Post-launch Experiences with the AIRS Physical Retrieval Algorithm.

by

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Organizations That Have Contributed to AIRS

AIRS-AMSU-HSB

Atmospheric Infrared Sounder

Advanced Microwave Sounding Unit

Humidity Sounder for Brazil

Overview of This Talk

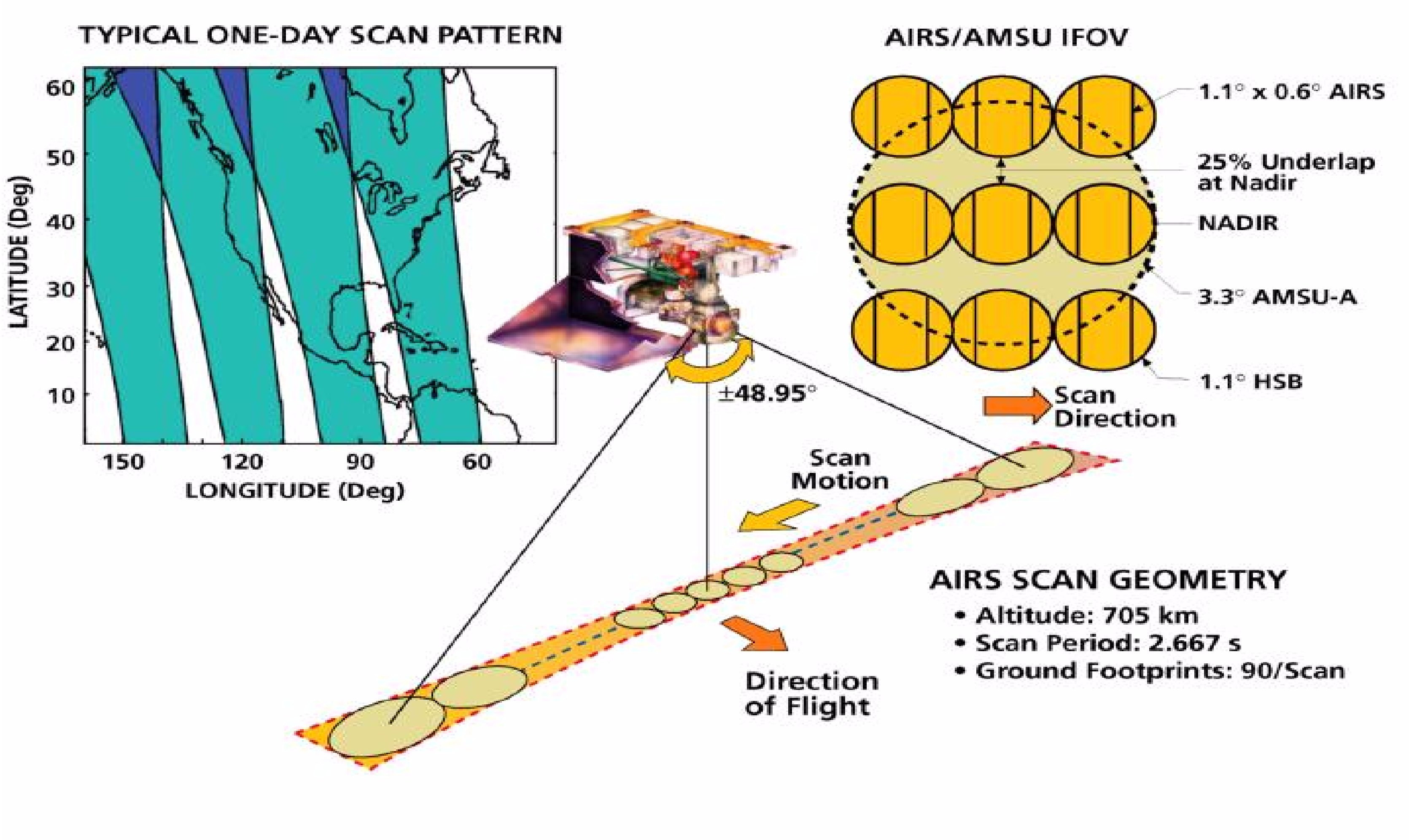
- **Brief Introduction to the AIRS, AMSU, HSB instruments**
- **Overview of the GSFC Algorithm**
  - **Cloud Clearing Philosophy in an Integral Component**
  - **Minimization Approach is Optimized for Cloud Clearing**
- **Post-launch issues**
  - **Microwave side-lobe corrections**
  - **Tuning versus Error Term Experiments**
- **Trace Gas Retrievals - The new frontier of remote sounding?**
- **Future Work**

Brief Introduction to the

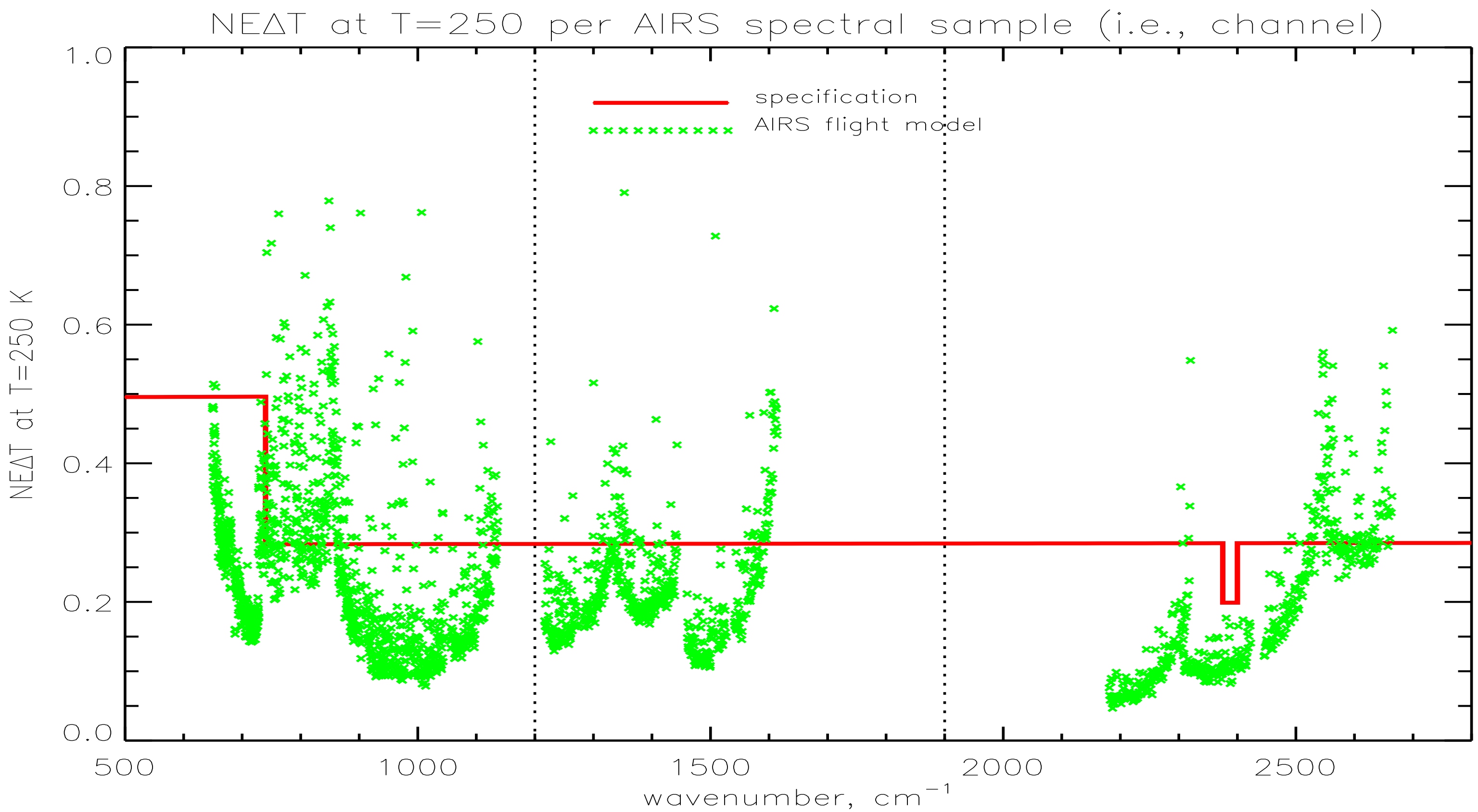
AIRS, AMSU, HSB Instruments

AQUA was Launched on May 4, 2002

Illustration of the AIRS/AMSU Field-of-Regard (FOR)



NEΔT at T_r=250 K for AIRS 1.1° FOV



All noise values are per AIRS spectral channel for a 250 K scene. 72% of the 2378 channels meet or exceed the specification.

Summary of Geophysical Products

$T(p)$	vertical temperature profile
$q(p)$	vertical water vapor profile ($\approx$ 8 g/kg @ surface)
$L(p)$	vertical liquid water profile (f/ AMSU/HSB)
$O_3(p)$	vertical ozone profile ($\approx$ 8 ppmv @ 6 mb)
T_s	surface temperature
$\epsilon(\nu)$	spectral surface emissivity, (*e.g.*, 0.95 @ 800 cm^{-1})
$\rho_\odot(\nu)$	spectral surface reflectivity of solar radiation
P_{cld}	cloud top pressure for $\leq$ 2 cloud levels
$\alpha_{\text{cld,fov}}$	cloud fraction for $\leq$ 2 cloud levels and 9 FOV's
CO_2	total column carbon dioxide ($\approx$ 363 ppmv)
$CH_4(p)$	methane profile ($\approx$ 1.65 ppmv)
$CO(p)$	carbon monoxide profile ($\approx$ 0.11 ppmv)

Ancillary Information Needed for Retrieval

P_s	surface pressure (f/ forecast)
θ	satellite zenith angle
$\theta_\odot$	solar zenith angle
$\epsilon_{\text{cld},\nu}$	spectral cloud emissivity for $\leq$ 2 cloud levels

Constraints on Algorithm Development

- **Weather Products must exist within 3 hours of data acquisition (including 1.5h orbit & down-link)**
  - **Execute quickly**
  - **Minimal ancillary information**

- **Climate Products should exist with 48 hours of data acquisition**
  - **Obtain "best" answer using all useful ancillary information**
  - **Minimize first guess dependence (*i.e.*, minimal *a-priori* information)**
  - **Minimize changes in methodology to avoid discontinuities in record (*i.e*, minimize "training" files).**
  - **Usually implies reprocessing of data.**

Overview of AIRS

Cloud Clearing Methodology

Cloud Clearing Methodology

This cloud clearing methodology has a long heritage starting from the original papers (Smith, 1968, Chahine, 1974), Chahine, 1975, Chahine, 1977, Chahine *et al.* **1977, McMillin and Dean 1982, Smith** *et al.* **1992, and work performed at GSFC (Susskind,** *et al.* **2003; Joiner and Rokker 2002, Susskind,** *et al.* **1998). The fundamental features of the AIRS cloud clearing algorithm are**

- **Use the 9 AIRS cloud scenes without any** *a-priori* **constraint such as preferential grouping.**
- **Compute both CCR's and** error estimates **for the CCR's, specifically taking into account the noise amplification induced by the linear extrapolation and the spectrally correlated component of the error.**
- **Compare the clear state estimate with the AIRS retrieval products and reject cases that violate any of the assumptions of cloud clearing.**

Example of Cloud Clearing in 2 FOV's

For two FOV's and one cloud *formation* the cloudy radiances, $\boldsymbol{R_i(n)}$, in the two FOV's can be written in terms of an effective cloud fraction, $\boldsymbol{\alpha}$, in each FOV.

$$\begin{aligned} \boldsymbol{R_1(n)} &= \boldsymbol{(1-\alpha_1)\cdot R_{clr}(n)+\alpha_1\cdot R_{cld}(n)} \qquad (1.1) \\ \boldsymbol{R_2(n)} &= \boldsymbol{(1-\alpha_2)\cdot R_{clr}(n)+\alpha_2\cdot R_{cld}(n)} \qquad (1.2) \end{aligned}$$

Using a clear radiance estimate, $\boldsymbol{R_{est}\simeq R_{clr}}$, an extrapolation parameter, $\boldsymbol{\eta}$, can be determined by least squares (LSQ) fitting

$$\boldsymbol{R_{est}(n)=R_1(n)+\eta\cdot(R_1(n)-R_2(n))} \qquad (1.3)$$

The parameter $\boldsymbol{\eta}$ can also be solved for directly from the cloud fractions by substituting Eqn.1.1 & 1.2 into Eqn. 1.3

$$\boldsymbol{\eta=\frac{\alpha_1}{\alpha_2-\alpha_1}} \qquad (1.4)$$

Real Cloud Formations Are More Complex

In general, the use of the effective cloud fraction, α, to determine the value of η is problematic.

- **Cloud optical depth is a strong function of wavenumber.**
- **If cloud fractions are taken from a different instrument (*e.g.*, AIRS visible channels), the instrument FOV, time, location of observation, and spectral characteristics are all significant factors.**
- **For multiple cloud formations the problem is ill-posed.**

Instead we use a "CO_2 slicing" approach:

- **Use many AIRS channels with weighting functions spanning the troposphere.**
- **Use all nine cloudy FOV's to determine # of cloud types.**
- **Solve for a minimum number of η's.**

Example of the Transformation of FOV's

For example, imagine a set of 9 FOV's where the first five are nearly clear and the last four are almost 100% cloudy. We can transform these FOV's and solve for a single parameter, which we will call $\boldsymbol{\zeta}$.

$$\hat{\boldsymbol{R}}_k(\boldsymbol{n}) = \boldsymbol{U}_{k,i} \cdot \boldsymbol{R}_i(\boldsymbol{n}) \tag{1.5}$$

$$\boldsymbol{U}_{k,i} = \begin{pmatrix} \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & \frac{1}{5} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix} \tag{1.6}$$

$$\boldsymbol{R}_{clr}(\boldsymbol{n}) = \boldsymbol{U}_{1,i} \cdot \boldsymbol{R}_i(\boldsymbol{n}) + \hat{\boldsymbol{\zeta}}_1 \cdot (\boldsymbol{U}_{1,i} \cdot \boldsymbol{R}_i(\boldsymbol{n}) - \boldsymbol{U}_{2,i} \cdot \boldsymbol{R}_i(\boldsymbol{n})) \tag{1.7}$$

The $\boldsymbol{\zeta}$'s can be transformed to the traditional $\boldsymbol{\eta}$ parameters

