Neural Network Estimation of Atmospheric Profiles Using AIRS/IASI/AMSU Data in the Presence of Clouds

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ITSC-16

May 12, 2008

This work was sponsored by the National Oceanic and Atmospheric Administration under contract FA8721-05-C-0002. Opinions, interpretations, conclusions, and recommendations are those of the authors and are not necessarily endorsed by the United States Government.

Why Another Retrieval Algorithm??

The SCC/NN retrieval algorithm I'll discuss today should complement current physical / 1DVAR algorithms AND data assimilation routines by offering the following advantages:

- **Excellent retrieval accuracy and yield**
  - **Comparable to state-of-the-art methods (results presented today)**
  - **Especially accurate in areas of heavy clouds and over land where modeling is difficult**
  - **Highly-accurate "first-guess" could help initialize physical / 1DVAR algorithms and/or backfill when these algorithms don't converge**
- **Error/cloud characterization:**
  - **Averaging kernels and full error-covariance matrix**
  - **Quality control variables**
  - **Cloud parameters**
- **SPEED!!**
  - **Approximately 1000 retrievals per second using IASI (all channels) and AMSU with desktop PC**
  - **Very appealing for data assimilation and direct broadcast applications**

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Outline

- **Brief algorithm overview**
  - **Stochastic cloud clearing (SCC)**
  - **Projected Principal Components compression**
  - **Multilayer feedforward neural networks (NN)**
- **SCC performance with Quality Control (QC)**
- **SCC+NN performance comparisons with AIRS L2 Version 5 algorithm**
- **Infrared Atmospheric Sounding Interferometer (IASI) Information Content Analysis**
- **IASI versus AIRS: SCC/NN temperature retrieval performance**
- **Future Work / Summary**

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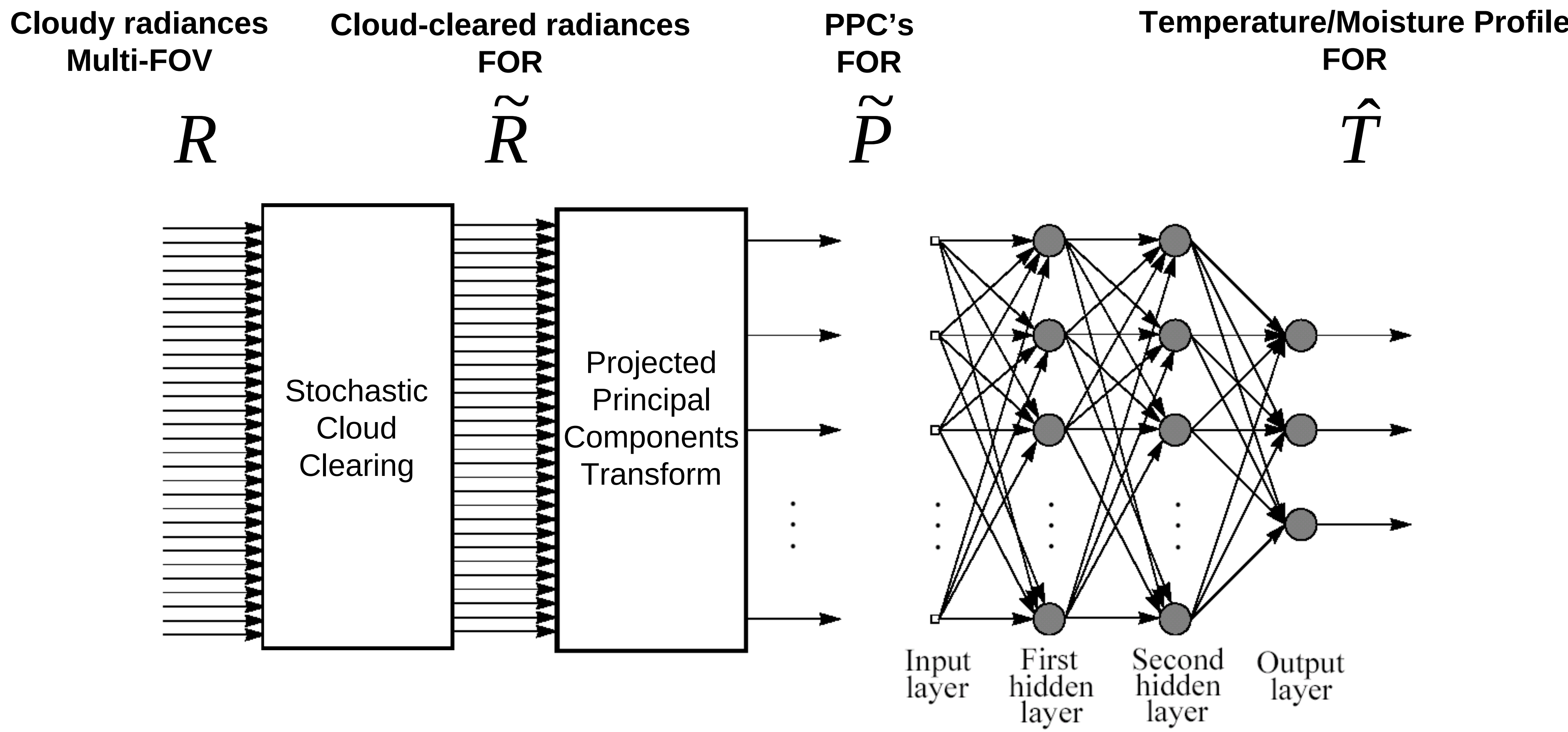
Algorithm Block Diagram



Stochastic Cloud Clearing

- **SCC estimates cloud contamination solely *based on statistics.***
  - **Hyperspectral IR and microwave observations are collocated to ground truth (ECMWF, radiosondes, etc.)**

- **Key concept: Principal component analyses of ΔR, not R.**
  - **Principal components of cloudy radiances can distribute cloud signal to non-cloud-impacted channels, etc.**
  - **Also mitigates crosstalk from surface emissivity variability**

- **Nonlinearity is accommodated using stratification (sea/land, latitude, day/night), multiplicative scan angle correction, etc.**

- **Advantages**
  - **Simple: SCC does not need physical models (retrieval or radiative transfer).**
  - **Fast: Based on matrix addition and multiplication**

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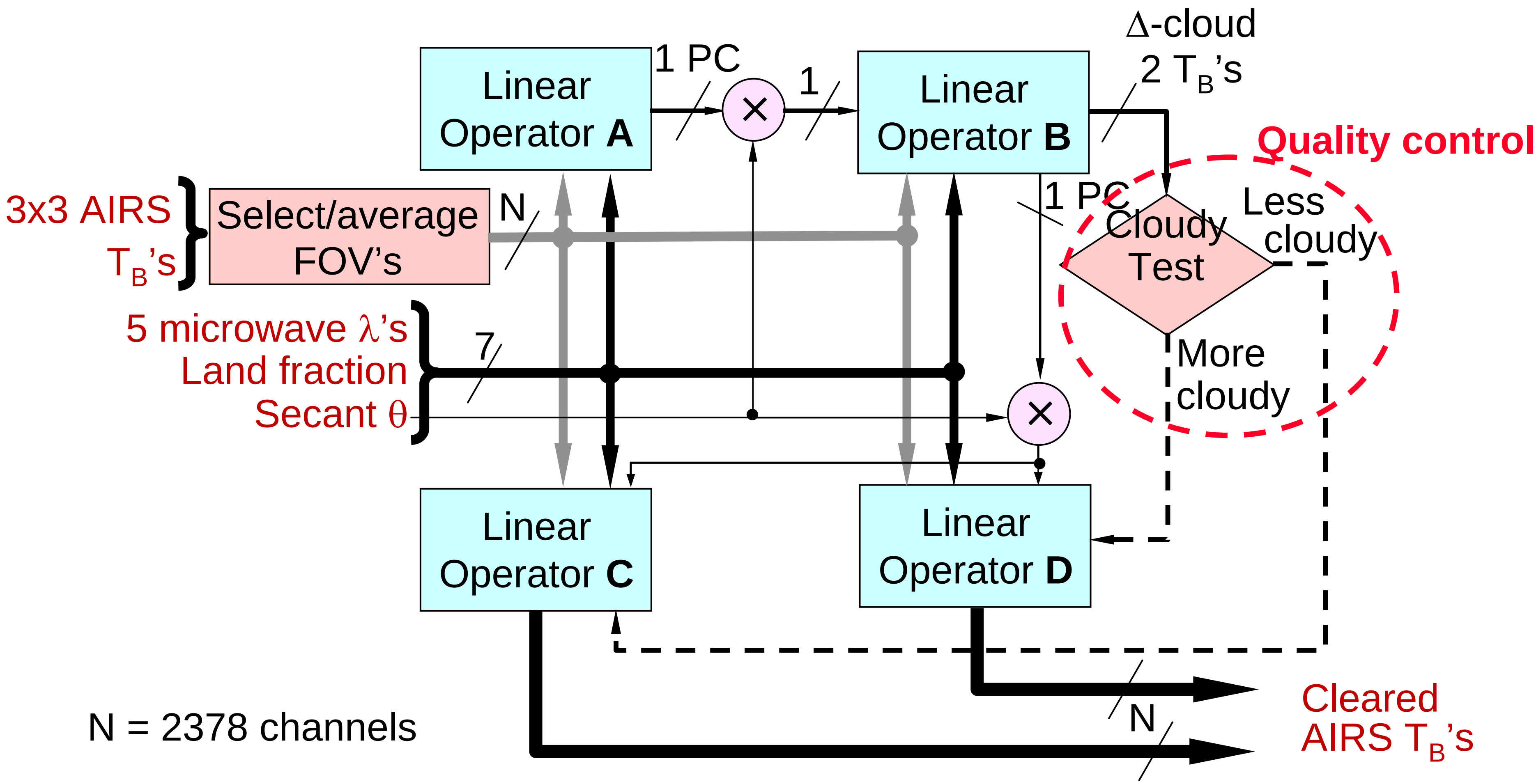
Block Diagram of SCC Algorithm

