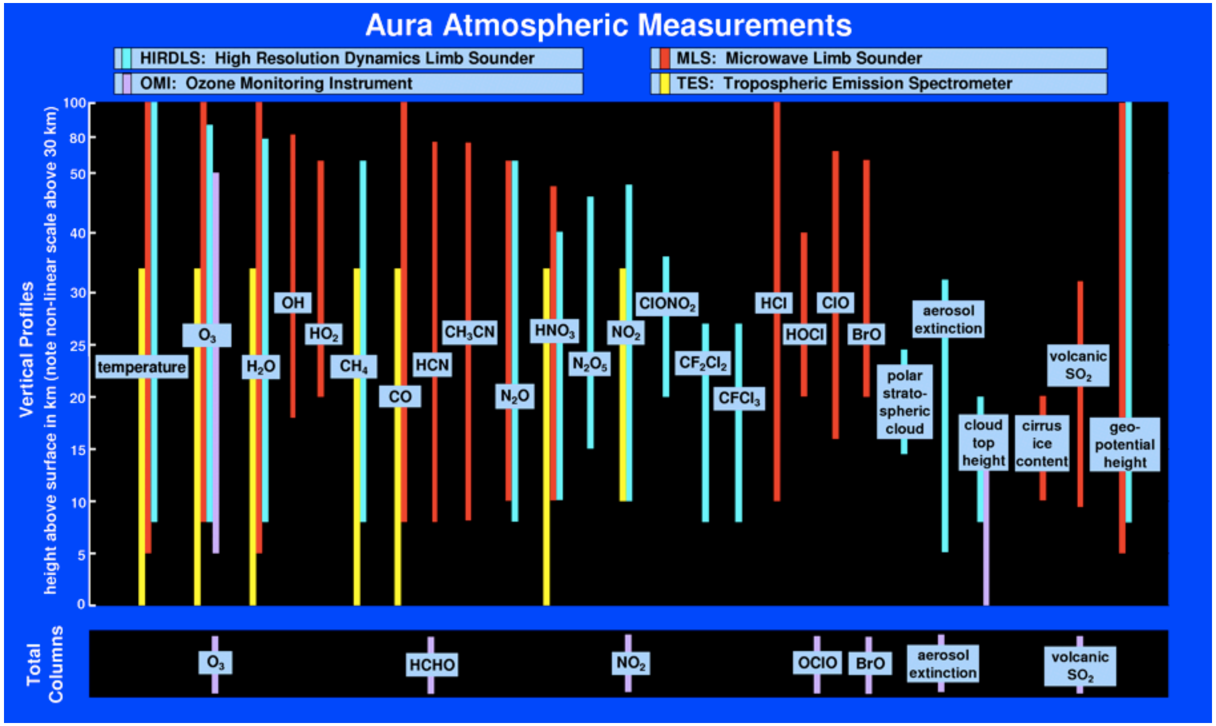
- ✓ **The advantage of Ensemble Kalman filter (EnKF) is its easy implementation for complicated systems; i.e., without development of adjoint code for CTMs.**

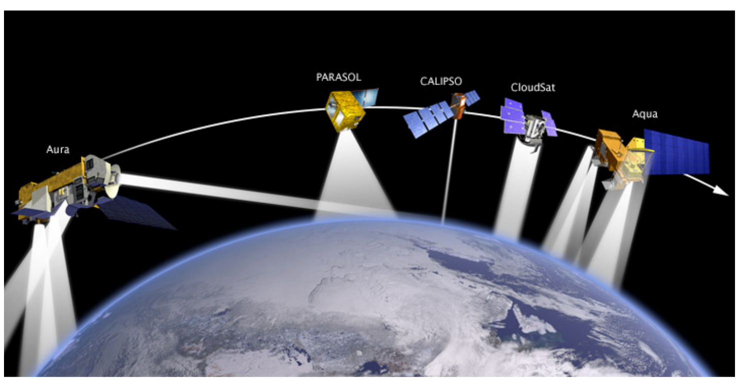

Stratosphere
Hydrosphere
Biosphere & Human A
Greenhouse Gases
Reactive F
Lightning
BC
CHASER
Chemistry Climate Model
地球シミュレータ
Modeling
+
The A-Train
PARASOL 1:33
CALIPSO 1:31:15
CloudSat 1:31
Aqua 1:30
OCO 1:15
Aura 1:38
OMI
TES
MLS
MOPITT
Observation
Observation
Ensemble forecast
Analysis
Guess
Miyoshi pers. comm.
Ensemble Kalman Filter
Data Assimilation
(Miyazaki et al., 2012a, 2012b)
NOx emissions 1970 [ktons gridbox−1 year−1]
3-D concentration
Surface & lightning emissions
Polluted Earth !

TES O3 & CO



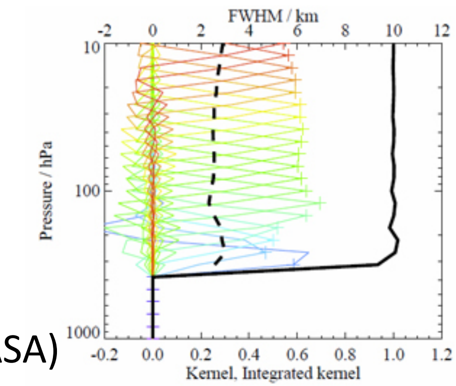
(Parrington et al., 2009)





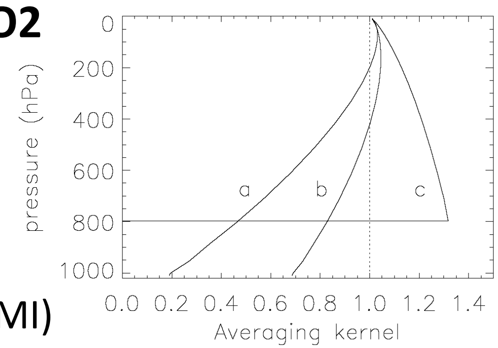
TES, MLS, OMI on AURA
MOPITT on TERRA

MLS O3 & HNO3



(NASA)

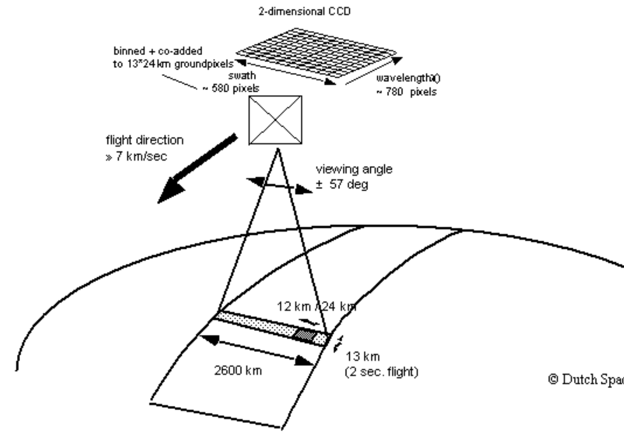
OMI NO2



(KNMI)

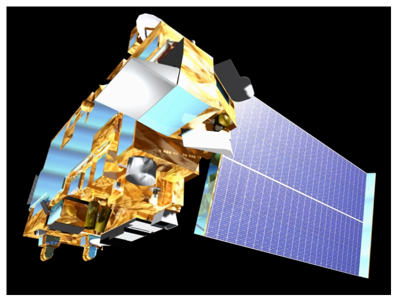
Tropospheric NO2 observations from space :

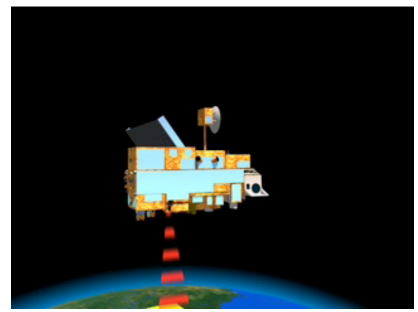
GOME	1995-2003	40 x 320 km	10:30 AM LT
SCIAMACHY	2003-	60 x 30 km	10:00 AM LT
OMI	2004-	13 X 24 km	1:30 PM LT
GOME-2	2007-	40 X 80 km	9:30 AM LT



(KNMI)

