Remote Sounding with Advanced Infrared and Microwave Instruments

Chris Barnet

NOAA/NESDIS/STAR

University of Maryland, Baltimore County (Adjunct Professor)

AIRS Science Team Member

NPOESS Sounder Operational Algorithm Team Member

GOES-R Algorithm Working Group – Chair of Sounder Team

NOAA/NESDIS representative to IGCO

Wednesday July 25, 2007

Workshop on Applications of Remotely Sensed Observations in Satellite Data Assimilation

Sounding Theory Notes for the discussion today is on-line

voice: (301)-316-5011 email: chris.barnet@noaa.gov

ftp site: ftp://ftp.orbit.nesdis.noaa.gov/pub/smcd/spb/cbarnet/

..or.. ftp ftp.orbit.nesdis.noaa.gov, cd pub/smcd/spb/cbarnet

Sounding NOTES, used in teaching UMBC PHYS-741: Remote Sounding and UMBC PHYS-640: Computational Physics (w/section on Apodization)

~/reference/rs_notes.pdf

~/reference/phys640_s04.pdf

These are *living* notes, or maybe a scrapbook – they are not textbooks.

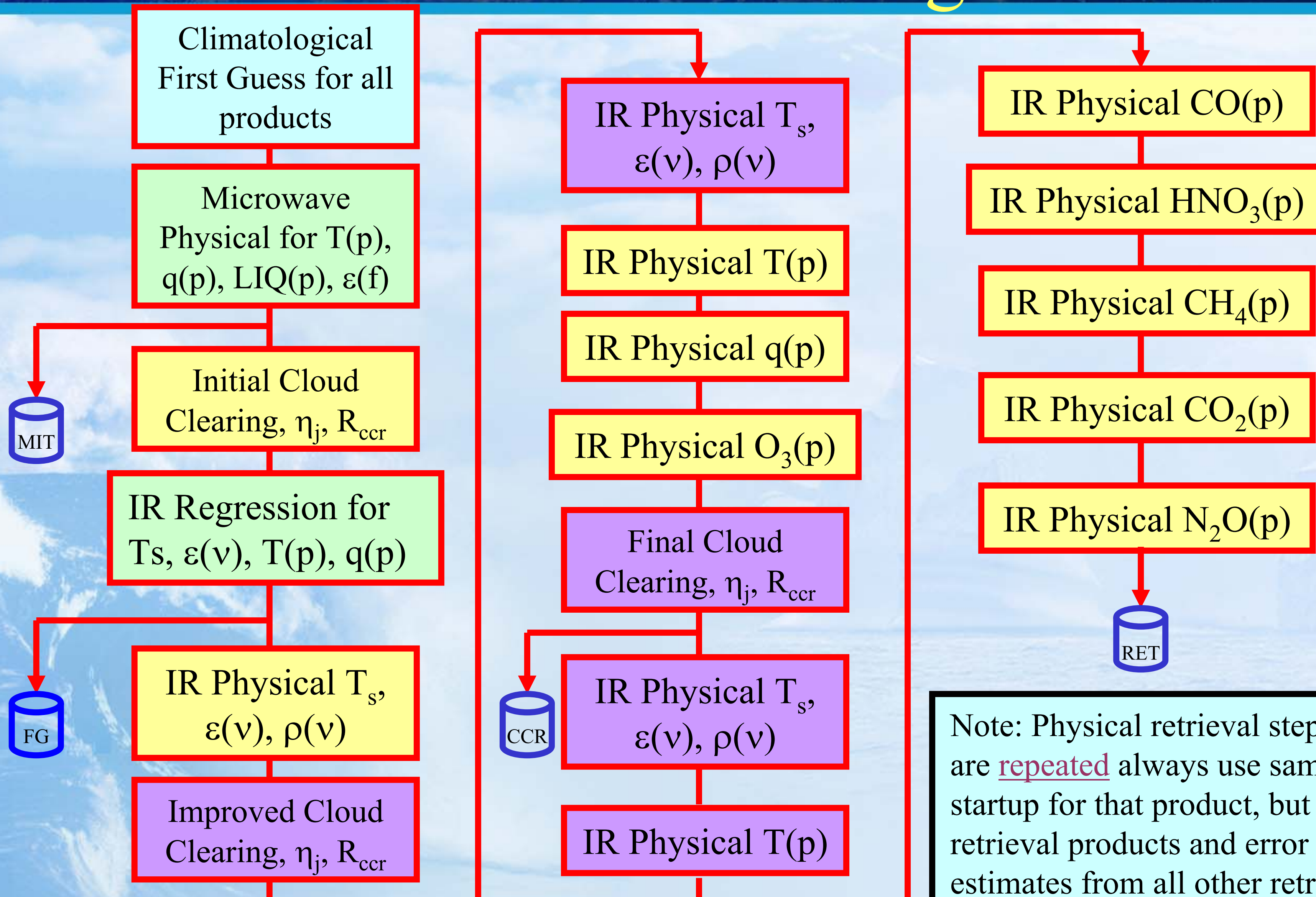
For an excellent text book on the topic of remote sounding is:

Rodgers, C.D. 2000. Inverse methods for atmospheric sounding: Theory and practice. World Scientific Publishing 238 pgs

Topics for Lectures

- Monday July 23, 2007
  - Introduction to AIRS & IASI and our plans to use *operational* sounders to retrieve atmospheric and surface products.
  - Introduction to Sounding Methodology
    - Cloud clearing
    - Statistical Regression Retrievals
- Tuesday July 24, 2007
  - Sidebar: Comparison of Dispersive and Interferometric Instruments
  - Introduction to Sounding Methodology (continued)
    - The forward model: Converting state vector to radiances.
    - The inverse problem: Converting radiances to a state vector.
- Wednesday July 25, 2007
  - Introduction to Sounding Methodology (continued)
    - Vertical Averaging Kernels & Error Covariance Matrices
  - Validation of Products
  - Atmospheric Carbon Retrievals

Simplified Flow Diagram of AIRS Science Team Algorithm



Note: Physical retrieval steps that are repeated always use same startup for that product, but it uses retrieval products and error estimates from all other retrievals.

1DVAR versus AIRS Science Team Method

1DVAR	AIRS Science Team Approach
Solve all parameters simultaneously	Solve each state variable (*e.g.*, T(p)), separately.
Error covariance includes only instrument model.	Error covariance is computed for all *relevant* state variables that are held fixed in a given step. Retrieval error covariance is propagated between steps.
Each parameter is derived from all channels used (*e.g.*, can derive T(p) from CO2, H2O, O3, CO, … lines).	Each parameter is derived from the best channels for that parameter (*e.g.,* derive T(p) from CO2 lines, q(p) from H2O lines, etc.)
A-priori must be rather close to solution, since state variable interactions can de-stabilize the solution.	*A-priori* can be simple, since this method is very stable.
Regularization must include *a-priori* statistics to allow mathematics to separate the variables and stabilize the solution.	Regularization can be reduced (smoothing terms) and does not require *a-priori* statistics for most geophysical regimes.
This method has large state matrices (all parameters) and covariance matrices (all channels used). Inversion of these large matrices is computationally expensive.	State matrices are small (largest is 25 T(p) parameters) and covariance matrices of the channels subsets are quite small. Very fast algorithm. Encourages using more channels.
Has never been done simultaneously with clouds, emissivity(ν), SW reflectivity, surface T, T(p), q(p), O3(p), CO(p), CH4(p), CO2(p), HNO3(p), N2O(p) – if any of these are constant, then it is no longer simultaneous.	*In-situ* validation and satellite inter-comparisons indicate that this method is robust and stable. There are still spectroscopy and algorithm improvements to work out.

Some Final Thoughts on Remote Sounding Approaches

- This discussion isn't new. It has been going on for more than 30 years!
- It really boils down to Physics versus Statistics – although in the modern era this distinction has been blurred.
  - Regression and Neural Network Approaches
  - Use of geophysical covariance to regularize the under-determined problem.
- Take a look at discussion at the end of Rodgers, C.D. 1977. "Statistical principles of inversion theory." in "Inversion Methods in Atmospheric Remote Sounding" (ed. Deepak) p.117- 138.
- This discussion is also transcribed in Section 22.2 of my notes (reference/rs_notes.pdf).
- As in all things, the answer may lie in the middle ground. We are exploring adding some *a-priori* statistics to help in certain geophysical domains (*e.g*., lower boundary layer T(p), etc.) and we may explore some simultaneous retrievals (T(p)/emissivity, etc.) to improve the products.

Retrieval Averaging Kernels (11 slides)

See

1)Rogers 2000, pg. 43-44 & pg. 83-85

2)Rodgers and Conner 2003

3) My notes – section 8.12.1

We Can Compute a Averaging Kernel via Brute Force

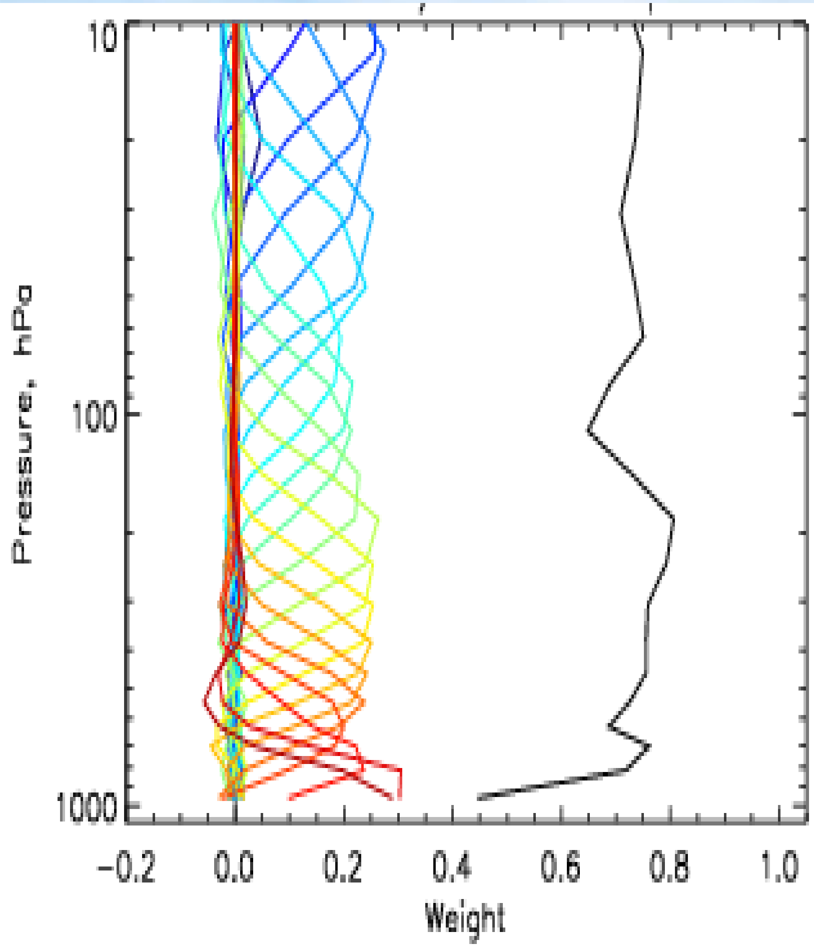
1. Start with the retrieval state, X_0
2. Perturb X_0 in some atmosphere layer by δX_k
3. Compute change in radiance, $R(X_0+\delta X_k)-R(X_0)$
4. Compute a new retrieval, X_k, using the perturbed radiance.
5. X_k-X_0 is the j^{th} column of A_{kj}
6. Goto Step 1 and compute another row of A

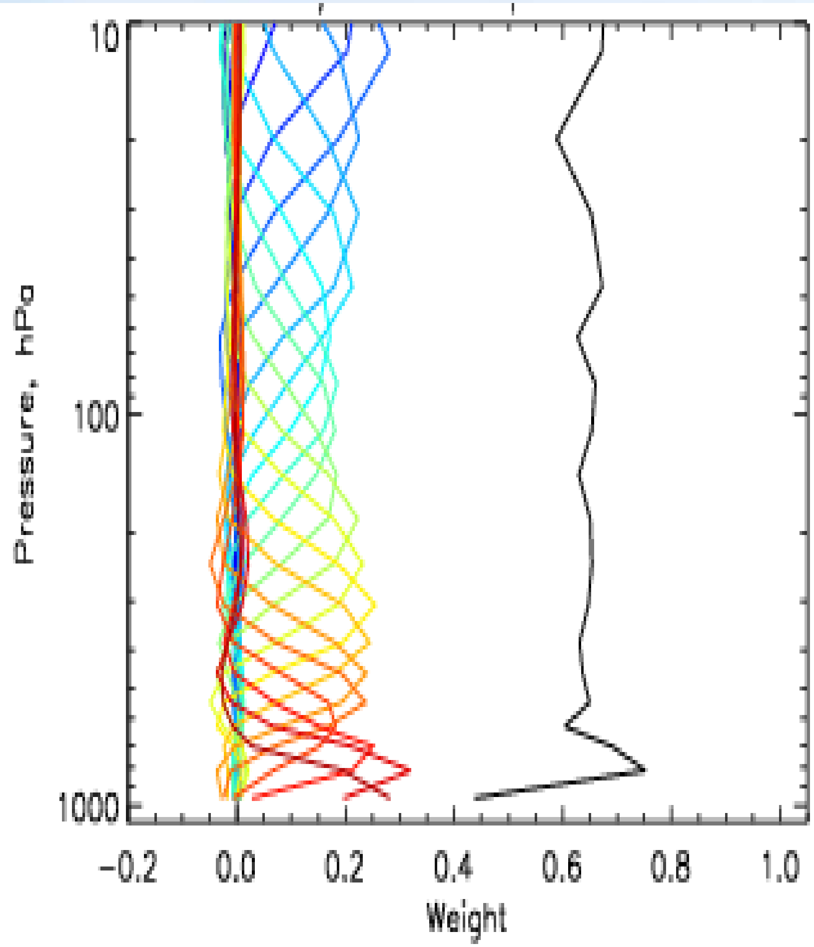
This method has the advantage that the entire system, including cloud clearing, regression, and multiple-interacting and non-linear retrieval steps, can be analysed.

The "Brute Force" Averaging provided a Sanity test for Internal Averaging Functions

A_{jk} & trace{A} via Brute Force for T(p)

A = G*K





Using the Inversion Equation to Derive Vertical Averaging Kernels

- Our Retrieval Equation Can Be Written As

$$X_j^i = X_j^A + \left[K_{j,n}^T \cdot N_{n,n}^{-1} \cdot K_{n,j} + C_{j,j}^{-1}\right]^{-1} \cdot K_{j,n}^T \cdot N_{n,n}^{-1} \cdot \left[R_n^{obs} - R_n(X^{i-1}) + K_{n,j} \cdot \left(X_j^{i-1} - X_j^A\right)\right]$$

$$K_{n,j} \equiv \frac{\partial R_n\left(\vec{X}^{i-1}\right)}{\partial X_j}\Big|_{X^{i-1}}$$

- Note that this equation is really a weighting average of the state determined via radiances and the *a-priori*.
  - The radiance covariance can be written as $K^TN^{-1}K$, in geophysical units, and
  - The product covariance is given by $[K^TN^{-1}K + C^{-1}]^{-1}$

We can Derive the Averaging Kernel from Our Minimization Equation

- As we approach a solution, we can linearize the retrieval about a state that is approach the "truth"

$$
\begin{aligned}
R_n^{obs} &\simeq R_n(\hat{X}) + \epsilon \\
X_j^i &= X_j^A + \boxed{\left[\hat{K}_{j,n}^T \cdot N_{n,n}^{-1} \cdot \hat{K}_{n,j} + C_{j,j}^{-1}\right]^{-1} \cdot \hat{K}_{j,n}^T \cdot N_{n,n}^{-1}} \cdot \\
&\qquad \left[\epsilon + \hat{K}_{n,j} \cdot \left(\hat{X} - X_j^A\right)\right]
\end{aligned}
$$

$$
\hat{K}_{n,j} \equiv \frac{\partial R_n\left(\vec{X}\right)}{\partial X_j}\Big|_{\hat{X}} \simeq K_{n,j}
$$

- And simplify by replacing the region highlighted in green above with the variable G

$$
\begin{aligned}
X_j^i - X_j^A &= G_{j,n} \cdot \left[\epsilon_n + K_{n,j} \cdot \left(\hat{X} - X_j^A\right)\right] \\
&= A_{j,j} \cdot \left(\hat{X}_j - X_j^A\right) + G_{j,n} \cdot \epsilon
\end{aligned}
$$

zero

Computing the Averaging Kernel

- The vertical averaging kernel is the amount of the derived state that came from the radiances

$$
\begin{aligned}
\boldsymbol{A}_{j,j} &\equiv \boldsymbol{G}_{j,n} \cdot \boldsymbol{K}_{n,j} \\
\boldsymbol{A}_{j,j} &\equiv \left[\boldsymbol{K}_{j,n}^{T} \cdot \boldsymbol{N}_{n,n}^{-1} \cdot \boldsymbol{K}_{n,j} + \boldsymbol{C}_{j,j}^{-1}\right]^{-1} \cdot \boldsymbol{K}_{j,n}^{T} \cdot \boldsymbol{N}_{n,n}^{-1} \cdot \boldsymbol{K}_{n,j}
\end{aligned}
$$

- And I-A is the amount that came from the prior

$$
\boldsymbol{I}_{j,j} - \boldsymbol{A}_{j,j} = \underbrace{\left[\boldsymbol{K}_{j,n}^{T} \cdot \boldsymbol{N}_{n,n}^{-1} \cdot \boldsymbol{K}_{n,j} + \boldsymbol{C}_{j,j}^{-1}\right]^{-1}}_{\text{Retrieval covariance}} \cdot \underbrace{\boldsymbol{C}_{j,j}^{-1}}_{\text{Inverse of a-priori covariance}}
$$

Value of the Vertical Averaging Function

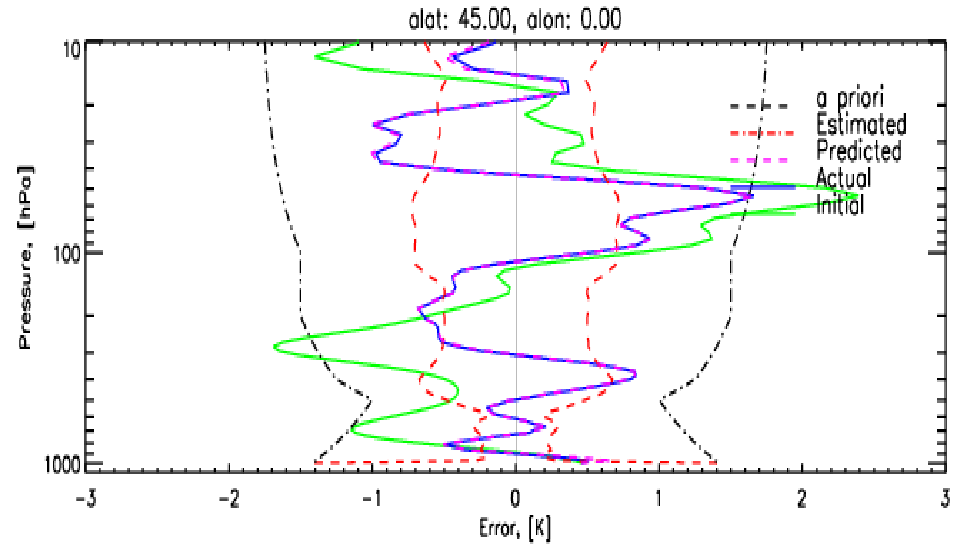
- A is the retrieval weighing of the channel kernel functions (think of a retrieval operator as an integrator of data)
- A tells you how much the observations were believed.
- I-A tells you how much of the *a-priori* was believed.
- When comparing other measurements (such as high vertical resolution sondes or aircraft) the validation measurements
  - Must have similar vertical smoothing and
  - Should be "degraded" by the fraction of the prior that entered the solution (*i.e.*, in regimes were we don't have 100% information content)
- When using AIRS products the A matrix
  - Tells you the vertical correlation between parameters
  - Tells you how much to believe the product and where to believe the product.
  - *A-priori* assumptions can be removed from the solution if we are in a linear domain.