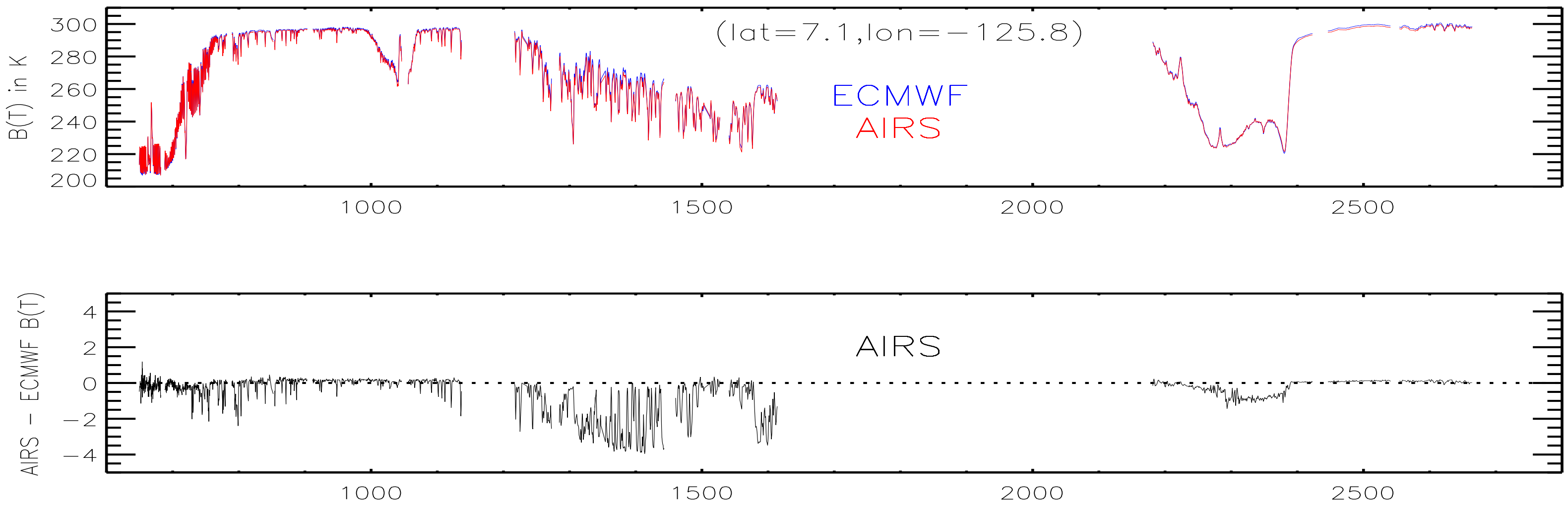
$$\boldsymbol{\eta}_i \equiv \boldsymbol{U}^T_{i,k} \cdot \boldsymbol{\zeta}_k \tag{1.8}$$

Transformation of FOV's

In the operational AIRS code the transformation matrix, $\boldsymbol{U_{k,i}}$ is determined by singular value decomposition of the cloudy radiances using 78 AIRS channels in the 15 μm and 4.3 μm bands that span the troposphere. We have shown (Susskind et al. 2003) that the transformed formulation has other advantages as well.

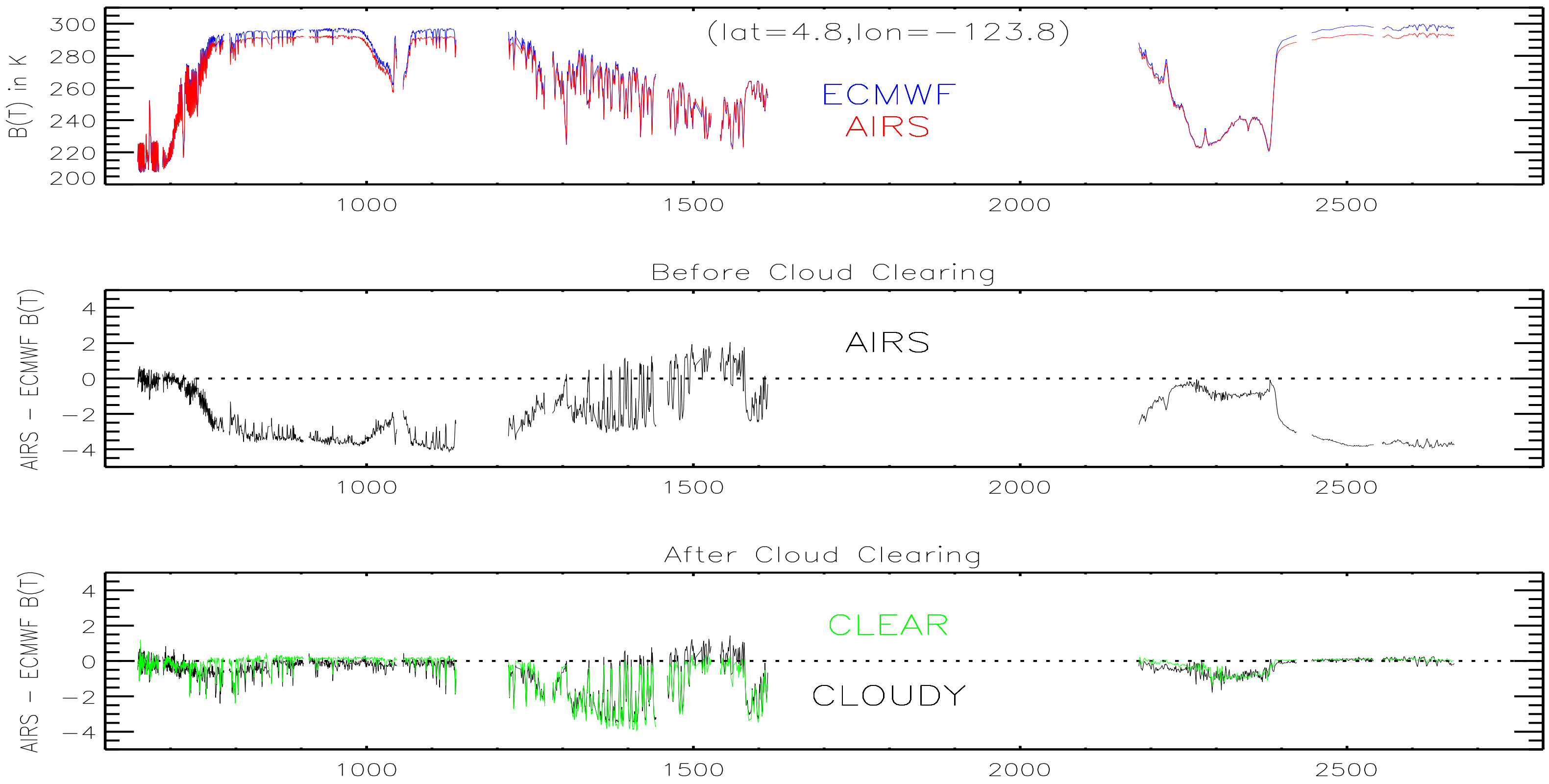
- The number of cloud formations can be determined.
- We solve for up to 4 ζ's, $\boldsymbol{R_{est}(n) = \overline{R}(n) + \zeta_k \cdot (\overline{R}(n) - U_{k,i} \cdot R_i(n))}$
- Estimate of the complexity of cloud formations.
- Compute an error estimate for CCR's consisting of
  - A noise amplification factor
  - A error covariance which includes as strong case dependent spectral correlation component from the errors in ζ.
- Cloud clearing step is repeated as geophysical knowledge and, therefore, the clear estimate is improved during retrieval steps.

Example AIRS CLEAR Scene



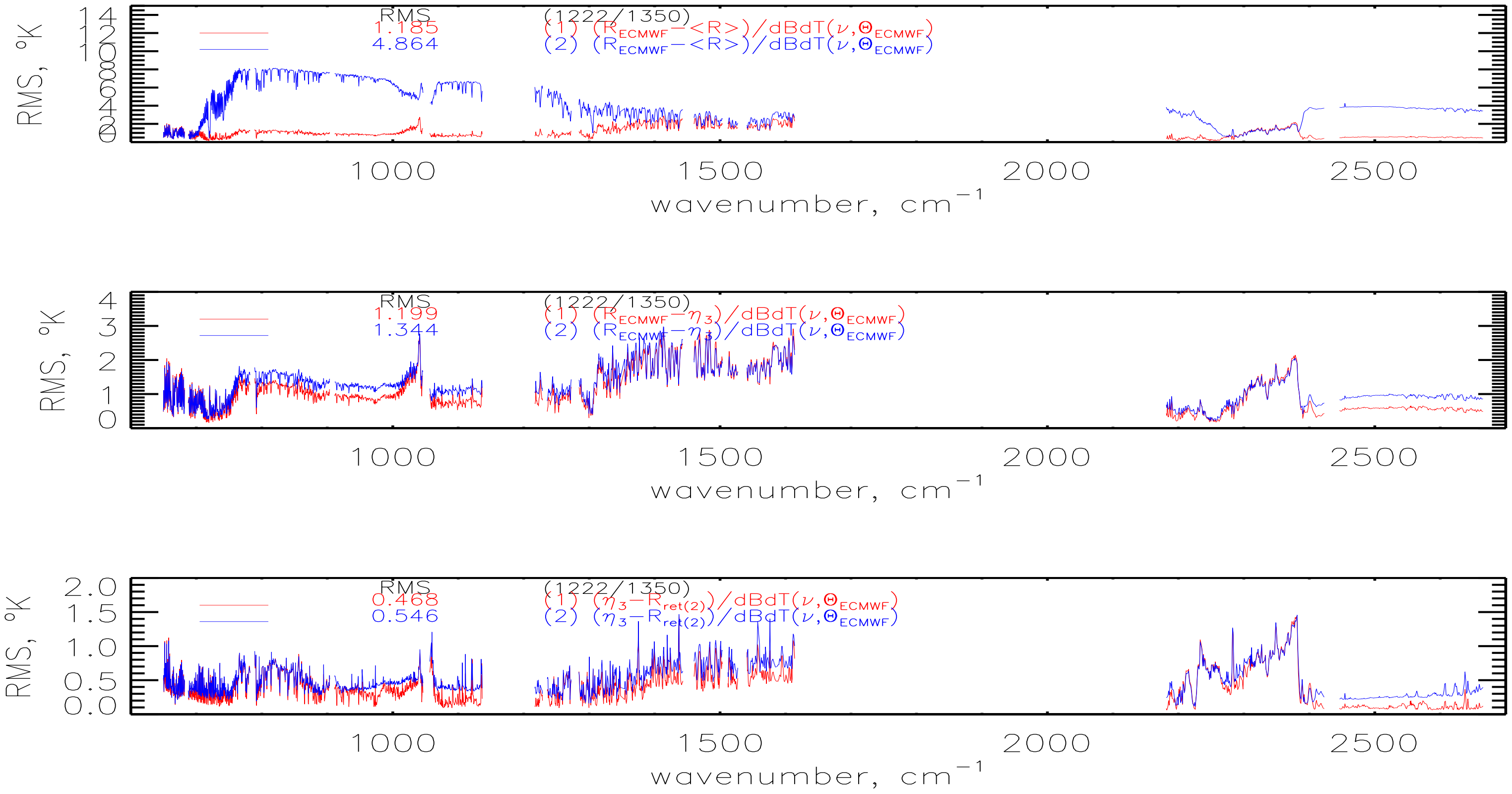
An example of a clear AIRS measurement made in the Pacific Ocean on Sep. 6, 2003 (Granule 100, AMSU Scan #28 FOV #14). The upper panel shows the average of nine AIRS FOV's (RED) and brightness temperature computed from the ECMWF analysis (BLUE). The lower panel shows the difference. Agreement in window regions indicates there are NO clouds. Other differences are probably meteorological.

Example AIRS Cloud Cleared Scene



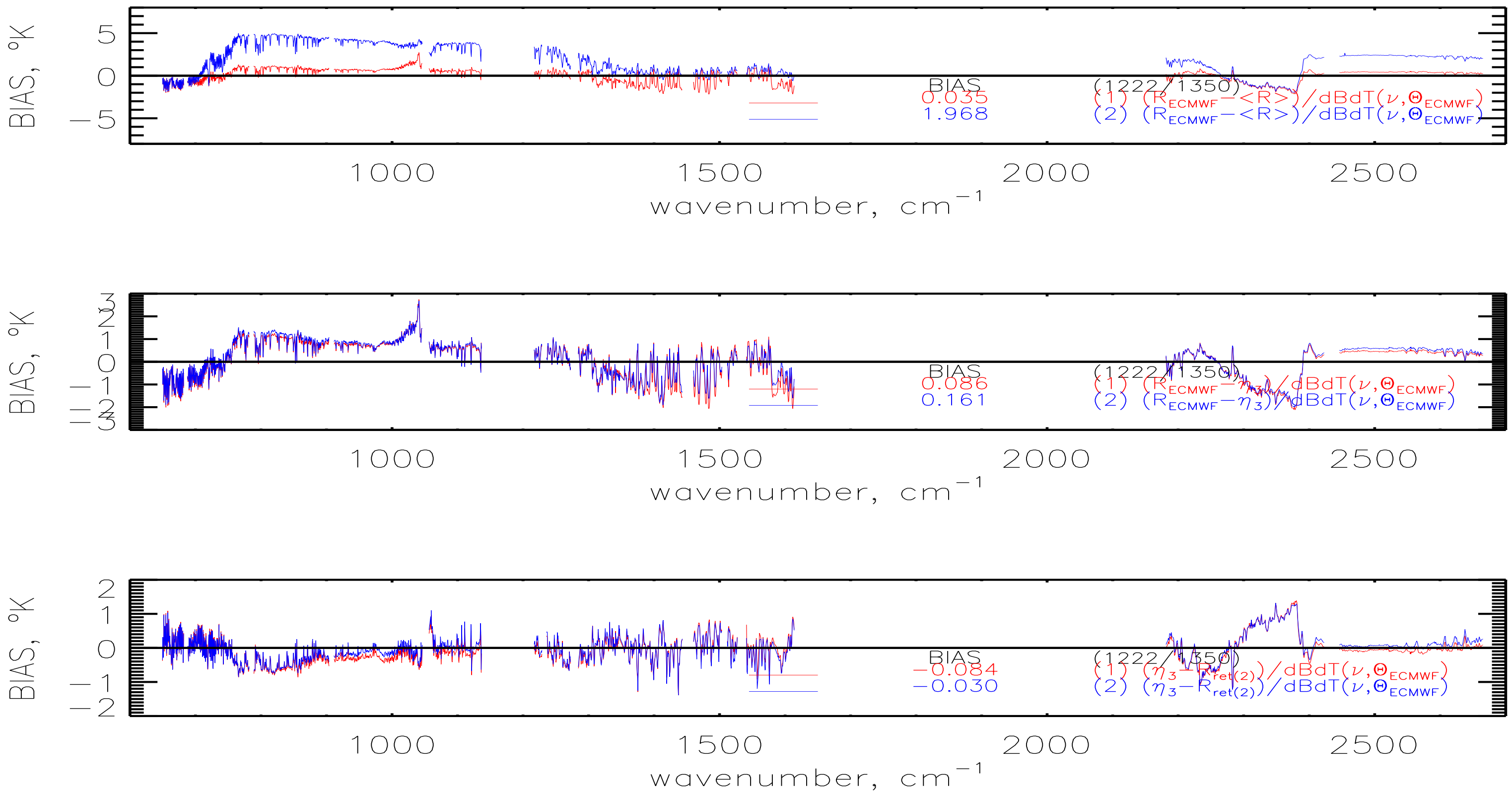
An example of a scene 330 km away with about 30% cloudiness (9/6/02 AMSU Scan #32, FOV #8). The top two panels are the same as the previuous figure. The lower panel shows the AIRS cloud cleared product (BLACK) has same agreement as clear scene (GREEN).