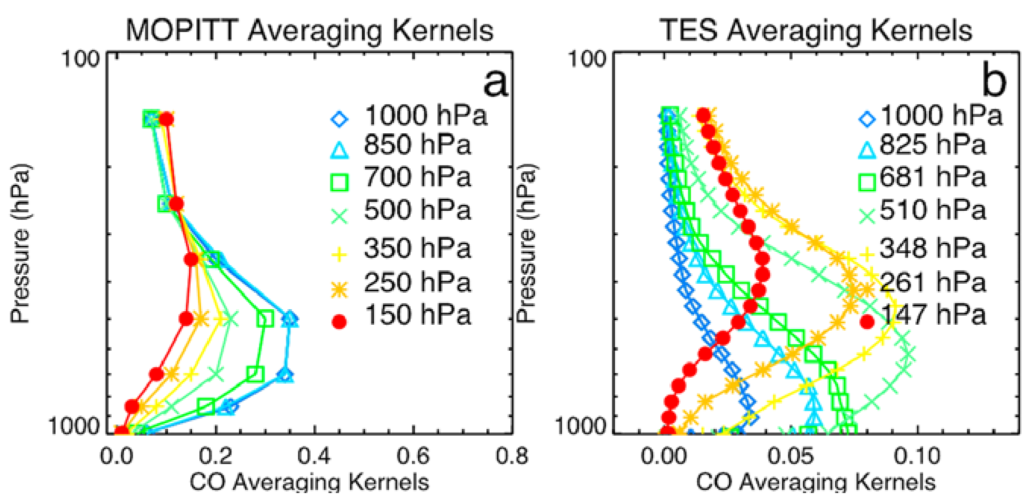
MOPITT on TERRA





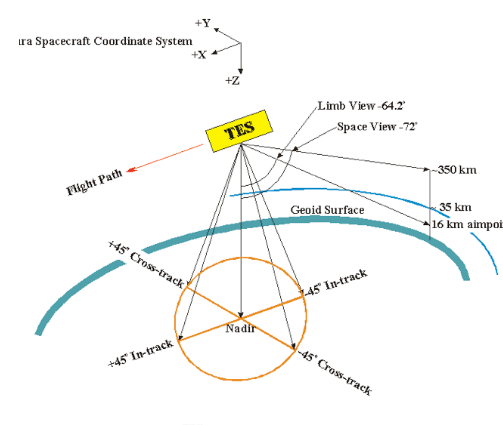
22*22 km

global coverage every 3 days

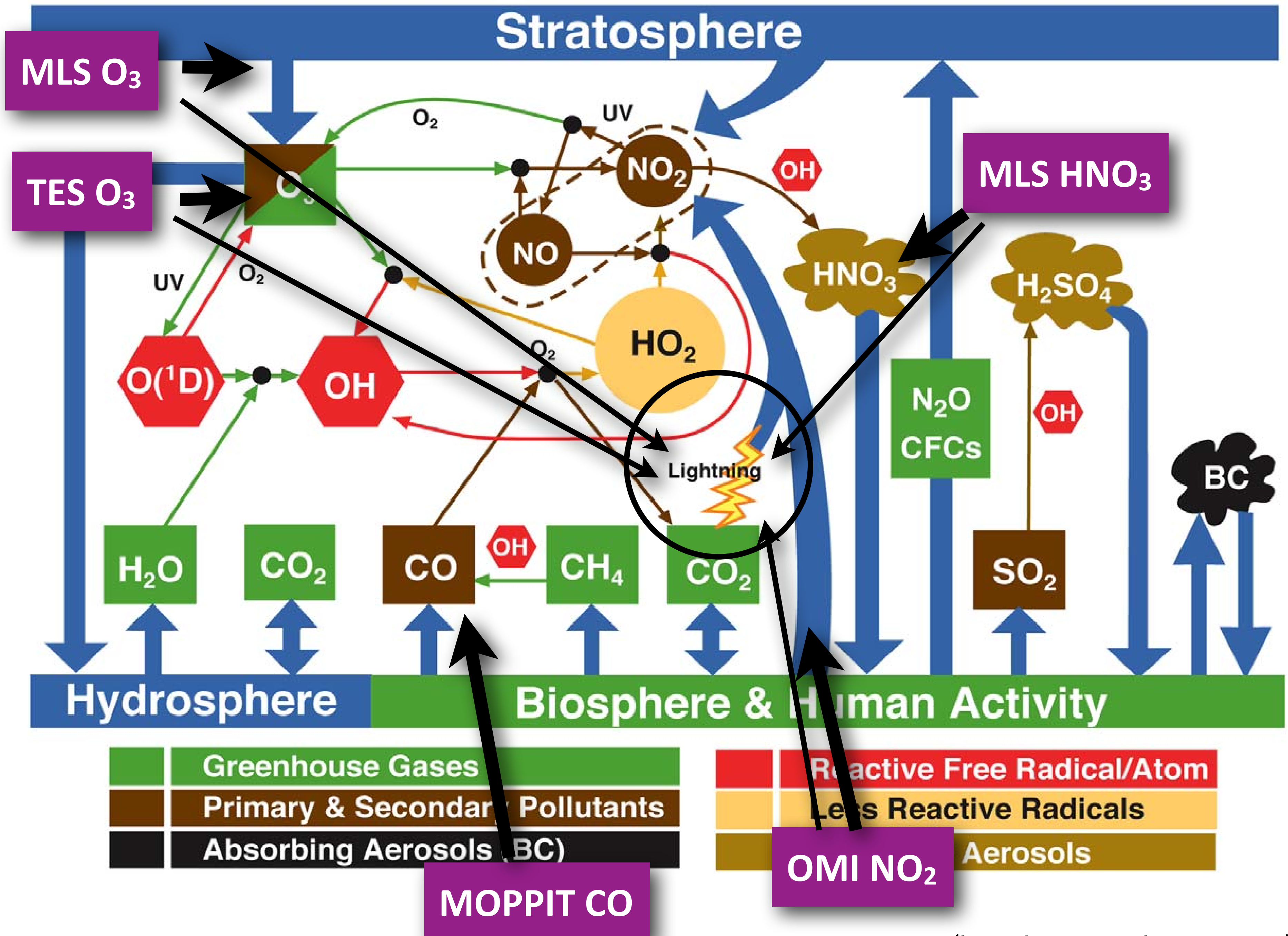


(Ho et al., 2009)

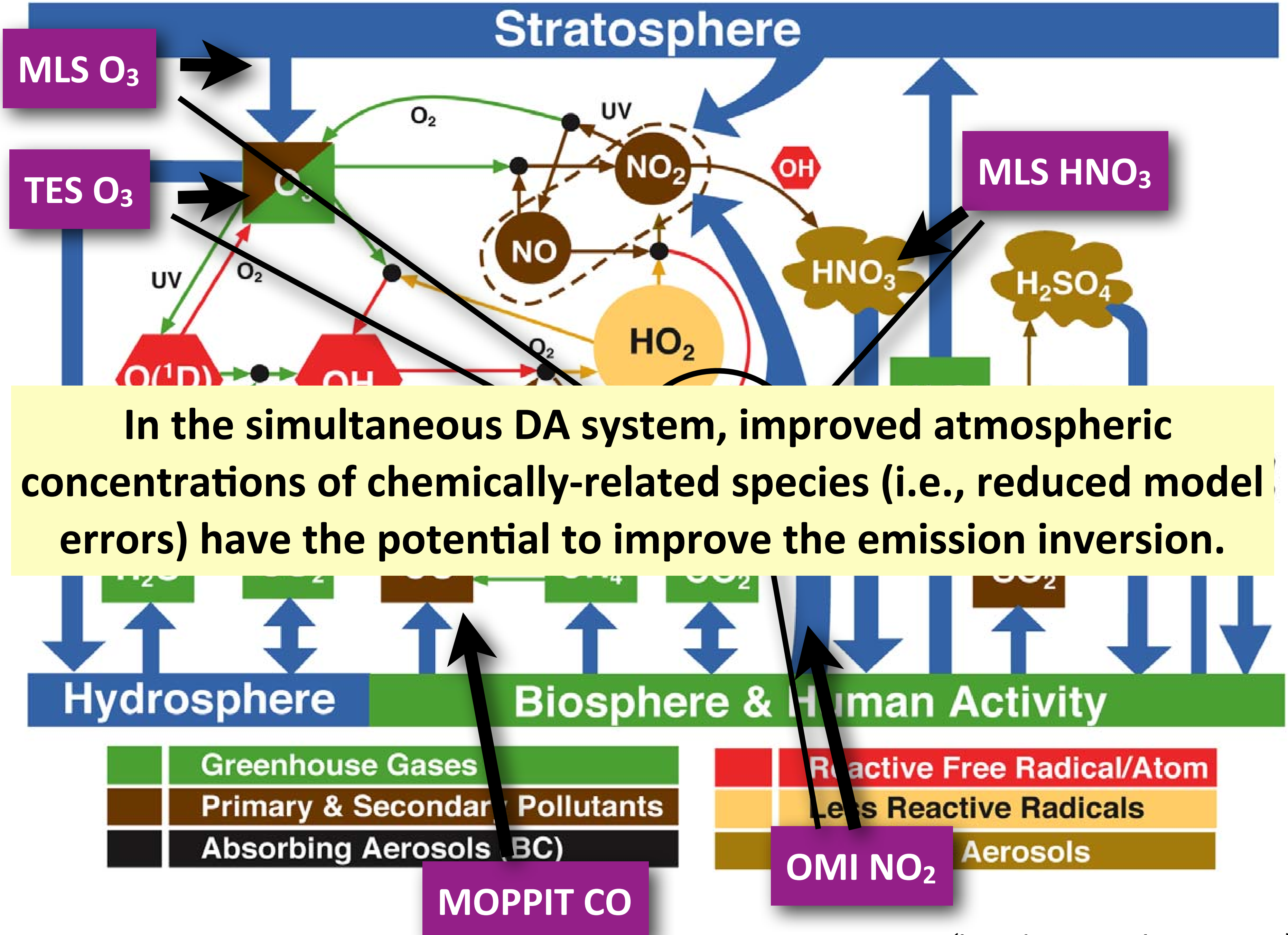
8*5 km



(NASA)



(based on a MIT lecture note)



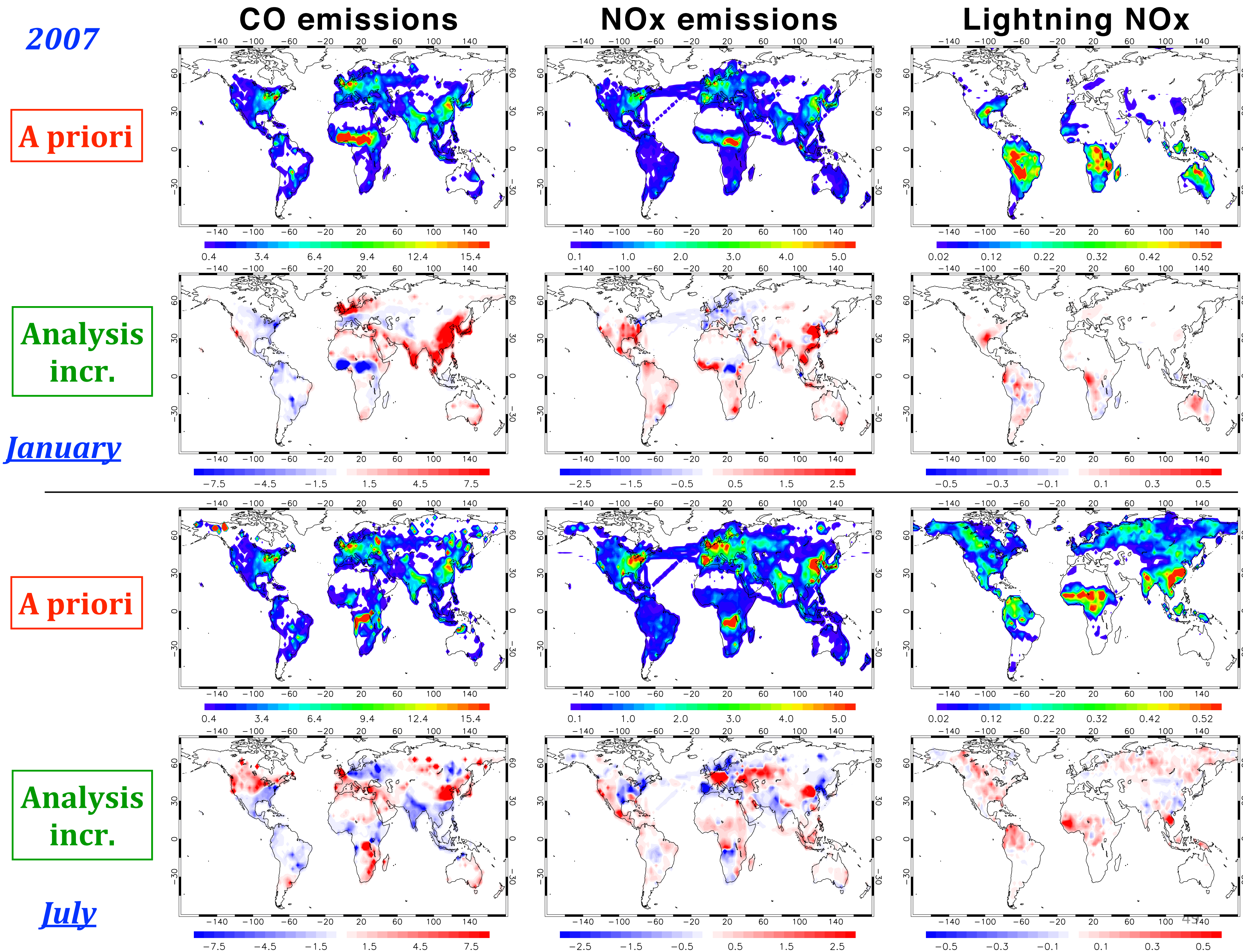
In the simultaneous DA system, improved atmospheric concentrations of chemically-related species (i.e., reduced model errors) have the potential to improve the emission inversion.