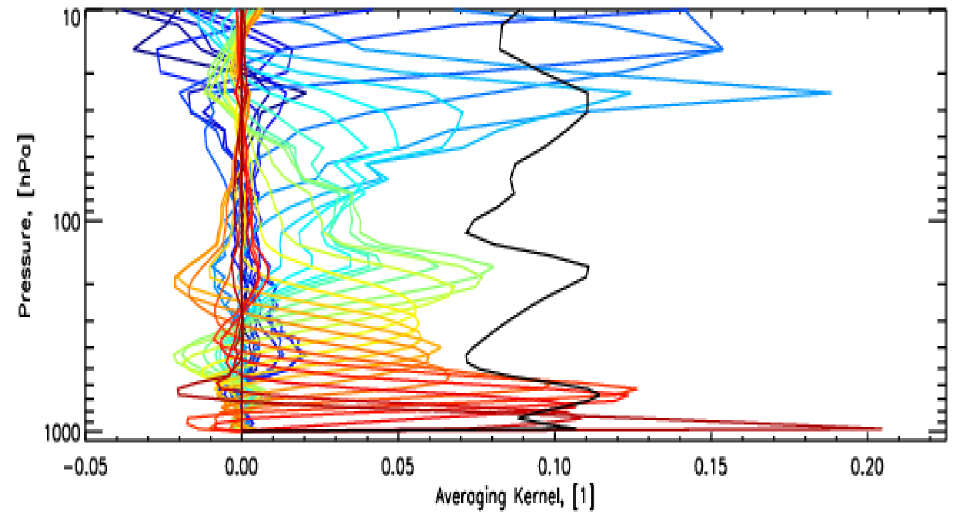
Error Estimates and Averaging Kernels for Temperature, Linear Analysis

Linear Error is Composed Of:
1. Instrument Error
2. Smoothing Term (Geophysical Functions)
3. Propagated Error Covariance

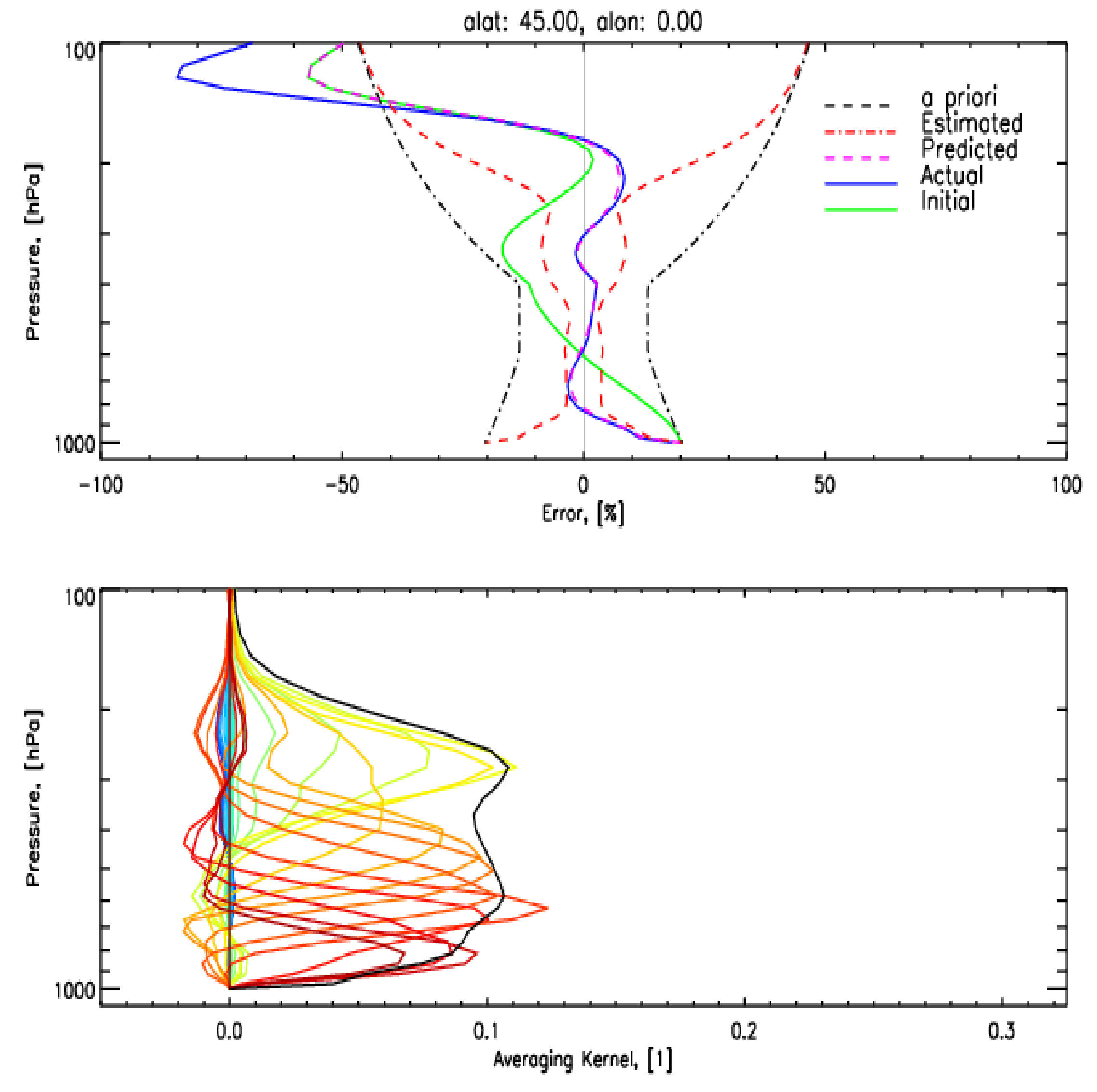
Actual retrieval error (blue) lies within the error estimate (red) for most of the atmosphere.

Predicted error using exact knowledge (magenta) of the errors of the Initial state error (green) lies on top of actual error (blue). That is, retrieval methodology is linear enough to propagate errors.





Error Estimates and Averaging Kernels for Moisture, Linear Analysis

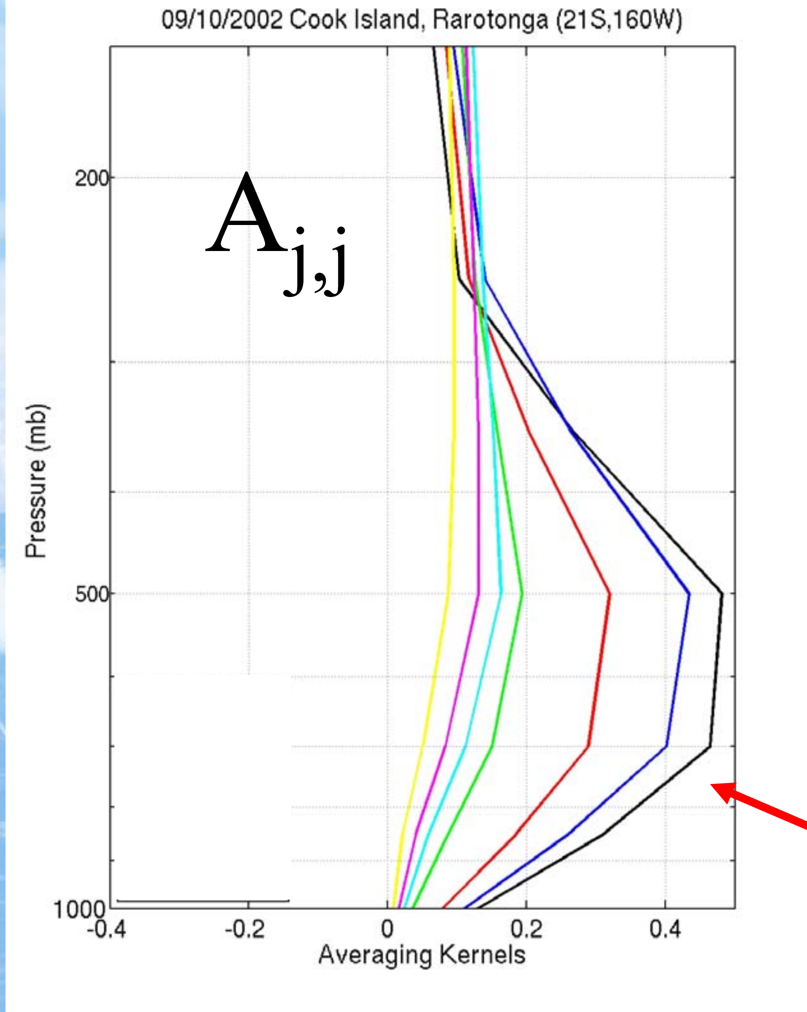


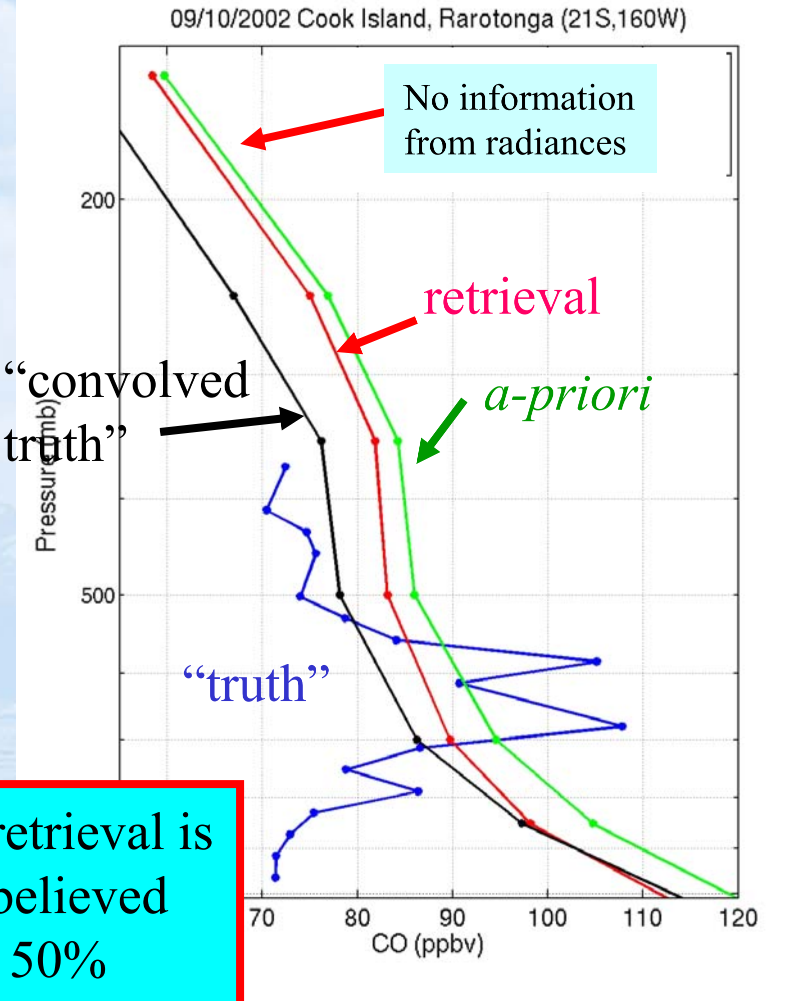
Actual retrieval error (blue) lies within the error bars (red) for most of the atmosphere.

Predicted error using exact knowledge (magenta) of the errors of the initial state (green) lies on top of actual error (blue)

Example #1: We can use averaging kernel to optimally smooth the truth for comparisons

AIRS CO Product





This retrieval is only believed at the 50% level

Example #2: Comparison of CO2 Product and Kawa 2004 Model for April 2005

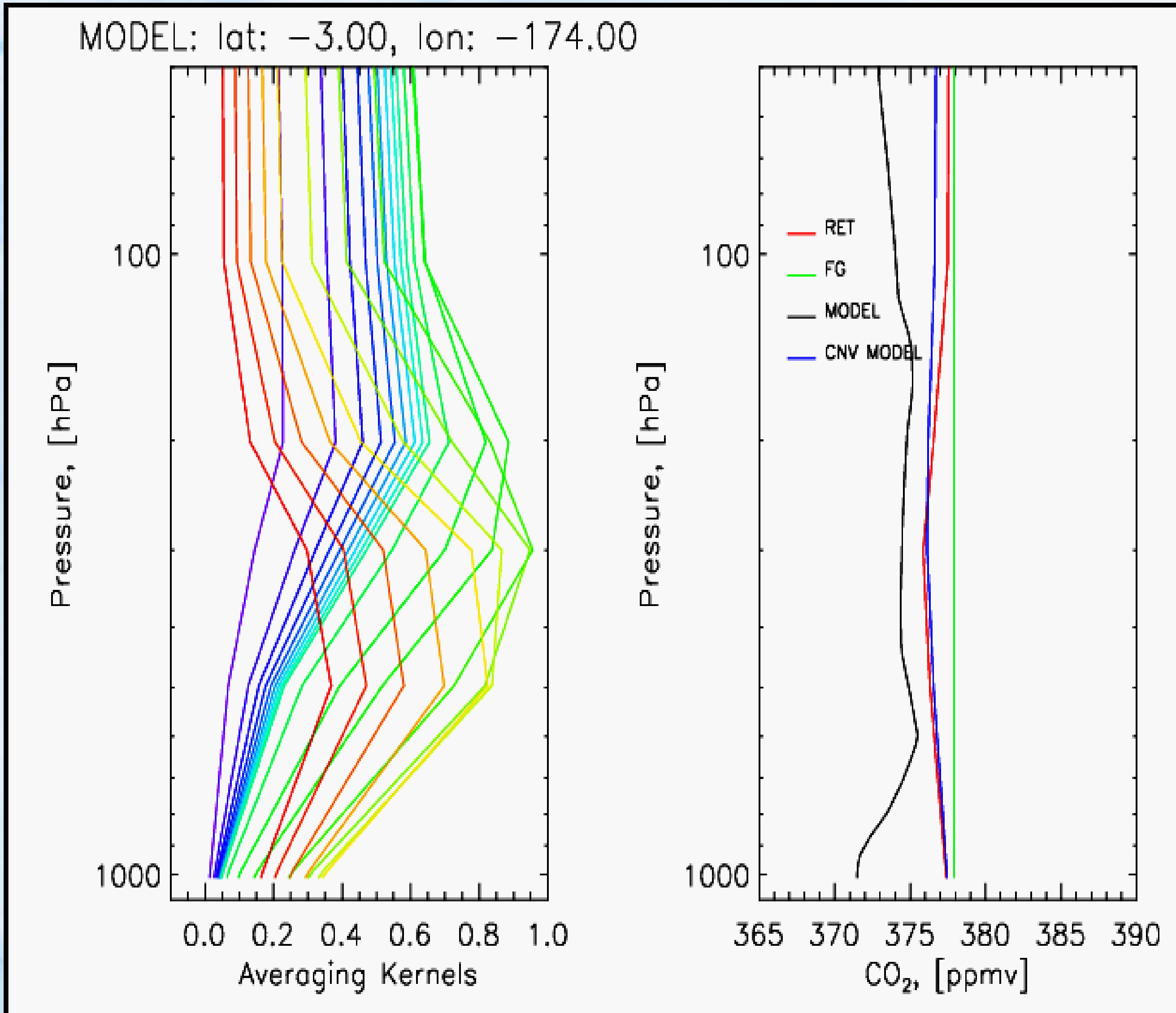
- **At first glance, it looks like the retrieval and model (used as the "truth") do not agree.**

$\hat{X}$

- **But if we apply the averaging kernel to the model and we "degrade" it with the retrieval *a-priori* , they agree quite well.**

$$X_j = A_{j,j} \cdot \hat{X}_j + (I - A_{j,j}) \cdot X_j^a$$

- **Again, this is because we do not have 100% of information coming from the satellite (this result is within the instrument and propagated error).**



We Think We Know How To Do This Without Serious Impact to Execution Time!