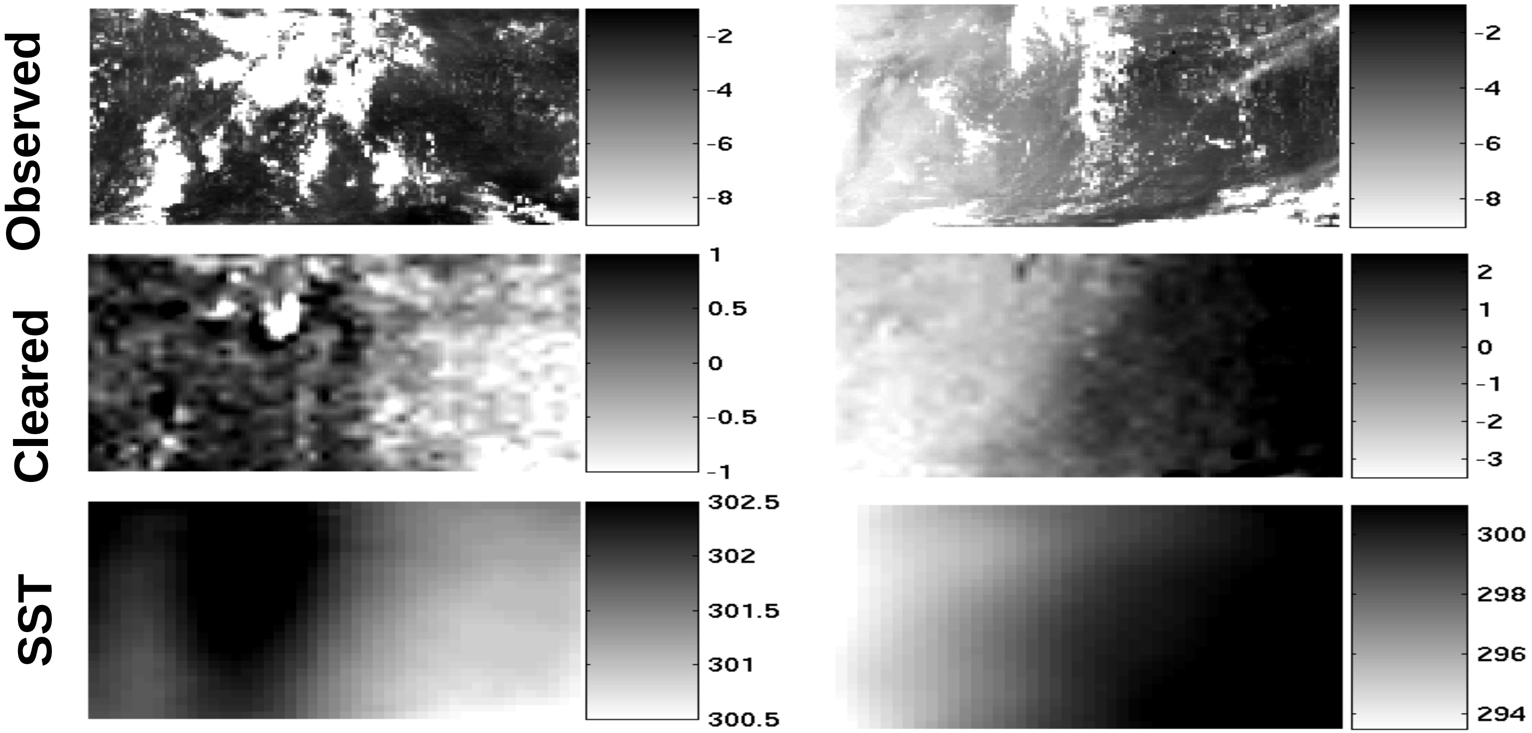


N = 2378 channels

C. Cho and D. H. Staelin, "Cloud clearing of AIRS Hyperspectral Infrared Radiances Using Stochastic Methods," J. Geophys. Res., 111, D09S18, doi:10.1029/2005JD006013, 2006.

Stochastic Cloud Clearing with AIRS/AMSU: Comparisons with Sea Surface Temperature

- Angle-corrected TB images at window channels



AIRS 2390.1cm^{-1}: near Hawaii AIRS 2399.9cm^{-1}: near SW Indian Ocean

- Clearing works well even if there is no hole (clear FOV)

Projected PCT (Canonical Correlations)

$$c(\cdot) = E[(\widehat{R}_r - R)^T(\widehat{R}_r - R)]$$

• It is sometimes useful to remove the PCA constraint of uncorrelated components:

$$\widehat{R}_r \triangleq \mathbf{L}_r \widetilde{R}$$

$$\mathbf{L}_r = \mathbf{E}_r \mathbf{E}_r^T \mathbf{C}_{RR}(\mathbf{C}_{RR} + \mathbf{C}_{\Psi\Psi})^{-1}$$

$$\mathbf{E}_r = [E_1 \,|\, E_2 \,|\, \cdots \,|\, E_r]$$

are the r most significant eigenvectors of

$$\mathbf{C}_{RR}(\mathbf{C}_{RR} + \mathbf{C}_{\Psi\Psi})^{-1}\mathbf{C}_{RR}$$

•The Wiener-filtered radiances are projected onto the r-dimensional subspace spanned by $\mathbf{E}_r$. It is this projection that motivates the name “projected principal components.”

•An orthonormal basis for this r-dimensional subspace of the original m-dimensional radiance vector space $\mathcal{R}$ is given by the r most-significant right eigenvectors, $\mathbf{V}_r$, of the reduced-rank linear regression matrix, $\mathbf{L}_r$.

$$\widetilde{P} = \mathbf{V}_r^T \widetilde{R}$$

Projected PCT (Canonical Correlations)

• Another useful application of the PPC transform is the compression of spectral radiance information that is correlated with a geophysical parameter, such as the temperature profile.

• The r-rank linear operator that captures the most radiance information which is correlated to the temperature profile is

$$\mathbf{L}_r = \mathbf{E}_r \mathbf{E}_r^T \mathbf{C}_{TR} (\mathbf{C}_{RR} + \mathbf{C}_{\Psi\Psi})^{-1}$$

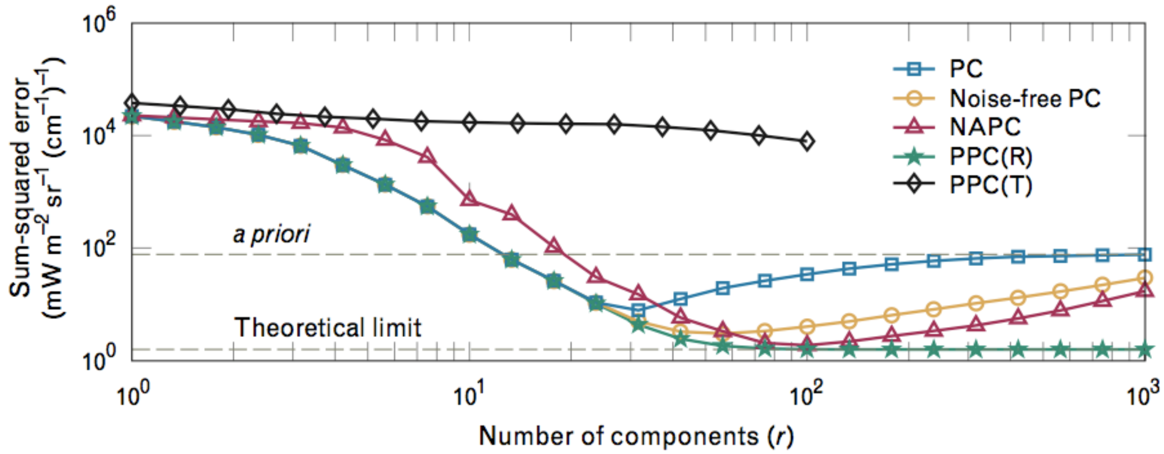
$$\mathbf{E}_r = [E_1 \,|\, E_2 \,|\, \cdots \,|\, E_r]$$

are the r most significant eigenvectors of

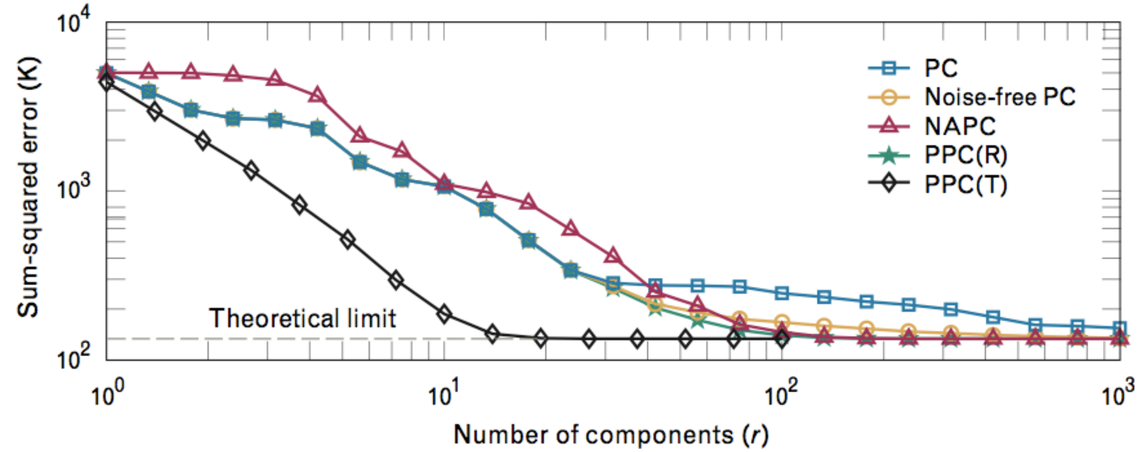
$$\mathbf{C}_{TR} (\mathbf{C}_{RR} + \mathbf{C}_{\Psi\Psi})^{-1} \mathbf{C}_{RT}$$

Performance Comparison of Principal Components Transforms

"Radiance Reconstruction Error"

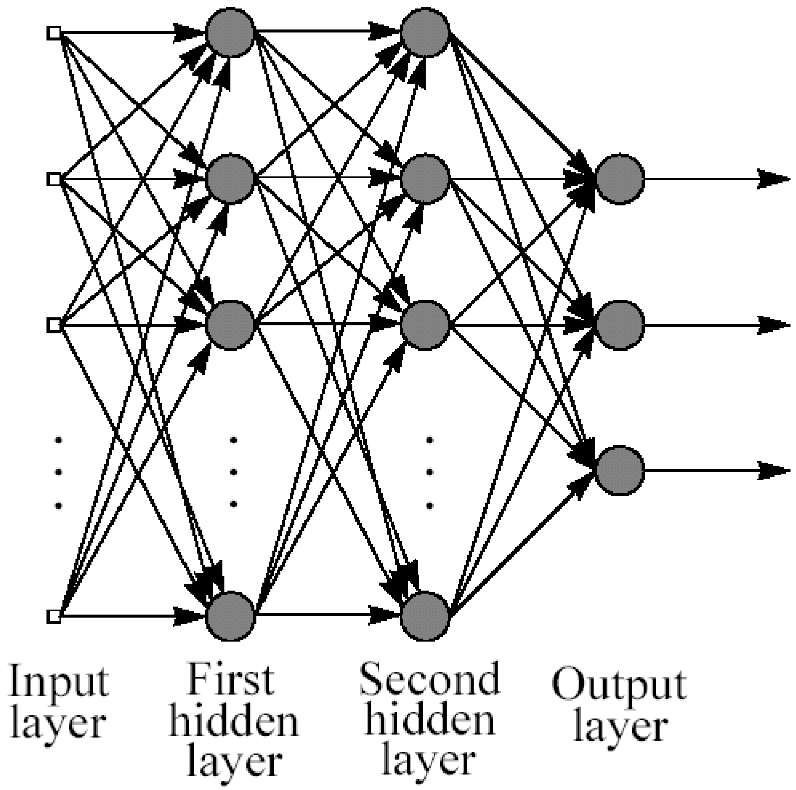


"Temperature Profile Estimation"



W. J. Blackwell, "A Neural-Network Technique for the Retrieval of Atmospheric Temperature and Moisture Profiles from High Spectral Resolution Sounding Data," *IEEE Trans. Geosci. Remote Sensing,* vol. 43, no. 11, Nov. 2005.