(based on a MIT lecture note)

CHASER-DAS (Miyazaki et al., 2012a, 2012b)

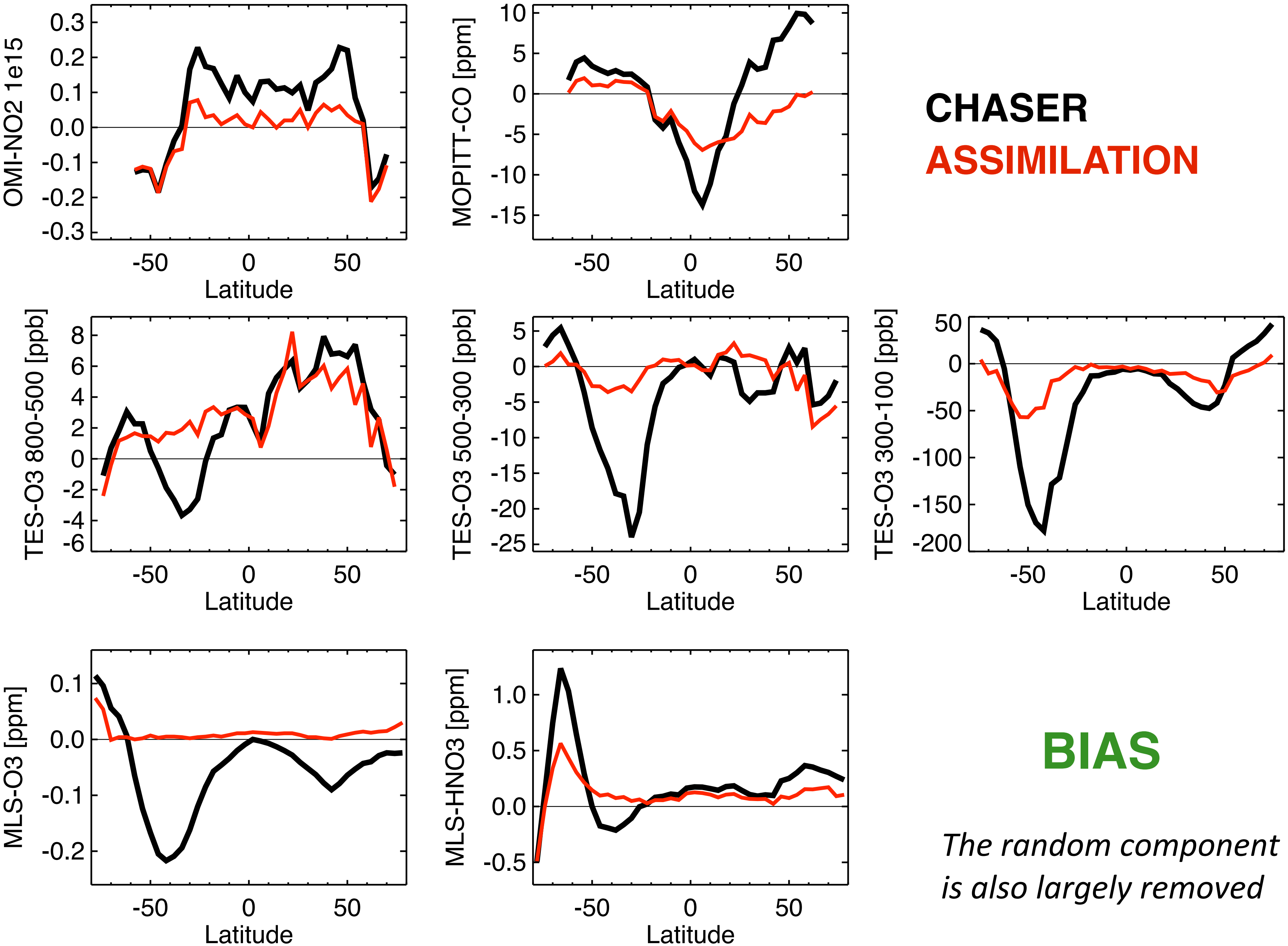
Assimilation scheme	Local ensemble transform Kalman filter (Hunt et. al., 2007)
Forecast model	CHASER (Sudo et al., 2002)
A priori emissions	EDGAR3.2 + GFED2 + REAS1 + GEIA, Price and Rind (1992)
State vector	NOx & CO emissions, lightning NOx, 35 chemical species
Obs operator	Averaging kernel and a priori information
Super Obs	applied for OMI NO_2 and MOPPIT CO data
Cycle	100 min.
Techniques	Spatial/variable covariance localization, covariance inflation
Assimilated data	OMI NO_2 (DOMINO2), TES O_3 (ver. 4), MOPITT CO (ver. 5), MLS O_3 & HNO_3 (ver. 3.3)
Validation data	SCIAMACHY NO_2, GOME-2 NO_2, TES CO, Ozonesonde (WOUDC/ SHADOZ), Aircraft (INTEX-B)

2007



CO emissions
NOx emissions
Lightning NOx
A priori
Analysis incr.
January
A priori
Analysis incr.
July
0.4 3.4 6.4 9.4 12.4 15.4
0.1 1.0 2.0 3.0 4.0 5.0
0.02 0.12 0.22 0.32 0.42 0.52
−7.5 −4.5 −1.5 1.5 4.5 7.5
−2.5 −1.5 −0.5 0.5 1.5 2.5
−0.5 −0.3 −0.1 0.1 0.3 0.5

Self-consistency check: Observation-minus-Forecast (OmF)



CHASER

ASSIMILATION

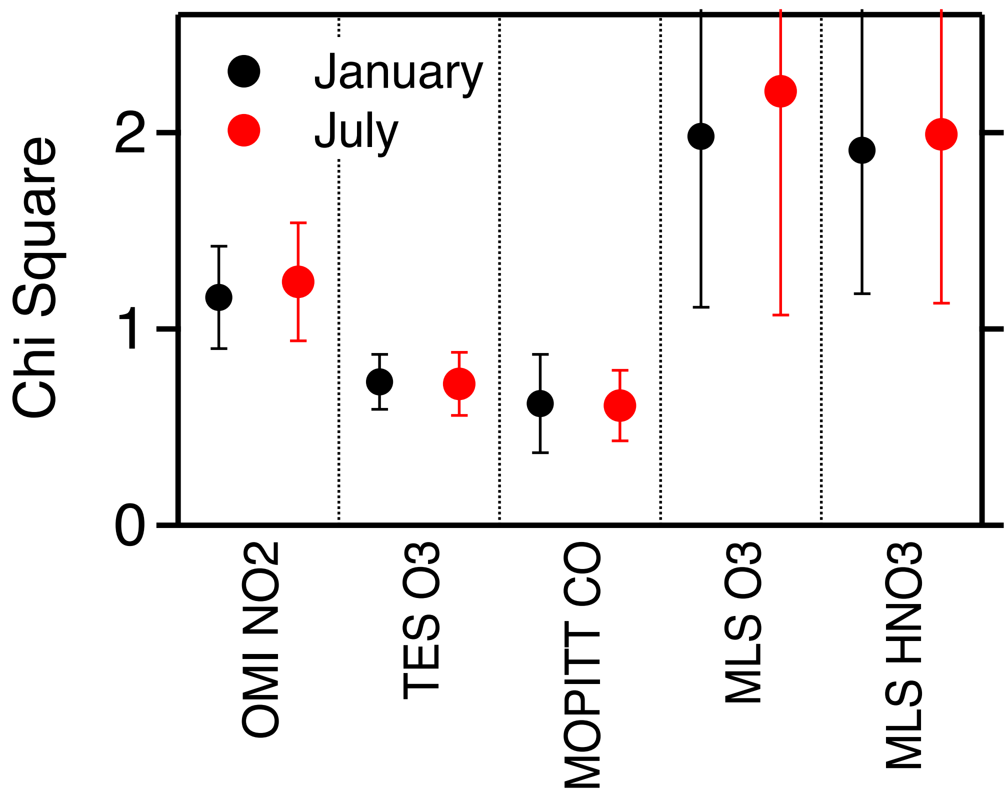
BIAS

The random component is also largely removed

Self-consistency check: Chi-square test

An important test for the quality of data assimilation is whether the differences between the innovations are consistent with the covariance matrices for the model forecast and observations.