- The "trick" is how to propagate the errors through all our steps in a cost effective manner.
  - Current methodology is to build an ad-hoc vertical correlation and propagate the diagonal of the retrieval error covariance.
- BUT – We can compute the full error covariance and then decompose it and propagate the full covariance (this has been proposed for the version 6 algorithm)

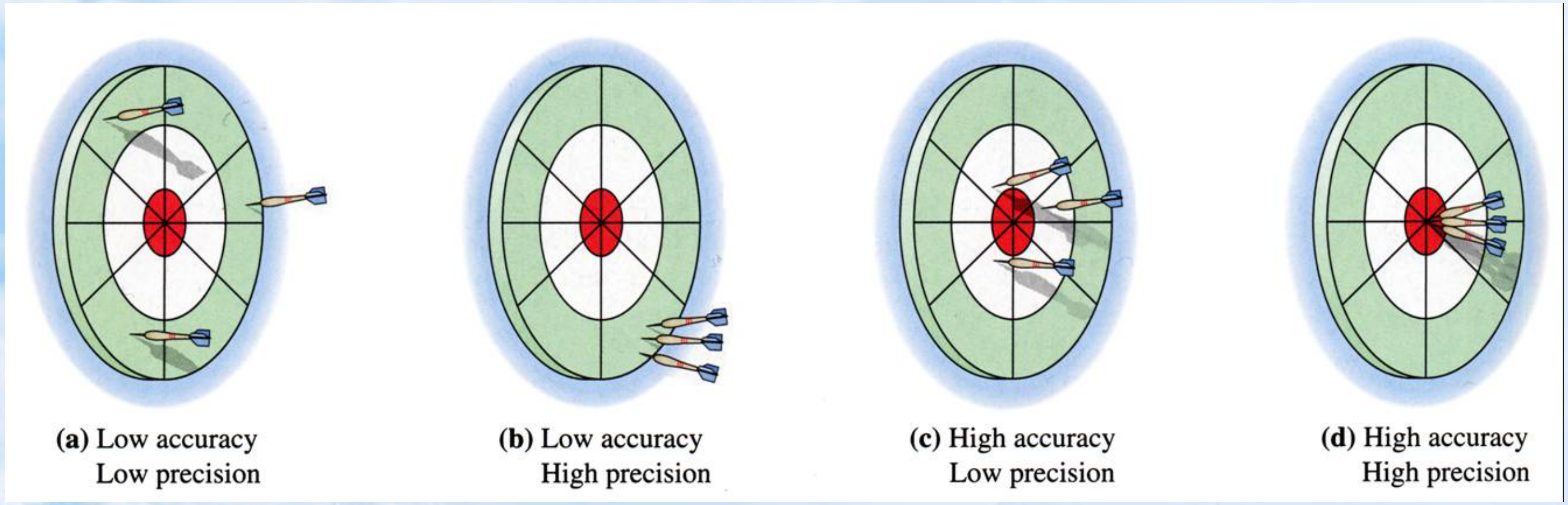
$$
\begin{aligned}
\mathbf{K}_{\mathrm{b}}\mathbf{S}_{\mathrm{b}}\mathbf{K}_{\mathrm{b}}^{T} &= \mathbf{K}\left(\sum_{i=1}^{N} \lambda_i \mathbf{u}_i (\mathbf{u}_i)^T\right)\mathbf{K}^T \\
&\approx \sum_{i=1}^{N} (\mathbf{R}(\mathbf{x} + \mathbf{u}_i\sqrt{\lambda_i}) - \mathbf{R}(\mathbf{x}))(\mathbf{R}(\mathbf{x} + \mathbf{u}_i\sqrt{\lambda_i}) - \mathbf{R}(\mathbf{x}))^T
\end{aligned}
$$

Validation (17 slides)

“what is truth”

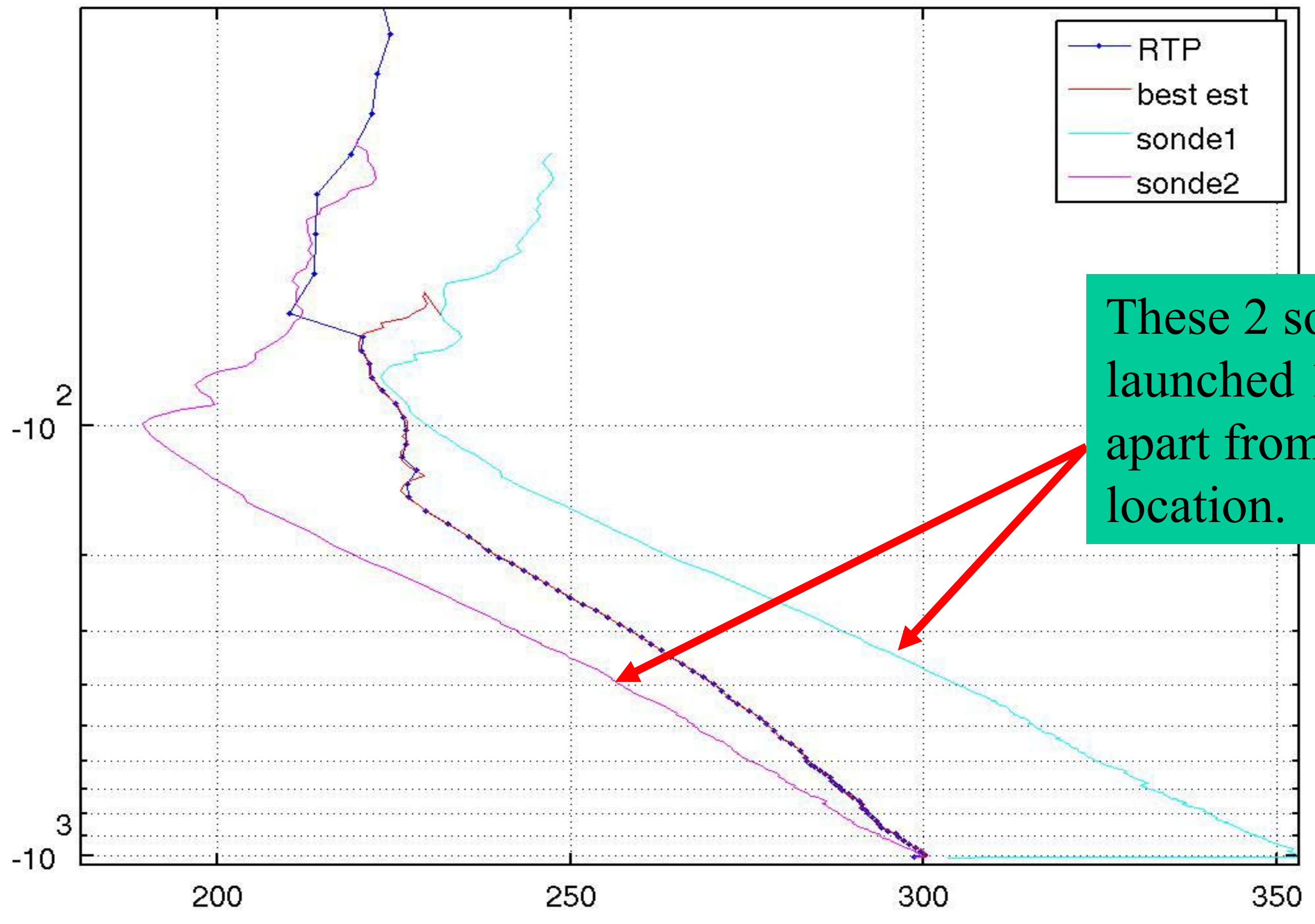
- Compare to ECMWF & NCEP Analysis (*e.g.,* Susskind, 2005)
  - Can compare complete global dataset
  - Differences can be model or retrieval errors
  - Implicitly validating against all other instruments (all assimilated space-borne, sondes, buoy’s etc.) used in analysis
- Compare to Radiosondes, Ozonesondes (e.g., See Tobin, 2006, Divakarla, 2006)
  - Only a couple hundred “dedicated” sondes are flown per year. Usually we fly 2 sondes so we can see lower and upper air at overpass time.
    - Sondes can take 1-2 hours to ascend
    - Sondes can drift 100’s of km’s during ascent.
  - A few hundred sondes are launched globally per day (usually at synoptic times) that are within 300 km and +/- 1 hour of our overpass.
    - Different sonde instruments, quality of launches, etc.
- *In-situ* intensive experiments with sondes, aircraft and LIDAR.
  - Have participated in INTEX-NA6 AEROSE, START, MILAGRO, INTEX-B, AMMA, and WAVES
- Inter-comparison of satellite products.
  - Aqua/AIRS has been compared to Aura/TES/MLS/OMI (8 minutes apart), CloudSat/Calipso (75 seconds apart) products.
    - Large number of global co-locations of “similar” products.
  - Aqua/AIRS has been compared to other satellites (*e.g.*, TOMS, SBUV, CERES)

The goal of validation is characterize accuracy and precision of products.



- Accuracy is the mean difference (bias) between observations and validation dataset.
  - $BIAS = (1/N)*\Sigma(X_2-X_1)$
  - Long-term characterization of accuracy is of significance in climate applications.
- Precision is the standard deviation (SDV) between observations and validation dataset.
- Uncertainty is the total difference (RMS)
  - $RMS = (SDV^2 + BIAS^2)^{1/2}$

An example of things that go wrong with "truth"



These 2 sondes were launched 1.5 hours apart from same location.

Other issues with Radiosondes (*e.g.*, see Eskridge et al. 2003)

- Many different types of sensors are used on radiosondes around the world. Therefore, quality of sonde data is site dependent.
- Temperature require corrections due to heating sources other than air
  - Infrared emission from balloon, clouds, surface
  - Solar heating = function of solar zenith angle
  - Conduction of hear along wires
  - Thermal inertia of sensor – lag time correction.

Vaisala RS-92

- Water vapor can require corrections due to evaporation
  - Radiosonde sensors (e.g., RS92) are measuring capacitance of a capacitor with a humidity sensitive dielectric.
    - Contamination from packaging
    - Out-gassing of polymer
  - Frost-point hygrometer measures optical depth of frost accumulated on cold mirror.

Validation and Monitoring of Core Products

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 111, D09S15, doi:10.1029/2005JD006116, 2006

Validation of Atmospheric Infrared Sounder temperature and water vapor retrievals with matched radiosonde measurements and forecasts

Murty G. Divakarla,[1] Chris D. Barnet,[2] Mitchell D. Goldberg,[2] Larry M. McMillin,[2] Eric Maddy,[3] Walter Wolf,[3] Lihang Zhou,[3] and Xingpin Liu[3]

Received 21 April 2005; revised 3 November 2005; accepted 23 November 2005; published 6 April 2006.

[1] An evaluation of the temperature and moisture profile retrievals from the Atmospheric Infrared Sounder (AIRS) data is performed using more than 2 years of collocated data sets. The Aqua-AIRS retrievals, global radiosonde (RAOB) measurements, forecast data from the National Center for Environmental Prediction Global Forecasting System

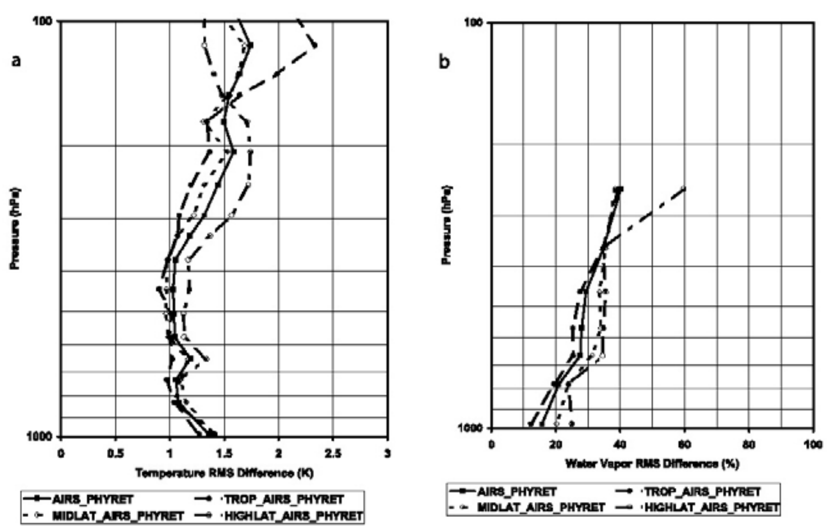
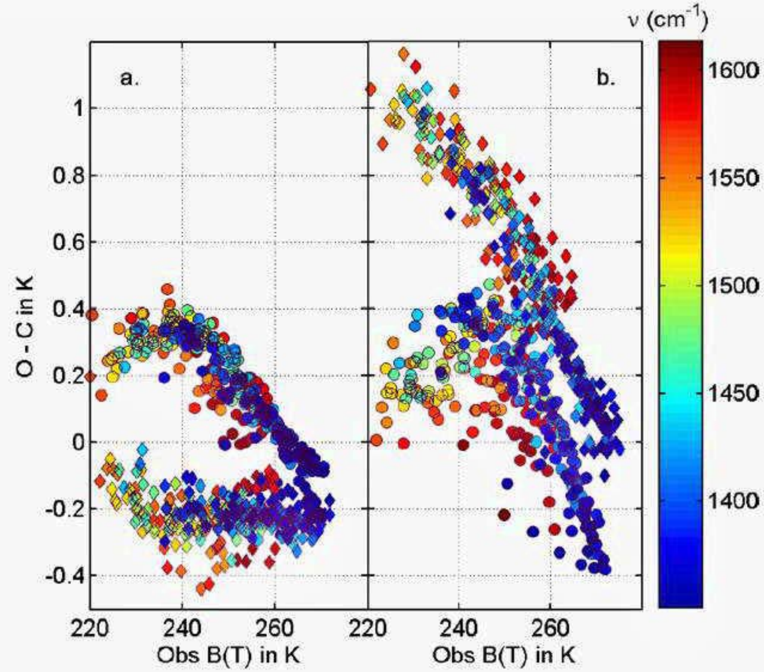


Figure 10. (a) Same as in Figure 9a but for the "sea" category. (b) Same as in Figure 9b but for the "sea" category.

- Validation of products versus operational sonde networks
  - Temperature
  - Humidity
  - Ozone
- Monitoring of radiance products.
- Validation and Evaluation core product effects on Trace Gas Products

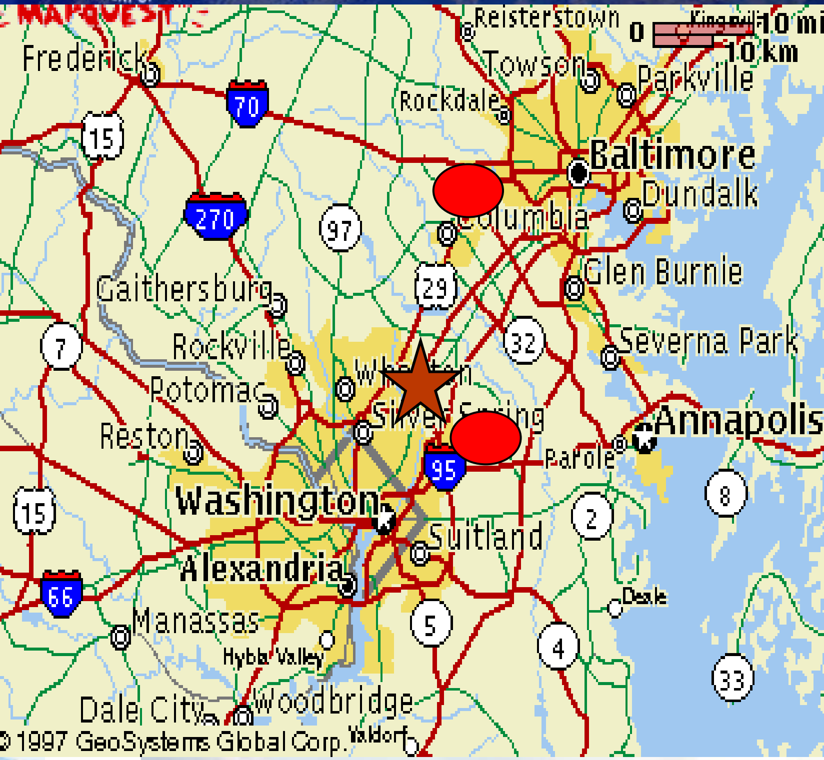
Comparing Measurements is inherently difficult

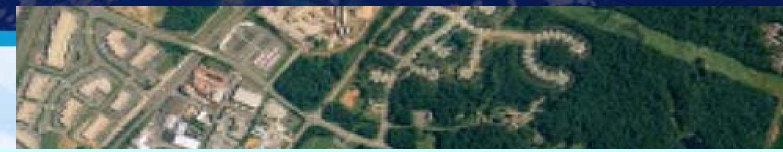
- AIRS instrument is extremely stable and can be used to test stability of *in-situ* systems
- Figure at right (Strow May 2005 science team meeting) shows day/night biases are a function of altitude.
- Frost-points are often used as a "gold-standard" to derive corrections for moisture sensors on sondes



Circles: Nighttime, Diamonds: Daytime a. Mean of all RS-90 validation campaign biases. b. Mean of all of H. Vömel's (NOAA/CMDL) frost-point hygrometer measurements.