Multilayer Feedforward Neural Networks

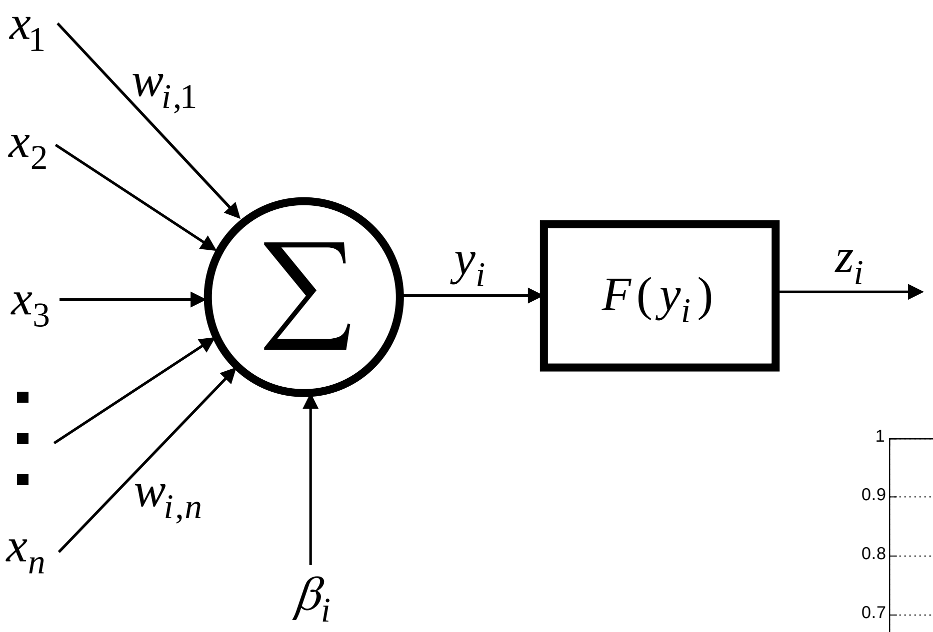


- Parameterized, nonlinear function

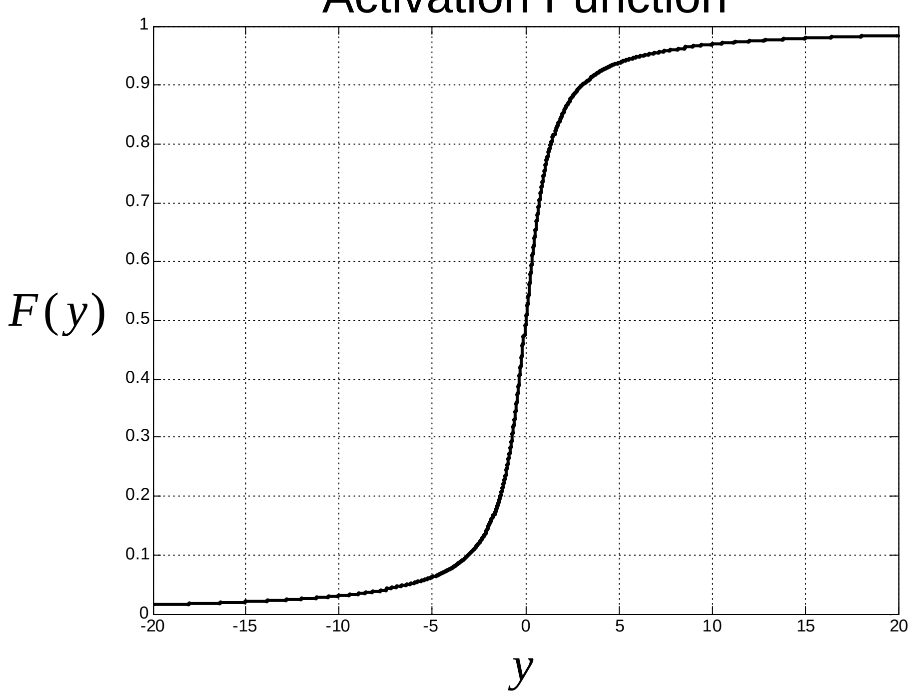
- Parameters ("weights" and "biases") are found by numerically minimizing some cost function (usually SSE)

- Sophisticated methods for finding optimal weights exist ("back-propagation" of errors)

Perceptron



Differentiable activation functions typically used to facilitate gradient searches



Perceptron weights and biases are iteratively adjusted by "back propagation" of errors.

Retrieval Performance Validation with AIRS/AMSU

Case 1: ECMWF atmospheric fields

- **>1,000,000 co-located AIRS/AMSU/ECMWF observations from ~100 days:**
  - **Every fourth day from December 1, 2004 through January 31, 2006**
  - **Used for training**
- **~250,000 profiles set aside for validation and testing sets**

Case 2: Radiosonde data

- **~50,000 quality-controlled radiosondes from NOAA FSL global database co-located with AIRS/AMSU observations**
  - **Used for validation**

Global: Cloudy, Land & Ocean, Day & Night

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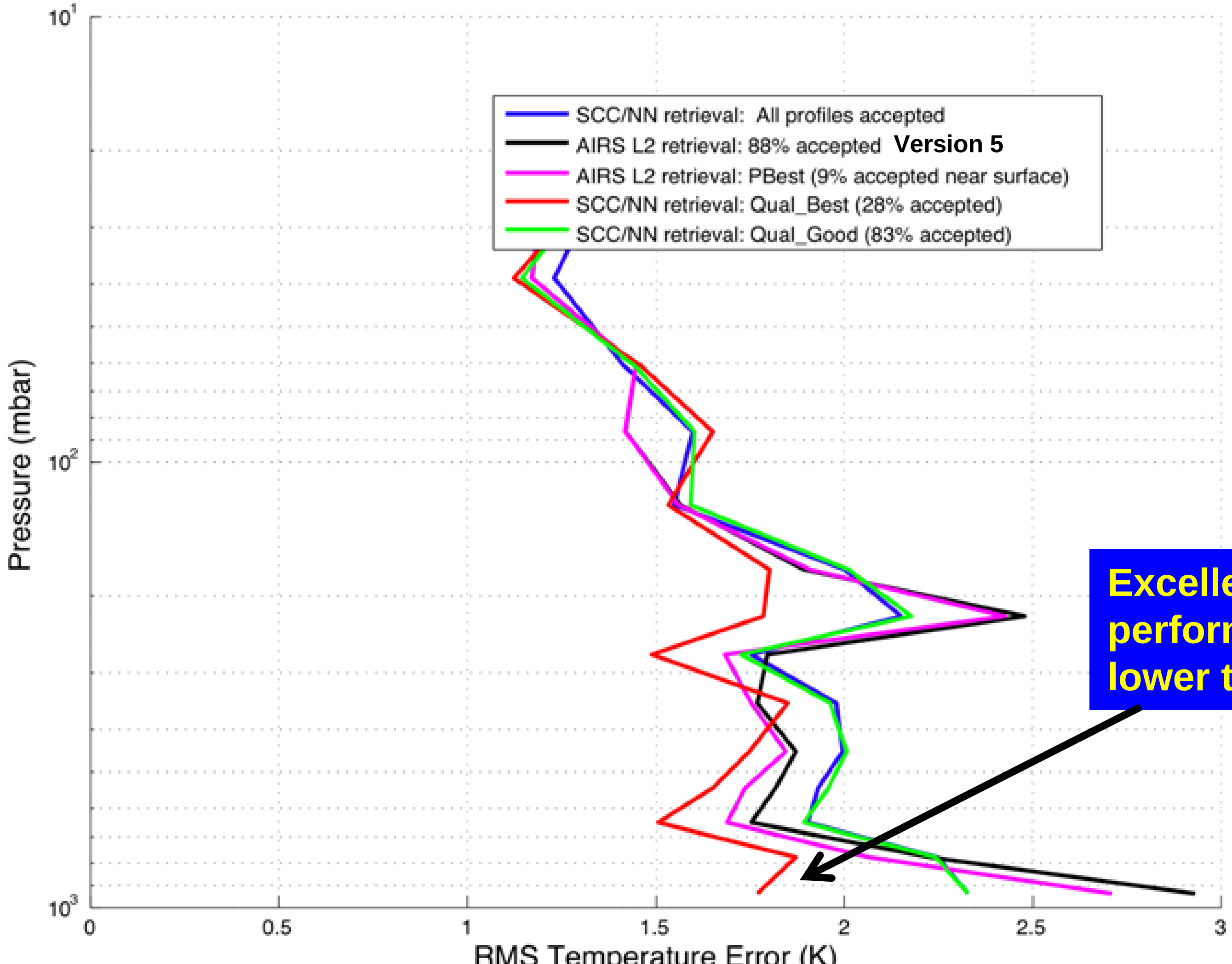
Descending, Land, Edge-of-Scan, Spring05