Cloud Clearing Radiance (CCR) RMS Statistic, 1 Granule



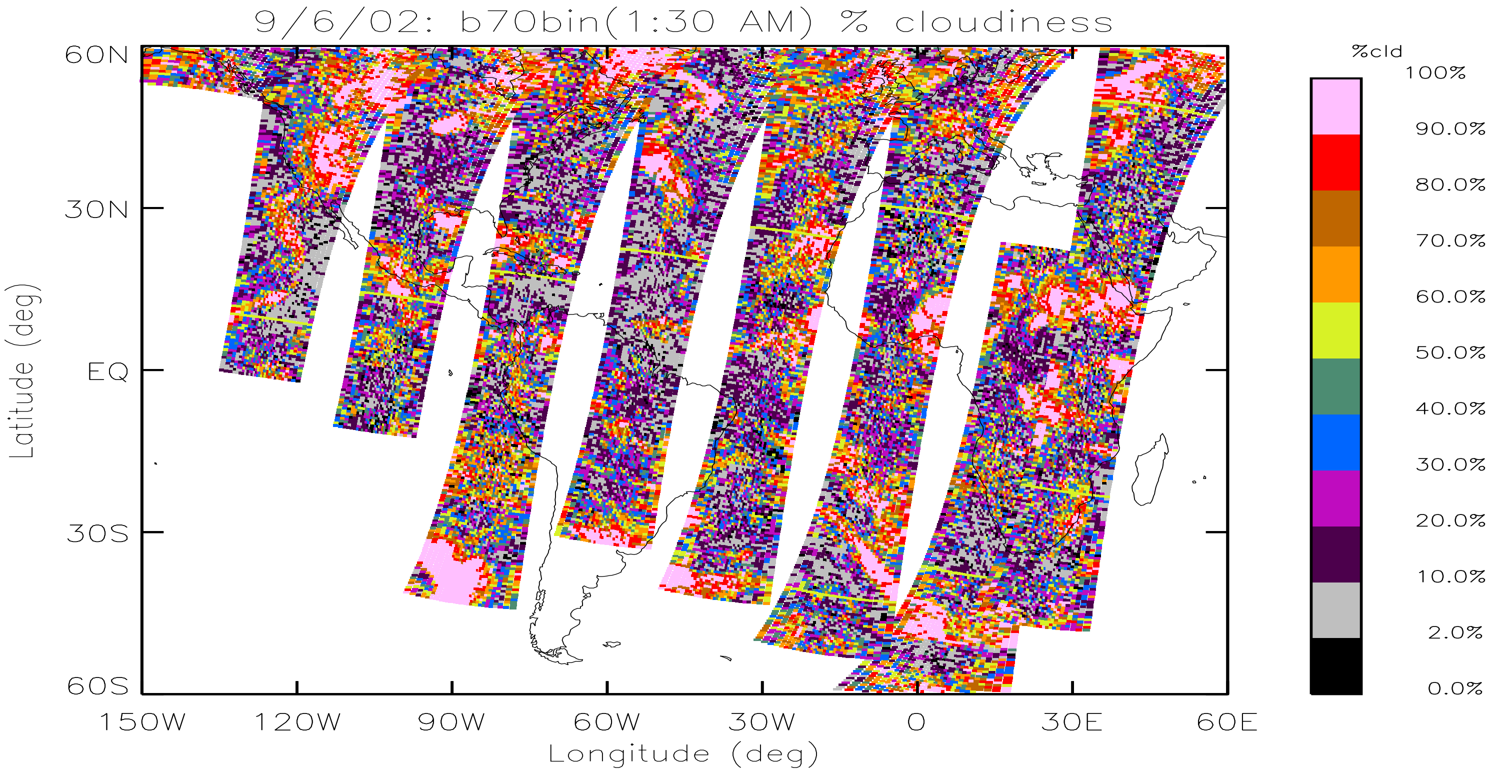
RED curves are CLEAR scenes, BLUE curves have CLOUDS. Top panel is R(ECMWF) - $<R(AIRS)>_{9}$. Middle panel is the R(ECMWF)-R(CCR). Bottom panel is R(CCR) minus the R(RETRIEVAL).

Cloud Clearing BIAS Statistic, 1 Granule



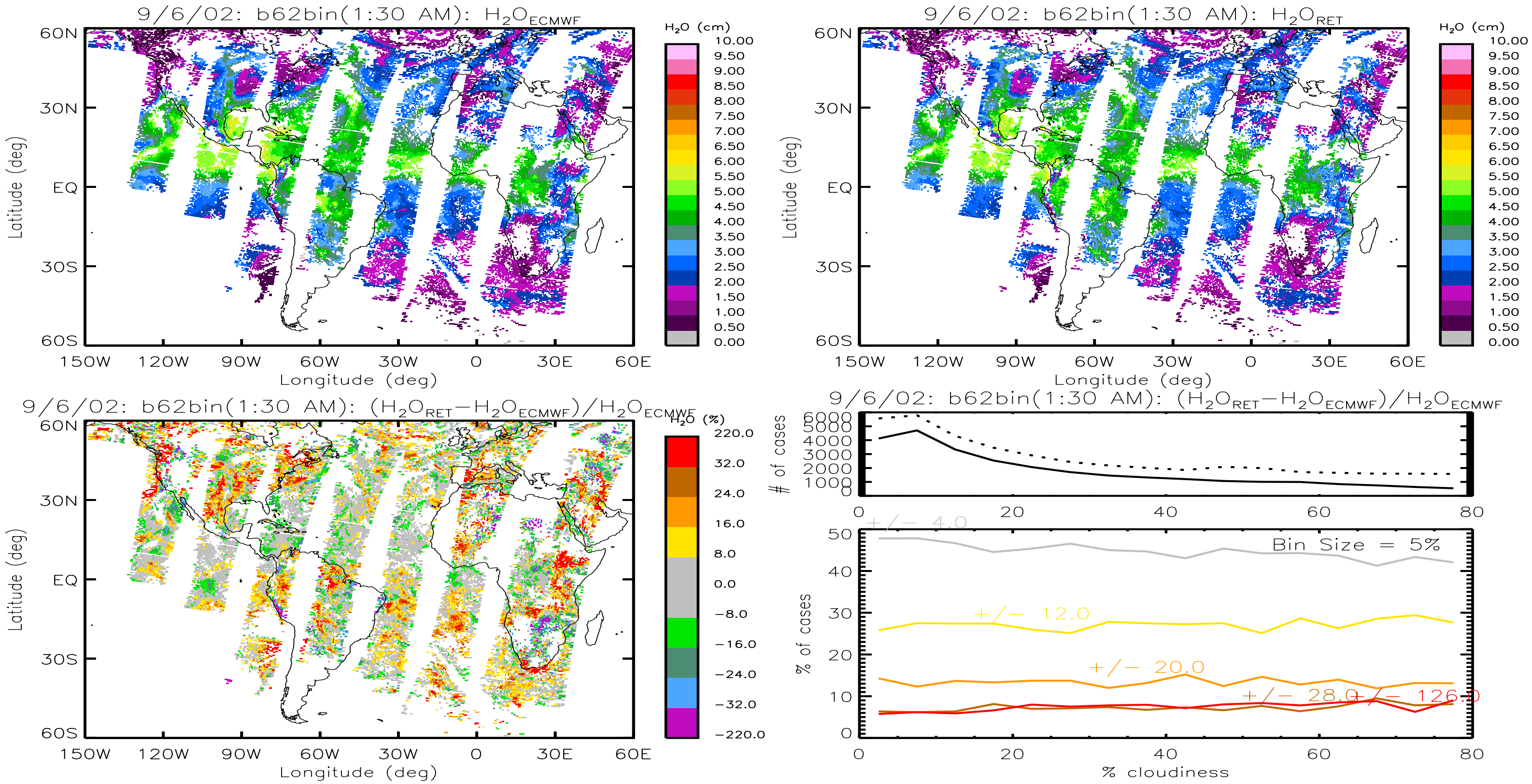
Same previous figure, but the BIAS of the differences between AIRS radiances and radiances computed from ECMWF or the RETRIEVAL are shown.

Example Yield of Cloud Clearing



The AIRS effective cloud fraction is a proxy for the difficulty of cloud clearing, that is, large amounts of clouds require more extrapolation.

Example Yield of Cloud Clearing



Total precipitable water from ECMWF (upper left panel) from a AIRS retrieval (upper right panel) and the difference (lower left panel). The differences as a function of the effective cloud fraction (previous figure) are shown for each color domain.

Overview of AIRS

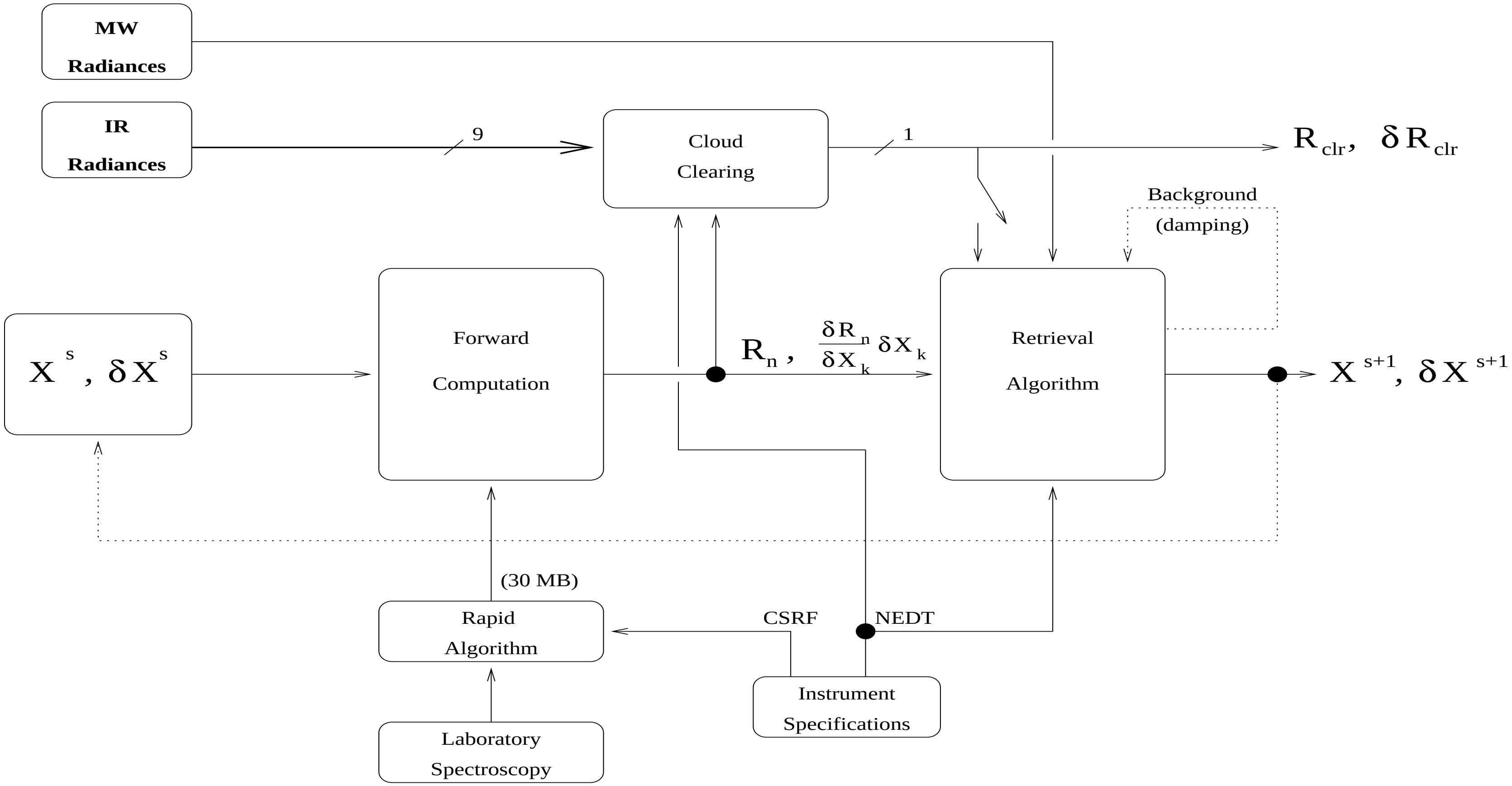
Science Team Algorithm

Philosophy of AIRS Team Algorithm

- **Utilize microwave products (MIT maximum likelihood algorithm) to estimate the infrared state for initial cloud clearing and microwave liquid water and emissivity products.**
- **Utilize statistical regression (NOAA/NESDIS) to provide the initial first guess state for the physical algorithm. This solution contains the fine vertical structure information.**
- **Utilize a physical retrieval (NASA/GSFC) to improve the state.**

  1. **Microwave and infrared observations are used in each step.**
  2. **Use microwave observations and products to reject cases with poor cloud clearing.**
     - Reject if O-C(couple retrieval) is too large
     - Perform microwave-only ret using coupled ret as first guess. Reject if $\Delta T(p)$ is too large.

Overview of the GSFC Multi-spectral Physical Retrieval System

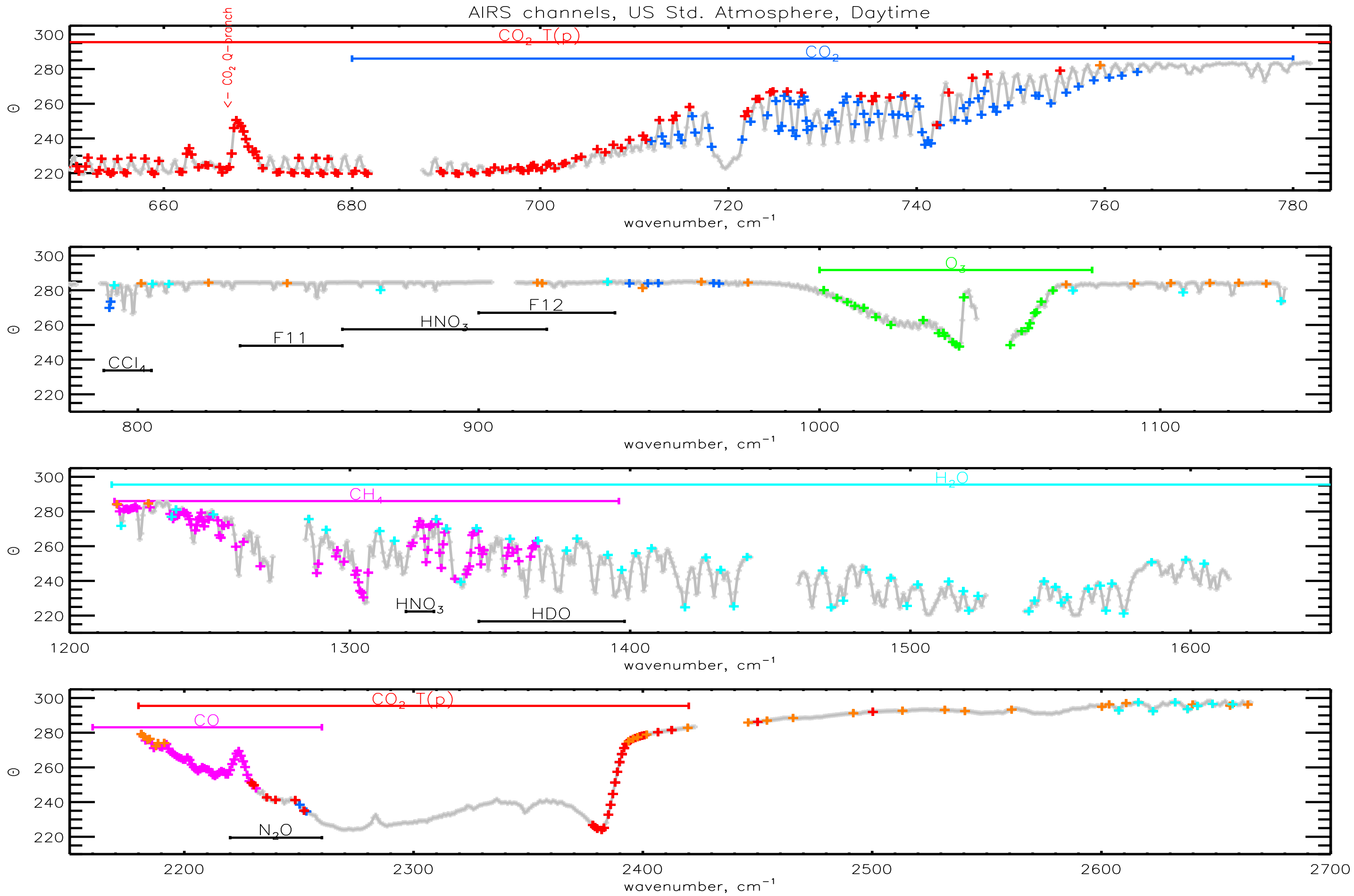


The atmospheric state, $\boldsymbol{X_L^{s,i}}$, *and the error estimate of that state,* $\boldsymbol{\delta X_L^{s,i}}$, *are used to minimize the residuals in observed minus computed radiances.*