Example of In-situ campaign: The Howard University Beltsville Research Campus



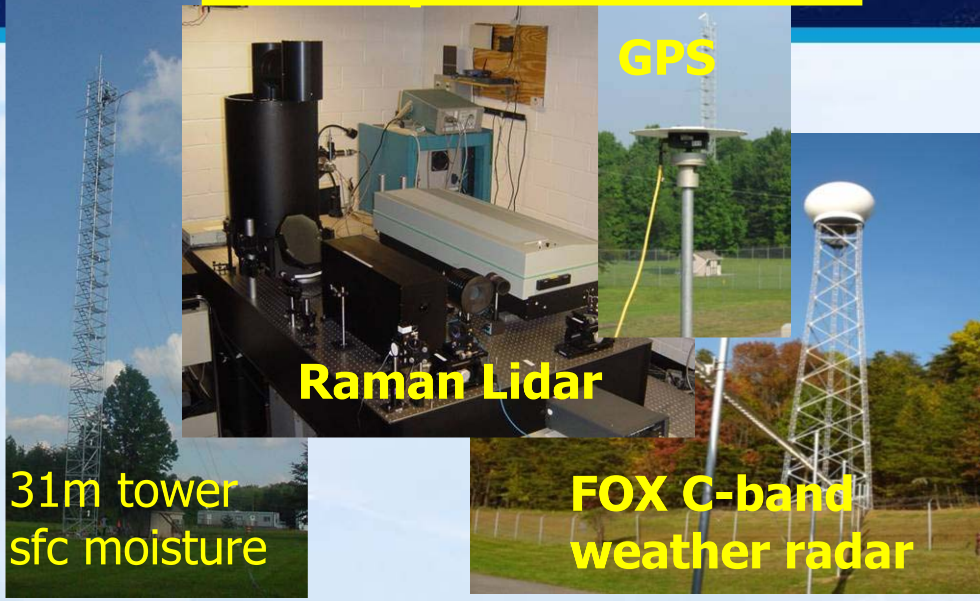


- Used to validate Aqua/AIRS, Aura/TES, EUMETSAT/IASI
- A semi-urban field site
    - Mid-Atlantic, urban experiences a wide range of meteorological conditions
    - Provides environment very different than ARM sites
- Difficult retrieval site
    - heterogeneous terrain
    - summertime polluted conditions
- Good for validation case studies representative of urban, polluted conditions
    - how good are the retrievals in the vicinity of the US capitol and where millions of people live?

Beltsville Campus Instrumentation

Aerosol-Cloud-Radiation

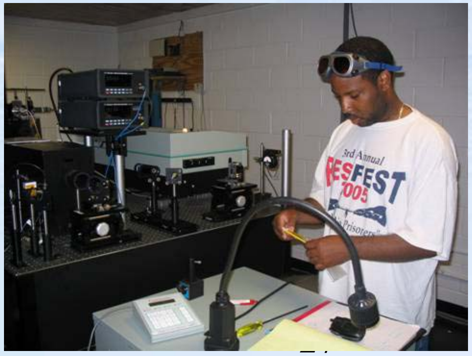
Atmosphere-Surface



Air Quality

Integrating Research and Student Training

Ozonesonde launch



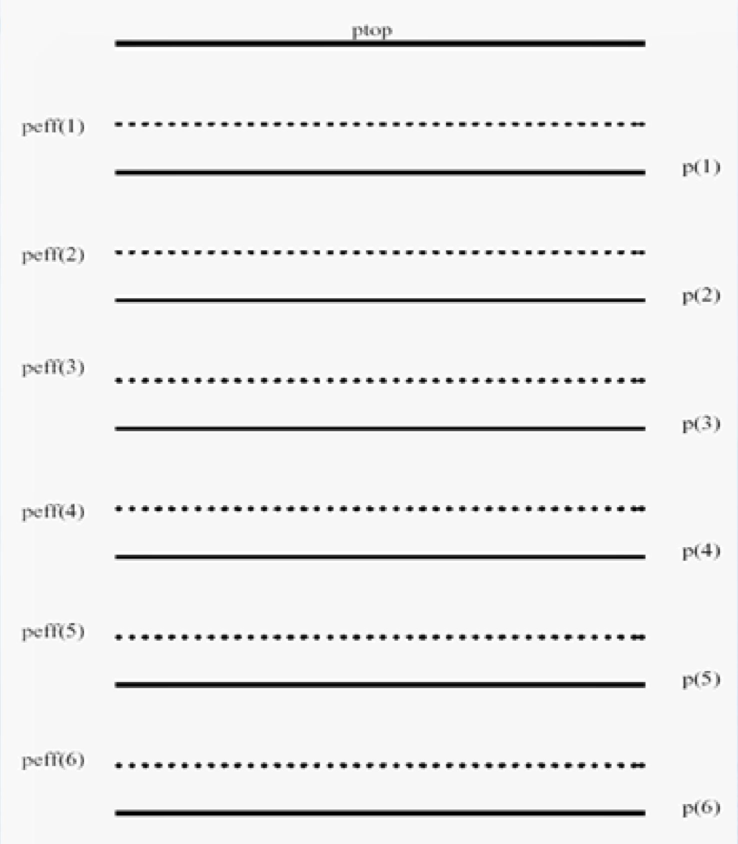
Lidar operations

Conversion of species from one pressure grid to another needs to be done correctly!

- Radiosondes measure water at specific levels (usually relative humidity). Usually 10's of thousands of points are measured in a single assent.
- This can be converted to a mixing ratio at a given level; however, there can be a lot of vertical structure (moist or dry layers) that are beyond any remote sounding instruments capability to measure.
- When comparing measurements it is important to
  - Have a common vertical resolution
  - Conserve the molecules to be compared (don't count molecules twice).

Conversion of level to layer quantities

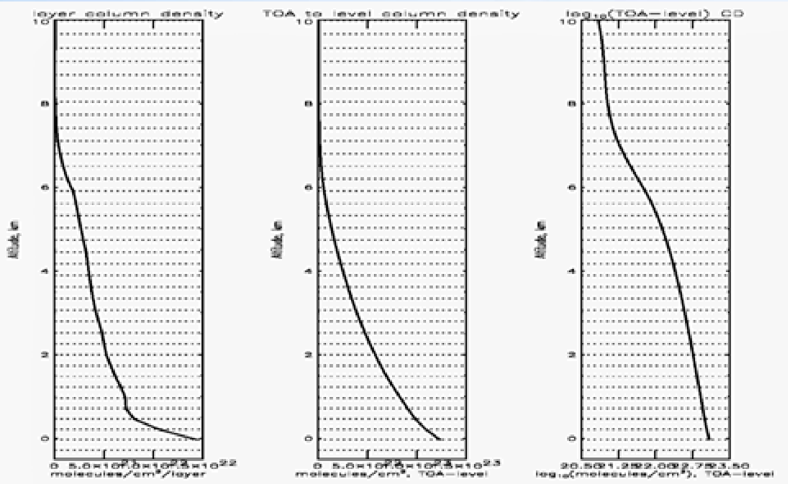
- Point measurements, such as mixing ratio, are made at effective pressure levels.
- Radiative transfer & conservation of molecules in validation requires knowledge of the number of molecules within a layer.
- Layers are defined by pressure level boundaries interleaved with the effective pressure of the mixing ratio.

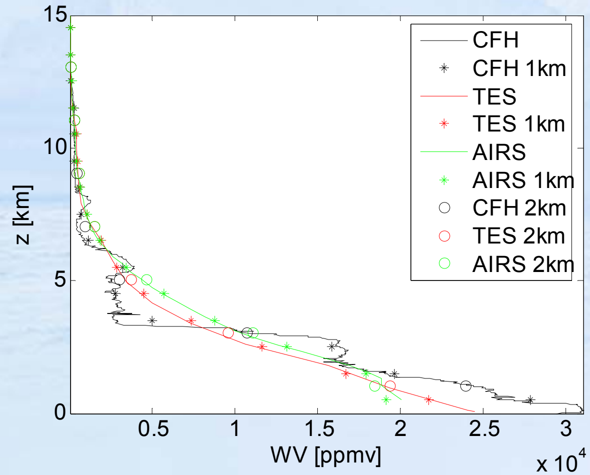


Example of a 6 layer vertical grid.

Steps to convert constituent profiles from one grid to another.

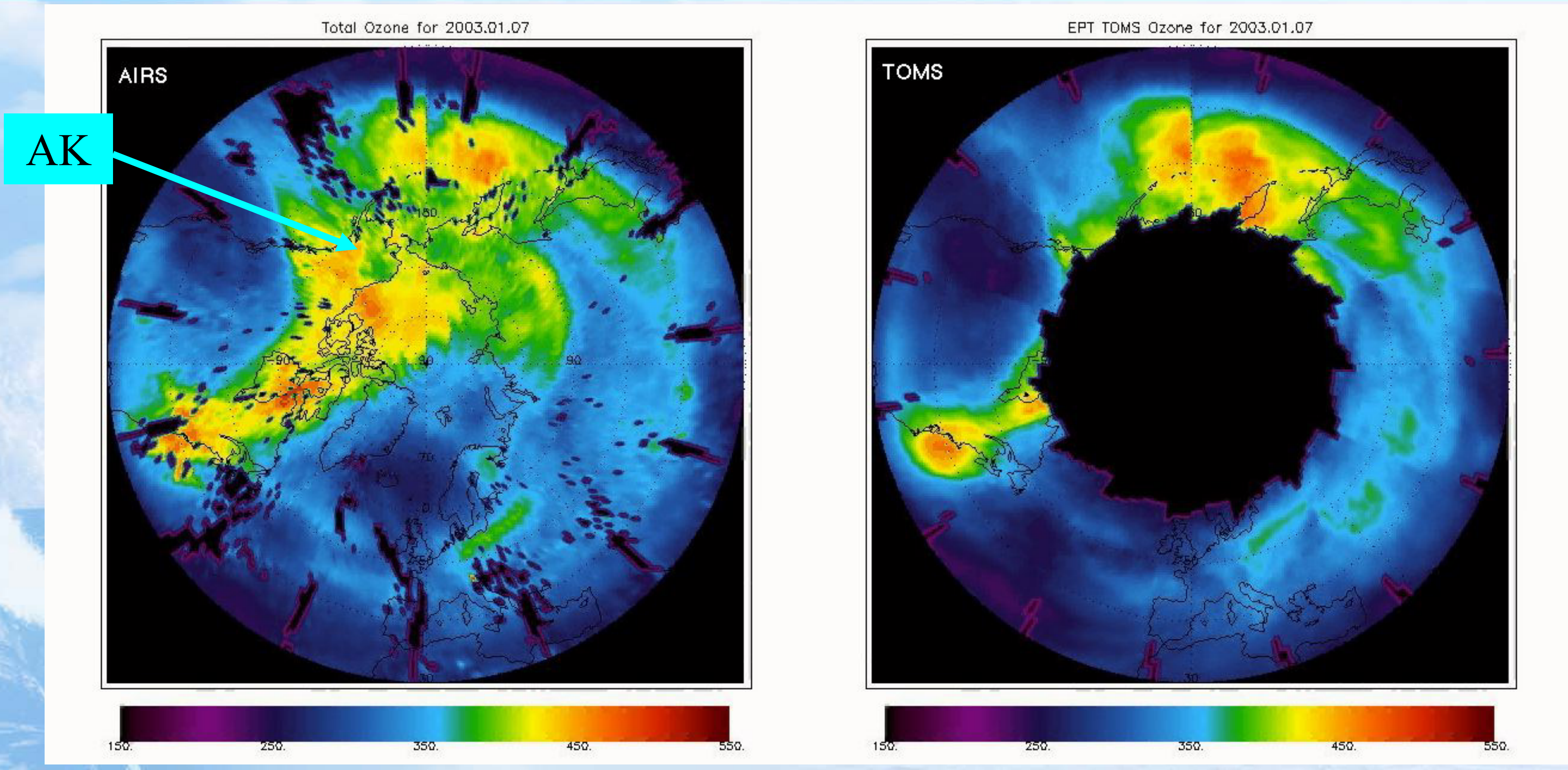
1. Convert relative humidity or mixing ratio to layer column density (LCD) in molecules/cm^2 in the layer.
   - Layers cannot overlap
2. Compute level to space column density
   - $CD(L) = \Sigma\, LCD(i),\ i \leq L$
3. If necessary, try to make the vertical function more linear by taking log's.
4. This is a monotonically increasing function that can be accurately interpolated.
5. Pick points that are layer boundaries of new pressure grid.
6. Take differences of new CD(L) (or log(CD(L))) to obtain new LCD's.
7. Convert new LCD's to mixing ratio's.





> You would think that all researchers could agree on an inter-comparison methodology – think again. This has been an embarrassing problem within the WAVE campaign.

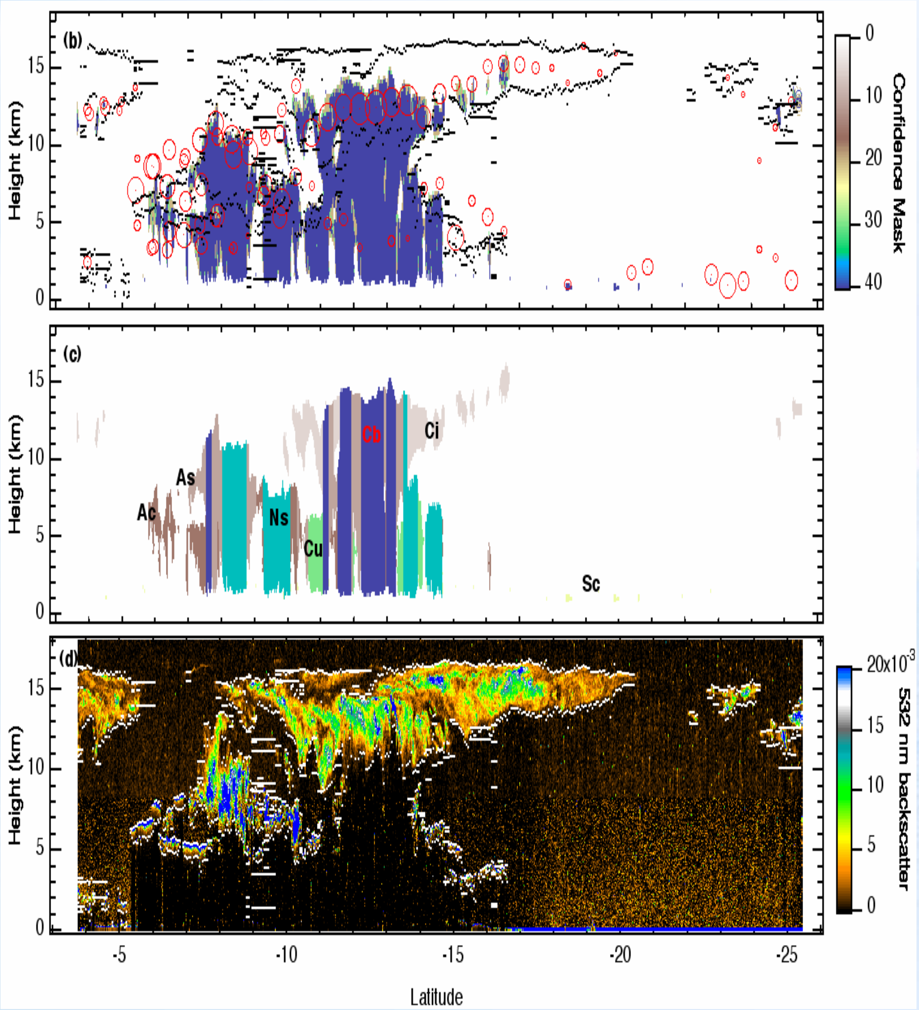
AIRS and TOMS Northern Polar Night
Mike Newchurch (UAH), Bill Irion (JPL)



Note: TOMS Ozone derived only when Sun is above horizon

Calipso/AIRS Intercomparisons

- Kahn et al. 2007 are comparing AIRS products (red circles) with cloud products derived from the recently launched Calipso & CloudSat
- Calipso/CALIOP is a 1064 nm & 532 nm LIDAR (0.3 km footprint, 30 m vertical resoluton).
- CloudSat is a microwave RADAR. 94 GHz (1.4 x 2.5 km product with 0.48 km vertical resolution).

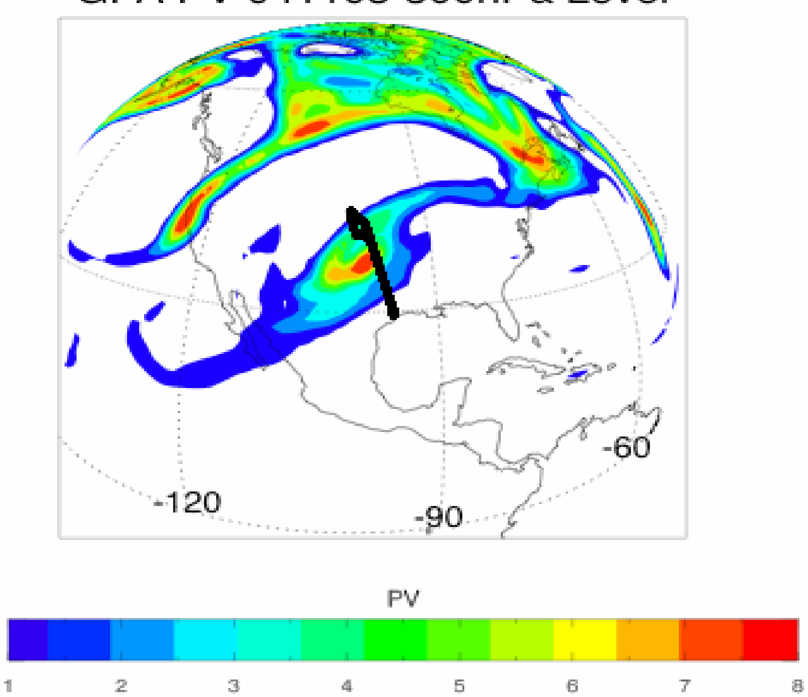


Stratospheric-Tropospheric Analysis of Regional Transport (START) Experiment

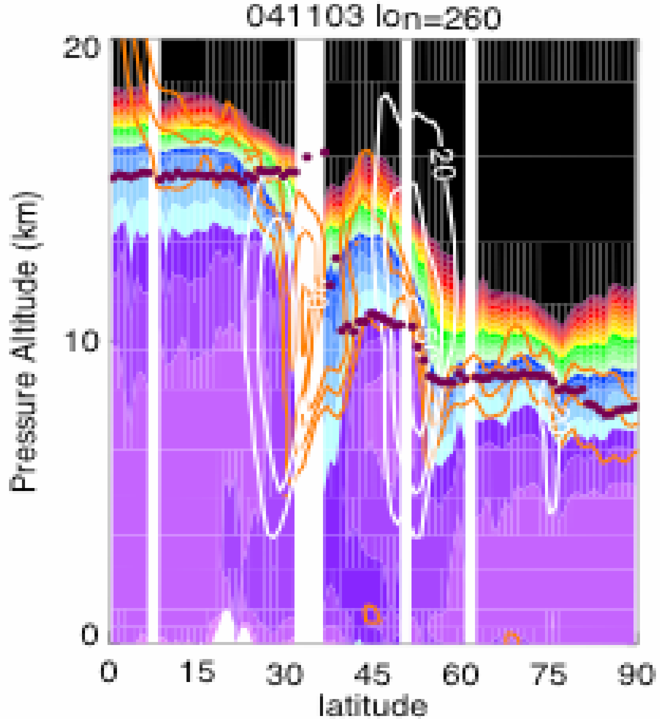
- Laura Pan is PI of START Ozone team
- Nov. 21 to Dec. 23, 2005, 48 flight hours using NCAR's new Gulfstream V "HAIPER" aircraft.
- Ozone measured with NCAR's UV-abs spectrometer

- NOAA NESDIS supported this experiment with real time AIRS L1b & L2 products, including ozone and carbon monoxide.
- Jennifer Wei is the NOAA/NESDIS liason to START team.
  - 3 stratospheric fold events were measured during this campaign
  - analysis is in process.