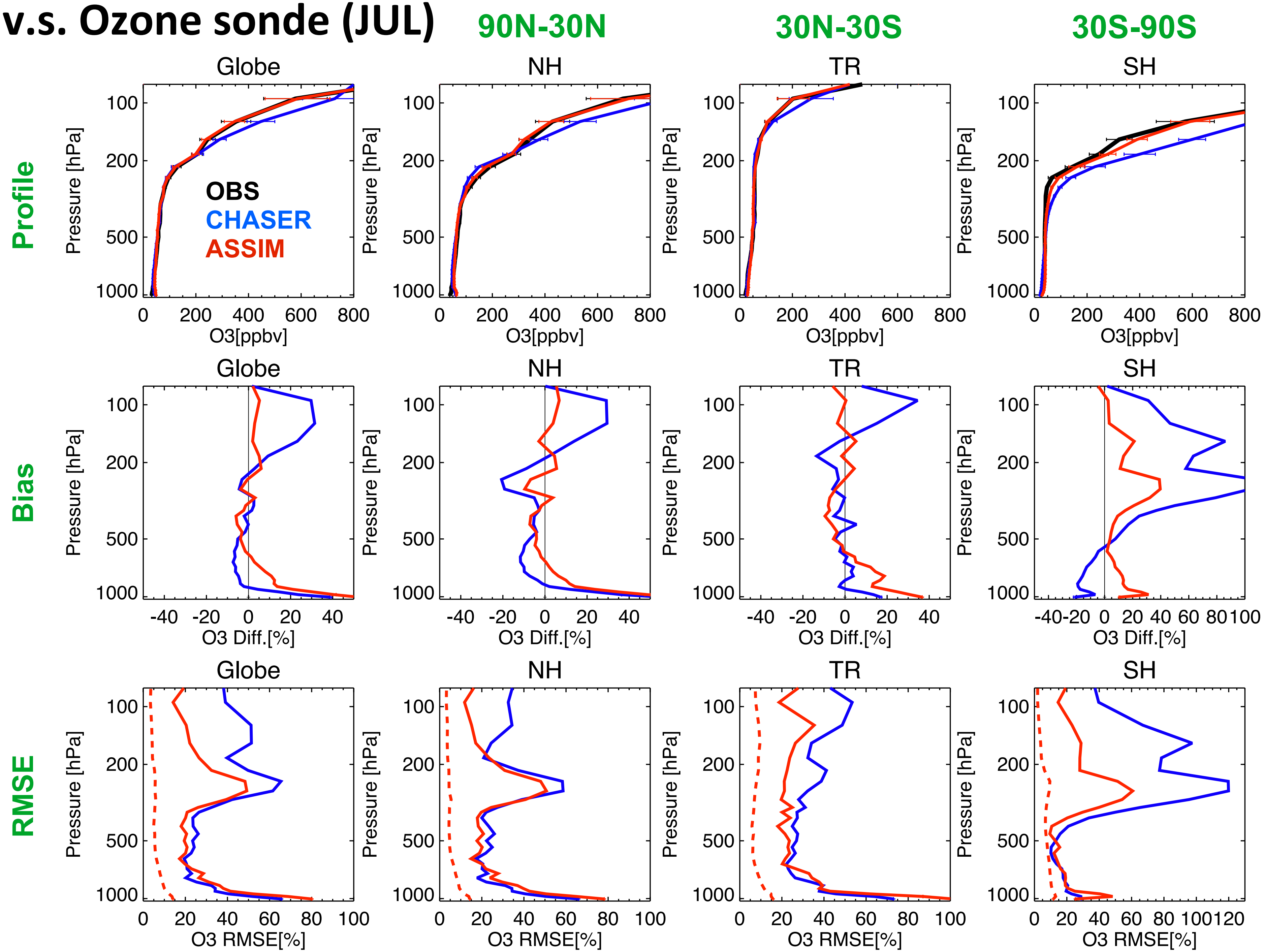
$$\mathbf{Y} = \frac{1}{\sqrt{m}} \left(\mathbf{H}\mathbf{P}^b\mathbf{H}^T + \mathbf{R}\right)^{-1/2} \left(\mathbf{y}^o - H\left(\mathbf{x}^b\right)\right). \qquad \chi^2 = \mathrm{trace}\,\mathbf{Y}\mathbf{Y}^T$$



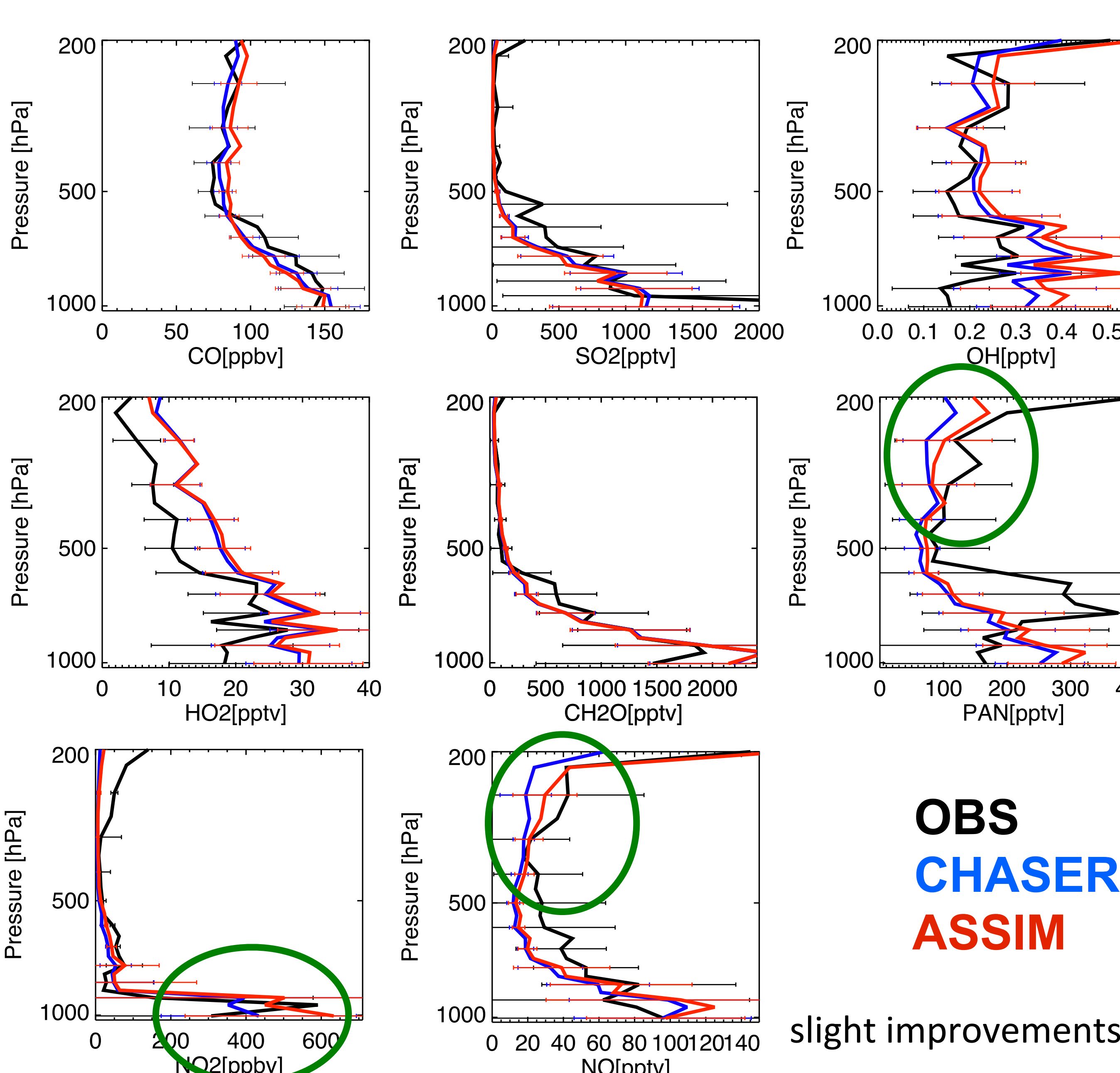
Google


Greenland
Iceland
Finland
Sweden
Norway
Russia
United Kingdom
Ukraine
Kazakhstan
Mongolia
Italy
Turkey
China
South Korea
Iraq
Iran
Afghanistan
Algeria
Libya
Egypt
Saudi Arabia
Thailand
Mauritania
Mali
Niger
Chad
Sudan
Nigeria
DR Congo
Tanzania
Angola
Namibia
Botswana
Madagascar
South Africa
Papua New Guinea
Australia
Indian Ocean
North Pacific Ocean
South Pacific Ocean
North Atlantic Ocean
South Atlantic Ocean
Southern Ocean
Venezuela
Colombia
Brazil
Perú
Bolivia
Chile
Argentina

v.s. Ozone sonde (JUL)