Cloudy Conditions, 910 Global Radiosondes

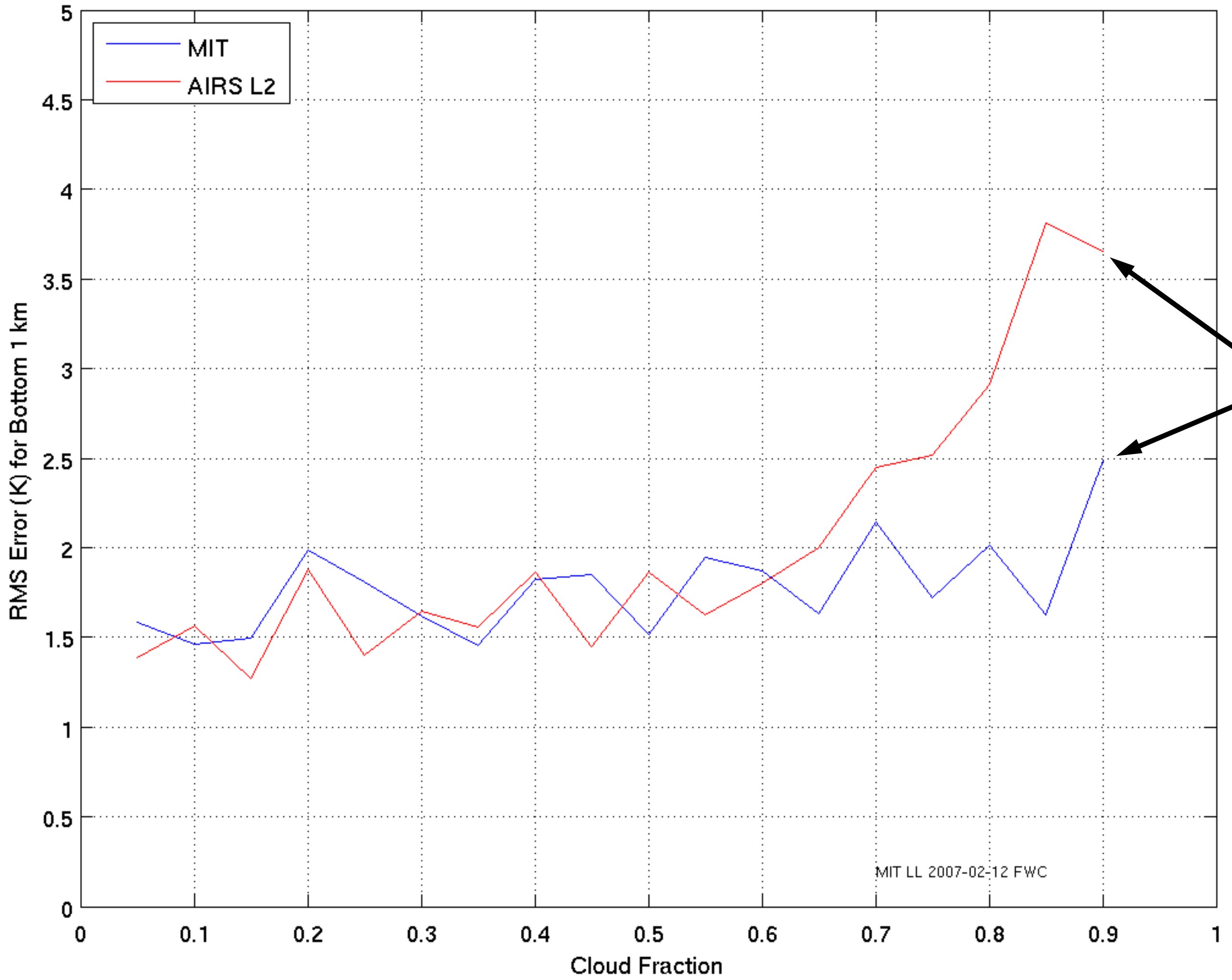


~1km vertical layers
AIRS+AMSU

Latitudes within ±60°

910 radiosondes are "truth"

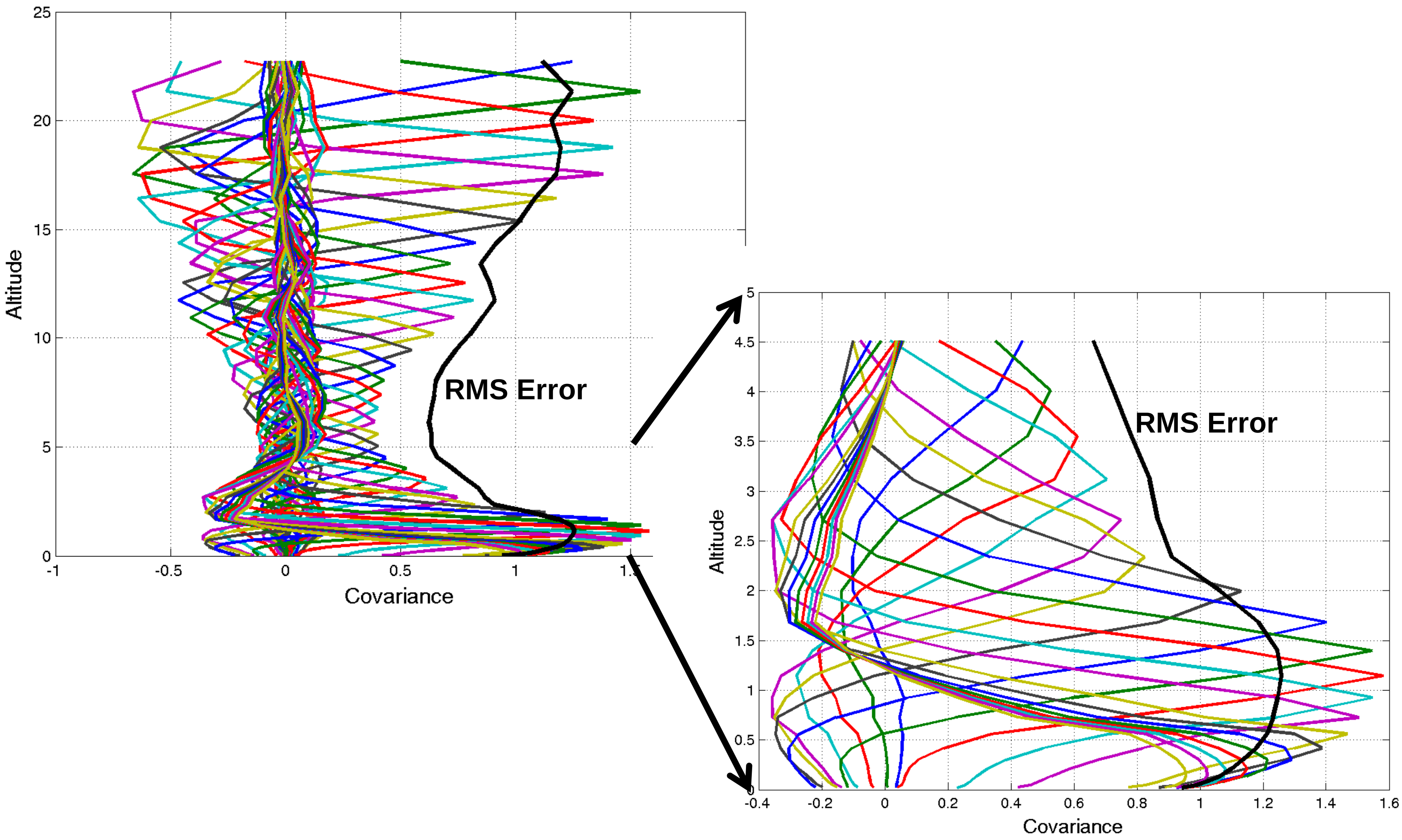
T(h) RMS Error Versus Cloud Fraction Common Ensemble



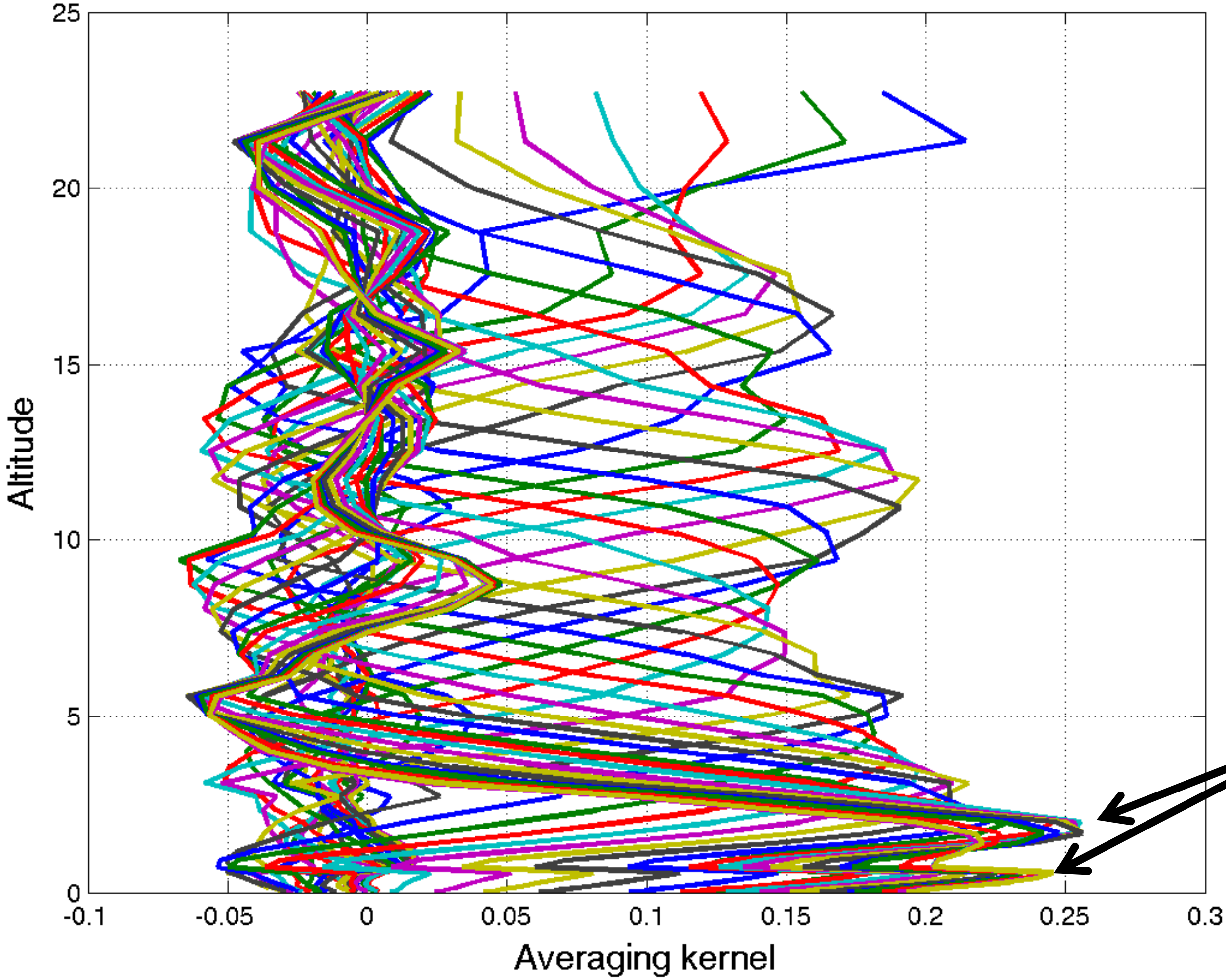
SCC/NN is much less sensitive to cloud amount !