This is the day the Aura Validation Experiment (AVE) mission sampled a tropopause fold near Houston



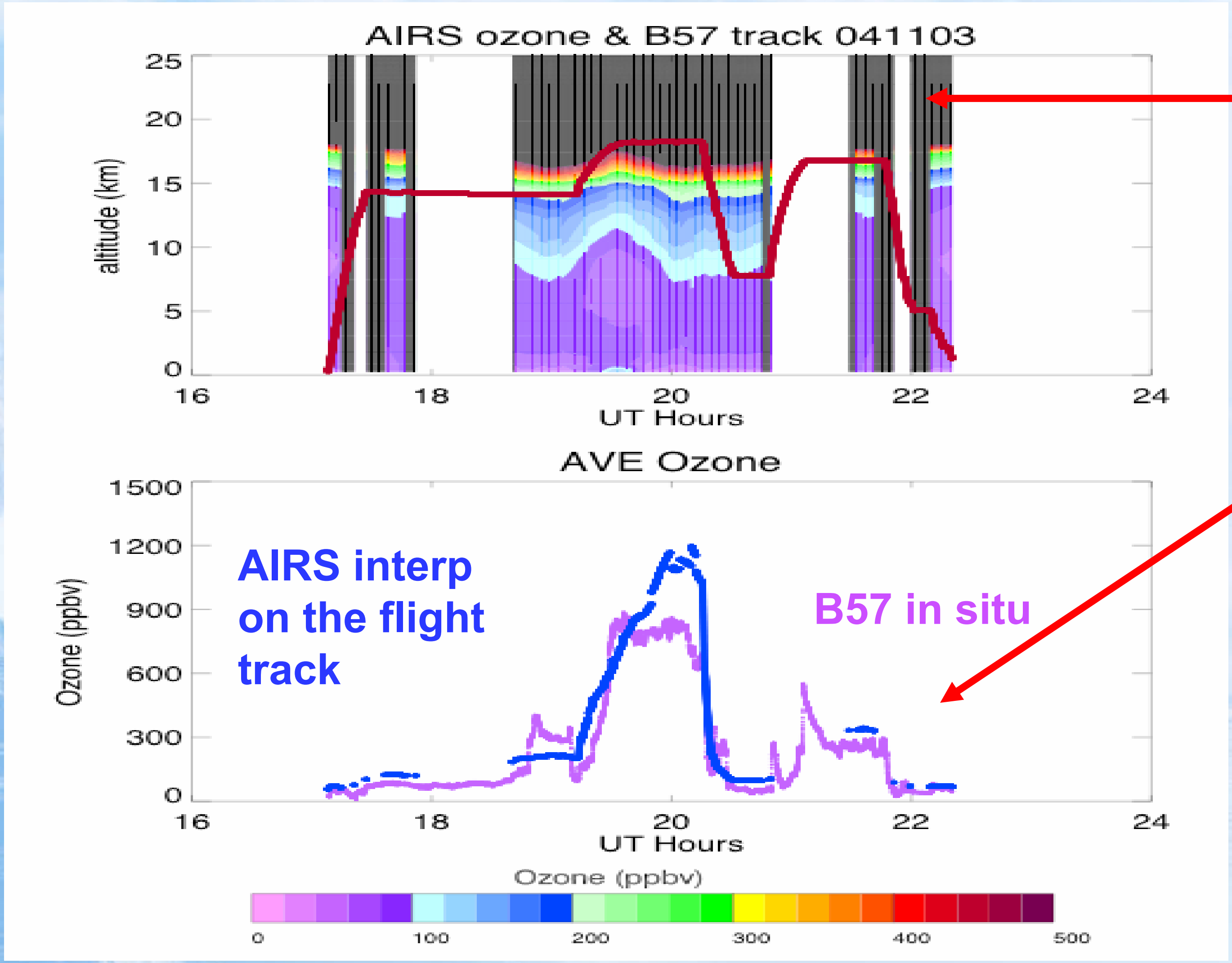
Black Line is Flight Track



Laura Pan, NCAR/ACD

Potential Vorticity (PV) is an important quantity for O3 dynamics

Example of Laura Pan's in-situ comparisons in dynamic regions (AVE campaign)



ignore the black columns - missing data

"Good agreement between AIRS and in situ between 50-500 ppb"

Movies

- WAVES_Launch_18July.avi
  - RS-92/Ozonesonde launch on July 18, 2006 from Beltsville MD.
- AIRS_AGU_video v2_720x480.mov
  - "Probably the best water vapor dataset available." Andrew Dessler
  - "The AIRS data is a key link in providing observations at pretty much unprecedented spatial and time scales over regions of the planet where we have never had observations of the planet before." Andrew Gettelman
  - "AIRS is really the first global satellite dataset that has a very high quality, both water vapor and ozone, in both data quality and spatial/temporal resolution that can contribute in tropopause regions." Laura Pan

Atmospheric Carbon Retrievals

1. Brief introduction to all AIRS/IASI trace gas products.
2. Show example of AIRS CO_2 product.

Trace Gas Product Potential from Operational Thermal Sounders

gas	Range (cm^{-1})	Precision	d.o.f.	Interfering Gases
H2O	**1200-1600**	**15%**	**4-6**	**T(p)**
O_3	**1025-1050**	**10%**	**1.25**	**H2O,emissivity**
CO	**2080-2200**	**15%**	**≈ 1**	**H2O,N2O**
CH_4	**1250-1370**	**1.5%**	**≈ 1**	**H2O,HNO3,N2O**
CO_2	**680-795 2375-2395**	**0.5% ?**	**≈ 1**	**H2O,O3**
Volcanic SO_2	**1340-1380**	**1000%**	**< 1**	**H2O,HNO3**
HNO_3	**860-920 1320-1330**	**50% ??**	**1.25**	**emissivity H2O,CH4,N2O**
N_2O	**1250-1315 2180-2250 2520-2600**	**5% ??**	**≈1**	**H2O H2O,CO**
$CFCl_3$ (F11)	**830-860**	**20%**	**-**	**emissivity**
CF_2Cl (F12)	**900-940**	**20%**	**-**	**emissivity**
CCl_4	**790-805**	**50%**	**-**	**emissivity**

Product Available @ NASA DAAC

Research Product Available at NOAA NESDIS

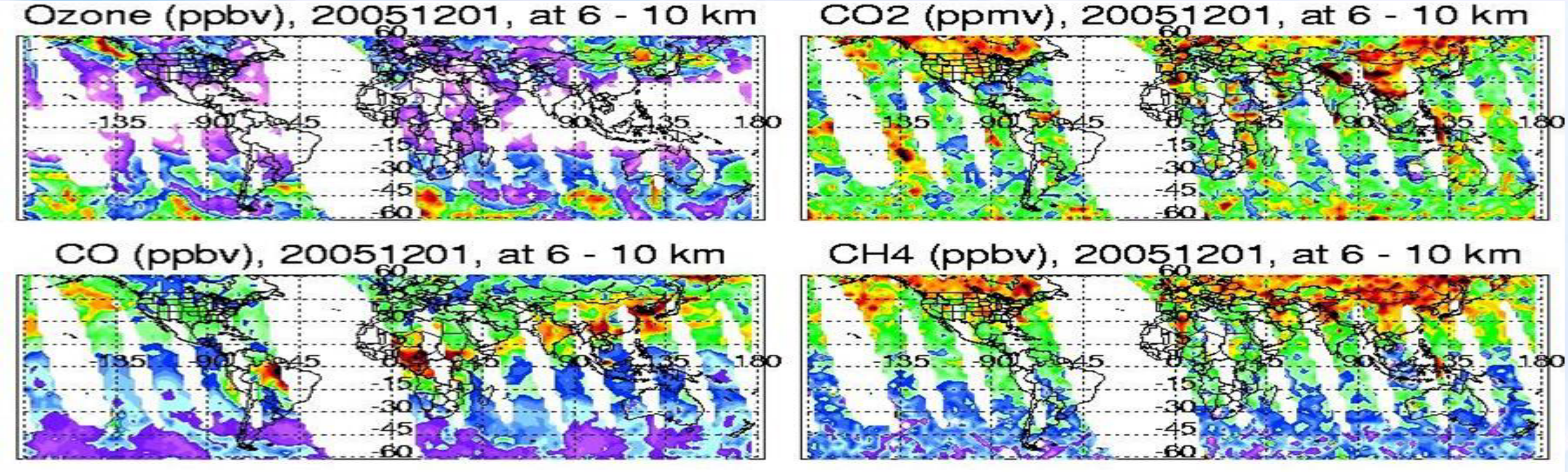
Held Fixed

Haskins, R.D. and L.D. Kaplan 1993

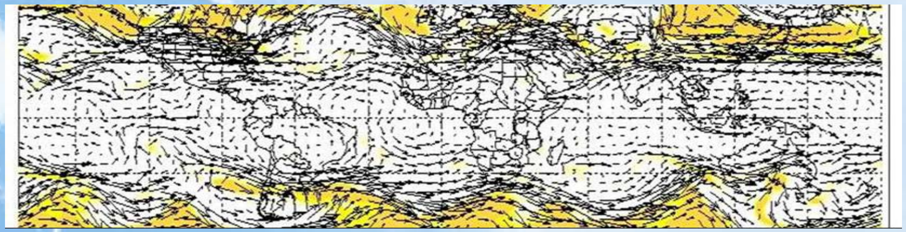
Retrieval of Atmospheric Trace Gases Requires Unprecedented Instrument Specifications

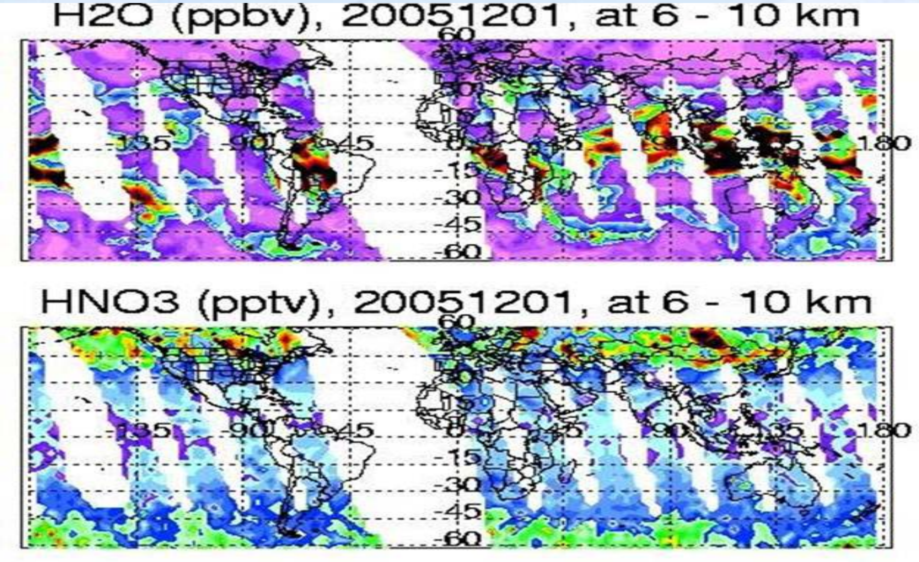
- **Need Large Spectral Coverage (multiple bands) & High Sampling (currently, we use 1680 AIRS and 14 AMSU channels in our algorithm)**
  - Increases the number of unique pieces of information
    - Ability to remove cloud and aerosol effects.
    - Allow simultaneous retrievals of T(p), q(p), O_3(p).
- **Need High Spectral Resolution & Spectral Purity**
  - Ability to isolate spectral features → vertical resolution
  - Ability to minimize sensitivity to interference signals..
- **Need Excellent Instrument Noise & Instrument Stability**
  - Low NEΔT is required.
  - Minimal systematic effects (scan angle polarization, day/night orbital effects, etc.)
- **Need accurate T(p) and q(p) determination (upstream algorithm must be accurate and stable).**

Example of Trace Gas Product Suite (Ascending Orbit, 1:30pm, Single Day)



NCEP PV/Wind 20051201_18 at 300 hPa



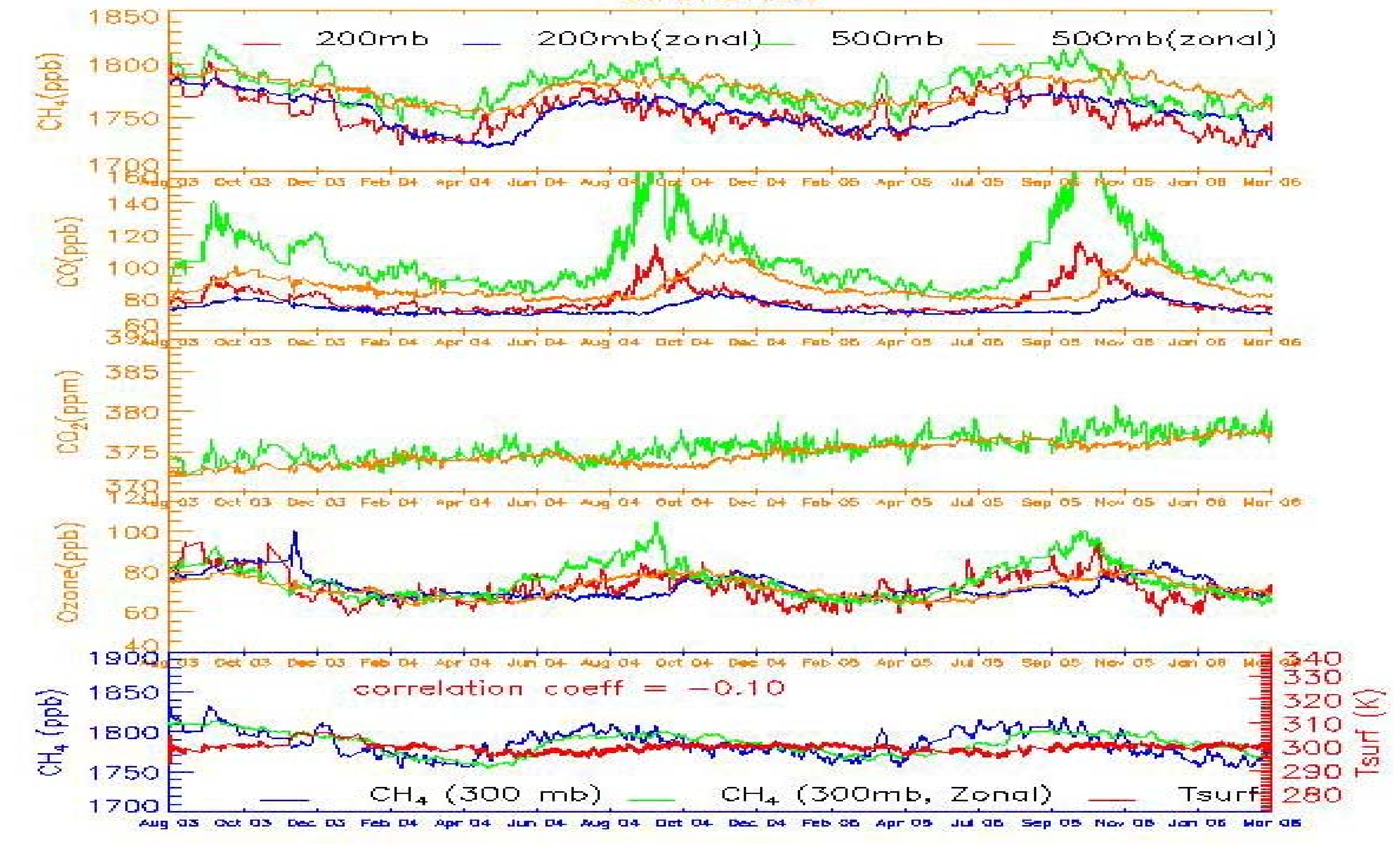


Stratospheric air masses (colored yellow in NCEP PV figure, where PVU ≥ 2) can be seen in AIRS upper tropospheric O3, CO, and HNO3 in the figures above. The H2O figure is scaled to show tropical convective features.