Philosophy of GSFC Physical Algorithm

- **Embed an information content analysis into each step to determine the optimal damping (regularization) for each case.**
  1. **Cloud cleared radiances are both case and iteration dependent.**
  2. **Propagate a formal geophysical error estimate through each step.**
  3. **Compute an estimate of the *a-priori* covariance at each step.**
- **Assume certain parameters are separable.**
  1. **For example, we can solve for T_{surf} holding all other variables, *e.g.*, water) constant, since T_{surf} is quite linear.**
  2. **BUT, if a step is repeated (*e.g.*, when an error estimate has been improved) NEVER use the products from the previous step.**
- **Select channels that are "spectrally pure", that is**
  1. **Have a high sensitivity to what is being solved for.**
  2. **Have a low sensitivity to the parameters held constant.**
- **Minimize the number of vertical and spectral parameters to solve by using vertical and spectral functions. (*i.e.*, impose smoothness constraints).**

Channels used in the AIRS retrieval algorithm



Specification of Vertical and Spectral Functions

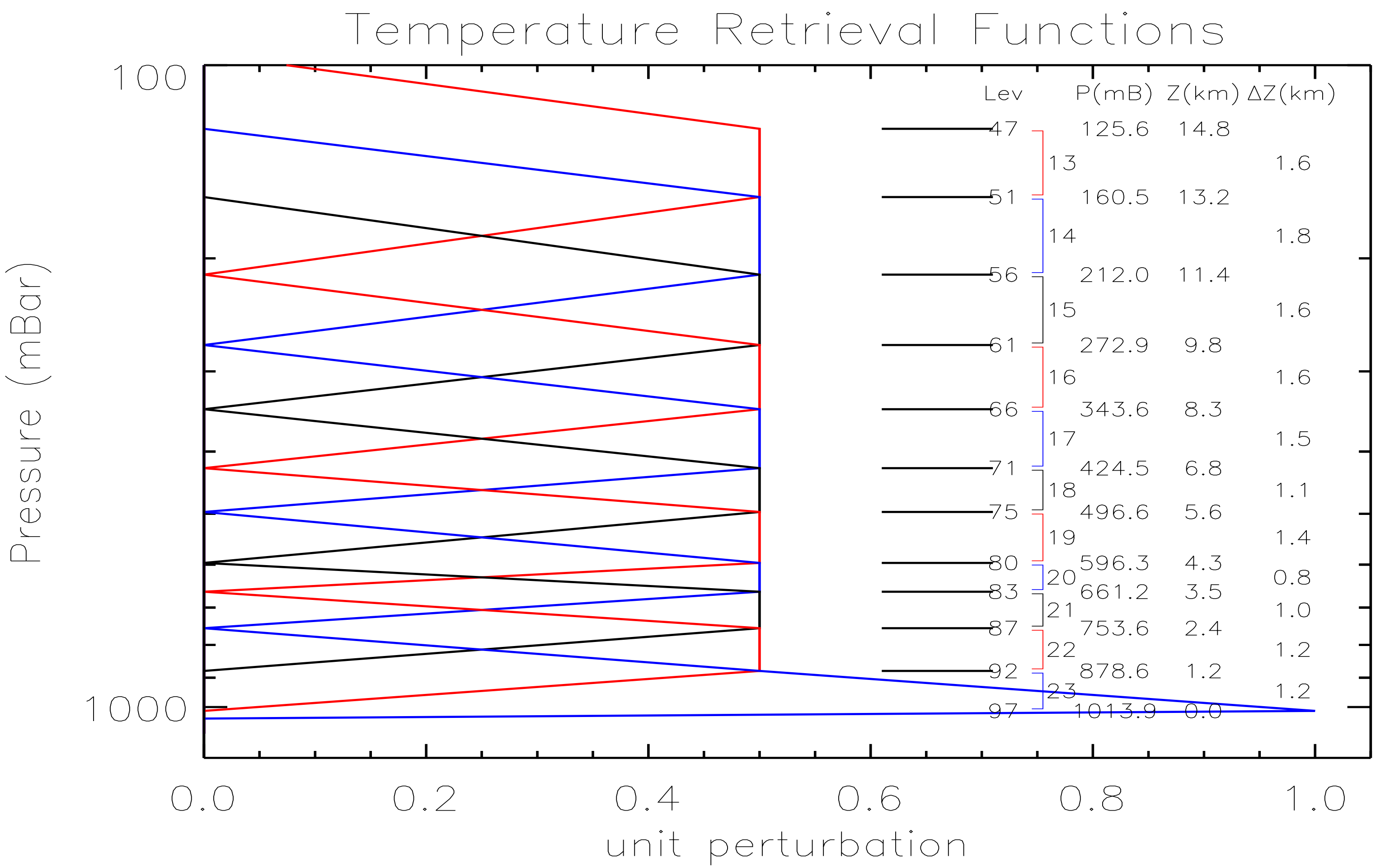
- **A fine vertical grid is required for accurate computation of the absorption coefficient, $\kappa_i(\nu, p(z), X, \theta)$ and radiances.**
- **But, we do not have enough vertical information to solve for that many parameters.**
- **Functions, $F_{L,j}$, and parameters, $\Delta A_j^{s,i}$, are chosen in a trade-off between resolution and stability (analygous to Backus & Gilbert trade-off, (Hanel, 1992).**

$$X_L^{s,i} = X_L^{s,i-1} + \sum_j F_{L,j} \cdot \left(\Delta A_j^{s,i} \otimes \Delta \hat{A}_j^{-1} \right) \tag{2.1}$$

- **Vertical functions are overlapping trapezoids.**
- **Spectral functions are overlapping triangles.**
- **Sub-sets of vertical and spectral functions must sum to unity.**

$$\sum_j \left(F_{L,j} \right) = 1 \tag{2.2}$$

Example of functions, $F_{L,j}$, for $T(p(L))$ retrieval



TUNING and ERROR TERMS

For discussion, assume a retrieval equation looks like

$$\boldsymbol{\Delta X_i} = \left[\boldsymbol{S'_{i,n'} \cdot W_{n',n} \cdot S_{n,i} + H_{i,i}}\right]^{-1} \cdot \boldsymbol{S'_{i,n'} \cdot W_{n',n}}$$
$$\cdot \left[\boldsymbol{O - C(n) - \Psi_n^{s,i} + T(n)}\right] \tag{2.3}$$

- $\boldsymbol{S_{n,i}}$ **is the sensitivity of channel** $\boldsymbol{n}$ **to parameter** $\boldsymbol{i}$**,**
- $\boldsymbol{O - C(n)}$ **is the observed radiances minus the radiances computed from the current state of** $\boldsymbol{X}$**.**
- $\boldsymbol{\Psi_n^{s,i}}$ **is the background term derived from** *a-priori* **contribution.**
- $\boldsymbol{T(n)}$ **is radiance tuning, if applied.**

The weighting matrix, $\boldsymbol{W_{n',n}}$ **is derived from the cloud cleared radiance error and** *a-priori* **covariance,** $\boldsymbol{N_{n',n}}$**. In addition, we could have other error sources, such as rapid transmittance algorithm (RTA) and spectroscopy errors,** $\boldsymbol{E_{n',n}}$**.**

$$\boldsymbol{W_{n',n}} = \left[\boldsymbol{N_{n',n} + E_{n',n}}\right]^{-1} \tag{2.4}$$

Information Content in Parameter Covariance Matrix

$$\boldsymbol{\lambda}_k^{s,i} \equiv \boldsymbol{U}_{k,j}^{s,i'} \cdot \left[\boldsymbol{S}_{j,n'}^{s,i'} \left(\boldsymbol{N}_{n',n}^{s,i}\right)^{-1} \boldsymbol{S}_{n,j}^{s,i}\right] \cdot \boldsymbol{U}_{j,k}^{s,i} \tag{2.5}$$

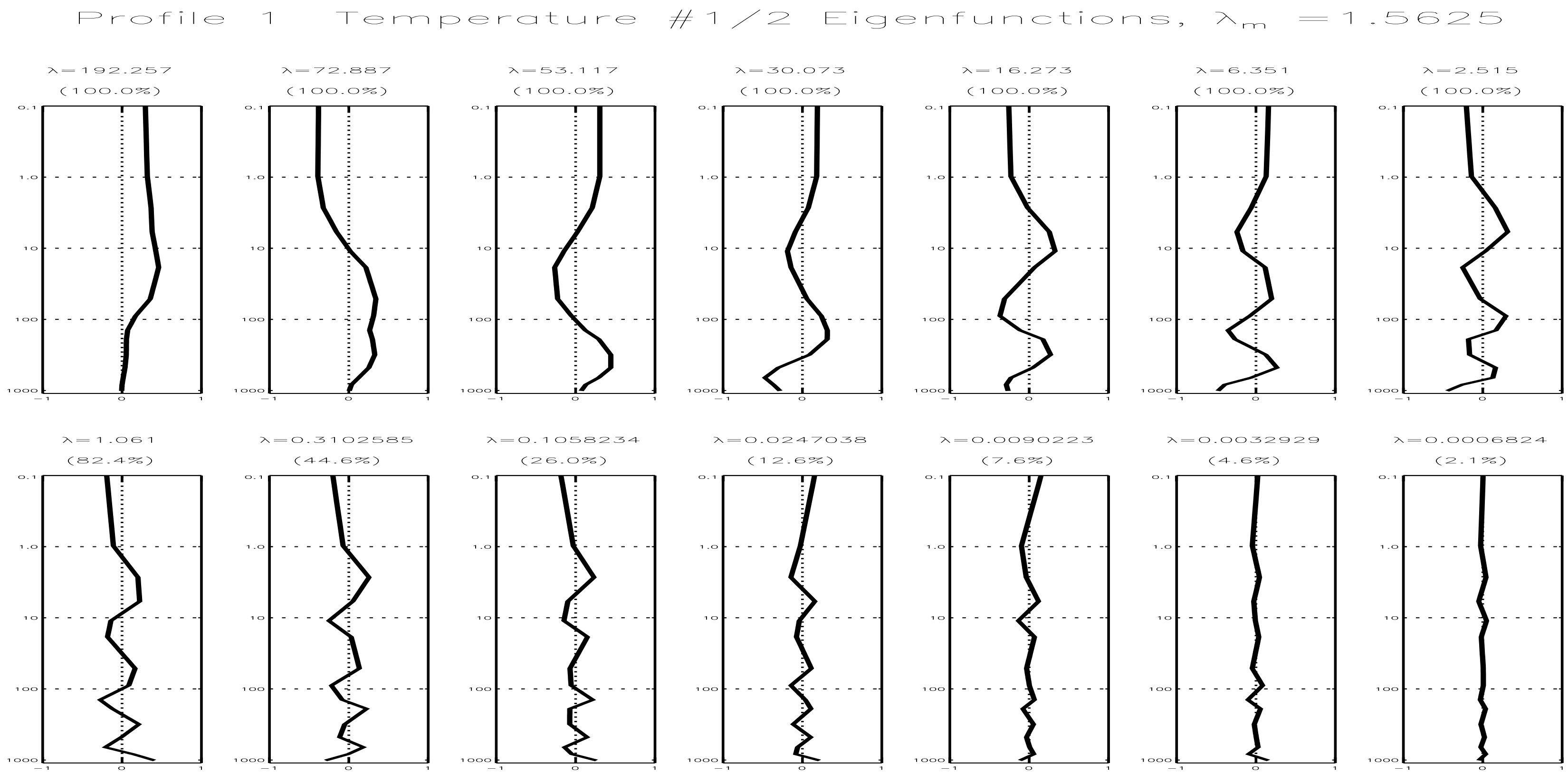
$\boldsymbol{U}_{j,k}^{s,i}$, can be thought of as a linear transformation of the original functions to a new set of orthogonal functions,

$$\boldsymbol{G}_{L,k}^{s,i} \equiv \left(\boldsymbol{F}_{L,j} \otimes \boldsymbol{\Delta}\hat{\boldsymbol{A}}_j\right) \cdot \boldsymbol{U}_{j,k}^{s,i} \tag{2.6}$$

We can analyze the eigenvalue, $\boldsymbol{\lambda}_k^{s,i}$, to determine how much this transformed function should be believed, if at all.