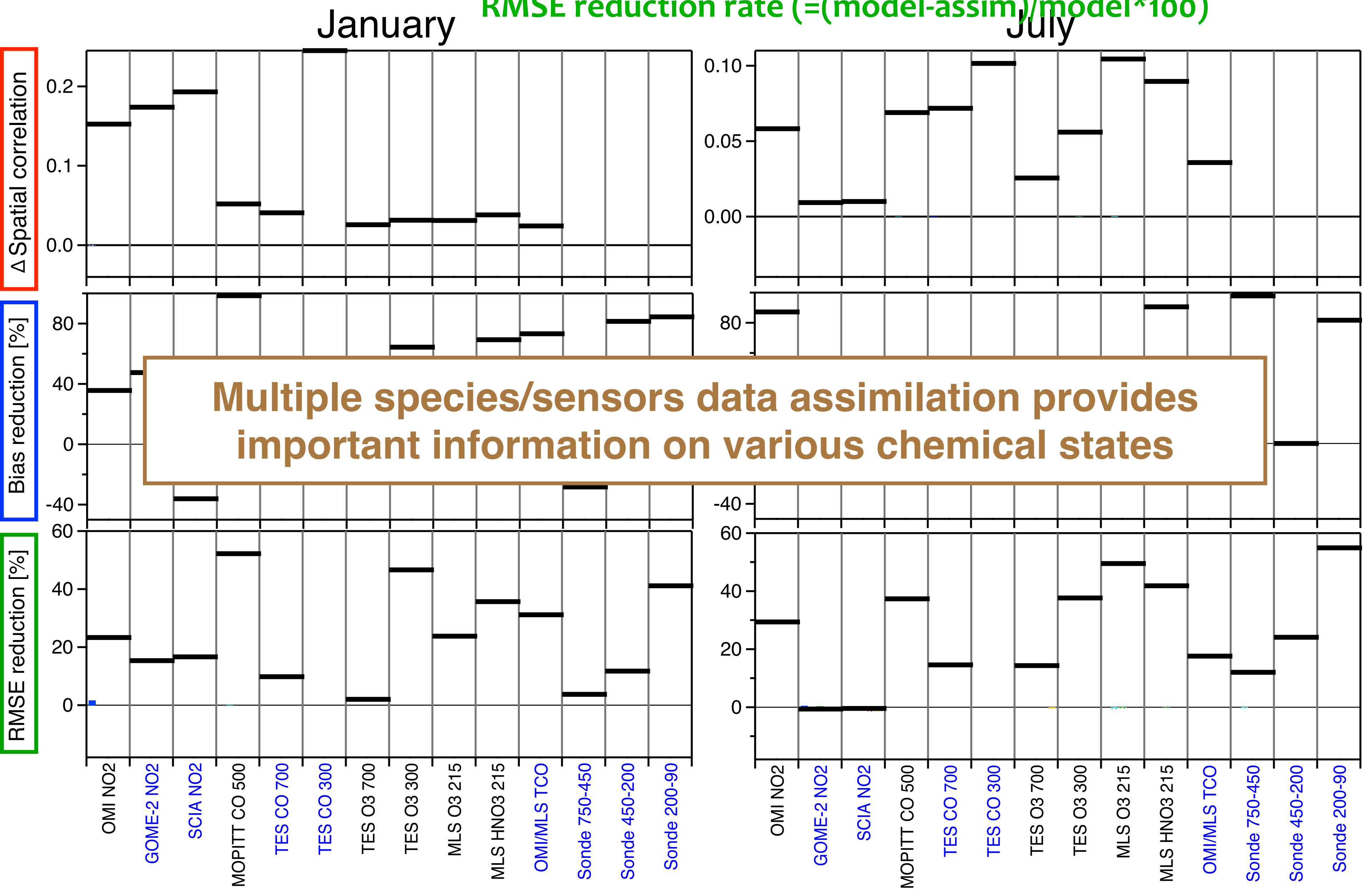
v.s. INTEX-B aircraft data



slight improvements on non-assimilated species

Validation

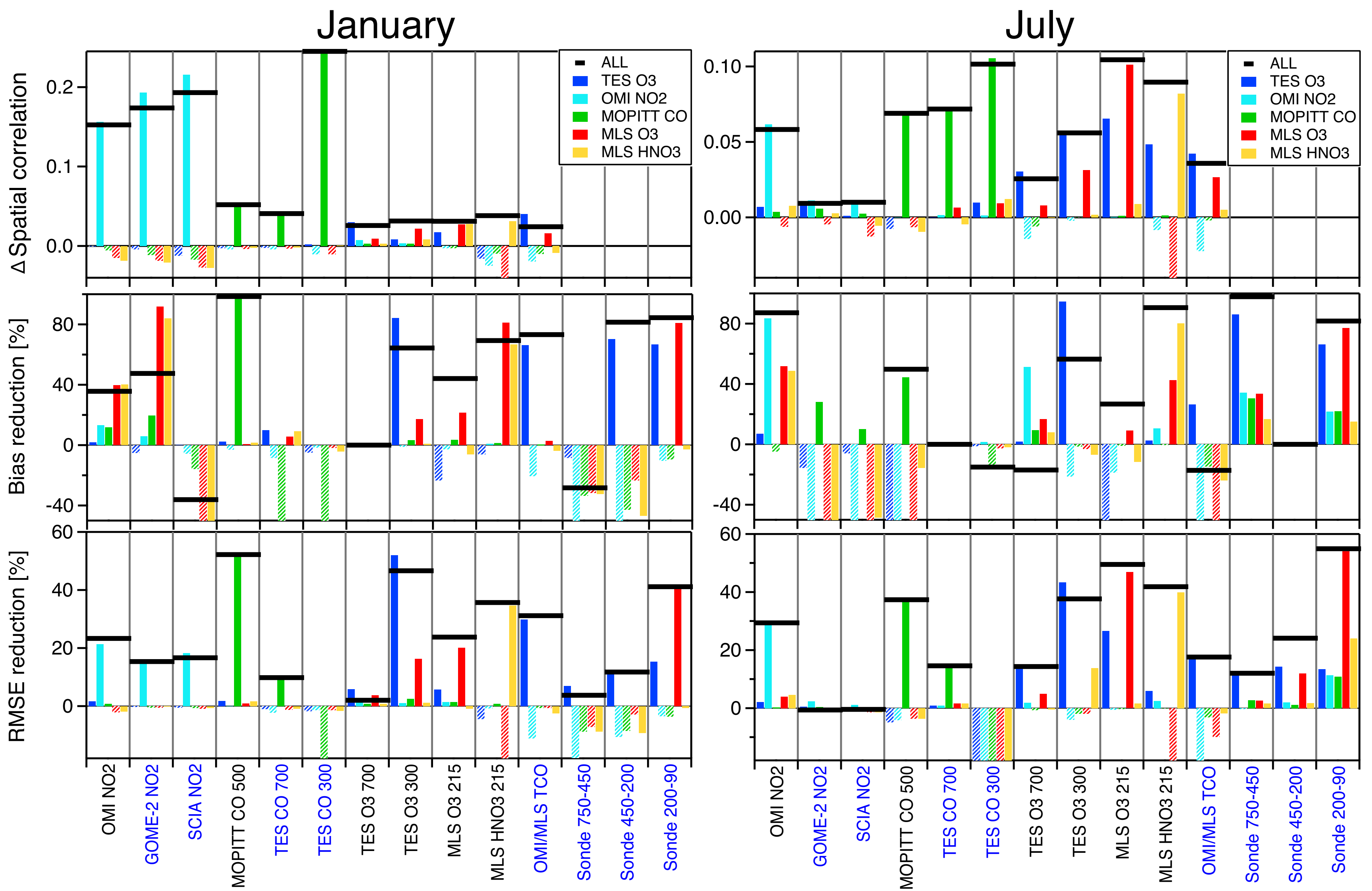
Spatial correlation diff. (=assim-model)
BIAS reduction rate (=(model-assim)/model*100)
RMSE reduction rate (=(model-assim)/model*100)



Multiple species/sensors data assimilation provides important information on various chemical states

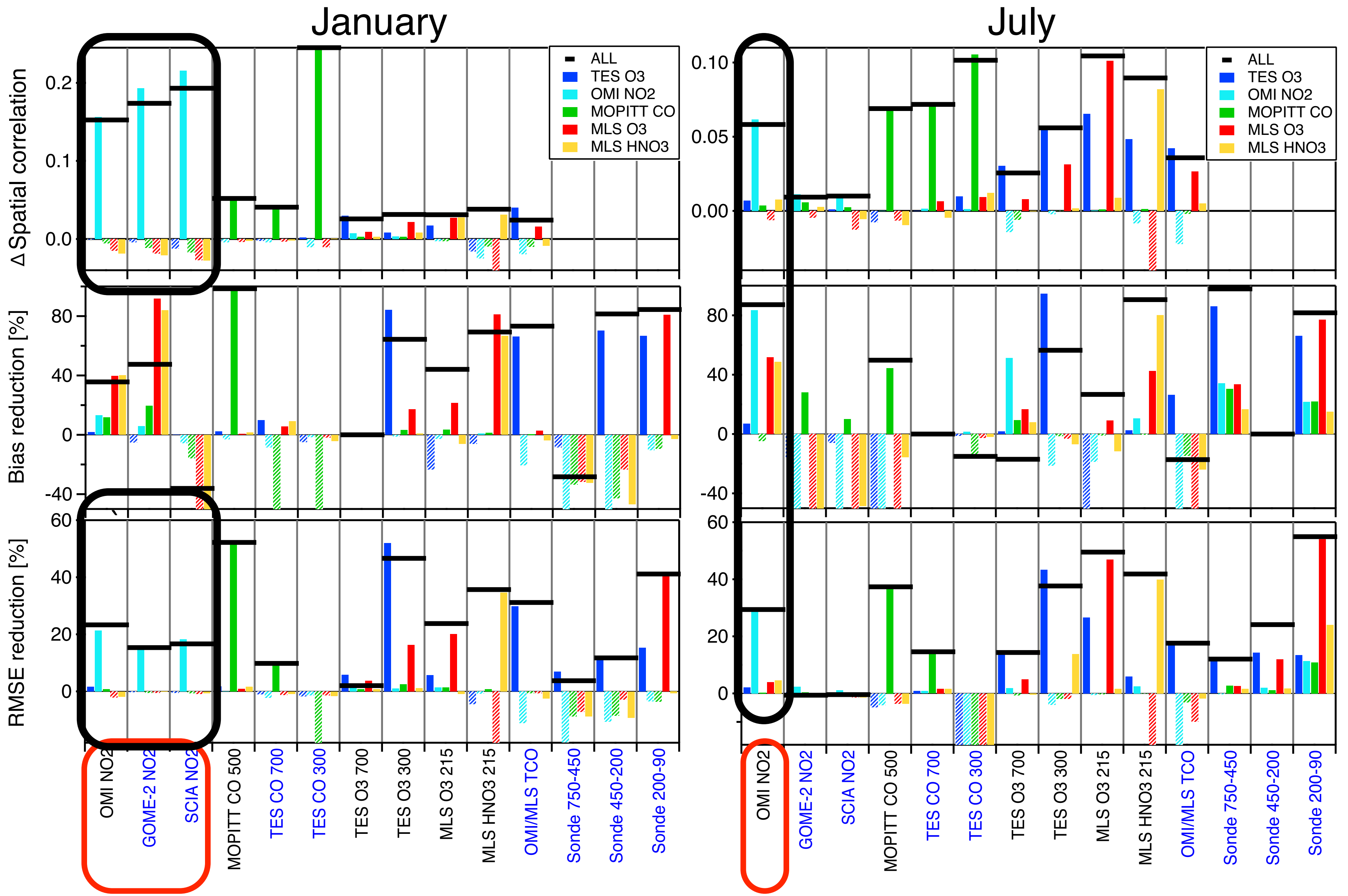
Assimilated data   Independent data

Observing System Experiments (OSEs)



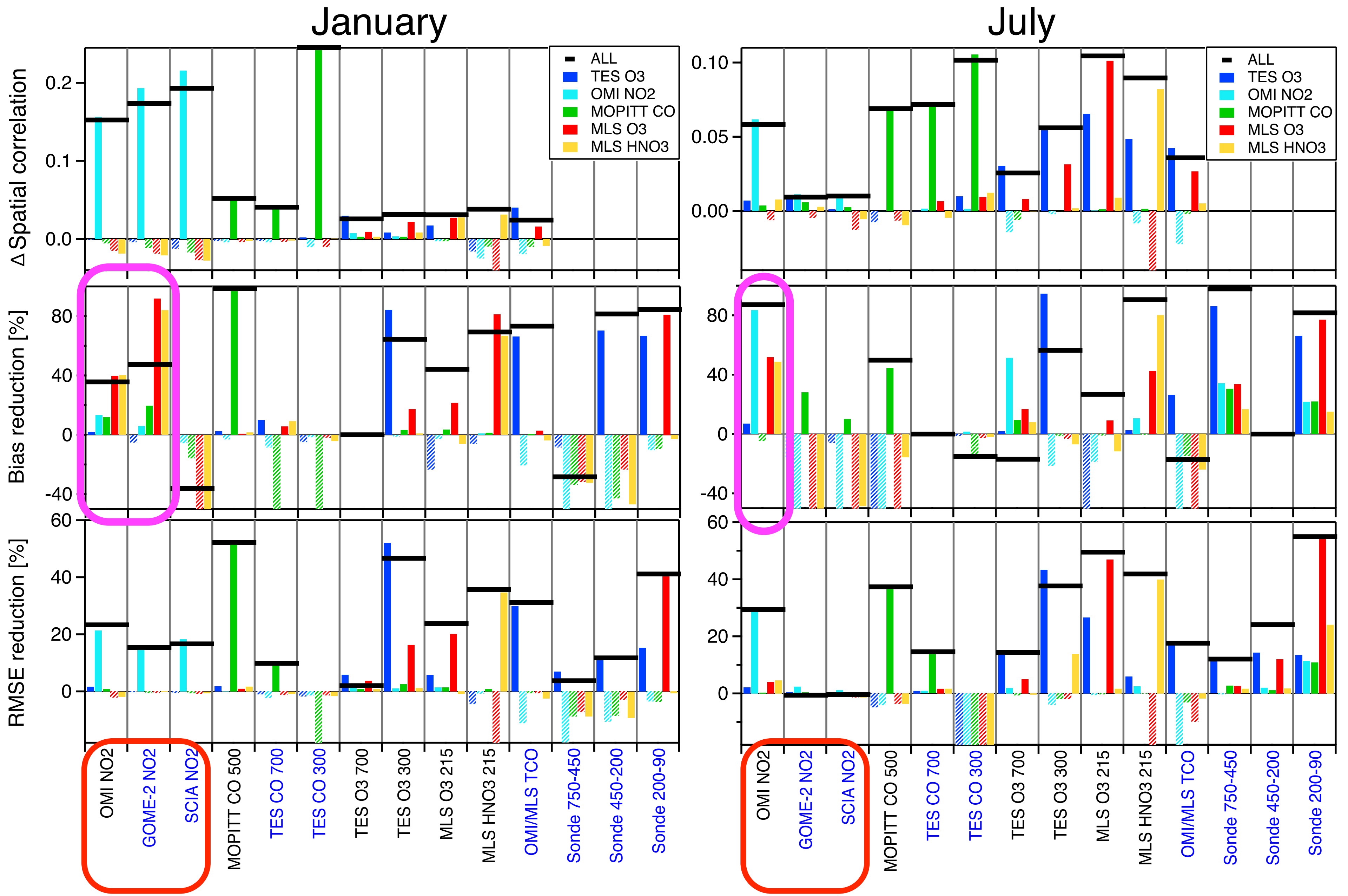
Observing System Experiments (OSEs)