Utility of Trace Gas Correlations

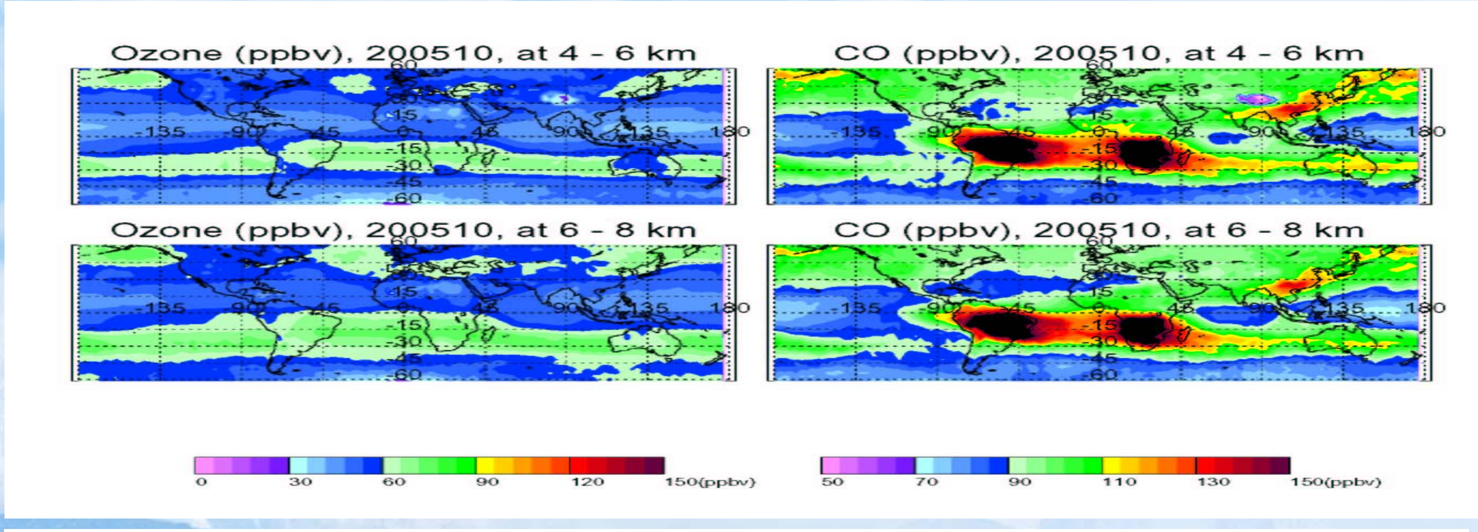
- To identify interesting dynamical regimes for scientific study.
  - Identify regions of atmospheric stratospheric/tropospheric exchange (STE)
  - Identify source regions of trace gases (*e.g.*, biomass burning, pollution).
  - Identify regions of interesting transport (*e.g.*, Brewer Dobson circulation of CH_4 and CO_2) or photochemistry (*e.g.*, O3 production from CO).
- A diagnostic tool to help improve satellite measurements of trace gases
    - Problems in specific situations (*e.g.*, deserts, topography, isothermal)
    - Improper spectral separation of gases (*e.g.*, HNO3/CH4)

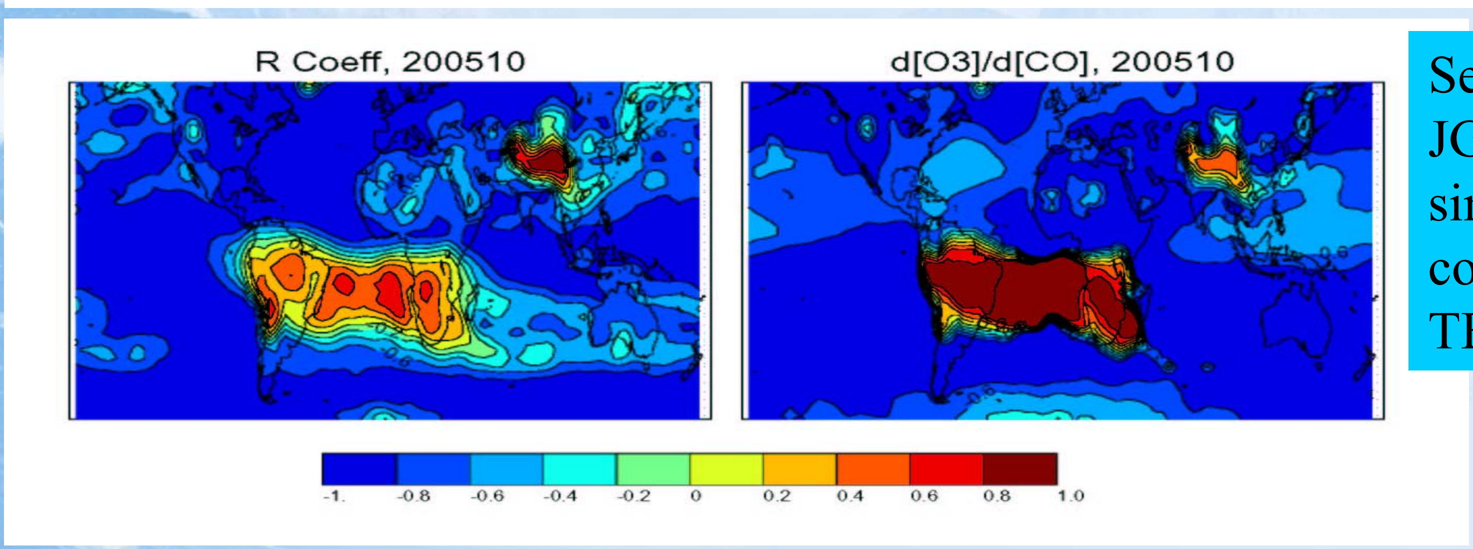
29 month time-series of AIRS products
South America Zone (-25 ≤ lat ≤ EQ , -70 ≤ lon ≤ -40)



AIRS operational products confirm tropospheric ozone production from biomass burning as seen by TES

Version 5.0 (w/o O_3 regression)

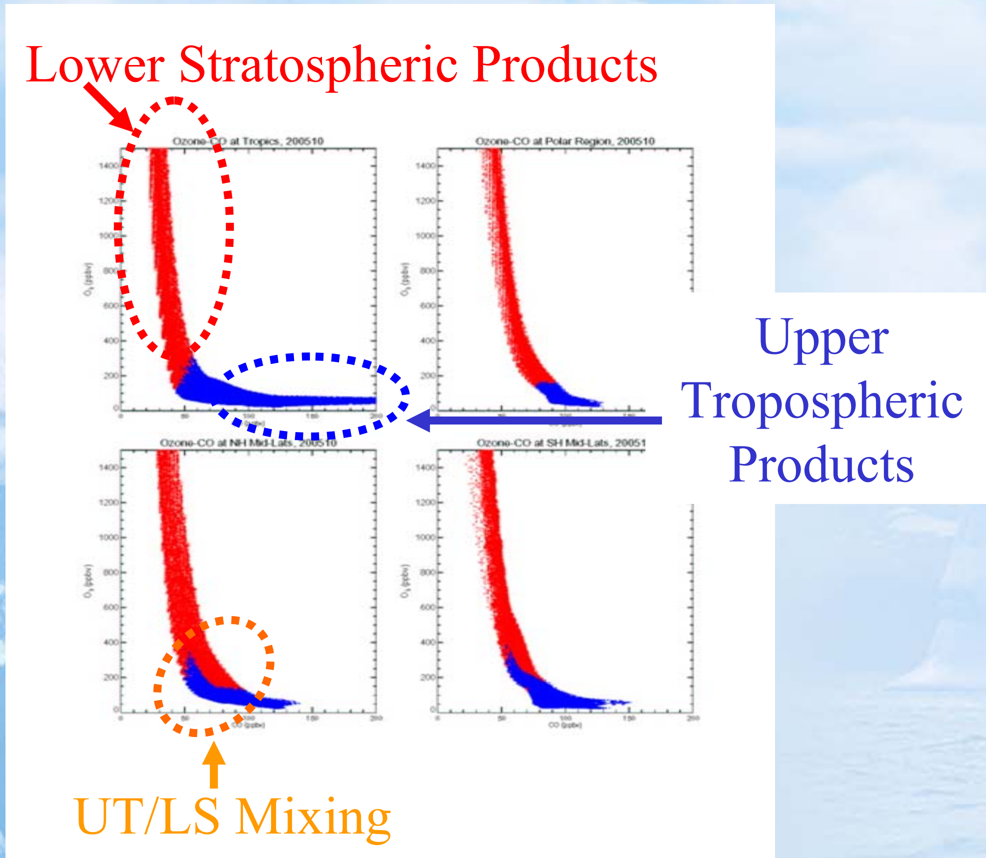




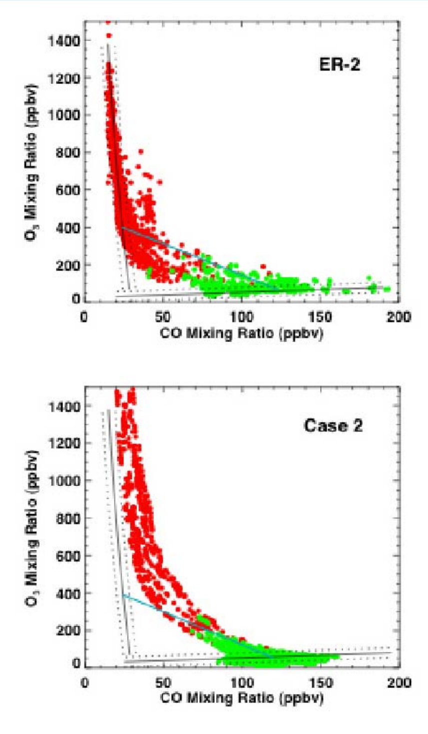
See Zhang et .al JGR 2007 for similar comparison using TES

Tracer-Tracer Correlations help define UT/LS Mixing

AIRS Retrievals



Expectation from aircraft obs and models



See L. Pan et al. JGR 2007 for details of methodology and utility in product characterization. Chemical discontinuity at tropopause caused by changes in thermal and dynamic fields (Brewer-Dobson circulation)

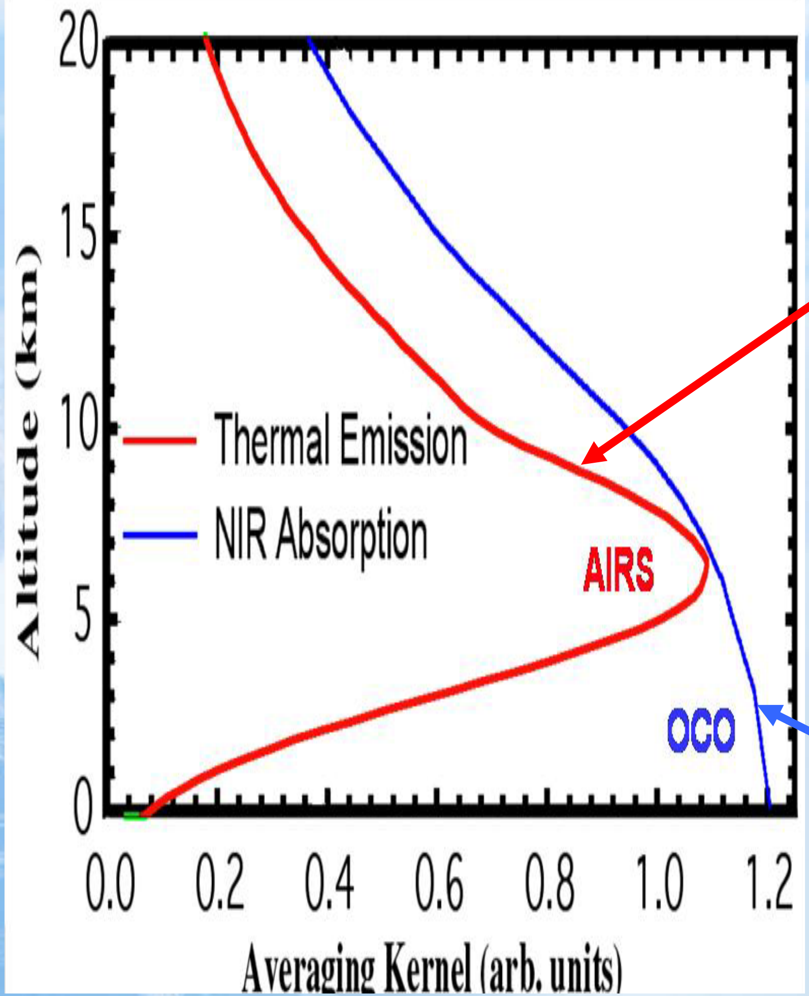
Motivation for Carbon Trace Gases

- Fossil fuel emissions are rapidly increasing the amount of atmospheric carbon dioxide (CO_2) that results in a increase in the energy of the atmosphere.
  - Understanding sources and sinks of atmospheric CO_2 and the transport and lifetime in the atmosphere is a critical component of understanding climate change.
- Atmospheric methane (CH_4) has a larger climate impact
  - Quantifying emissions from wetlands, agriculture, landfills, fires, etc. is important to understanding the atmospheric concentration.
  - Regulating methane emissions could mitigate a significant portion of the anthropogenic climate impact.
  - Rapid warming in polar regions has the potential of a large positive feedback due to melting of Pleistocene-age ices and rapid emissions of large amounts of CH_4
- Carbon monoxide (CO) and ozone (O_3) can help distinguish sources and of atmospheric carbon and characterize transport.

Comparison of Different Satellite Methods for Retrieval of CO2

	Passive-Thermal	Passive-Solar	Active
Source Function	Planck Function	Sun	LASER
Measures	Mid-trop column	Total Column	Total Column/Profile
Clouds	Correction via cloud clearing	Clear or Solve for Microphysics	Clear or Solve for Microphysics
Aerosols	Minimal impact to mid-trop.	Solve for aerosol microphysics	Measure independently.
Surface Issues	Very little sensitivity	Need reflectivity, ρ	Need reflectivity, ρ
Interference	Strong interaction with T(p), q(p)	Weak interaction with T(p), q(p)	Very weak interference
Data availability	20+ years, launch almost guaranteed	Research grade, 2-3 mission, no follow-on	Future missions
Main utility	Improve transport Upper boundary for OCO.	Reduce uncertainty of the carbon budget	Carbon budget

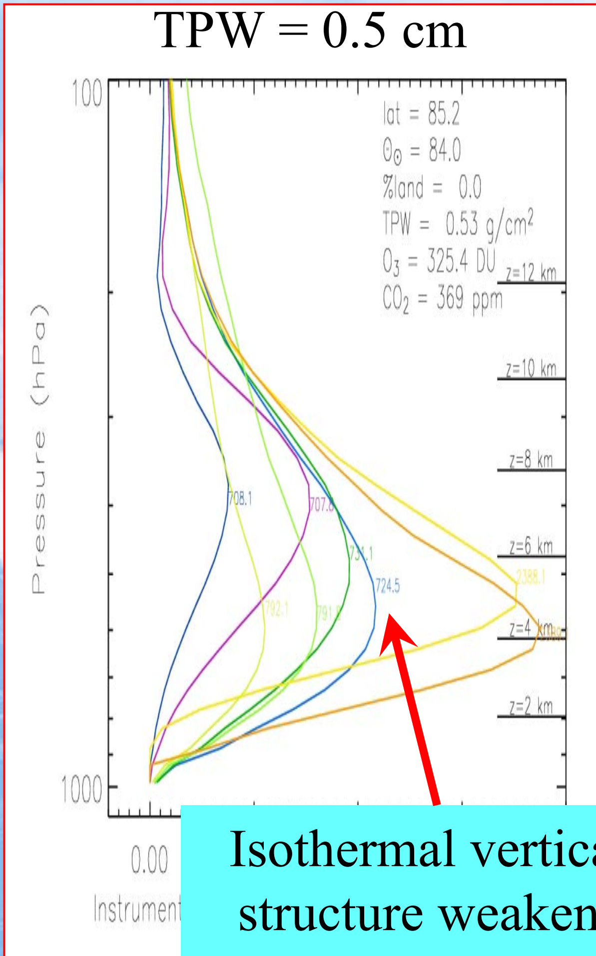
Utilization of thermal product requires knowledge of vertical averaging



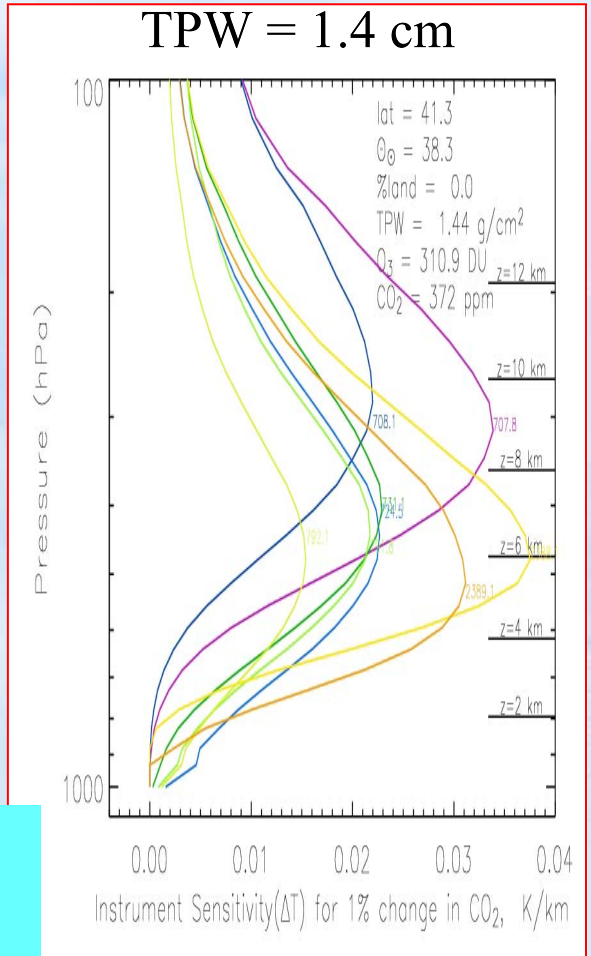
- Thermal instruments measure mid-tropospheric column
  - Peak of vertical weighting is a function of T profile and water profile and ozone profile.
  - Age of air is on the order of weeks or months.
  - Significant horizontal and vertical displacements of the trace gases from the sources and sinks.
- Solar/Passive instruments (*e.g.*, SCIA, OCO) & laser approaches measure a total column average.
  - Mixture of surface and near-surface atmospheric contribution
  - Age of air varies vertically.

LW Thermal CO_2 Kernel Functions are also Sensitive to H_2O, T(p), & O_3(p).