- **The regularization operator, $\boldsymbol{H}_{i,i}$, tends to remove higher vertical frequencies and is sometimes called a smoothing operator.**
- **In the GSFC algorithm, $\boldsymbol{\lambda}_k$ is used to determine $\boldsymbol{H}_{i,i}$ therefore, high $\boldsymbol{N}_{n',n}$ or $\boldsymbol{E}_{n',n}$ results in high $\boldsymbol{H}_{i,i}$.**

Example of GSFC Regularization



For temperature functions, the new set of vertical functions, $\boldsymbol{F_{L,j} \cdot U^{s,i}_{j,k}}$ *are shown for the AIRS temperature retrieval information content analysis.*

Estimation of LSQ Errors

Geophysical functions, $\boldsymbol{X_L^s}$ are constructed from the changes at each iteration and the functions (Eqn. 2.1).

$$\boldsymbol{X_L^{s,i} = X_L^{s,i-1} + \sum_j F_{L,j} \cdot \left(\Delta A_j^{s,i} \otimes \Delta \hat{A}_j^{-1} \right)} \tag{2.7}$$

The errors in the parameters are estimated from the formal least squared fitting errors (see PHYS640 notes).

$$\boldsymbol{\left(\delta \tilde{A}_j^{s,i}\right)^2 = \left(\delta \tilde{A}_j^{s-1,0}\right)^2 + \left[S_{j,n'}^{s,i'} \left(N_{n',n}^{s,i} \right)^{-1} S_{n,j}^{s,i} + H_{j,j} \right]^{-1}} \tag{2.8}$$

The errors in the geophysical products are computed in the root-sum-squared (RSS) sense from parameter errors:

$$\boldsymbol{\left(\delta X_L^{s,i}\right)^2 = \left(\delta X_L^{s,i-1}\right)^2 + \sum_j \left(F_{L,j} \cdot \left(\delta \tilde{A}_j^{s,i} \otimes \Delta \hat{A}_j \right)\right)^2} \tag{2.9}$$

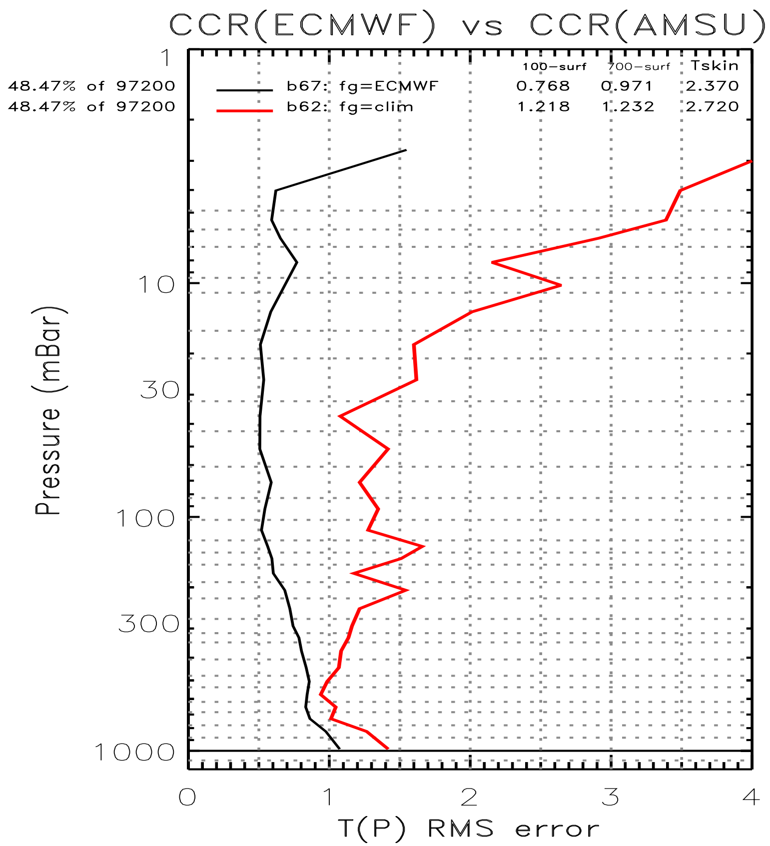
These error estimates can be used to compute $\boldsymbol{\left(N_{n',n}^{s,i}\right)^{-1}}$ and, therefore, propagated into the next retrieval step.

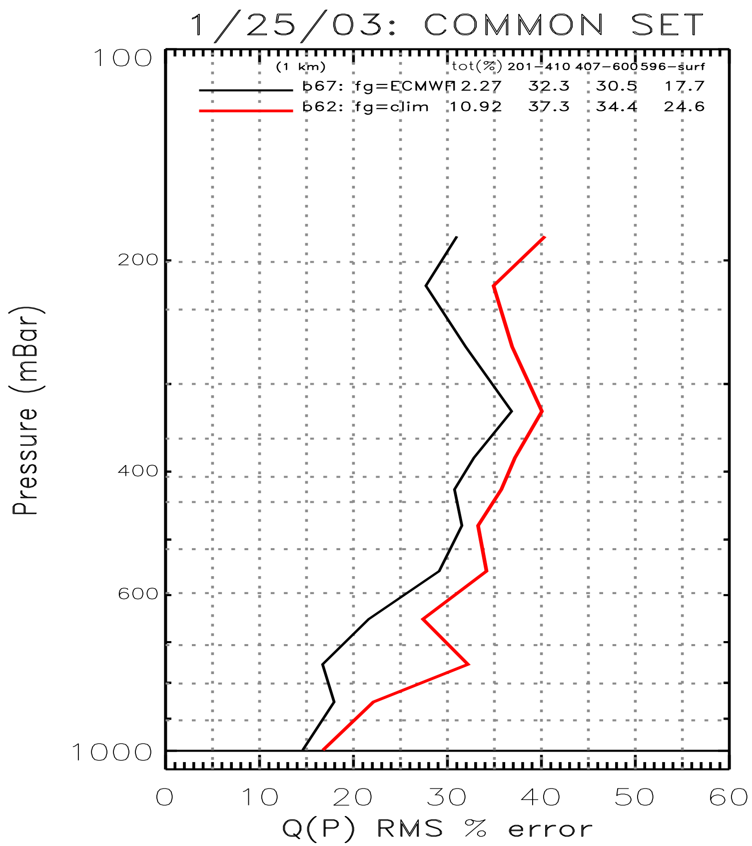
Some Post-Launch Issues

Issues with AMSU's Estimate of CLEAR State

- **Microwave side-lobe corrections (SLC's) for the Aqua platform are more complex than the POES platforms and have NOT been applied to date.**
- **A large microwave tuning has been employed to mitigate SLC issues.**
- **A poor AMSU first guess has a negative impact on cloud clearing and, therefore, all AIRS products.**
- **To understand the impact to AIRS products, we are using a model analysis as a first guess state:**
  1. **To assess the impact of AMSU SLC issues on the AIRS products.**
  2. **To assess the need for tuning and/or RTA improvements.**
- **The logic comparing to the same model used as a first guess is quite CIRCULAR, but illustrative. Future work will be to compare to AIRS over-pass sondes and LIDAR measurements.**

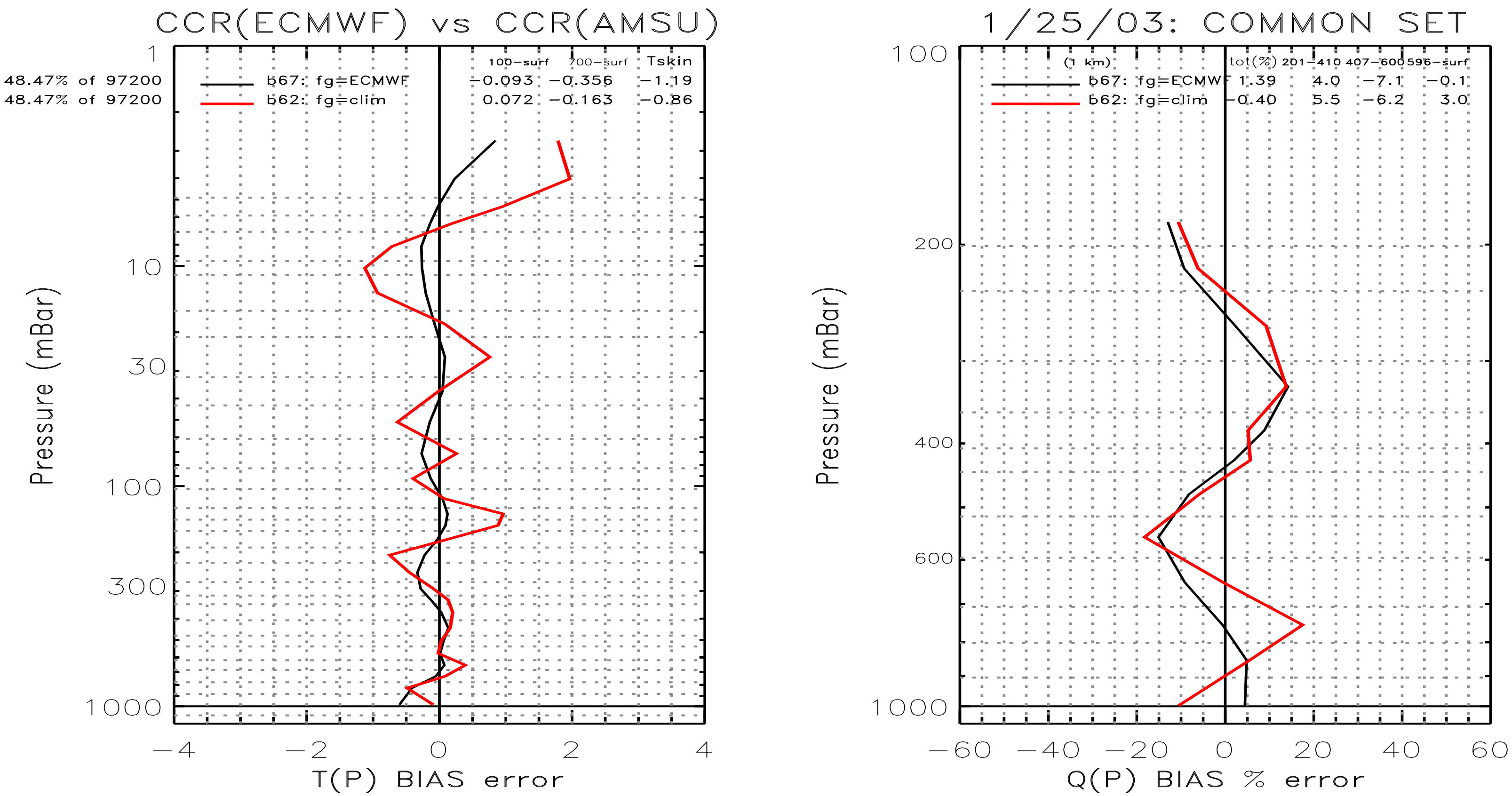
Illustration of Impact of AMSU Problems - RMS





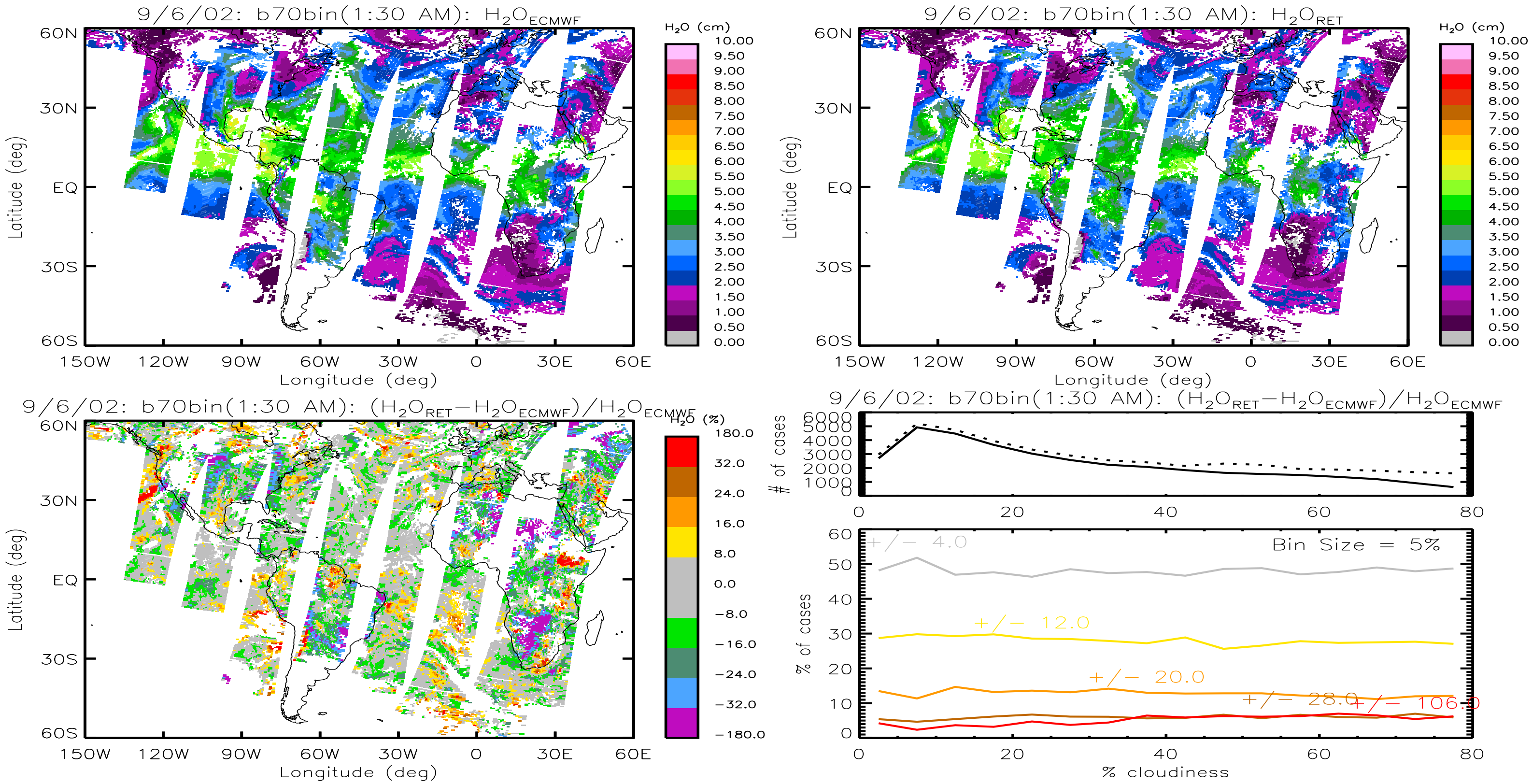
The RMS difference for those cases that were accepted by both an experiment in which ECMWF was used to estimate $\boldsymbol{R}_{est}$ *and AMSU was NOT used versus the baseline system with AMSU used to estimate* $\boldsymbol{R}_{est}$*. Only complete removal of AMSU improves results.*