Land, All latitudes, Radiosondes

Typical NN Retrieval Error Covariance

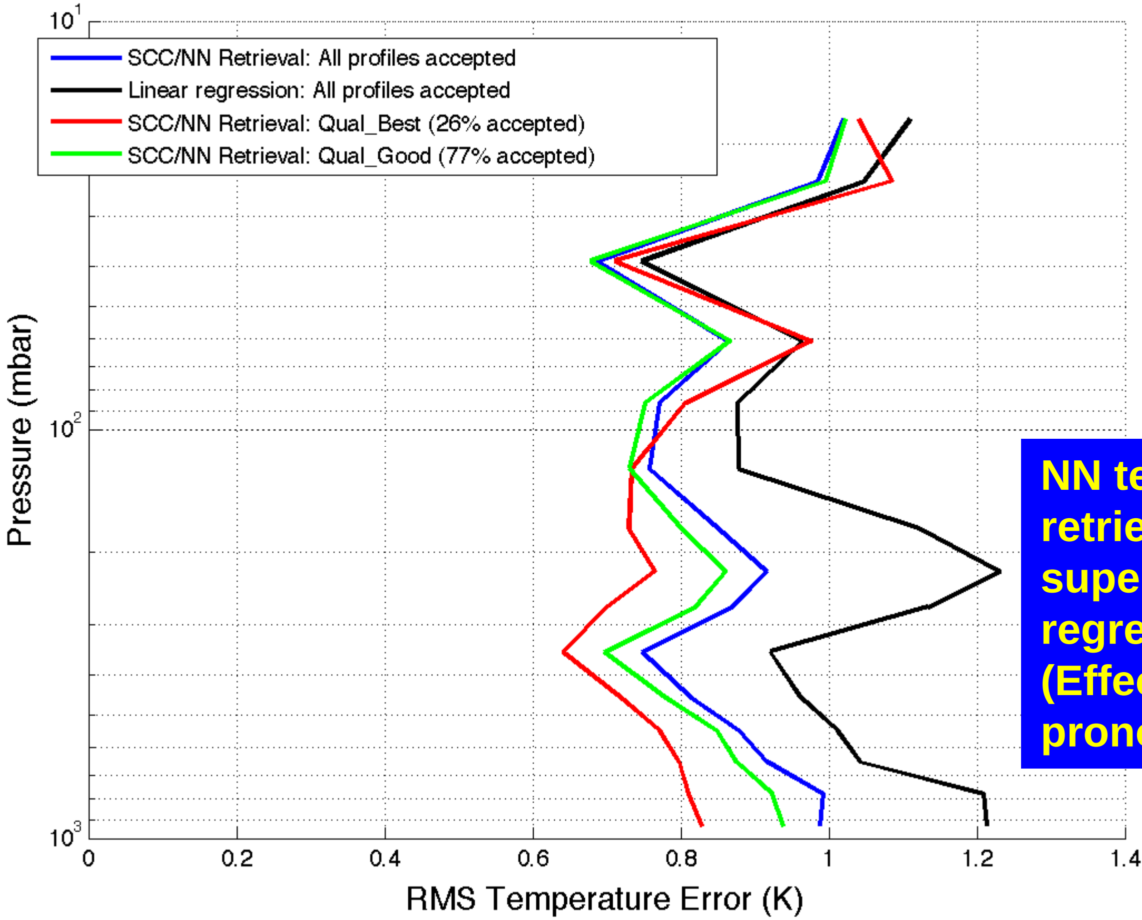


Typical NN Retrieval Averaging Kernels



Very high vertical resolution in lower troposphere !

IASI Temperature Retrievals Over Ocean



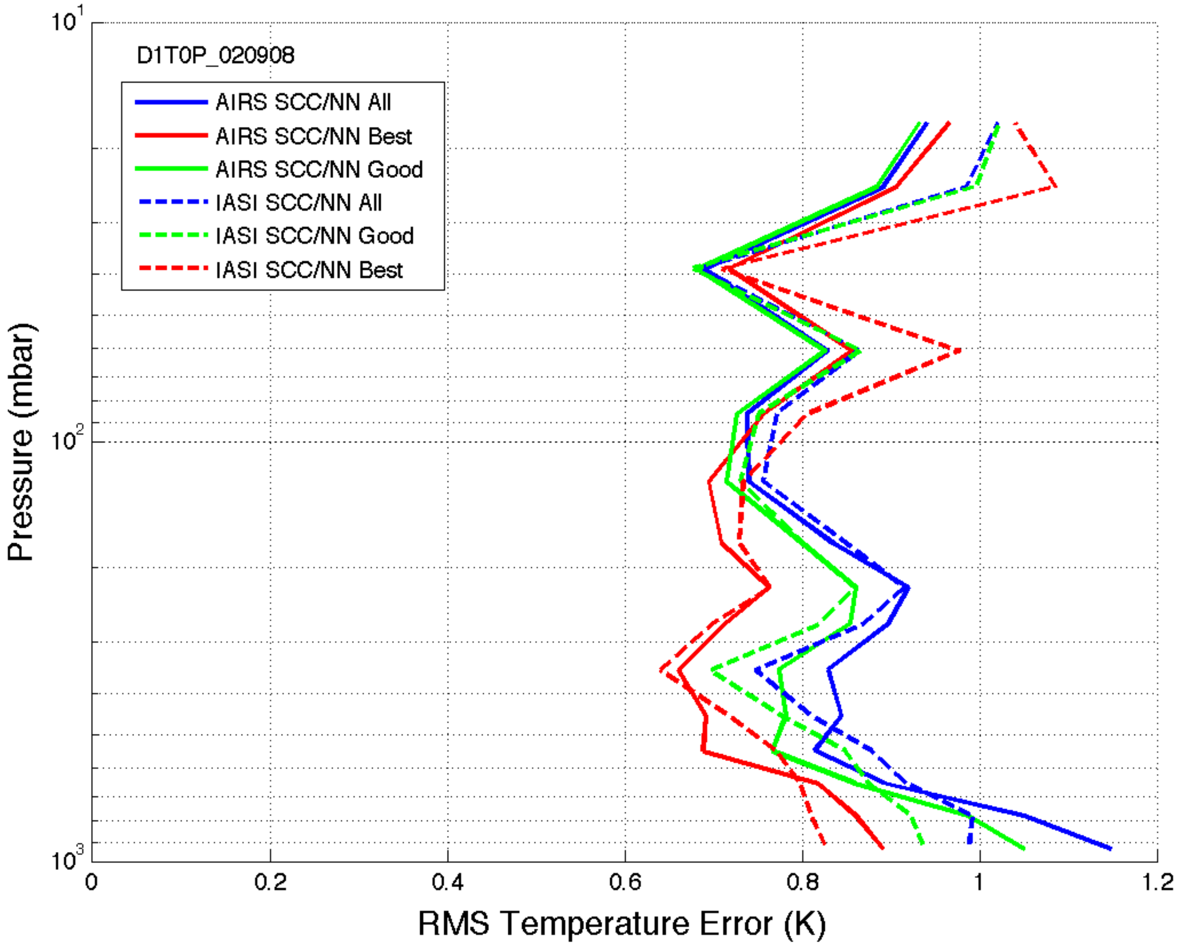
NN temperature retrieval is vastly superior to linear regression !
(Effect is even more pronounced over land.)

~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is "truth"

AIRS versus IASI: Ocean, Night



~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”

Future Work

- **Additional and more extensive performance assessments**
  - **Match-ups with radiosonde data**
  - **Integration with latest AIRS Level 2 algorithm (V6)**
- **Algorithm optimizations, especially for IASI and CrIMSS**
  - **Improved handling of land, including elevated surface terrain and surface emissivity**
  - **Retrieval extensions to include ozone, trace gases, and cloud microphysical properties**
- **Experiments with data assimilation and direct broadcast applications**
  - **We're looking for collaborators – please contact me if interested**

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Summary and Conclusions

- **SCC/NN RMS retrieval accuracies and yield substantially exceed those of the AIRS L2 algorithm (V5) in cloudy conditions over land. Moisture retrievals show similar characteristics.**

- **SCC/NN algorithm is characterized by full error covariance matrix, quality control, and averaging kernels, facilitating its use with other retrieval and assimilation methodologies.**

- **High computational efficiency (1000 retrievals/sec) makes SCC/NN particularly attractive for near-real-time data assimilation and direct broadcast applications.**

- **Thanks to NPOESS IPO and NASA NPP/AIRS Science Teams for financial and logistical support for this work.**

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Backup Slides

Philosophical Musings

- **Physical / 1DVAR retrievals are only as good as the models**

- **Empirical statistical retrievals (i.e., using real observations, not simulated observations) are only as good as the ground truth**

- **Cloud and surface emissivity models, while progressing rapidly, are still inadequate to provide retrievals with highest possible fidelity in "problem areas" (Cloudy/Land)**

- **Sophisticated statistical/stochastic methods can be very helpful here:**
  - **Cloud/SE modeling error greatly exceeds profile ground truth error**
  - **There is hope: INFORMATION CONTENT IS IN THE RADIANCES**

- **My contention (to be supported by evidence in today's talk): Presently, the best statistical retrievals, which are essentially 4-D interpolators of the ground truth, exceed the accuracies of the best physical retrievals IN CLOUDS OVER LAND**