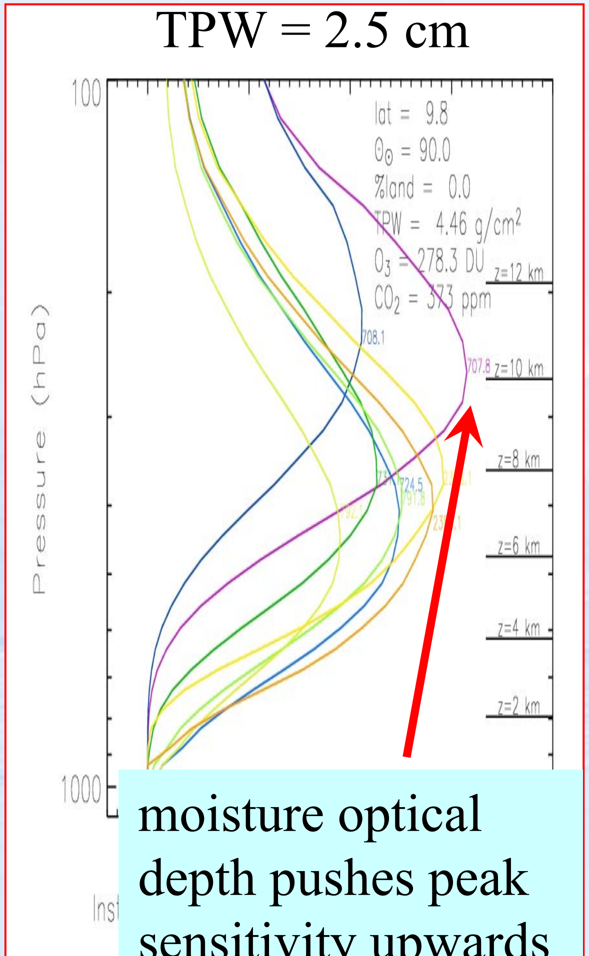
Polar



Mid-Latitude



Tropical



Isothermal vertical structure weakens sensitivity

moisture optical depth pushes peak sensitivity upwards

Why are CO_2 channel functions broad & all at the same altitude while T(p) functions have profile information?

- Spectroscopy: The CO2 lines are strong narrow lines. Temperature affects the width (and hence the channel transmittance) while # of CO2 molecules affects the strength. Once the line is saturated (near the surface, where p is large) we loose sensitivity.

$$\kappa_i(\nu, p, T, \theta) \simeq \sum_{j=1}^{J} \frac{N_i \cdot S_{ij}}{\pi} \frac{\gamma_{ij}}{(\nu - \nu_{ij})^2 + (\gamma_{ij})^2} \cdot \sec(\theta)$$

$$\gamma_{ij} \simeq \gamma_{ij}^0 \cdot \frac{p}{P_0} \cdot \sqrt{\frac{T}{T_0}}$$

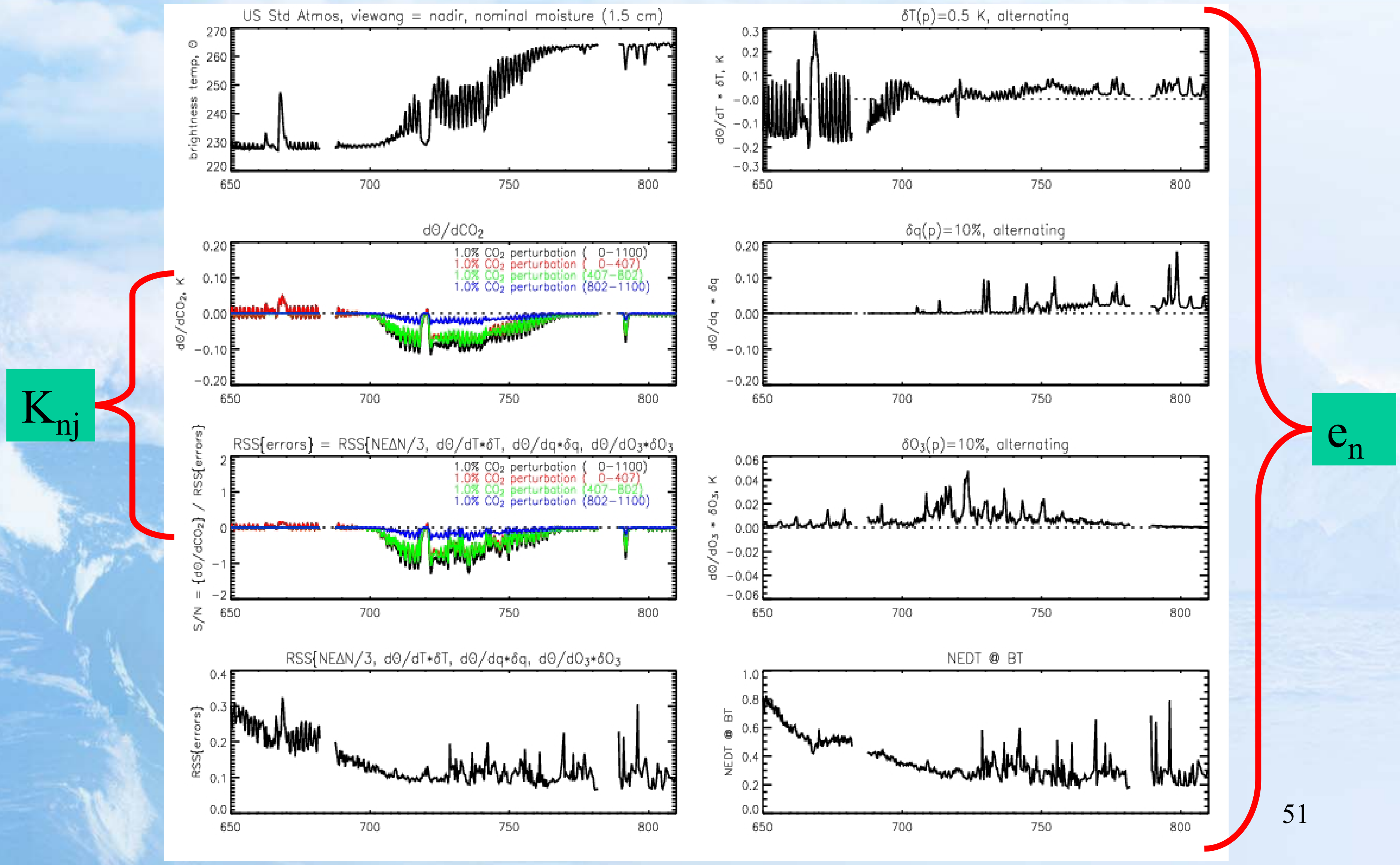
- Radiative transfer: The temperature enters both in the absorption coefficient and in the Planck function.

$$R_n(\vec{X}) \simeq \int_\nu \Phi_n(\nu) \int_p B_\nu(T(p)) \cdot \frac{\partial \exp\left(-\int_{z'=\infty}^{z(p)} \sum_i \kappa_i(\vec{X}, p, \ldots) dz'\right)}{\partial p} \cdot dp \cdot d\nu$$

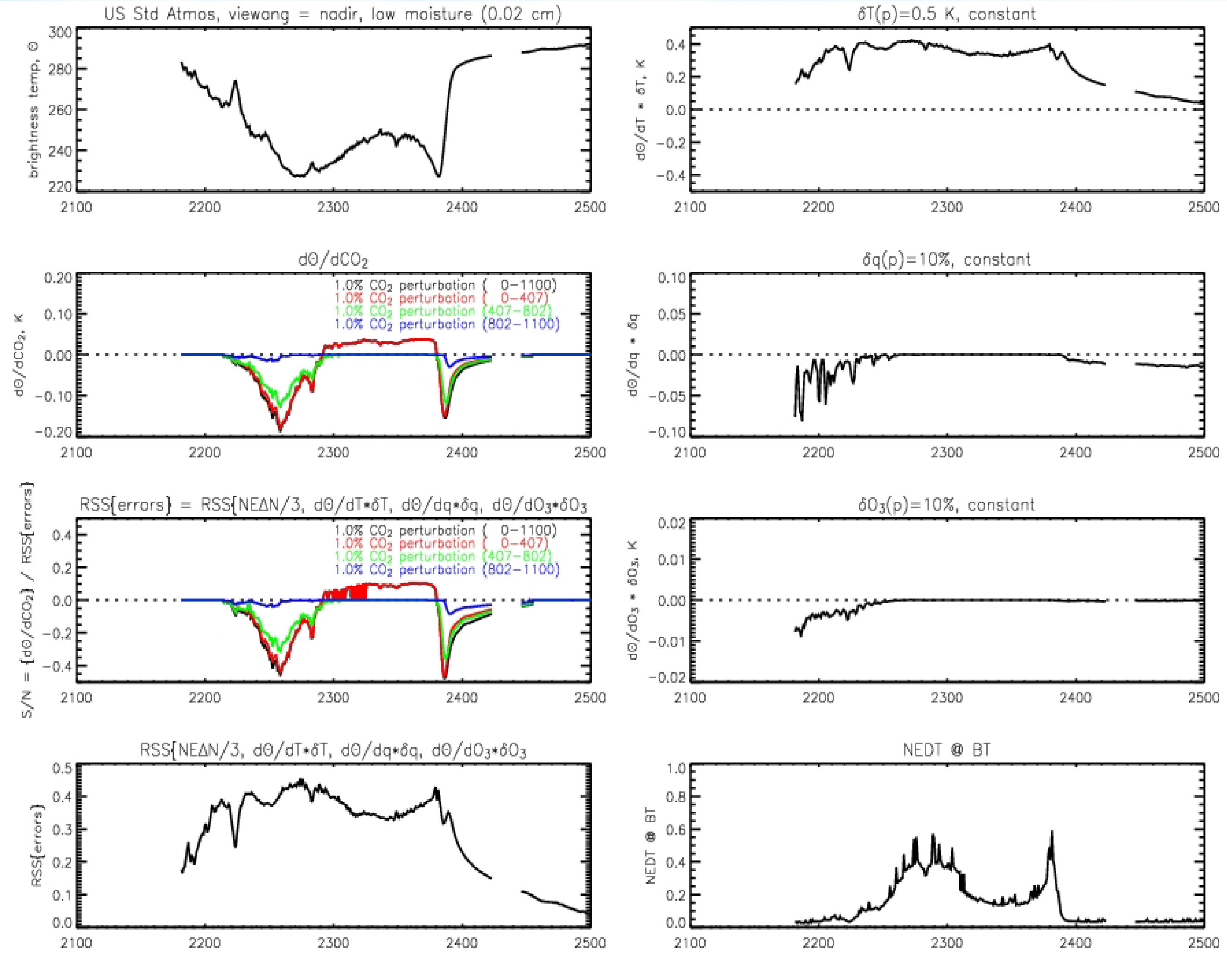
… And many groups are working on AIRS CO_2 algorithms

P.I.	Methodology	Type of Scenes	Temperature/CO2 Separation
Alain Chédin & Cyril Crevoisier	Neural Network	Clear	57 GHz O2 (Aqua/AMSU)
Richard Engelen	4DVAR	Clear	57 GHz O2 (all AMSU's) & radiosonde
Moustafa Chahine	Partial Vanishing Derivatives (unconstrained LSQ)	Clear & Cloudy	Multi-spectral (15 vs 4 μm) and 57 GHz (Aqua/AMSU)
Larrabee Strow	Unconstrained LSQ	Clear	T(p) = ECMWF
William Blackwell	Neural Network	Clear	T(p) = ECMWF
Chris Barnet	Regularized LSQ (optimal estimation)	Clear & Cloudy	Multi-spectral IR (15 & 4 μm) and 57 GHz (Aqua/AMSU)

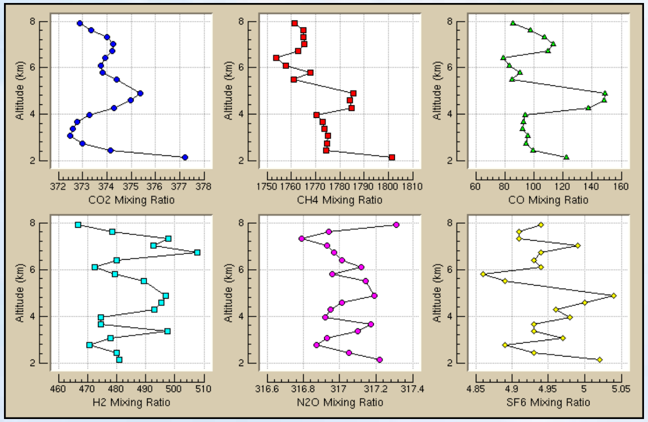
Sensitivity Analysis for CO_2 retrieval in 15 μm band



Sensitivity Analysis for CO2 retrieval in 4 μm band

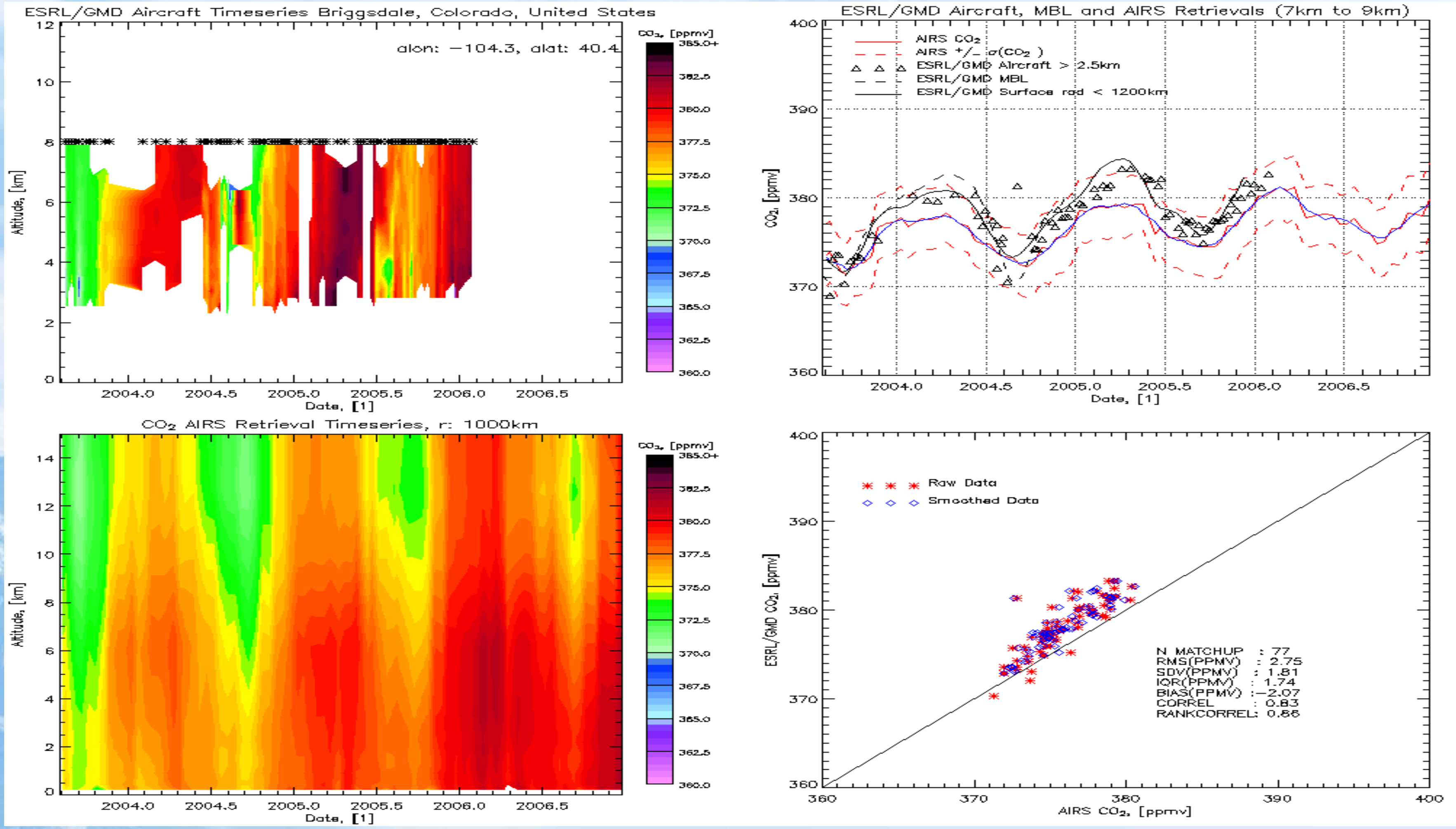


Comparisons to ESRL/GMD aircraft observations (Bakwin, JGR, 2003)