Direct
Indirect

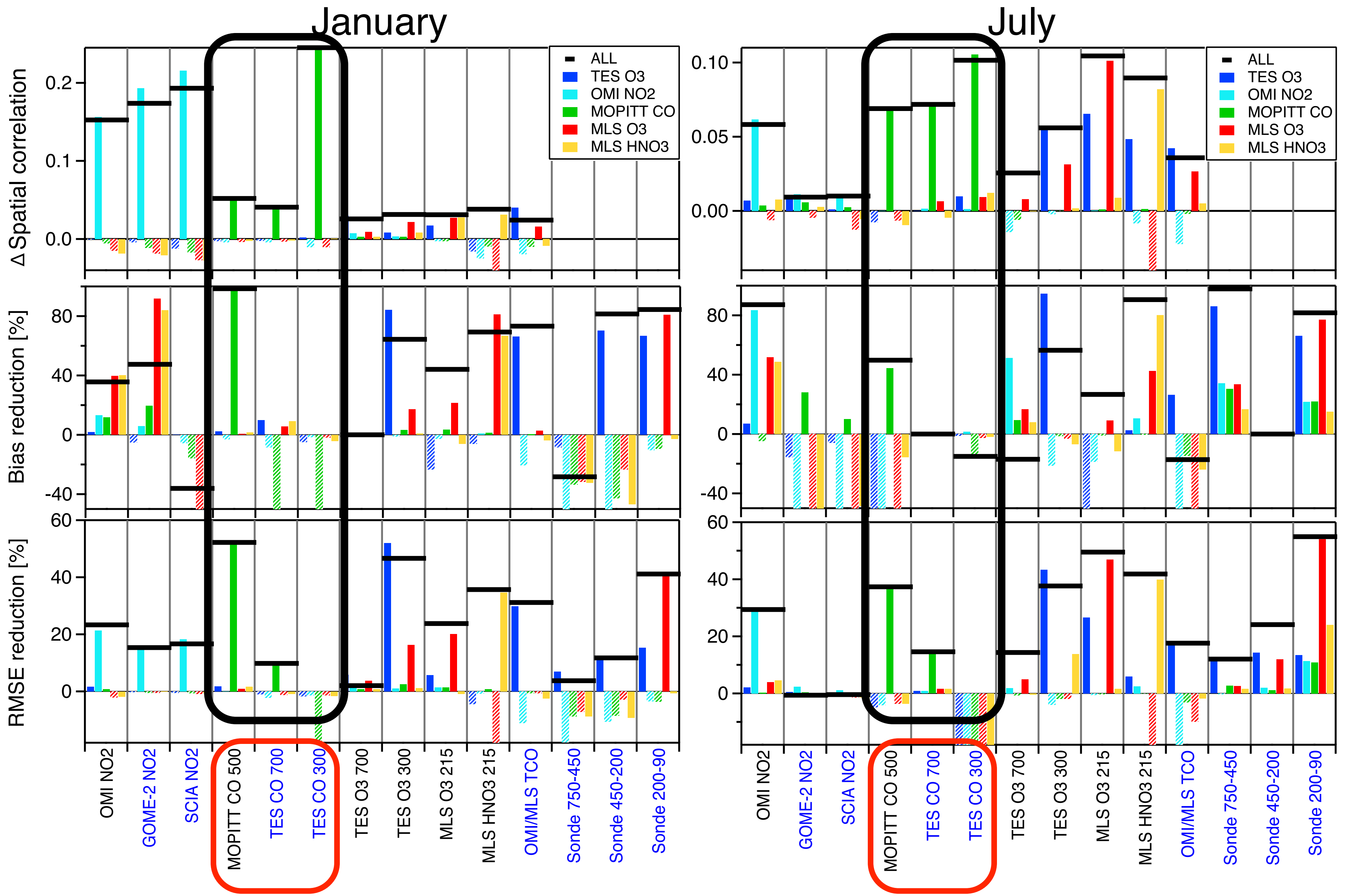


Observing System Experiments (OSEs)

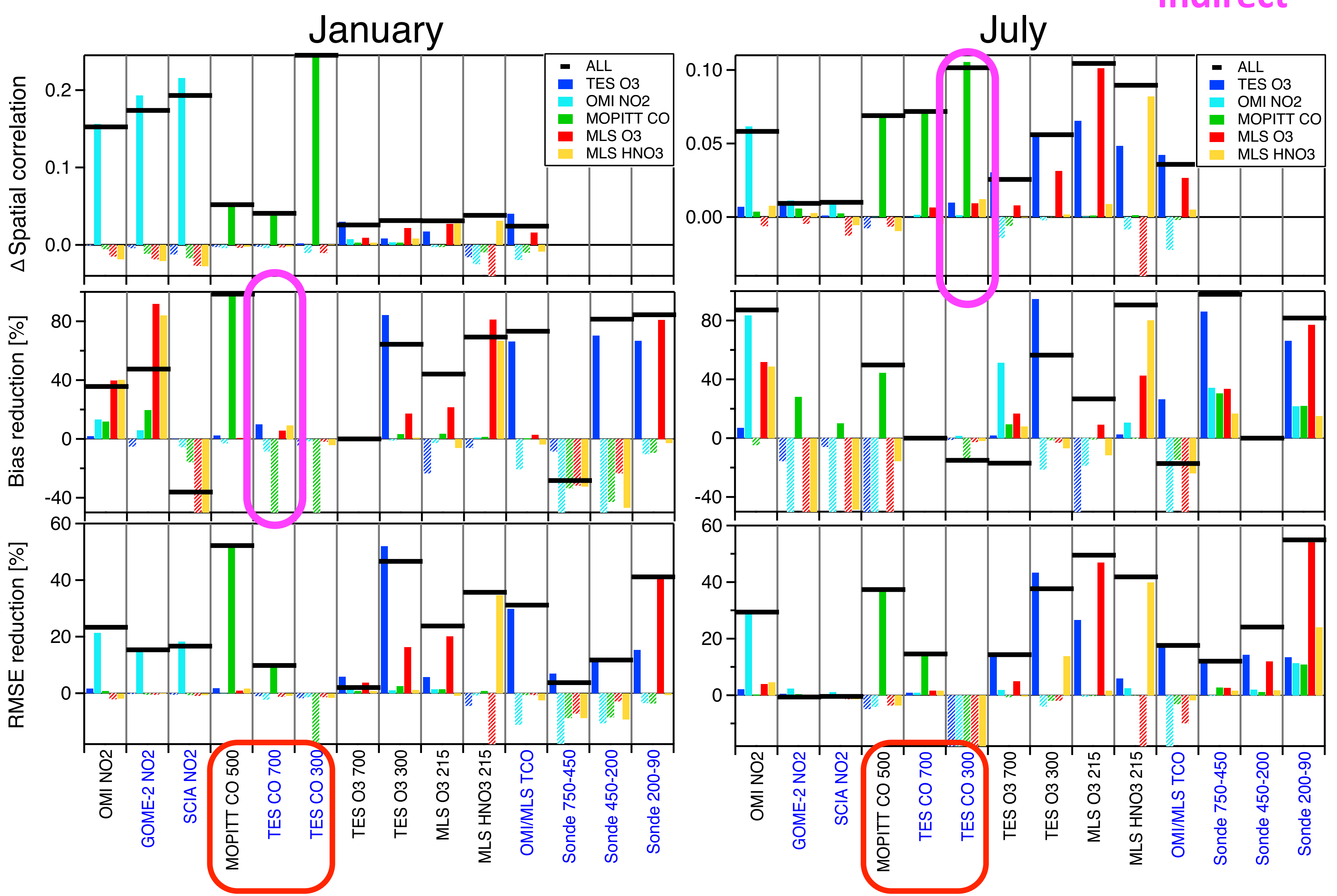
Direct
Indirect



Observing System Experiments (OSEs)