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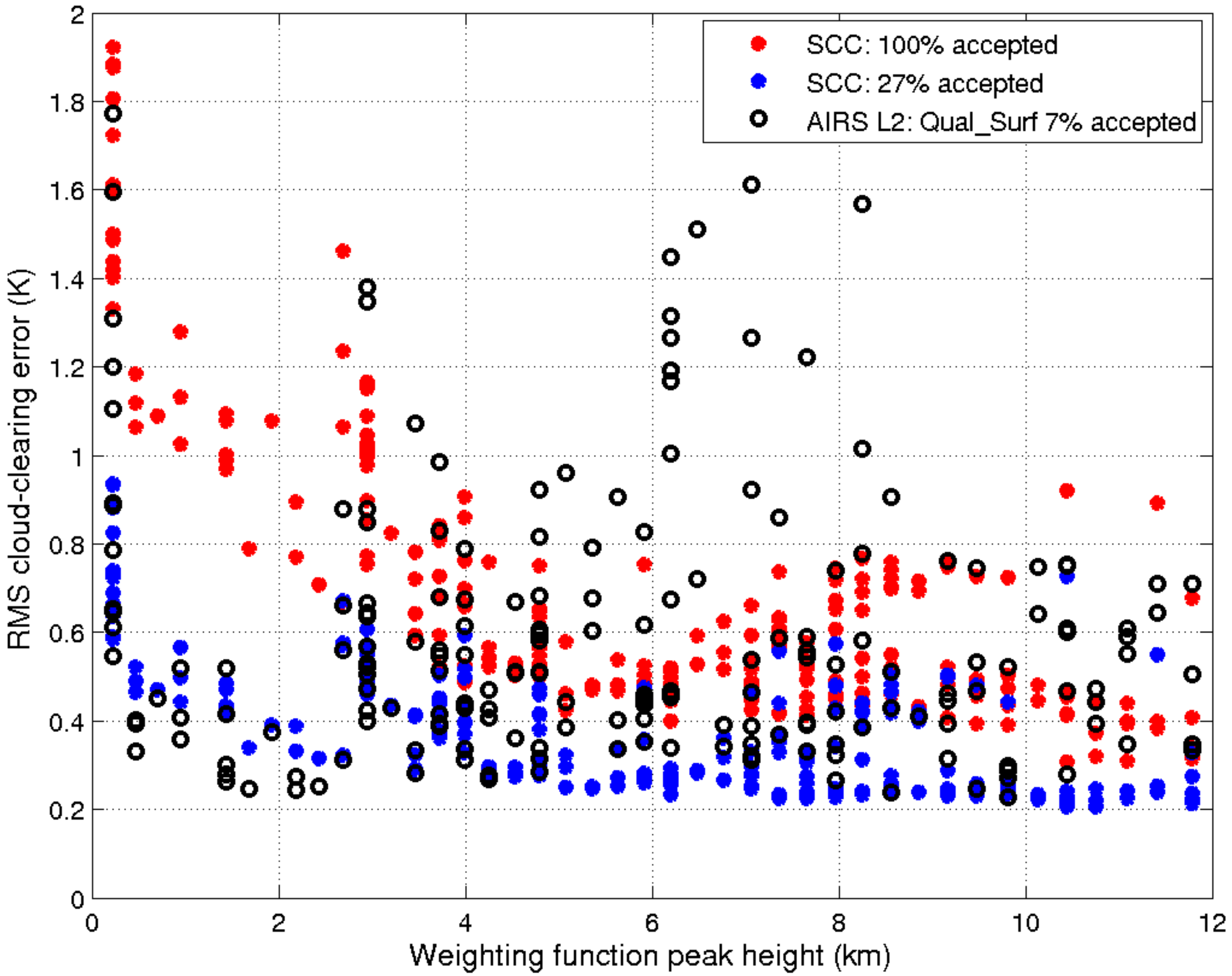
Stochastic Cloud Clearing Quality Control



Ocean, All latitudes

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Algorithm Overview (Part I)

- Temperature and moisture profile retrievals are produced in all cloud conditions
- Cloud-cleared radiance estimates are produced for all 2378 AIRS channels
- Retrieval is global:
  - All latitudes
  - Ocean and land
  - Day and night
- Quality control has been implemented
- IR-only option implemented
- Very fast: Cloud-cleared radiances and retrieved profiles generated for one field of regard in ~1 msec using PC!!
  - Two-three orders of magnitude faster than current operational methods
  - One-two orders of magnitude faster than iterative, pseudochannel methods

Algorithm Overview (Part II)

- **Algorithm is composed of linear and non-linear statistical operators**
  - **Projected principal components transform**
  - **Neural network estimation**

- **Coefficients are derived empirically, off-line:**
  - **Co-location of sensor measurements with “truth” (Radiosondes, NWP, etc.)**
  - **Model-generated data**
  - **Data stratification is used for:**
    - **Sensor scan angle**
    - **Latitude**
    - **Solar zenith angle**
    - **Surface type**
    - **Surface elevation**

Principal Components Transform (PCT)

- Objectives:
  - Remove noise from spectral radiance observations (exploit redundancy)
  - Compress radiance information into fewer components

$$\widehat{R}_r \triangleq \mathbf{G}_r \widetilde{R} \qquad\qquad \mathbf{C}_{\widetilde{R}\widetilde{R}} = \mathbf{C}_{RR} + \mathbf{C}_{\Psi\Psi}$$

- Cost function: Minimize sum-squared error between estimated noise-free radiances and actual noise-free radiances

$$c(\cdot) = E[(\widehat{R}_r - R)^T(\widehat{R}_r - R)]$$

- Noise-Adjusted Principal Components (NAPC) transform:

$$\mathbf{G}_r = \mathbf{C}_{\Psi\Psi}^{1/2}\mathbf{W}_r\mathbf{W}_r^T\mathbf{C}_{\Psi\Psi}^{-1/2}$$

- Where $\mathbf{W}_r^T$ are the r most significant eigenvectors of the whitened covariance matrix:

$$\mathbf{C}_{\widetilde{W}\widetilde{W}} = \mathbf{C}_{\Psi\Psi}^{-1/2}(\mathbf{C}_{\widetilde{R}\widetilde{R}})\mathbf{C}_{\Psi\Psi}^{-1/2}$$

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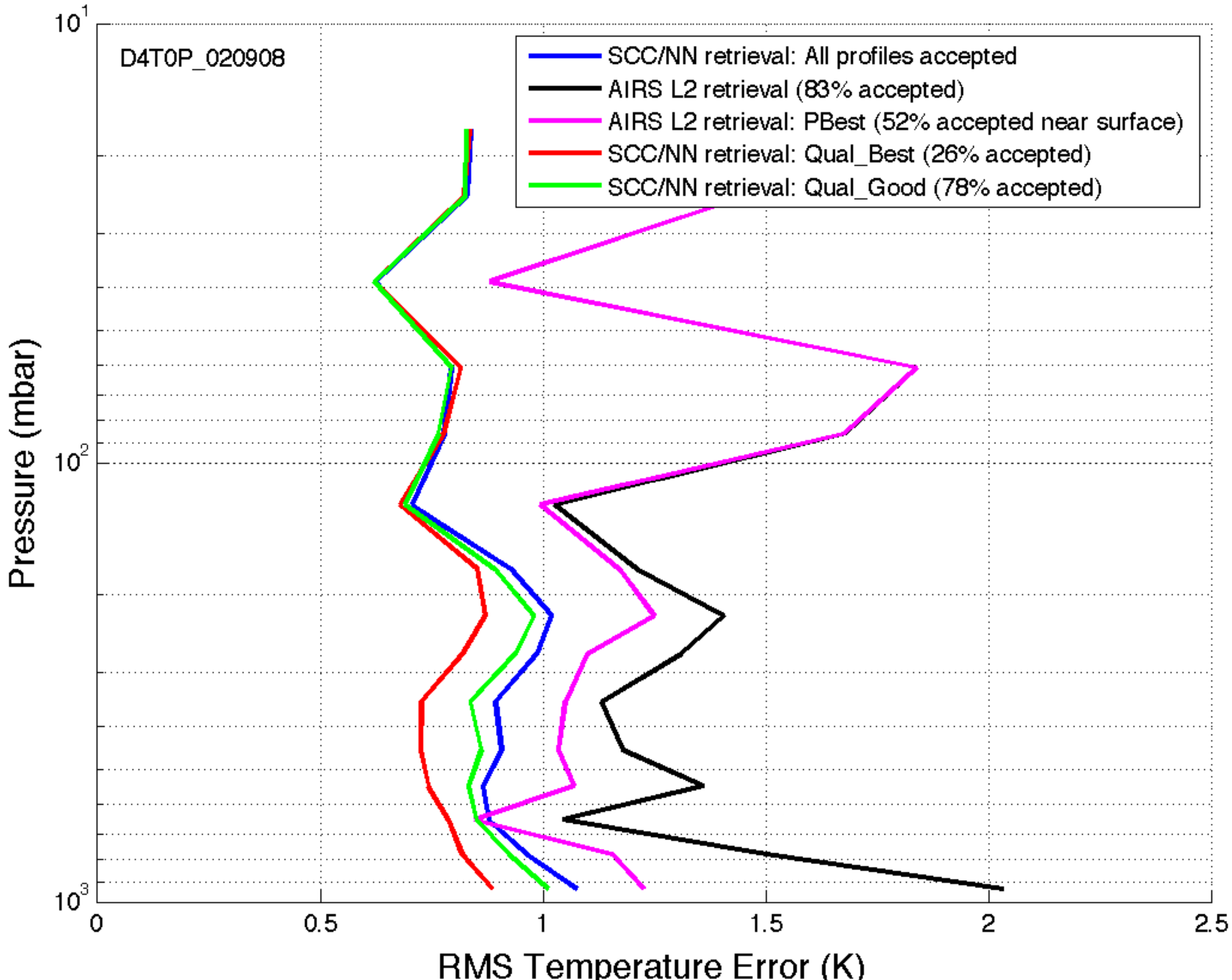
SCC/NN versus AIRS L2 (Version 5) Descending, Ocean, Edge-of-Scan, Spring