Illustration of Impact of AMSU Problems - BIAS



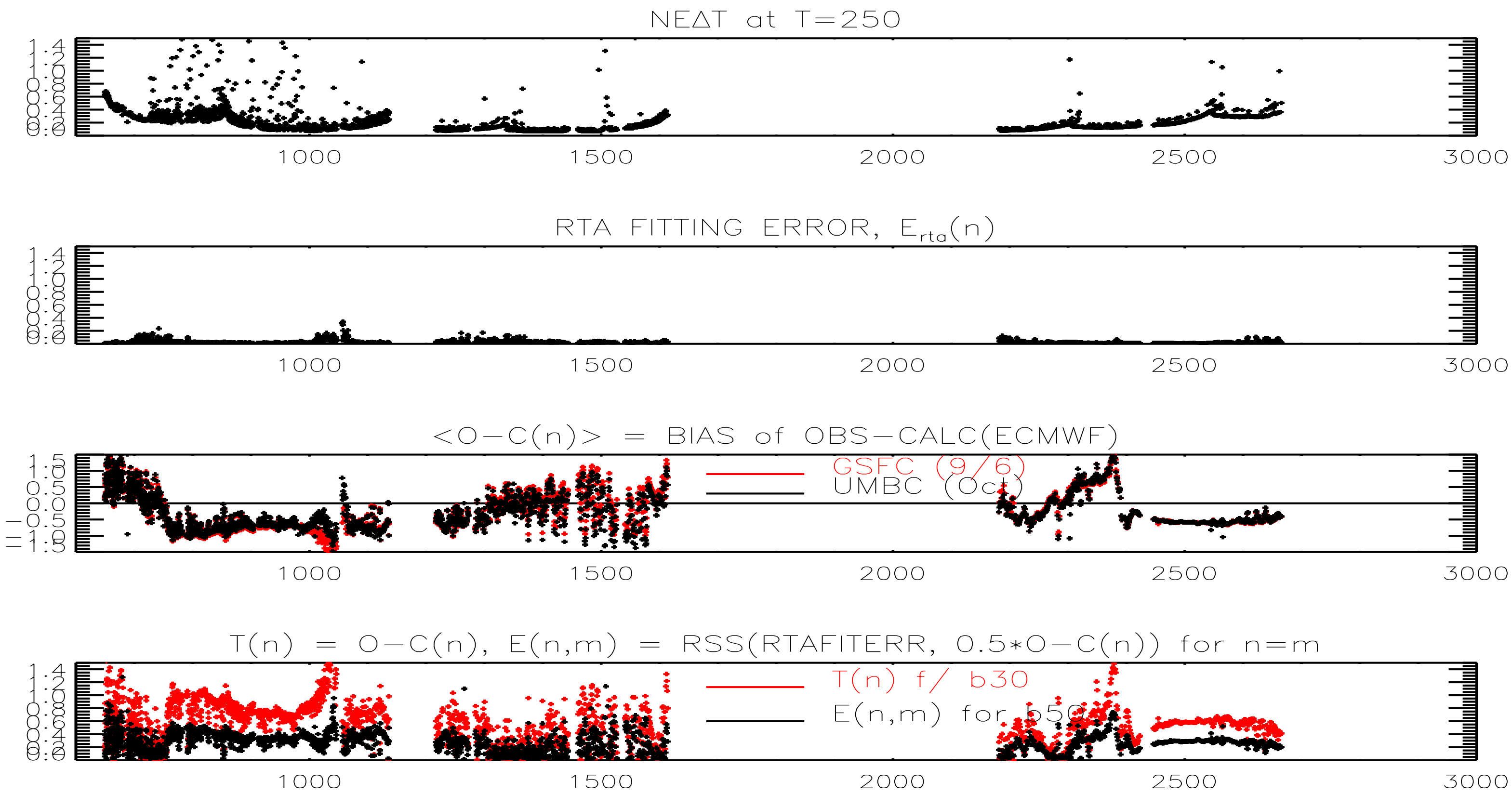
Same as previous figure except the BIAS of the difference is shown. AIRS T(p) retrievals appear to be un-biased w.r.t. ECMWF.

Example Yield of Cloud Clearing using fg=ECMWF



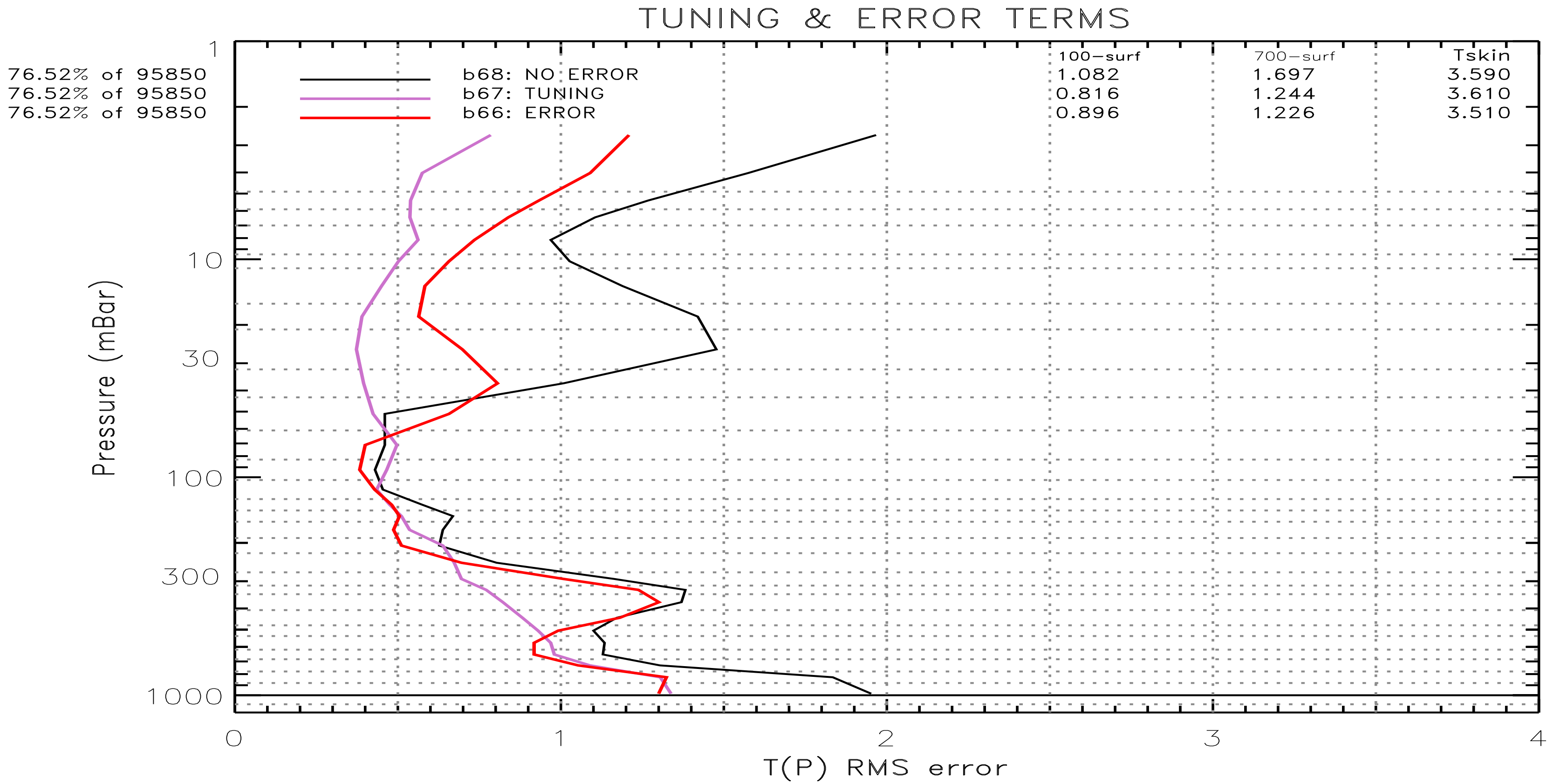
Total precipitable water from ECMWF (upper left panel) from a AIRS retrieval (upper right panel) and the difference (lower left panel). The differences as a function of the effective cloud fraction (previous figure) are shown for each color domain.

O-C's Used in the Tuning Experiments



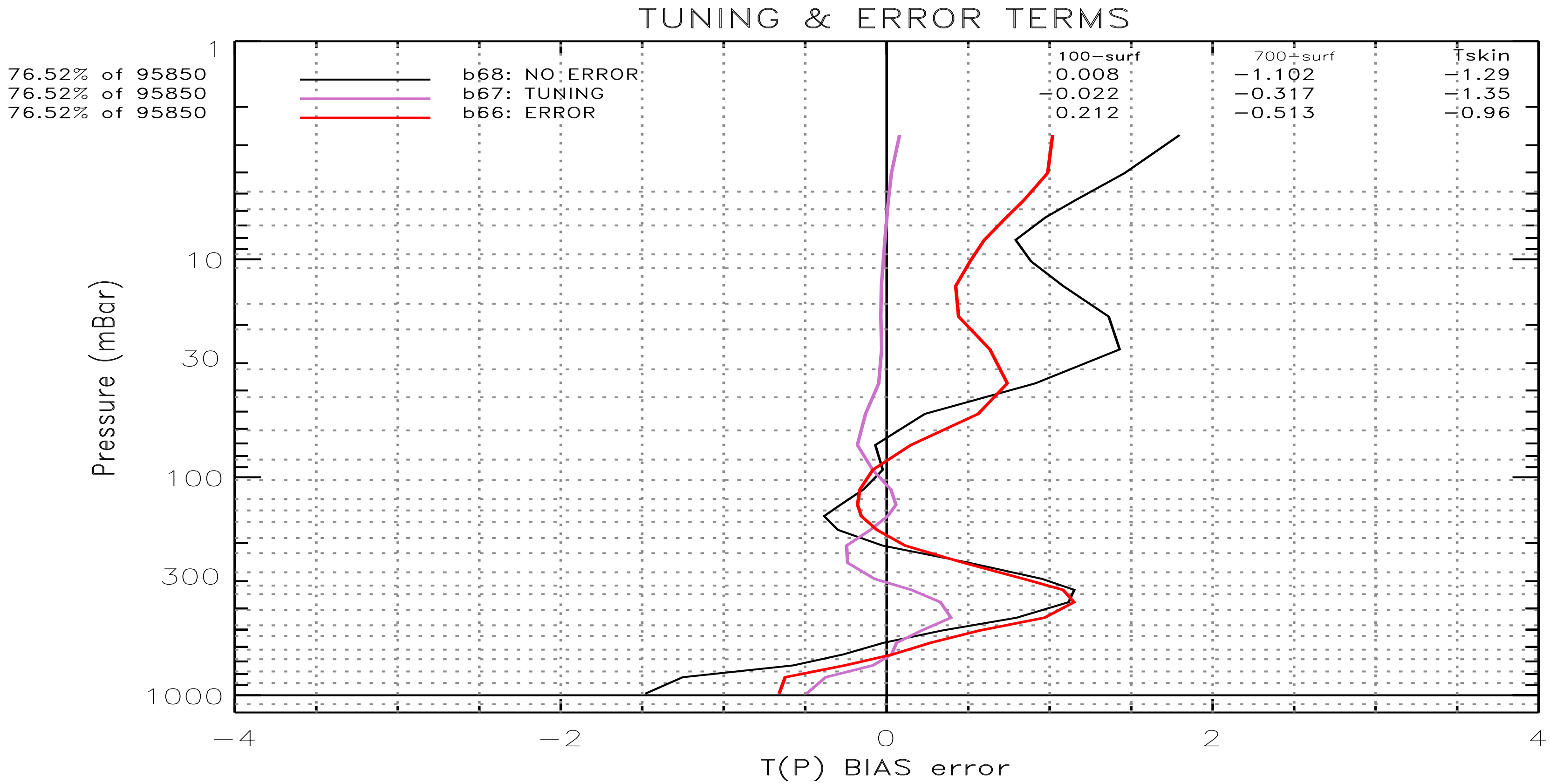
Top 2 panels are AIRS NEΔT and RTA errors respectively. Lower panels show O-C(n) w.r.t. ECMWF. Red curves are O-C(n) derived from $\approx$ 1000 clear cases on 09/02/2002. Black curves are O-C's derived from $\approx$ 200,000 clear cases in Oct. 2002.

Impact of Tuning - RMS



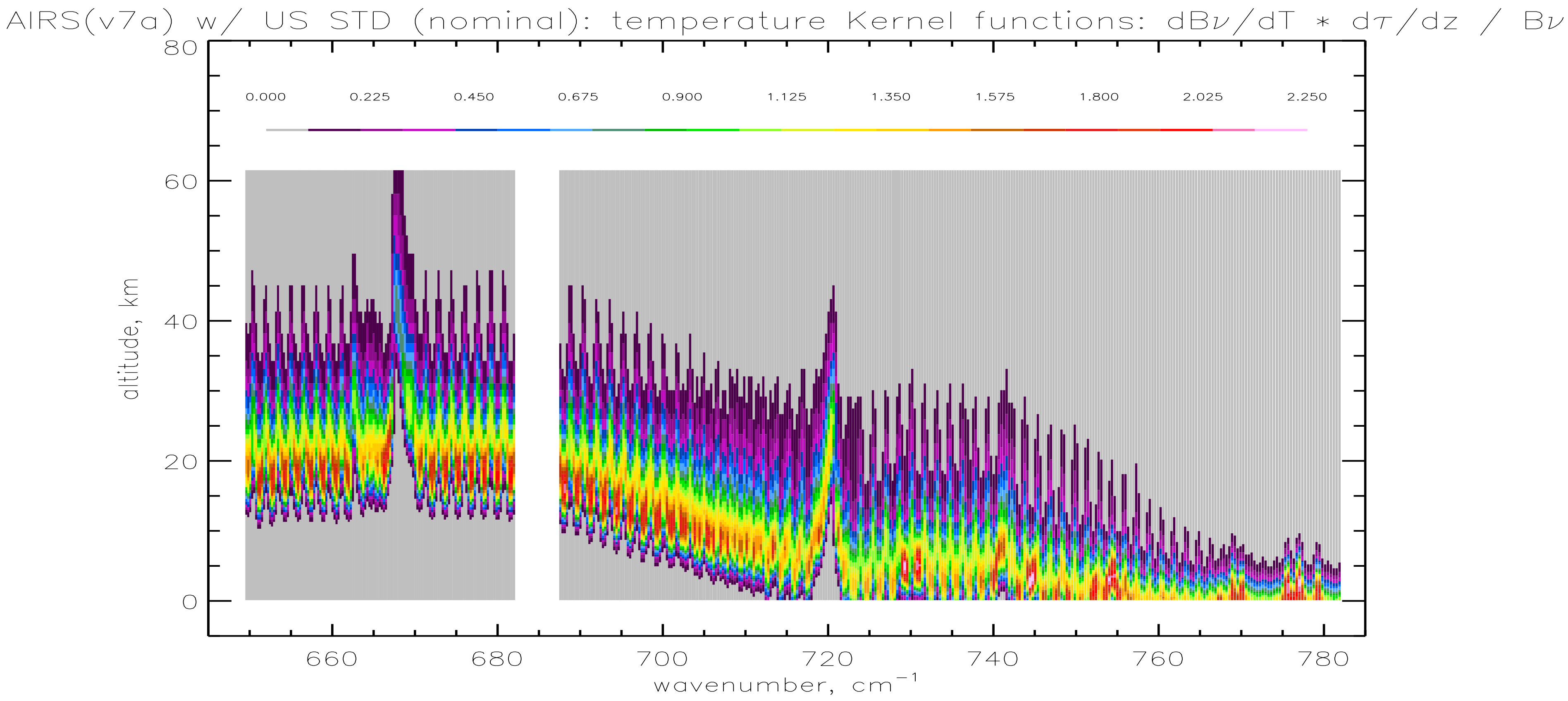
RMS of the fg=ECMWF experiment versus ECMWF for Sep. 6, 2002 with TUNING (MAGENTA); using the ERROR term (RED); and using NO TUNING and NO ERROR term (BLACK).

Impact of Tuning - BIAS



Same as previous figure except BIAS is shown. The reduction of errors in the 500 mb region appears to be a spectroscopy issue that will be resolved by our UMBC colleagues.