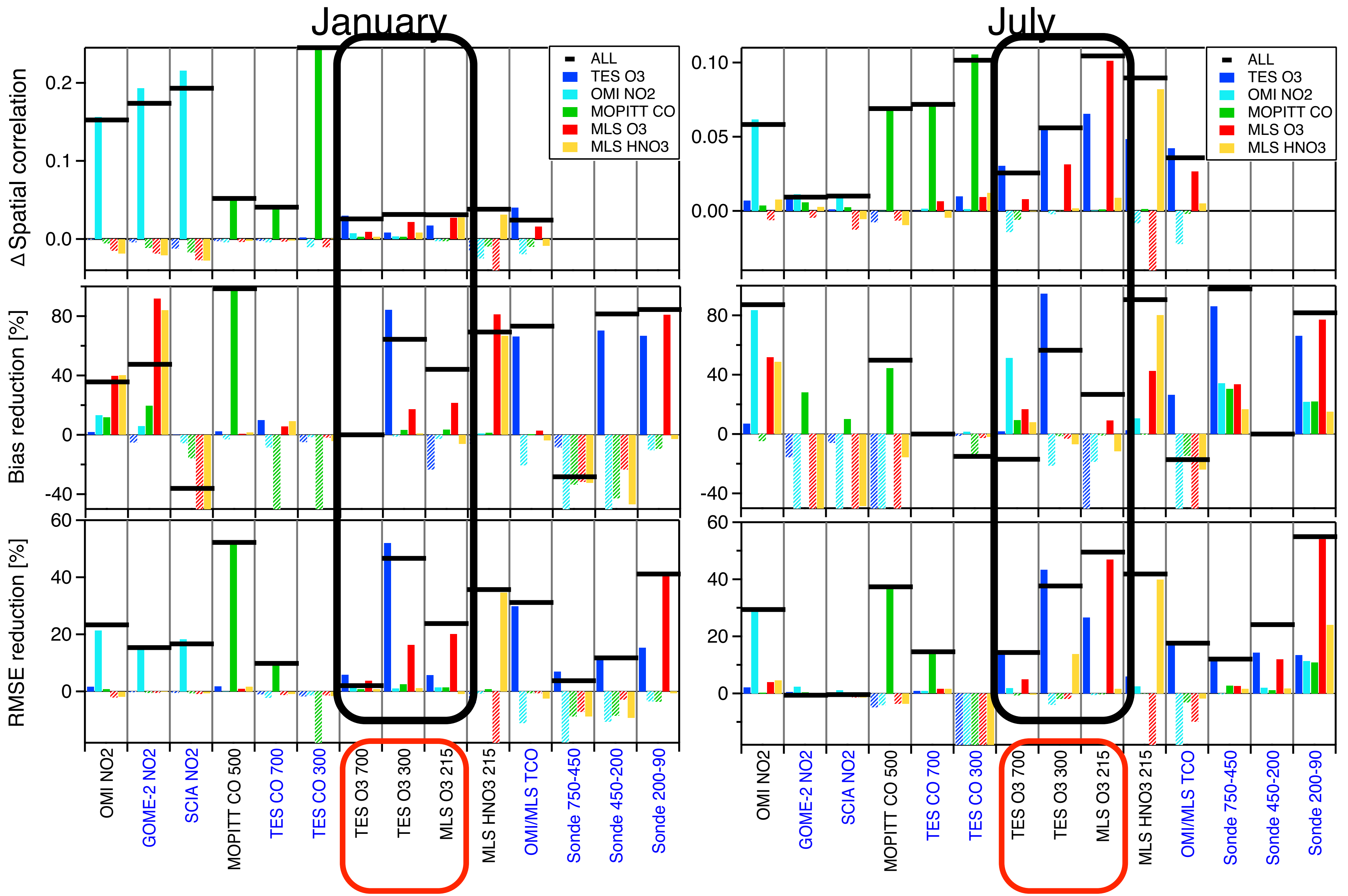


Observing System Experiments (OSEs)

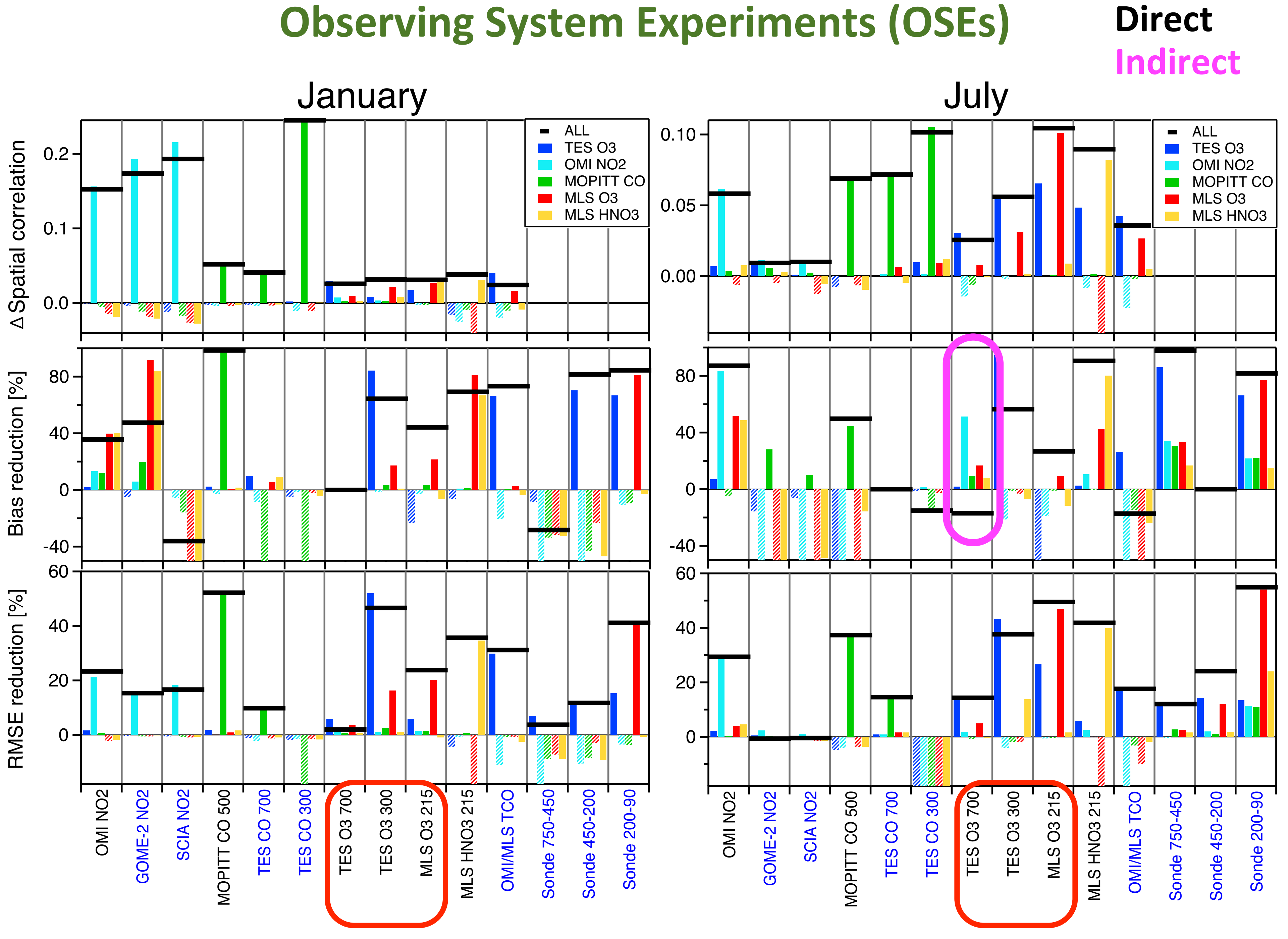


Observing System Experiments (OSEs)

Direct
Indirect

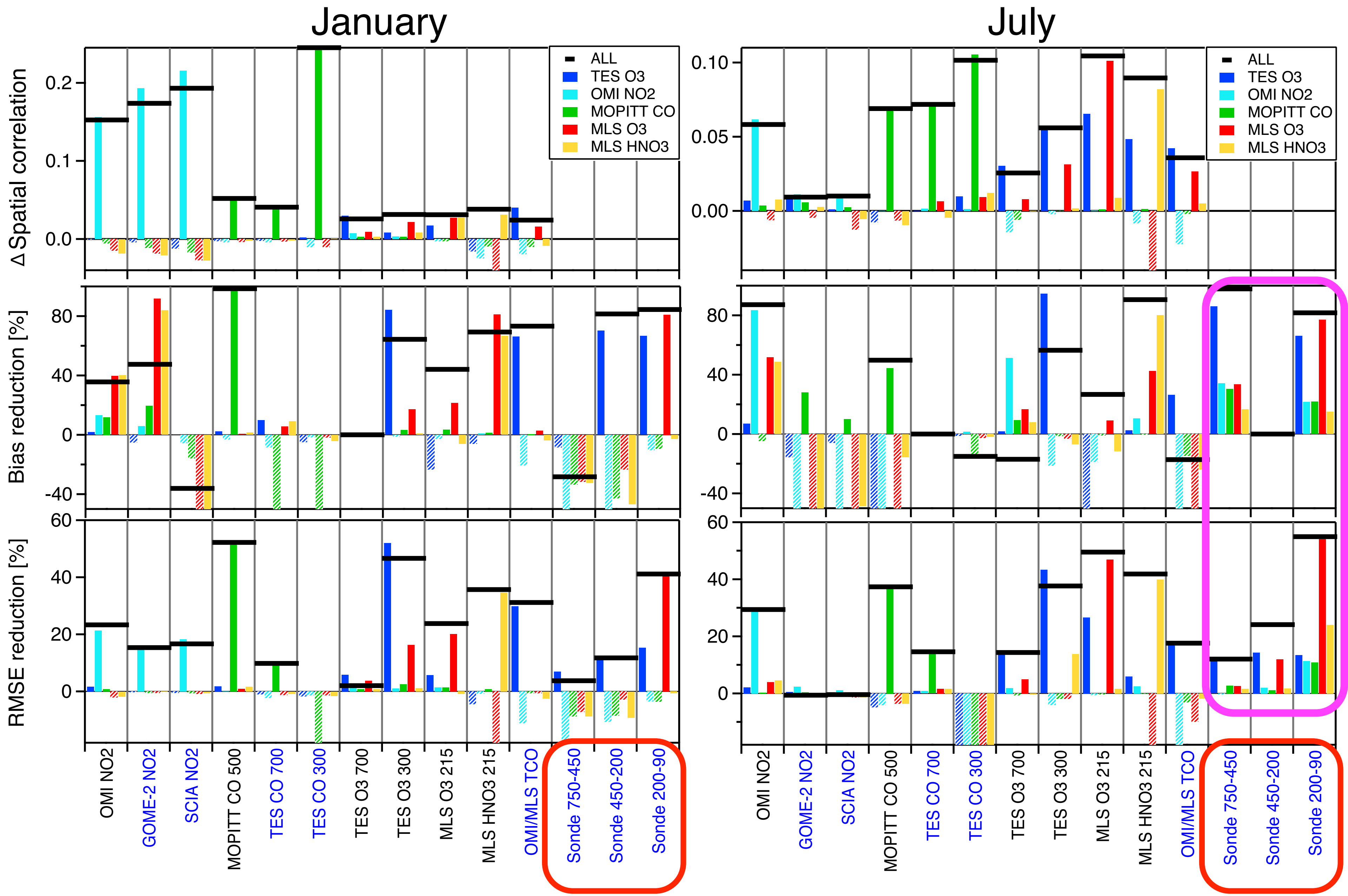


Observing System Experiments (OSEs)