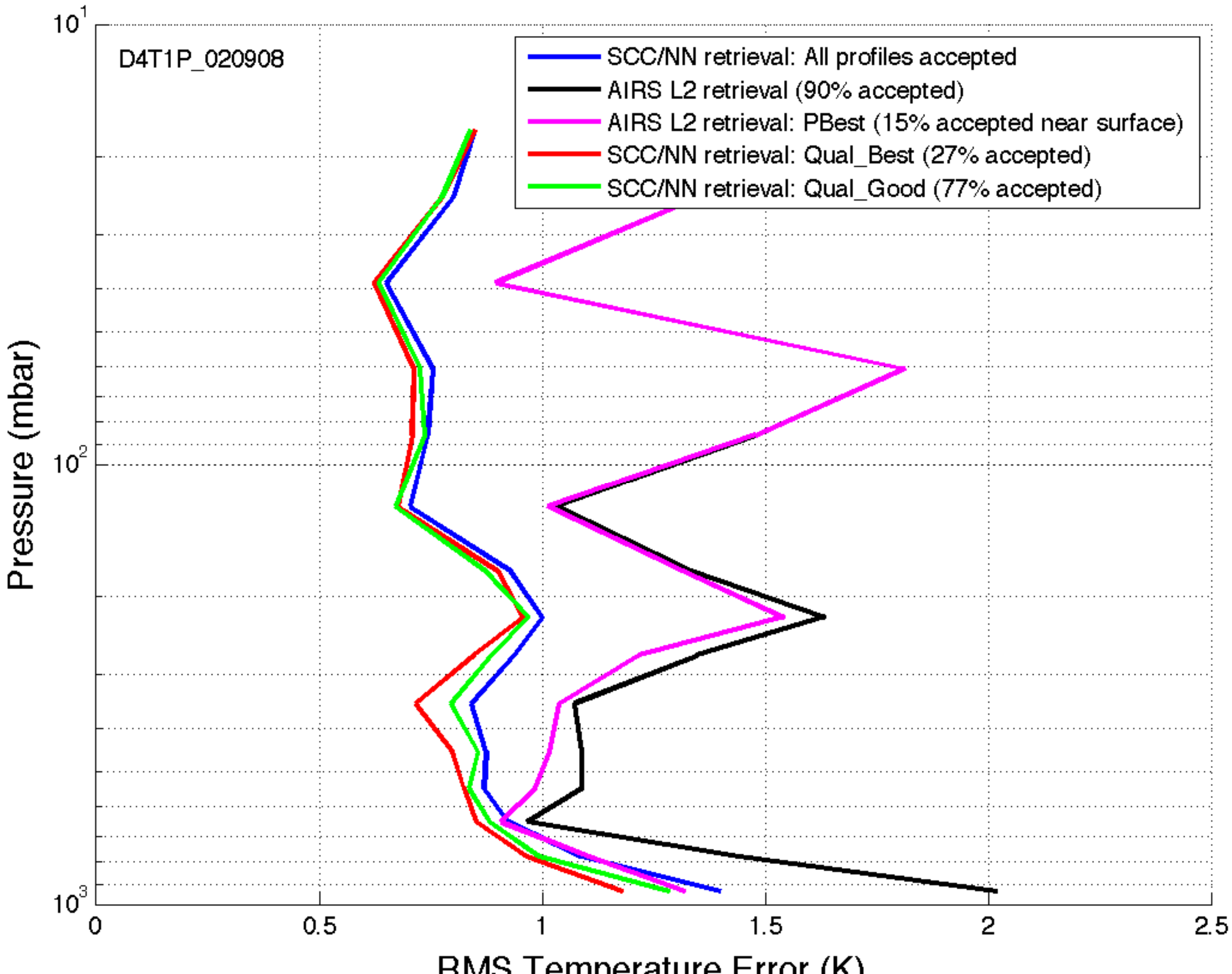


~1km vertical layers
AIRS+AMSU

Latitudes within ±60°

ECMWF is “truth”

SCC/NN versus AIRS L2 (Version 5) Descending, Land, Edge-of-Scan, Spring

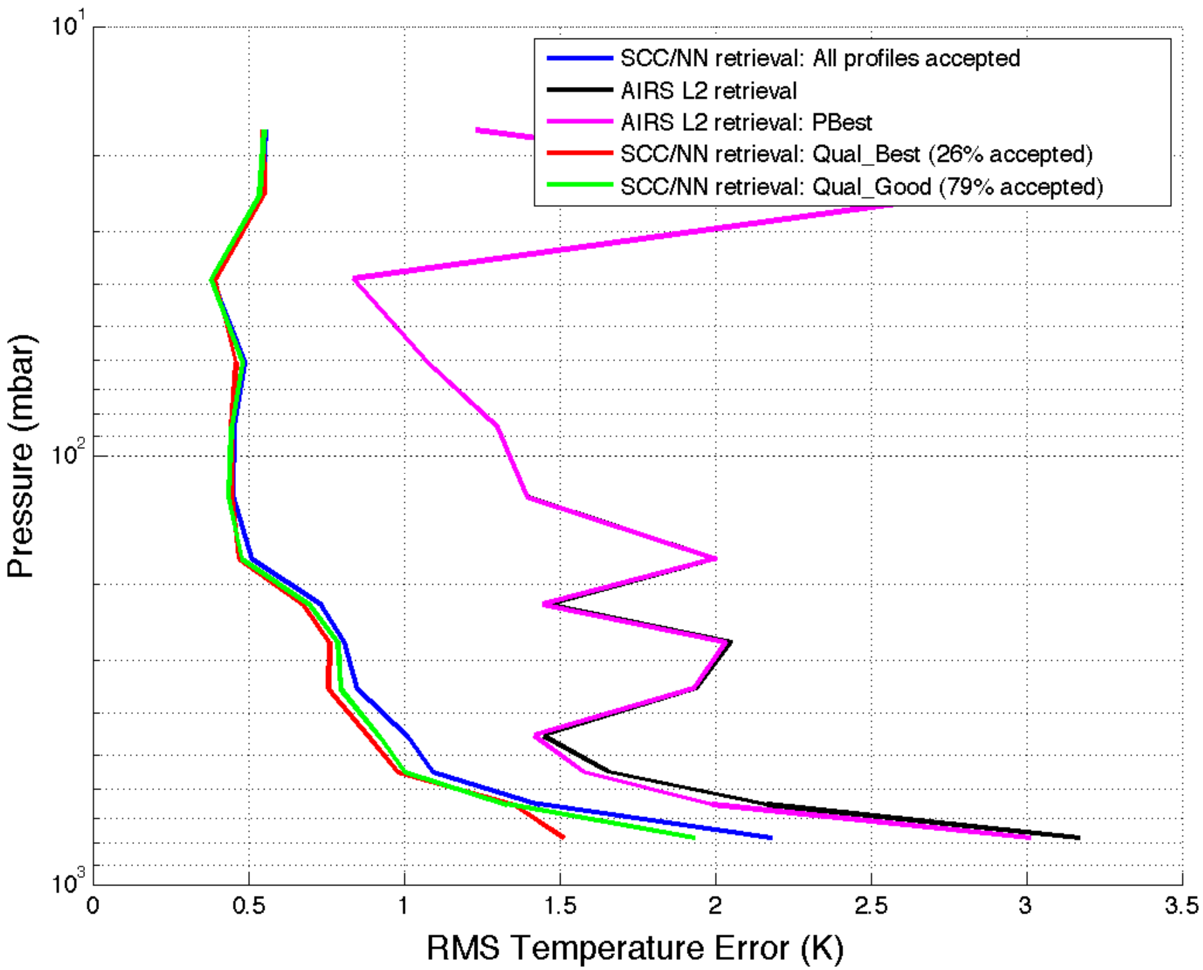


~1km vertical layers
AIRS+AMSU

Latitudes within ±60°

ECMWF is “truth”