AIRS 15 μm Kernel Function



Status of

AIRS Trace Gas Retrievals

Instruments Co-temporal with AIRS

Existing Instruments

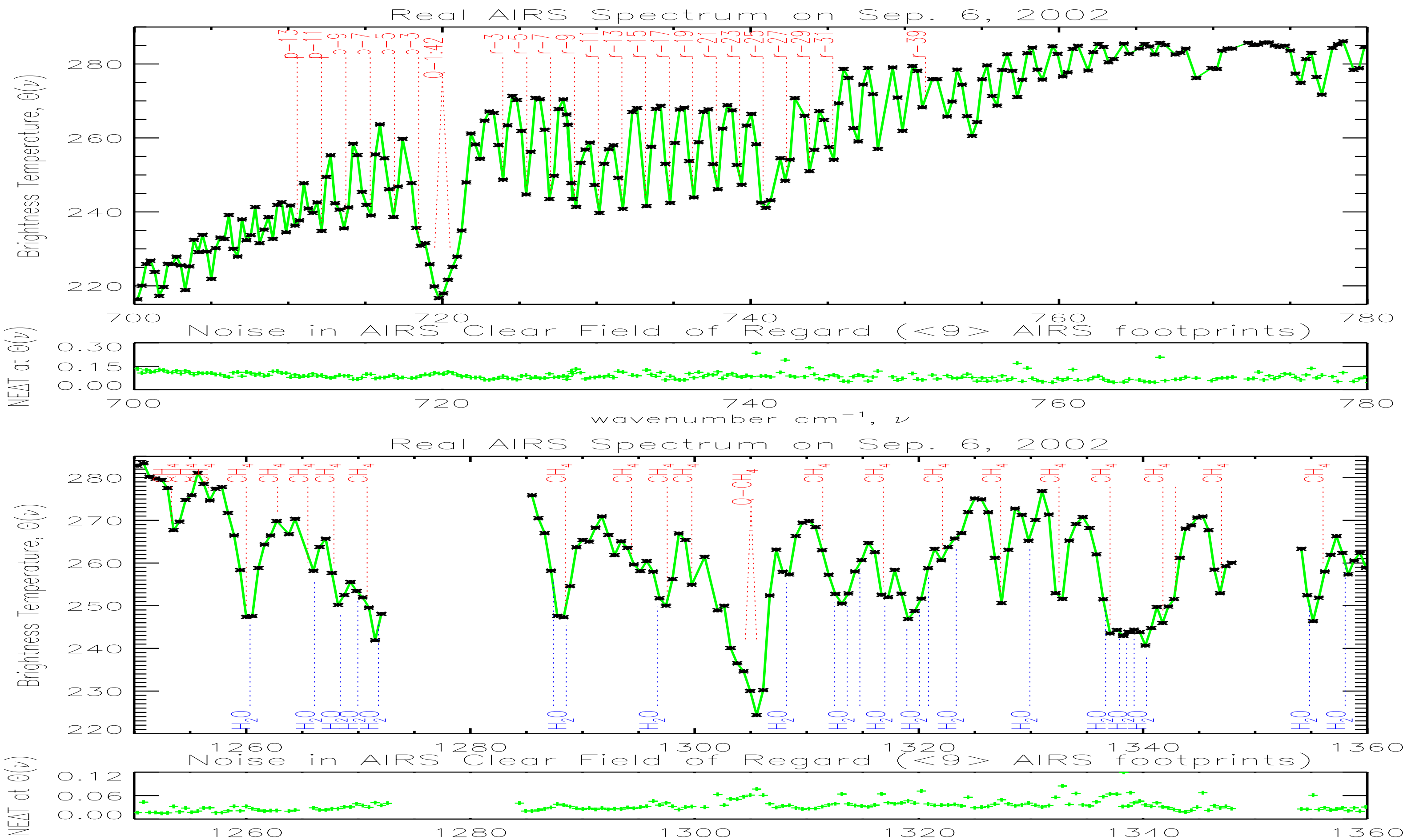
launch	instrument name	platform	band(s) (μm)	FOV (km)	carbon products	ancillary products
12/99	MOPITT	TERRA	2.2	22	CO & CH_4	none
3/02	MIPAS	ENVISAT	2.2, 7.7	(16)3x30	CO, CH_4, CO_2	O_3, H_2O
3/02	SCIAMACHY	ENVISAT	2.2	0.6x25	CO, CH_4, CO_2	O_3, H_2O
5/02	AIRS	AQUA	3.7 $\rightarrow$ 15	45	CO, CH_4, CO_2	$T(p)$, O_3, H_2O

Funded Instruments in Development

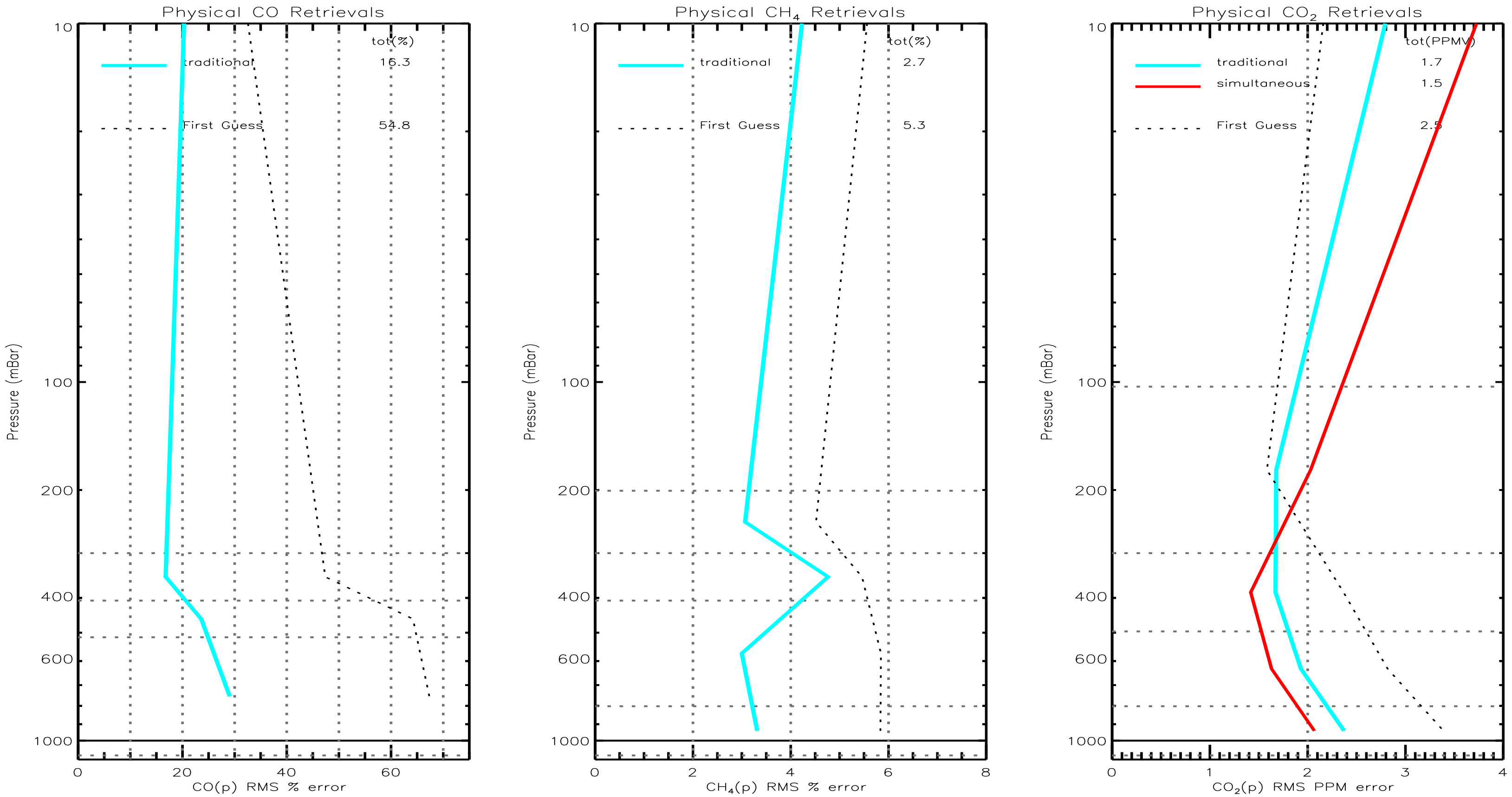
1/04	TES	AURA	3.3 $\rightarrow$ 15	(16)0.5x8.3	CO, CH_4, CO_2	O_3, H_2O
			3.3 $\rightarrow$ 15	(16)2.3x23	CO, CH_4, CO_2	O_3, H_2O
12/05	IASI	METOP-1	3.7 $\rightarrow$ 15	45	CO, CH_4, CO_2	$T(p)$, O_3, H_2O
6/06	CrIS	NPP	3.7 $\rightarrow$ 15	45	CH_4, CO_2	$T(p)$, O_3, H_2O
7/07	OCO	ESSP	1.58	1	CO_2	none

- **AIRS has sensitivity to CO, CH_4, and CO_2 in mid-troposphere.**
- **BUT, modelers NEED measurements of these gases in the boundary layer.**
- **CH_4 and CO_2 boundary-layer products are VERY difficult and a thermal sounder is NOT the ideal choice.**
- **The AIRS product is a low cost "path-finder" product.**

Bands used for CO_2 and CH_4 Sounding

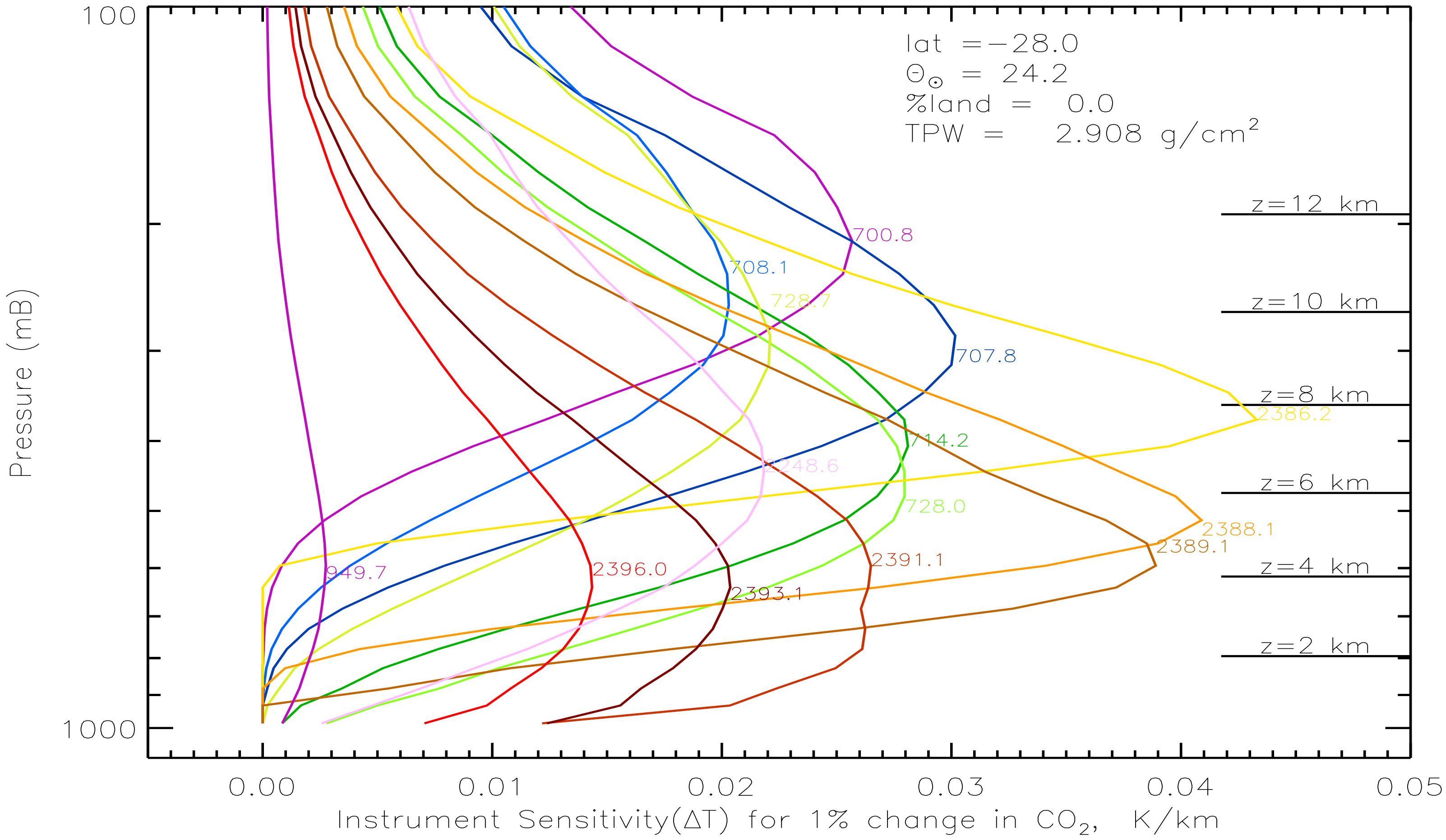


AIRS Trace Gas Simulation Experiments



Trace gas retrievals for CO (left panel), CH_4 (middle panel), and CO_2 (right panel). The black dashed lines in each panel is the RMS of the error in the first guess state. The BLUE lines is the ability of the delivery algorithm. The RED curve is the ability of research algorithm.

CO_2 Kernel Functions

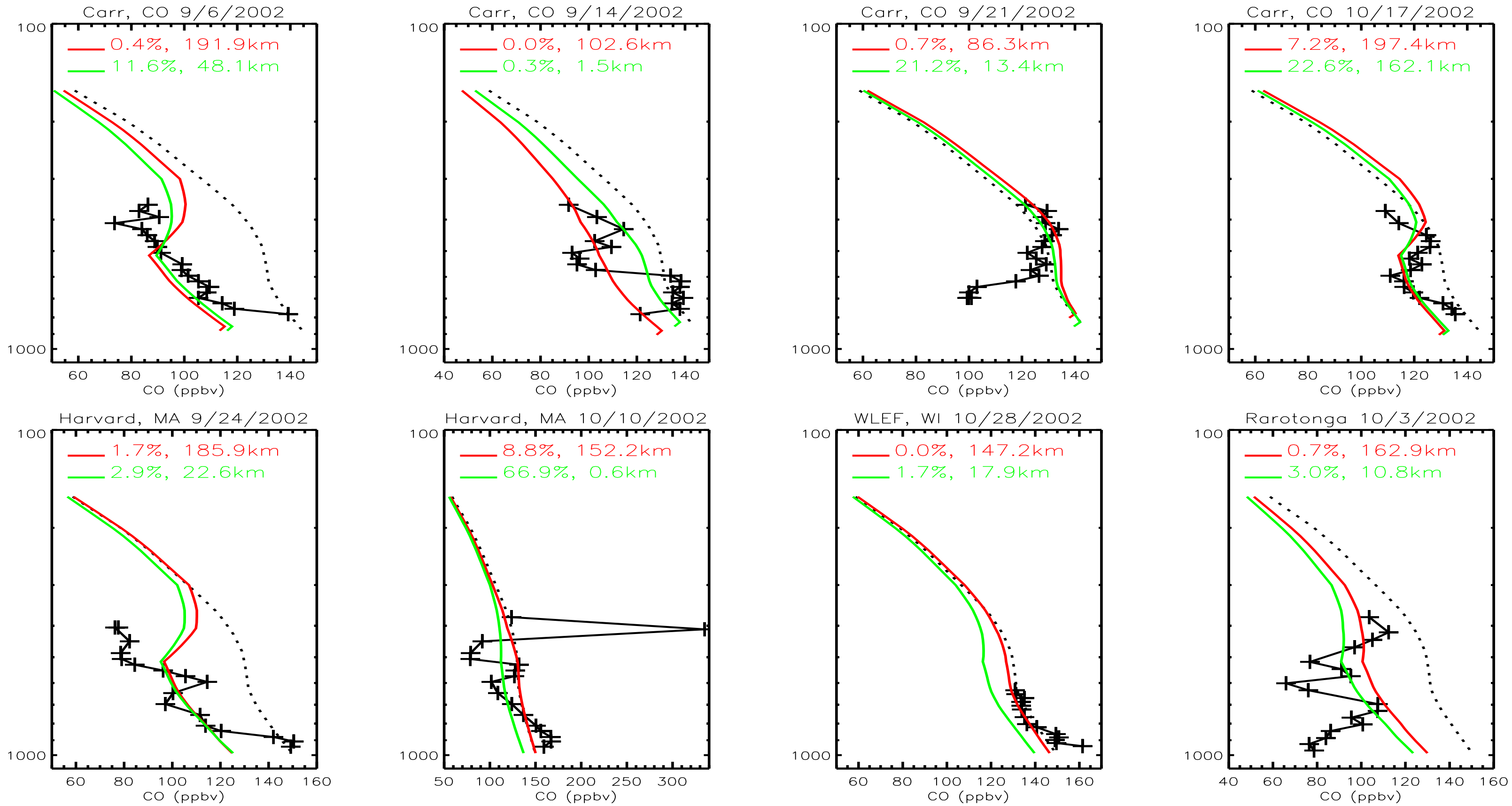


The vertical sensitivity to CO_2 of selected AIRS channels.