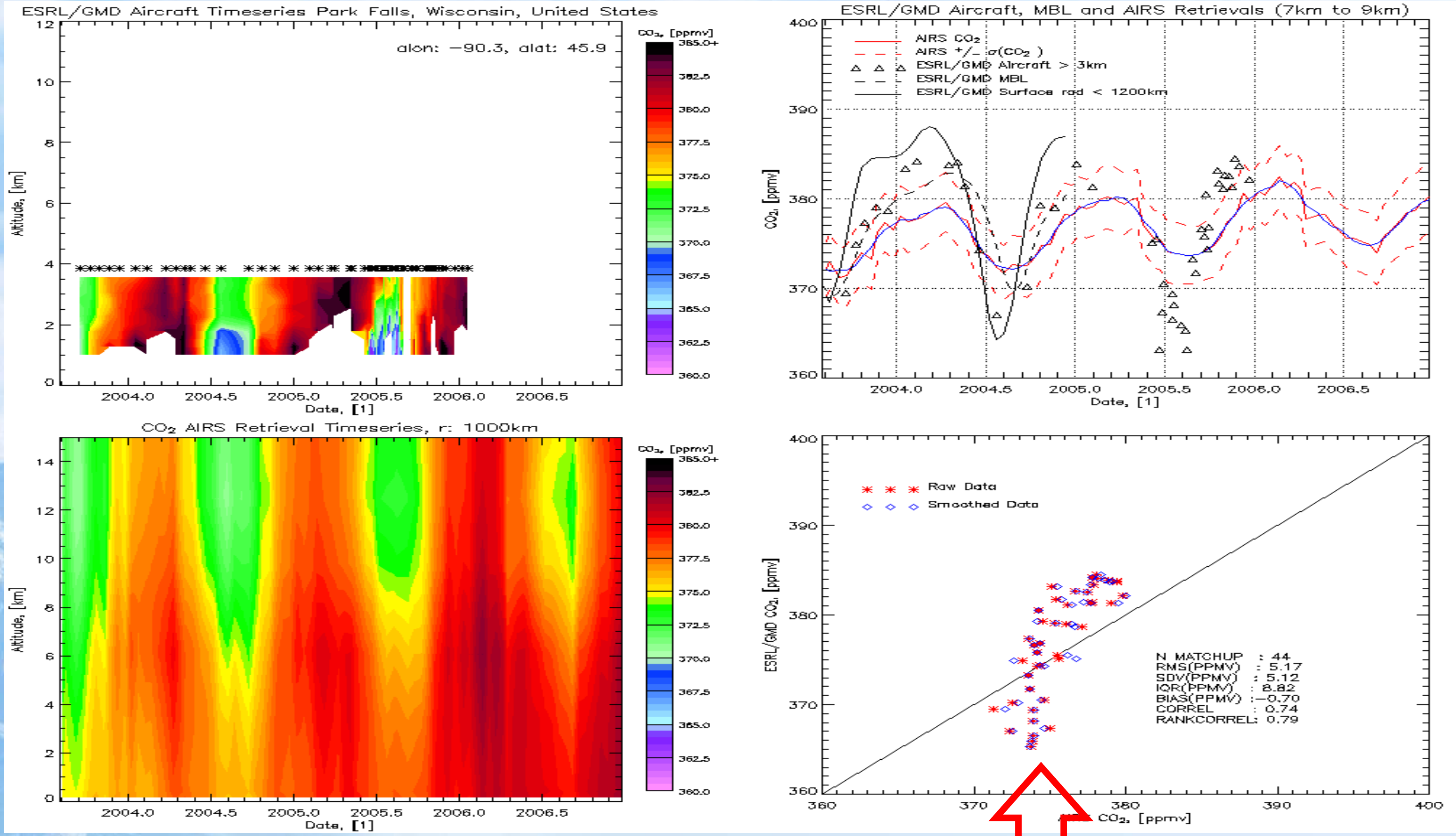


- Comparison of AIRS & ESRL/GMD flask observations..
  - Usually ≥ 5 hour time difference between aircraft and AIRS observations.
  - Aircraft altitude is typically ≤ 7 km.
  - Aircraft measures a small spatial region while it spirals downward.
- Aircraft measurement is vertically integrated to maximum flight height to emulate the thermal sounder measurement.
- Retrieval is spatially and temporally averaged of ≈ 50 “good” retrievals to achieve desired performance.

Comparison of NOAA CO_2 product with *in-situ* aircraft at Carr, CO



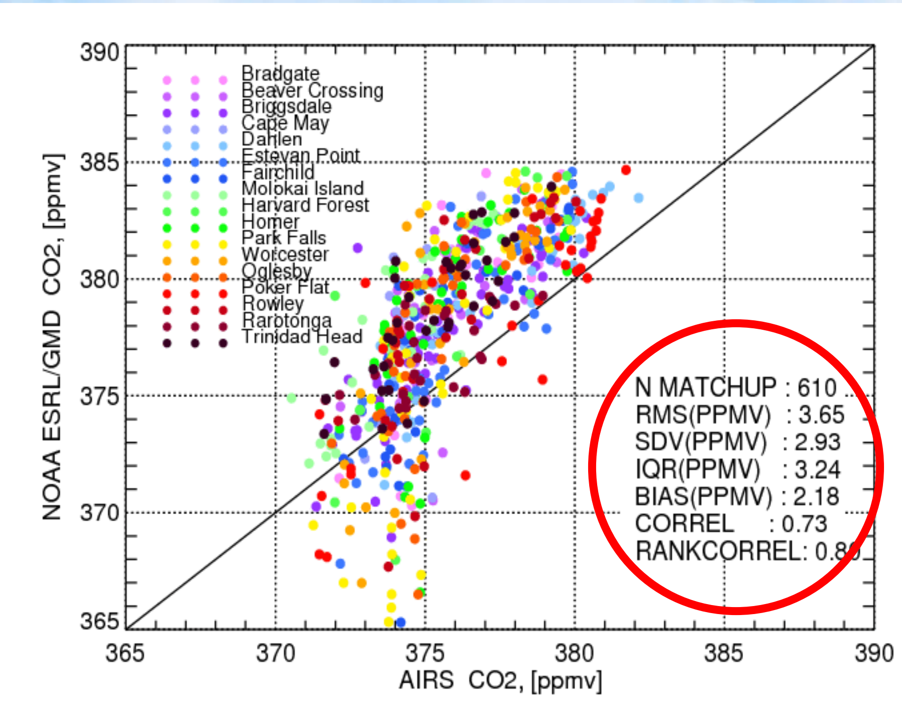
Comparison of NOAA CO_2 Product with *in-situ* Aircraft at Park Falls, WI



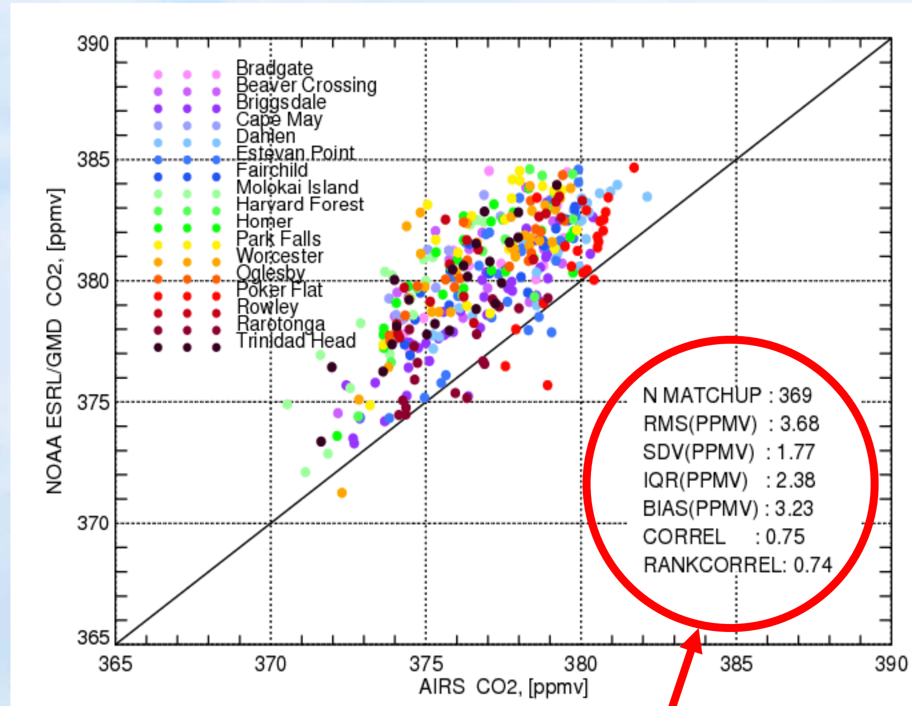
Example of problem in regions of CO2 drawdown

Comparison of NOAA CO2 with ALL ESRL *in-situ* Aircraft

All Observations



Excluding mid-summer cases



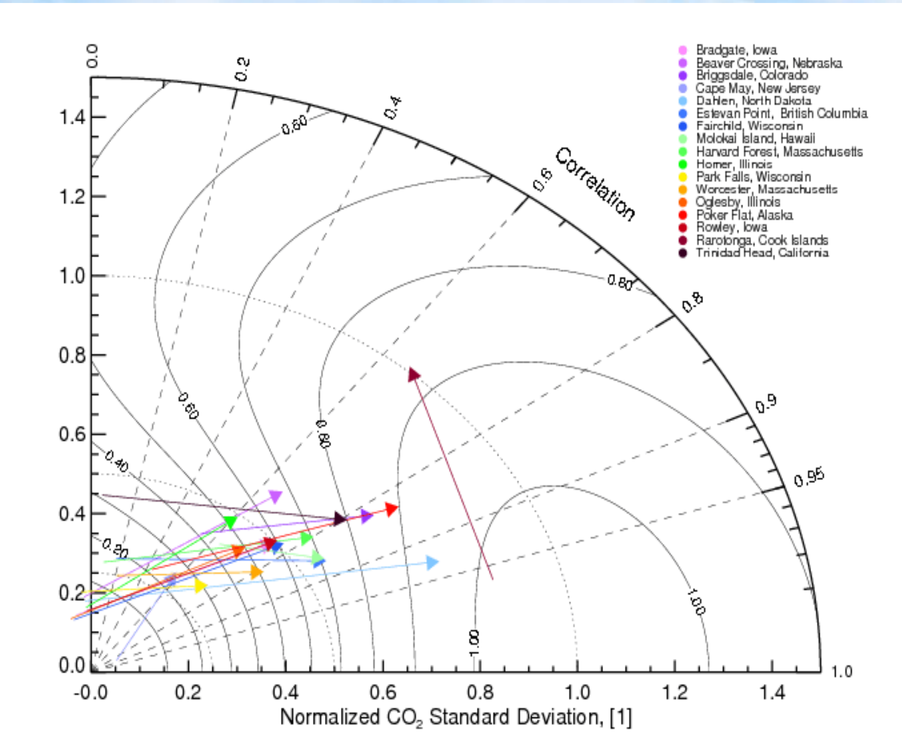
0.5% SDV from space!!

Low values of CO_2 are not seen in AIRS retrieval

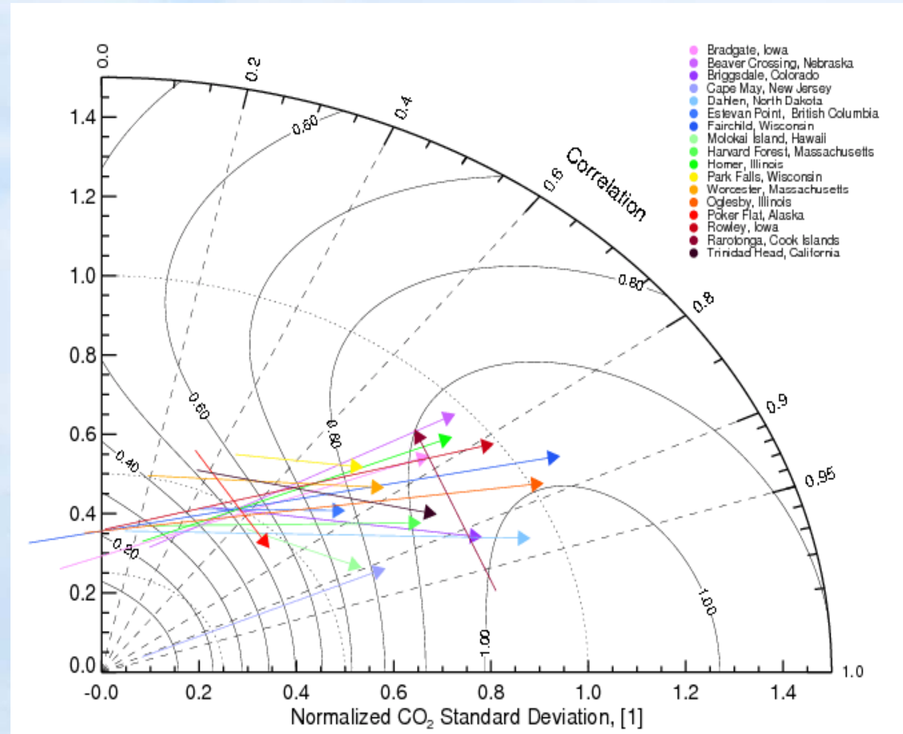
1. Aircraft samples a smaller volume (centered over forest) and, therefore, captures more of the photosynthetic drawdown
2. Difference in sampling time/diurnal effects (not likely).
3. Over-regularization

Taylor Diagrams (JGR 106, p.7183) illustrates skill in NOAA CO_2 product

All Observations



Excluding mid-summer cases



- Radius represents normalized standard deviation of AIRS product
- Angle is the correlation between AIRS product and *in-situ* aircraft
- Beginning of arrow is first guess, end of arrow is AIRS product
- Contours represent a “skill score” (Taylor Eqn. 14).

NOAA AIRS CO_2 Product is Still in Development

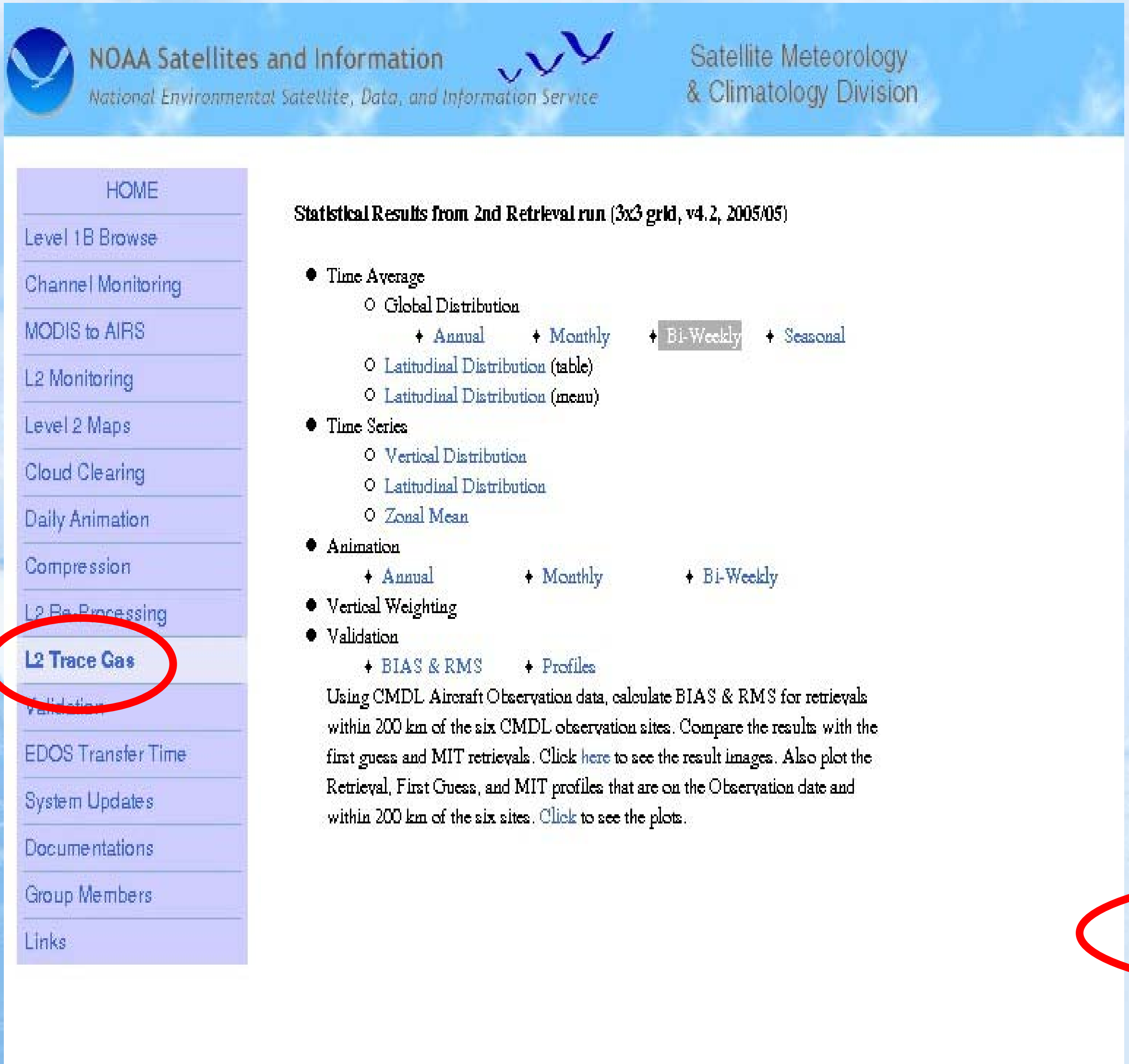
- Measuring a product to 0.5% is inherently difficult
  - Empirical bias correction (a.k.a. tuning) for AIRS is at the 1 K level and can affect the CO2 product.
  - Errors in moisture of ±10% is equivalent to ±0.7 ppmv errors in CO2.
  - Errors in surface pressure of ±5 mb induce ±1.8 ppmv errors in CO2.
  - AMSU side-lobe errors minimize the impact of the 57 GHZ O2 band as a T(p) reference point.
  - Bottom Line: ***Core product retrieval problems must be solved first***.
- Currently, we can characterize seasonal and latitudinal mid-tropospheric variability to test product reasonableness.
- The real questions is whether thermal sounders can contribute to the source/sink questions.
  - Requires accurate vertical & horizontal transport models
  - Having simultaneous O_3, CO, CH_4, and CO_2 products is a unique contribution that thermal sounders can make to improve the understanding of transport.

So maybe the utility of thermal sounders has yet to be exploited

- AIRS has produces the first global tropospheric measurement of CO_2 & CH_4.
- AIRS, IASI, and CrIS should provide a long-term dataset.
- AIRS has a unique capability to inter-compare tropospheric products of temperature, water, O_3, CO, CH_4, and CO_2.
- We expect to learn new things from this dataset.
- We are exploring diurnal signals and hope to identify large pollution or biosphere events over the lifetime of these instruments.
- We are exploring the use of trace gas correlations within the AIRS products as an analysis to help identify sources of trace gases.
- We want to work with transport modelers to compare our product to a realistic emission scenario for CO_2 with proper vertical weighing functions.
- Other ideas?

For more information:

http://www.orbit.nesdis.noaa.gov/smcd/spb/airs/index.html



Trace GAS web-pages allow a quick look at the trace gas products as a function of geography, time, and comparisons with *in-situ* datasets.

USERID & PASSWORD

Request via e-mail:

chris.barnet@noaa.gov

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