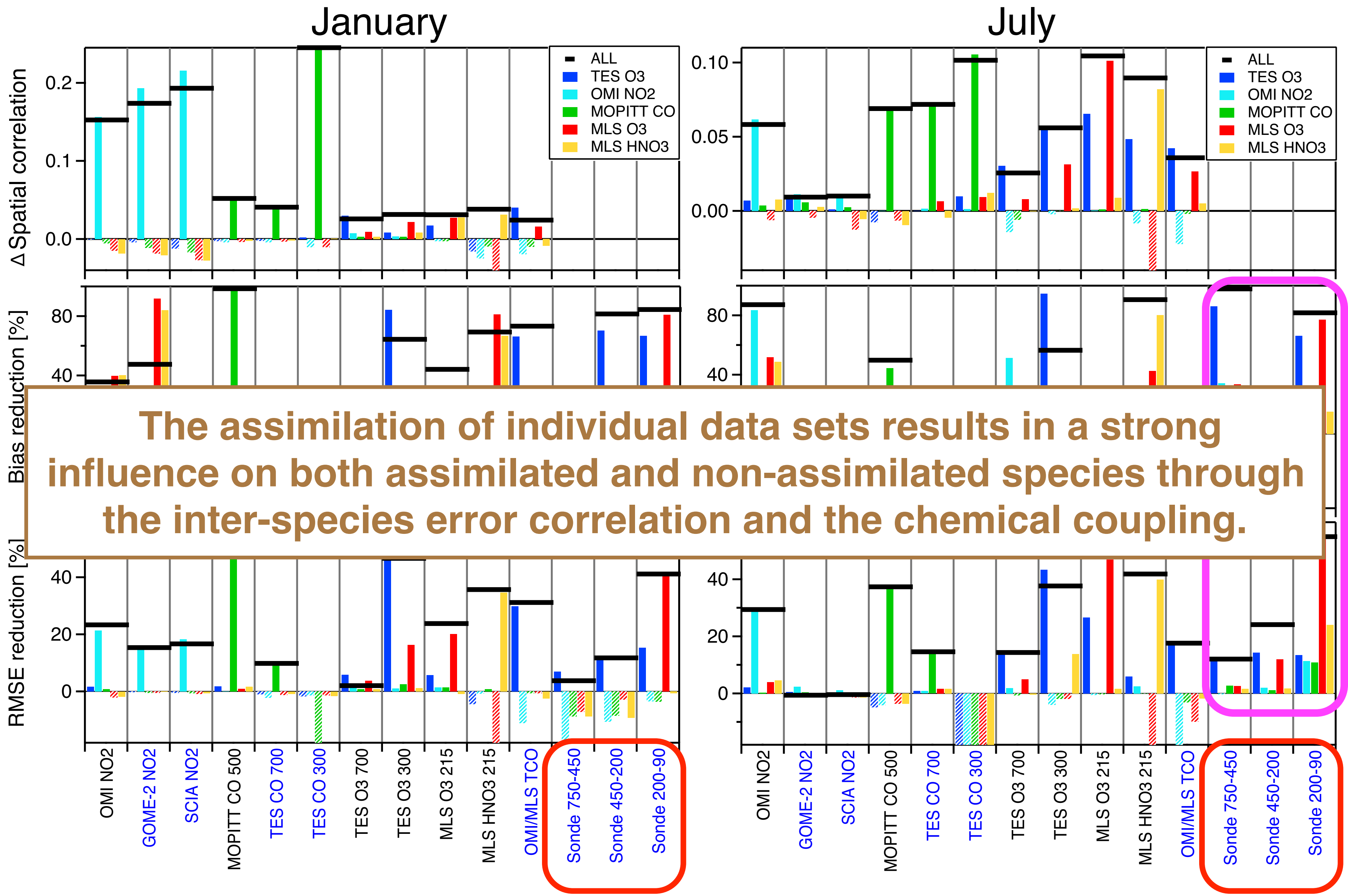
Observing System Experiments (OSEs)

Direct
Indirect



Observing System Experiments (OSEs)

Direct
Indirect



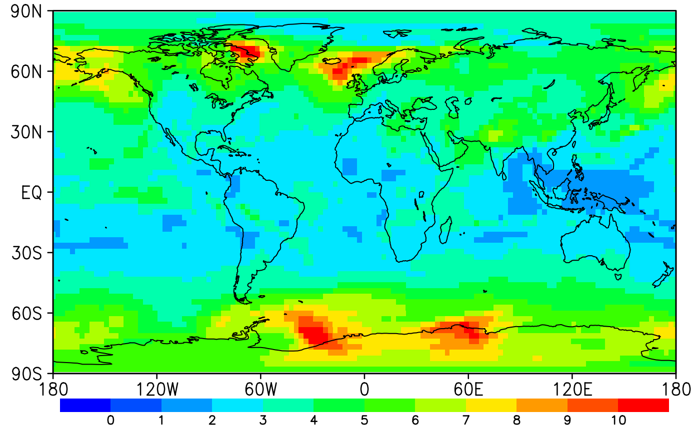
The assimilation of individual data sets results in a strong influence on both assimilated and non-assimilated species through the inter-species error correlation and the chemical coupling.

for the future development of both models and observations

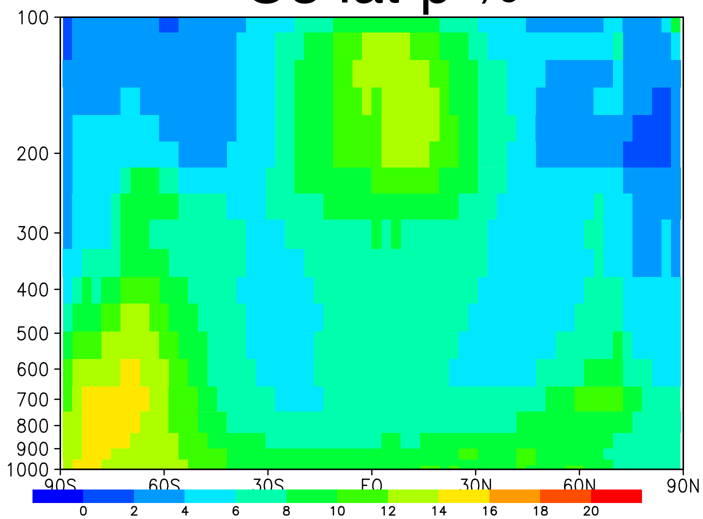
Analysis spread

requirement for further constraints from additional observations or high quality data

O3 700 hPa



O3 lat-p %

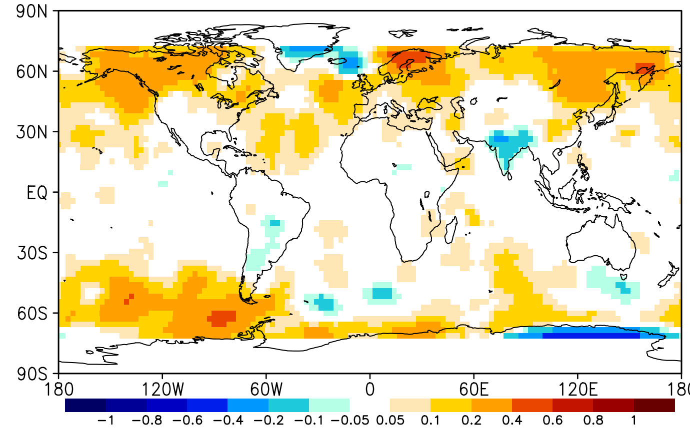


(analysis uncertainty)

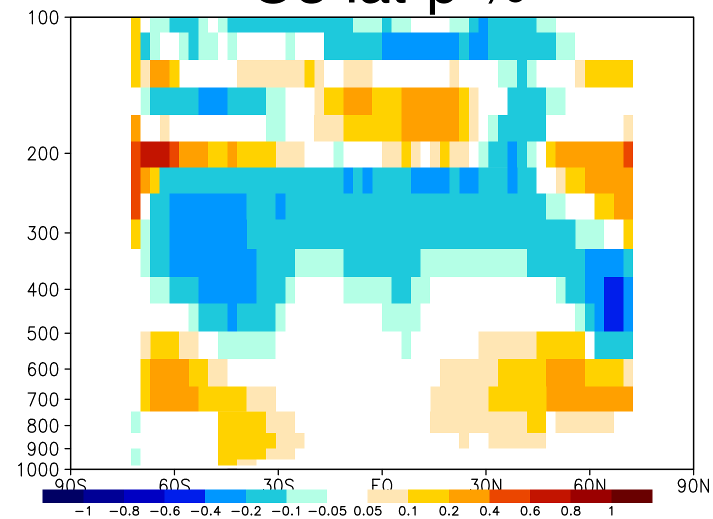
Analysis increment

useful to identify sources of the model error and improve the performance

O3 700 hPa



O3 lat-p %



(systematic model error)

Summary

Data assimilation is a powerful tool to make best use of all available observation data and study chemical/physical processes.

Advanced chemical data assimilation systems have been developed to combine observations of chemical compounds from multiple satellite.

The assimilation of individual data sets results in a strong influence on both assimilated and non-assimilated species through the inter-species error correlation and the chemical coupling.

The simultaneous adjustment of the emissions and concentrations is a powerful approach to correcting the tropospheric ozone budget and profile analyses.

Data assimilation for TTL studies

- Chemistry-climate coupling data assimilation (incl. H_2O) framework might be useful for better understanding chemistry/radiation/dynamics interactions controlling the TTL structure/variability (but might be strongly model-dependent).

- Aircraft data is expected to provide important constraints on the chemical states and the radiative forcing in the TTL region (but perhaps available only on campaign basis).

- still need to increase observations (number, resolution, e.g., GPS) and improve models (e.g., convective and microphysics parameterizations, resolution, diurnal variations).

- General circulation: Direct wind observations and momentum/heat budget information from any observations would be helpful.

- Very challenging

- **Miyazaki** et al., Simultaneous assimilation of satellite NO2, O3, CO, and HNO3 data for the analysis of tropospheric chemical composition and emissions, ACP, 2012. **(Chemical simultaneous DA)**
- **Miyazaki** et al., Global NOx emission estimates derived from an assimilation of OMI tropospheric NO2 columns,, ACP, 2012. **(OMI NO2 DA)**
- **Miyazaki** et al., Assessing the impact of satellite, aircraft, and surface observations on CO_2 flux estimation using an ensemble-based 4D data assimilation system, JGR, 2011. **(CO_2 DA system, OSSE study)**
- **Miyazaki,** Performance of a local ensemble transform Kalman filter for the analysis of atmospheric circulation and distribution of long-live tracers under idealized conditions, JGR, 2009. **(CO_2 DA system, OSSE study)**
- **Miyazaki** et al., Formation mechanisms of latitudinal CO_2 gradient in the upper troposphere over the subtropics and tropics, JGR., 2009 **(CO_2 transport/aircraft data analysis)**
- **Miyazaki** et al., Global-scale transport of carbon dioxide in the troposphere, JGR, 2008. **(CO_2 transport/modeling)**
- **Maki** et al., New techniques to analyze global distributions of CO_2 concentrations and fluxes from non-processed observational data, Tellus, 2010. **(QC for DA)**
- **Maki** et al., The Impact of Ground-Based Observations on the Inverse Technique of Aeolian Dust Aerosol, SOLA, 2011. **(Dust emission inversion)**
- **Sekiyama** et al., Data assimilation of CALIPSO aerosol observations. ACP, 2010. **(Aerosols DA)**
- **Sekiyama** et al., The Effects of Snow Cover and Soil Moisture on Asian Dust: II. Emission Estimation by Lidar Data Assimilation, SOLA, 2011. **(Aerosols DA)**
- **Sekiyama** et al.,: A simulation study of the ensemble-based data assimilation of satellite-borne lidar aerosol observations, GMDD., 2012. **(Aerosols OSSE)**
- **Iwasaki** et al., Comparisons of Brewer-Dobson Circulations diagnosed from Reanalyses, JSMJ, 2009. **(BD inter-comparison among reanalyses)**