Trace Gas Retrieval Approaches

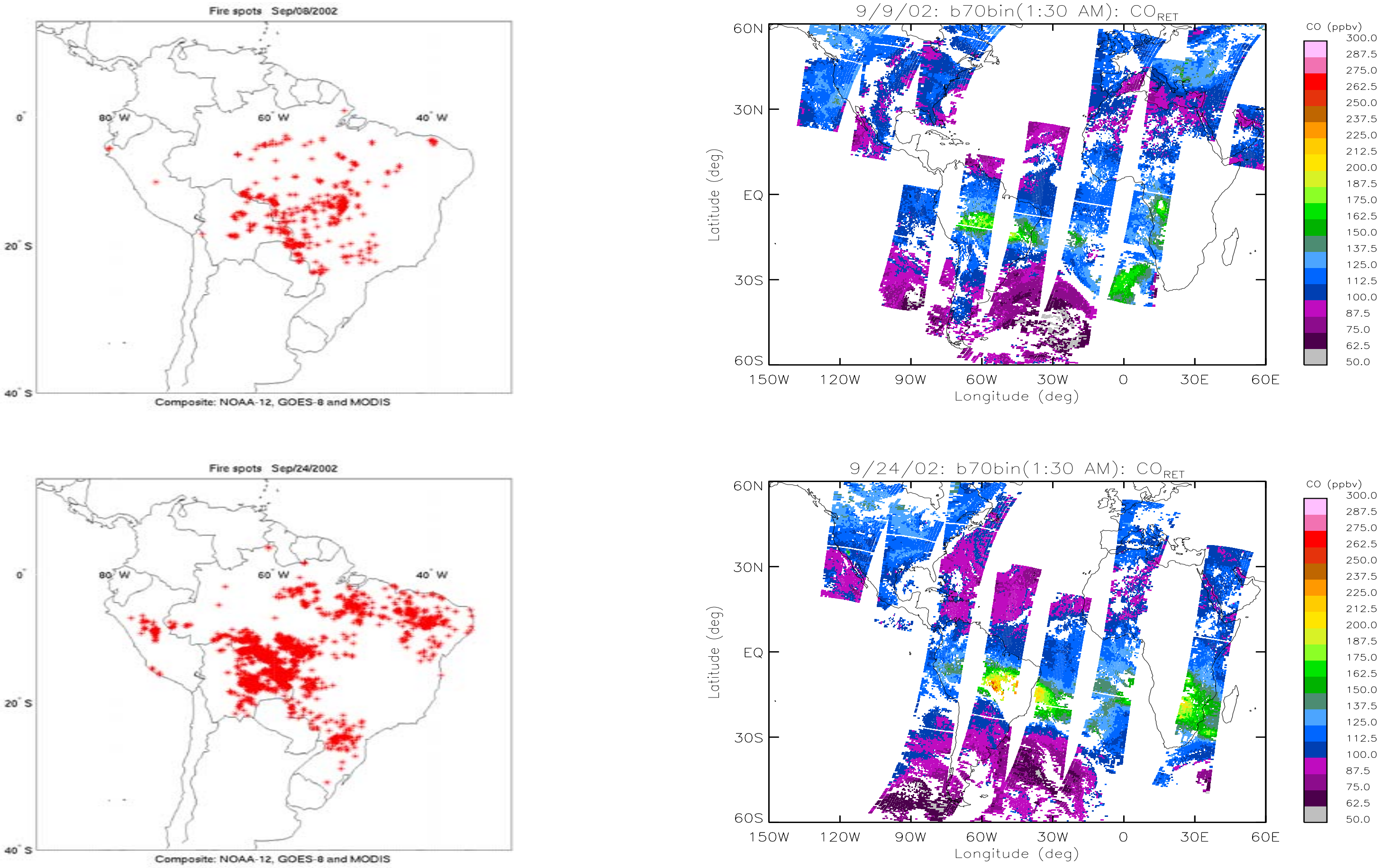
- **Statistical Regression:**
  - An excellent possibility or providing a first guess CO_2 profile for the physical algorithm.
  - Should retrieve a realistic shape and a shape-preserving physical retrieval for CH_4 and CO_2.
- **Residual Minimization:**
  Originally proposed by Chahine (1972). Residuals of a large number of channels are computed as a function of CO_2. The the minimum of a smoothed function is the retrieved CO_2.
- **Traditional Retrieval:**
  A physical retrieval using the same methods employed by the AIRS Science Team algorithm (Susskind et al., 2003).
- **Simultaneous Retrieval:**
  A simultaneous physical retrieval of CO_2 and $T(p)$ eliminates sensitivity to errors in $T(p)$ and improves both products.

Preliminary Look at CO Product



Intercomparison of AIRS retrievals (RED=clearest and GREEN=nearest) with CMDL aircraft measurements of CO. CMDL data ("+" symbols and black solid line) provided by Peter Bakwin and Paul Novelli, NOAA/OAR. The dotted black curve is our CO first guess (a constant profile).

Preliminary Look at CO Product



Example of the fire counts (left) and the preliminary AIRS CO product (right) for a day with low (top) and high (bottom) fire counts.

Future Directions

- **Improve AMSU Clear Estimate**
  A technique employed at NOAA (Goldberg *et al.*, 2003) in which the off-axis AMSU FOV's are statistically corrected to an AMSU FOV at nadir will be investigated soon.
- **Investigate Use of MODIS and/or Models to Improve $\boldsymbol{R_{est}}$ and products.**
- **Characterization of the AIRS products and error estimates.**
  - **Work with AIRS validation groups and concentrate on *in-situ* measurements during AIRS over-passes to understand tuning and retrieval stability issues.**
  - **Improve error estimates of CCR's and products for modelers.**
- **Generate A Large Volume of Trace Gas Product**
  1. **Look for CO_2 domes in large cities caused by an accumulation of automobile exhaust during meteorological inversions.**
  2. **Look for CH_4 emissions from agriculture, land-fills, gas-leaks.**
  3. **Work with Modeling Collaborator to Search for CO_2 Sources & Sinks.**

Backup

Slides

Current Collaboration Acivities

Joan Alexander (NWRA)	Grav. Waves
Aryln Andrews (GSFC)	CO & CO_2 Inversion Modeling
Robert C. Balling, Jr. (ASU)	CO_2 Domes
Roberto Calheiros (INPE)	T(p), q(p)
Randy Kawa (GSFC)	CO_2 Inversion Modeling
Changsheng Li (UNH)	CH_4
Wallace McMillan (UMBC)	CO, CH_4, CO_2,fire
Ken Minschwaner, (NMIMT)	UTH & T(p)
Steve Pawson (GSFC)	CO_2 Assimilation
Dave Tobin (UW/SSEC)	T(p), q(p)
Dave Whiteman (GSFC)	UTH

Remote Sounders Really Measure Absorbing Properties (Transmittance) of Gases

All remote sounding concepts rely upon measurement of the atmospheres effect on atmospheric transmittance, $\boldsymbol{\tau}$. For example, to compute layer-to-space transmittance, $\boldsymbol{\tau}^{\uparrow}$

$$\boldsymbol{\tau}_{\nu}^{\uparrow}(p, X, \theta) = \exp\left(- \int_{z'=z(p,X)}^{\infty} \sum_{i} \kappa_i(\nu, p(z'), X, \theta) \cdot dz' \right) \qquad (2.10)$$

	ν	**frequency in GHz (μW) or wavenumber (IR)**
	X	**geophysical state $(T(p), H_2O(p), O_3(p), \ldots, CH_4(p))$**
where,	κ_i	**absorption coefficient for species i**
	θ	**angle of observation from nadir**
	$z(p, X)$	**altitude as a function of pressure, p**

Channel Radiance

To compute radiances measured by an instrument, $R_n(X)$, we must integrate the monochromatic "forward" computation with the instrumental channel spectral response function (CSRF) for channel n, $\Phi(\nu, \nu_0(n))$, which has an effective frequency $\nu_0(n)$ and is defined as follows

$$R_n(X) = \int_{\nu} \Phi(\nu, \nu_0(n)) \cdot R(\nu, \theta, X) \tag{2.11}$$

Thus, the retrieval of geophysical quantities, such as the atmospheric water from satellite radiances, is highly non-linear, requiring inversion of the equations of the form

$$\boxed{R_n(X) \simeq \int_{\nu} \Phi_{\nu} \int_{p} B(T(p)) \cdot \frac{\partial \exp\left(-\int_{z'=\infty}^{z(p)} \sum_{i} \kappa_i(X, \ldots) dz'\right)}{\partial p} \cdot dp \cdot d\nu \qquad (2.12)}$$

Statistical Method

A statistical retrieval (a.k.a., regression) relates observations, $\tilde{\theta}_{n,k}$ for a channel n and FOV k with the geophysical state, $X_{L,k}$, specified as L parameters, as follows

$$\begin{aligned} X_{L,k} - < X_{L,k} >_k &= A_{L,n} \cdot \left[\tilde{\theta}_{n,k} - < \tilde{\theta}_{n,k} >_k\right] \\ &= A_{L,n} \cdot \Delta\tilde{\theta}_{n,k} \end{aligned} \tag{3.1}$$

- **$<>_k$ indicates an averaged over the "training" ensemble of K cases and removes the large scale structure.**
- **The matrix $A_{L,n}$ is computed via least squares solution of Eqn. 3.1 from a large ensemble of observations where the "truth" state, $X_{L,k}$, is known.**
- **$A(L)$ tends to look a lot like weighting functions for a given channel, n, and geophysical parameter set (*e.g.*, $X_L = T(L)$).**

Statistical Method

An example of the matrix components are

$$\boldsymbol{\Delta X_L} \equiv \begin{pmatrix} \boldsymbol{\Delta T_s} \\ \boldsymbol{\Delta \epsilon(\nu_1)} \\ \boldsymbol{\Delta \epsilon(\nu_2)} \\ \boldsymbol{\Delta T(1)} \\ \cdots \\ \boldsymbol{\Delta T(L)} \\ \\ \boldsymbol{\Delta \log(q(1)/q_s(1))} \\ \cdots \\ \boldsymbol{\Delta \log(q(L)/q_s(L))} \end{pmatrix}_{\boldsymbol{I}} = \begin{pmatrix} \boldsymbol{A_{11}} & \cdots & \boldsymbol{A_{1N}} \\ \boldsymbol{A_{21}} & \cdots & \boldsymbol{A_{2N}} \\ \cdots & \cdots & \cdots \\ \boldsymbol{A_{I1}} & \cdots & \boldsymbol{A_{IN}} \end{pmatrix} \cdot \begin{pmatrix} \boldsymbol{\Delta \tilde{\theta}_1} \\ \boldsymbol{\Delta \tilde{\theta}_2} \\ \cdots \\ \boldsymbol{\Delta \tilde{\theta}_N} \end{pmatrix} \qquad (3.2)$$

Advantages	**Disadvantages**
Very fast	**Requires knowledge of "truth"**
NO modeling of observations	$\boldsymbol{A_{L,n}}$ **needs stabilization**
Incorporates Geo-statistics	**Only linear relationships**

The Least Squares Solution

The change required to the parameters can be solved in a weighted least-squares sense. If there were no damping then the solution would be given by

$$\boldsymbol{\Delta A_j^{s,i}(0) = \left[S_{j,n'}^{s,i'} \left(N_{n',n}^{s,i}\right)^{-1} S_{n,j}^{s,i}\right]^{-1} \cdot S_{j,n'}^{s,i'} \cdot \left(N_{n',n}^{s,i}\right)^{-1} \cdot \left[R_{n,CCR}^{s} - R_n(X_L^{s,i-1})\right]} \tag{3.3}$$

This solution is usually highly unstable, given the under-determined nature of atmospheric retrievals. Traditional solutions regularize Eqn. 3.3. There are many methods but we can write most of them with a stabilizing matrix of the form, $\boldsymbol{H_{j,j}}$

$$\boldsymbol{\Delta A_j^{s,i} = \left[S_{j,n'}^{s,i'} \left(N_{n',n}^{s,i}\right)^{-1} S_{n,j}^{s,i} + H_{j,j}\right]^{-1} \cdot S_{j,n'}^{s,i'} \cdot \left(N_{n',n}^{s,i}\right)^{-1} \cdot \left[R_{n,CCR}^{s} - R_n(X_L^{s,i-1})\right]} \tag{3.4}$$

Using $\boldsymbol{H_{j,j}}$ tends to make the solution "stick" to the first guess and, therefore, make the retrieval first guess sensitive.

The Background Term

If the solution is iterated the difference between Eqn. **3.3** and Eqn. **3.4** is due to not believing a part of the $\left[R^s_{n,CCR} - R_n(X_L^{s,i-1})\right]$ residual. We can determine this part of the residual, which is called the background term, $\Psi_n^{s,i}$. The background term can be computed using the parameter changes that weren't made, as follows

$$\Psi_n^{s,i+1} = S_{n,j}^{s,i} \cdot \left(\Delta A_j^{s,i}(0) - \Delta A_j^{s,i}\right) \tag{3.5}$$

And then the background term is removed from subsequent steps of the minimization as follows,

$$\Delta \tilde{A}_j^{s,i} = U_{j,k}^{s,i} \cdot \frac{U_{k,j}^{s,i'} \cdot S_{j,n'}^{s,i'} \cdot \left(N_{n',n}^{s,i}\right)^{-1}}{\lambda_k + \Delta\lambda_k} \cdot \left[\left[R^s_{n,CCR} - R_n(X_L^{s,i-1})\right] - \Psi_n^{s,i-1}\right] \tag{3.6}$$

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