SCC/NN versus AIRS L2 (Version 5) Descending, South Pole*, Edge-of-Scan, Spring



~1km vertical layers
AIRS+AMSU

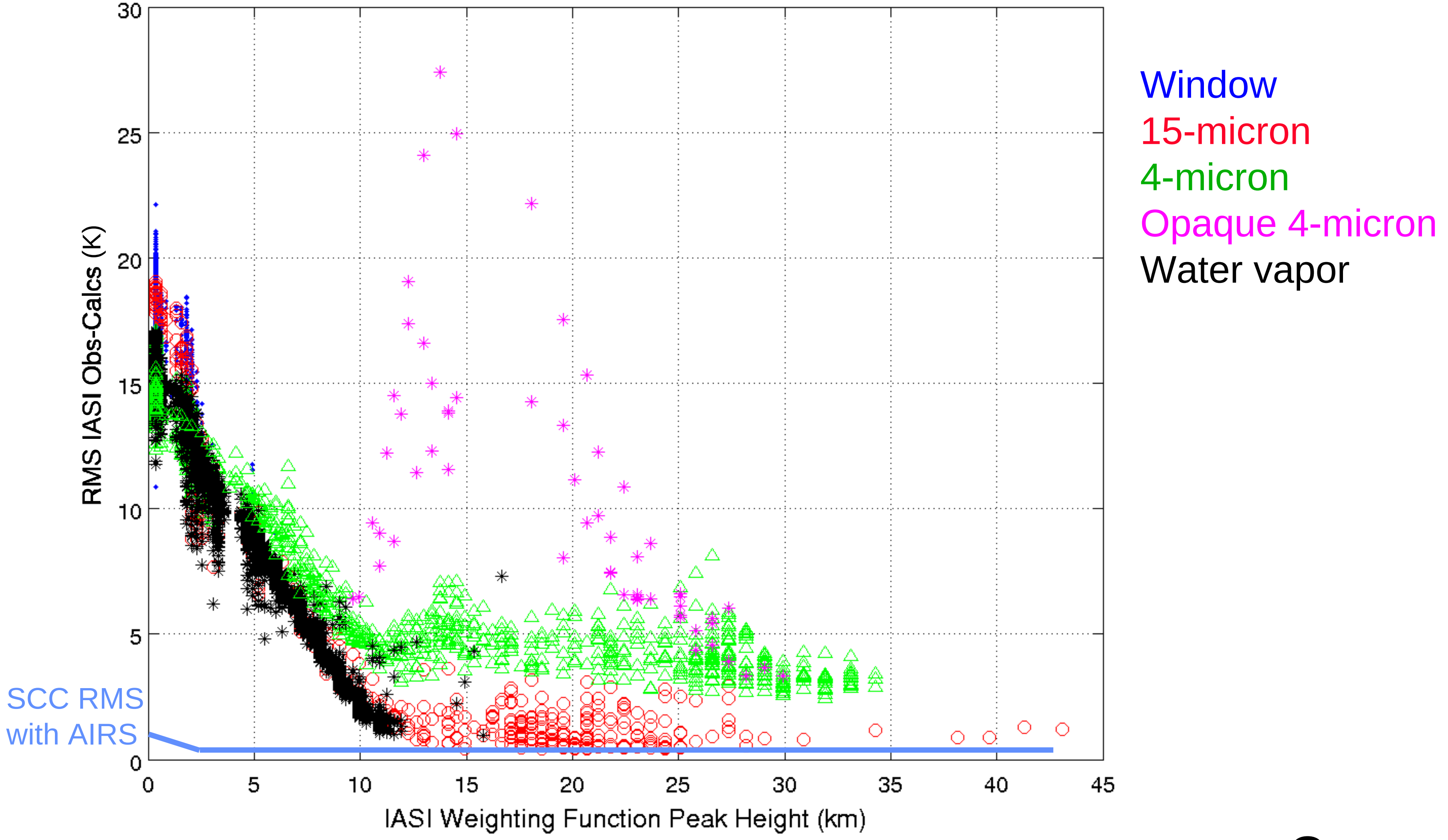
ECMWF is "truth"
Quality is suspect

*South Pole = Latitudes < -60°

IASI/ECMWF/SARTA Matchup Database

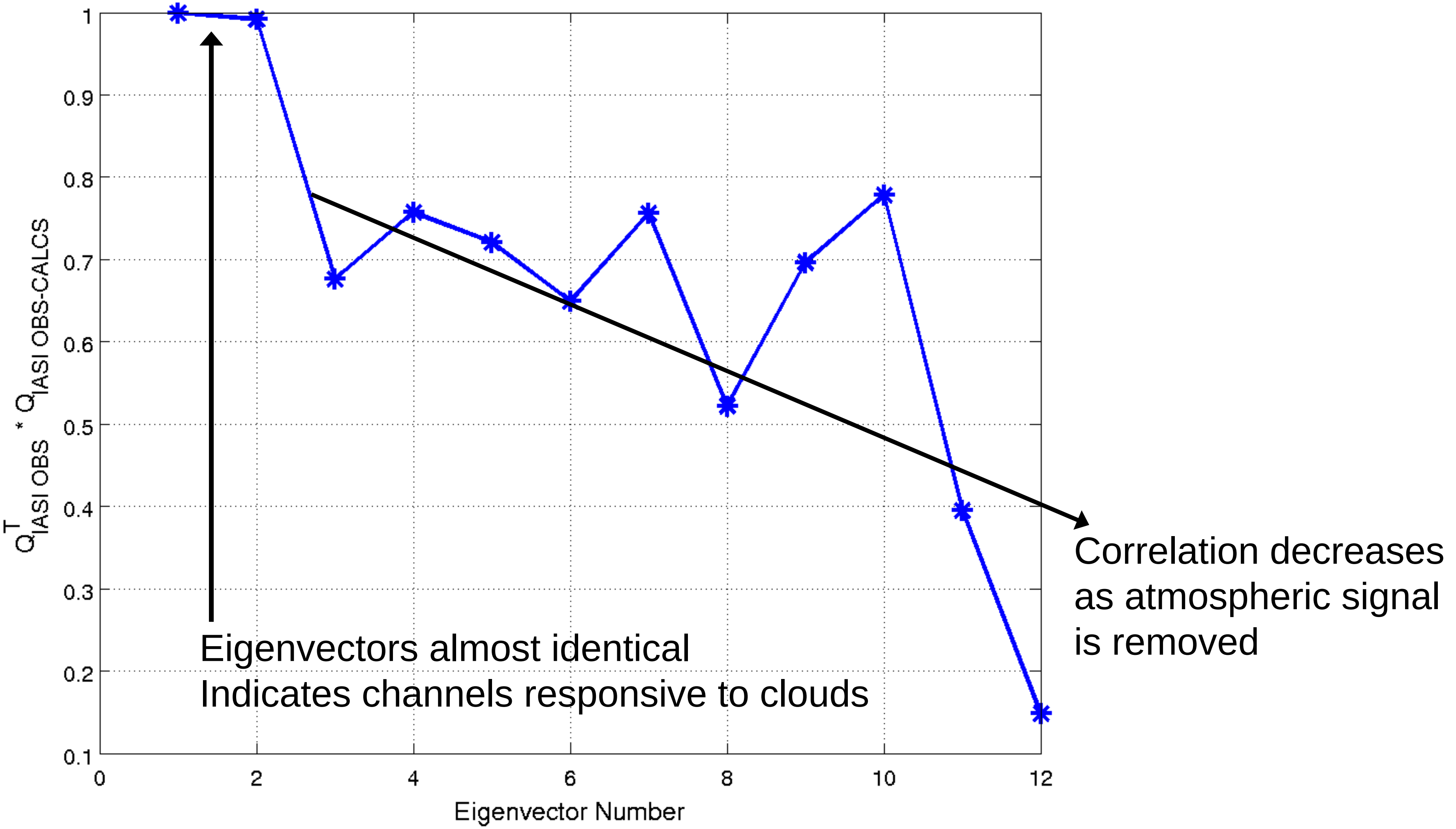
- **Global database spanning May07-Dec07**
- **Approximately 100,000 fields-of-regard**
  - **IASI observations (2x2)**
  - **ECMWF atmospheric fields**
  - **Radiosondes (available for some FOR's)**
  - **IASI clear-air spectra calculated with SARTA v1.05**
- **Database stratified by surface type, latitude, solar zenith angle, sensor scan angle, surface pressure**

RMS IASI Cloudy Obs - Clear Calcs (i.e., Before Cloud Clearing)



Ocean

Correlation of “IASI OBS” and “IASI OBS-CALCS” Eigenvectors



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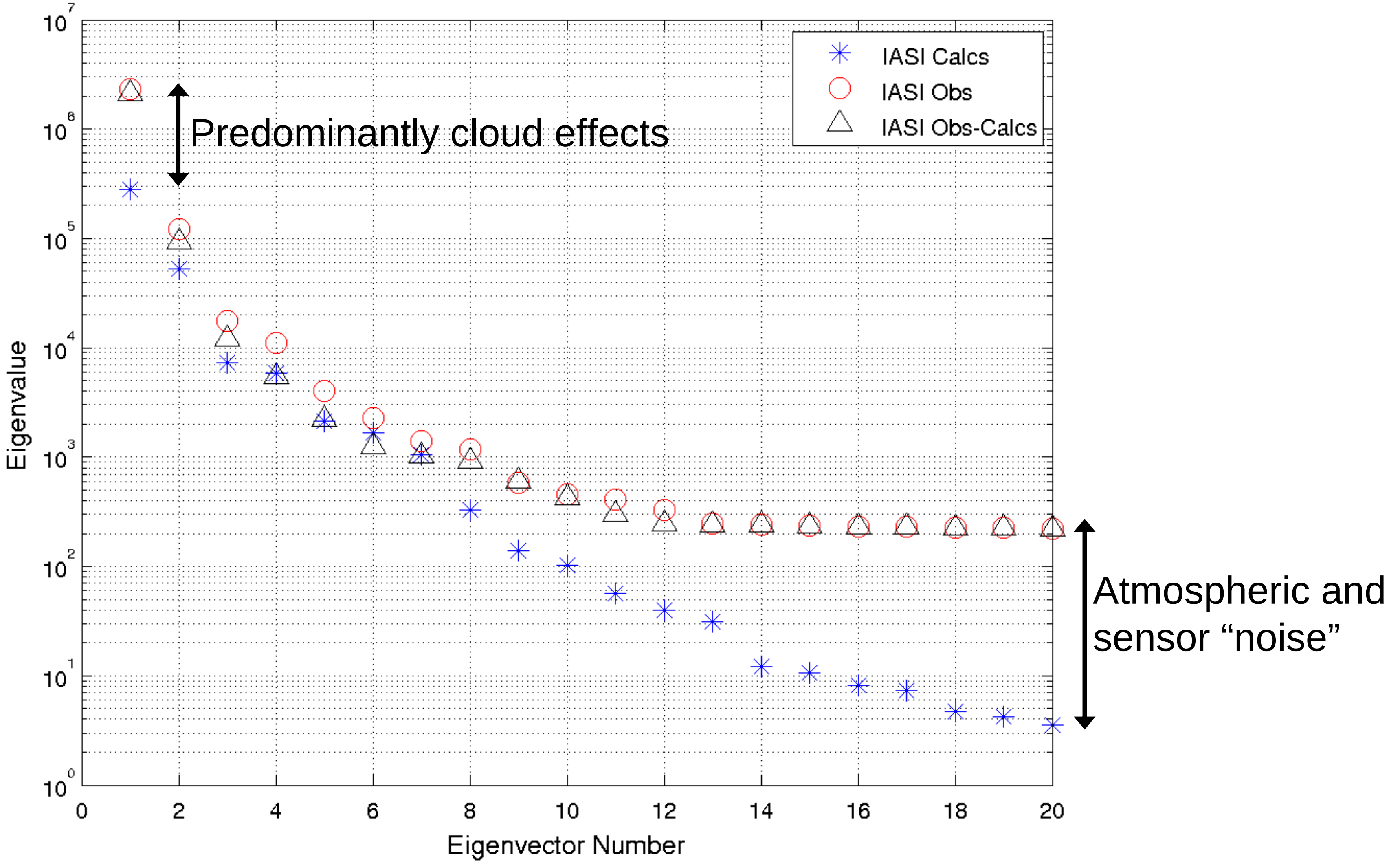
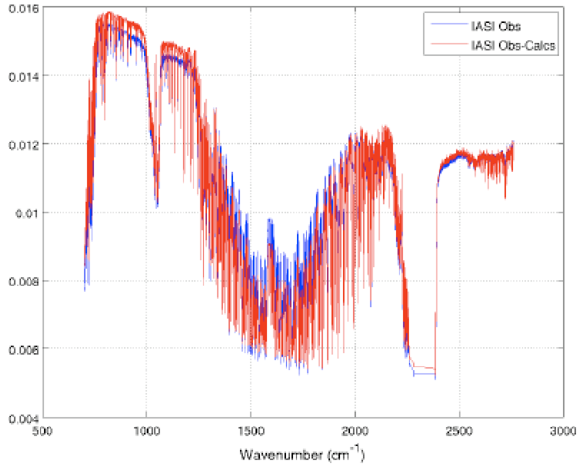
IASI Eigenanalysis

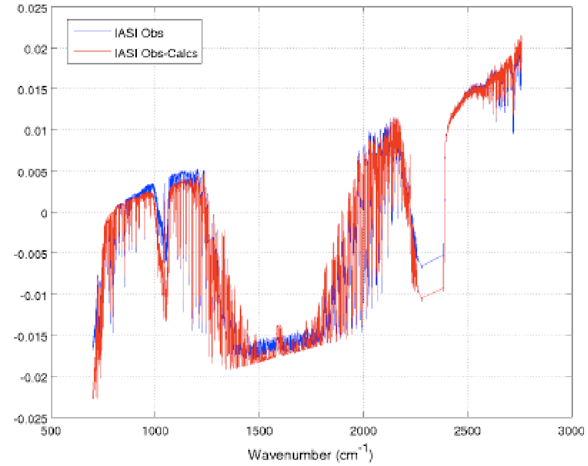


Ocean

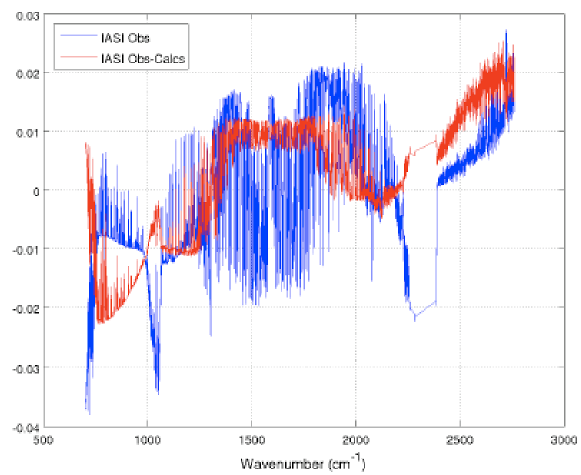
IASI "OBS" and "OBS-CALCS" Eigenvectors



(a) Eigenvector set #1

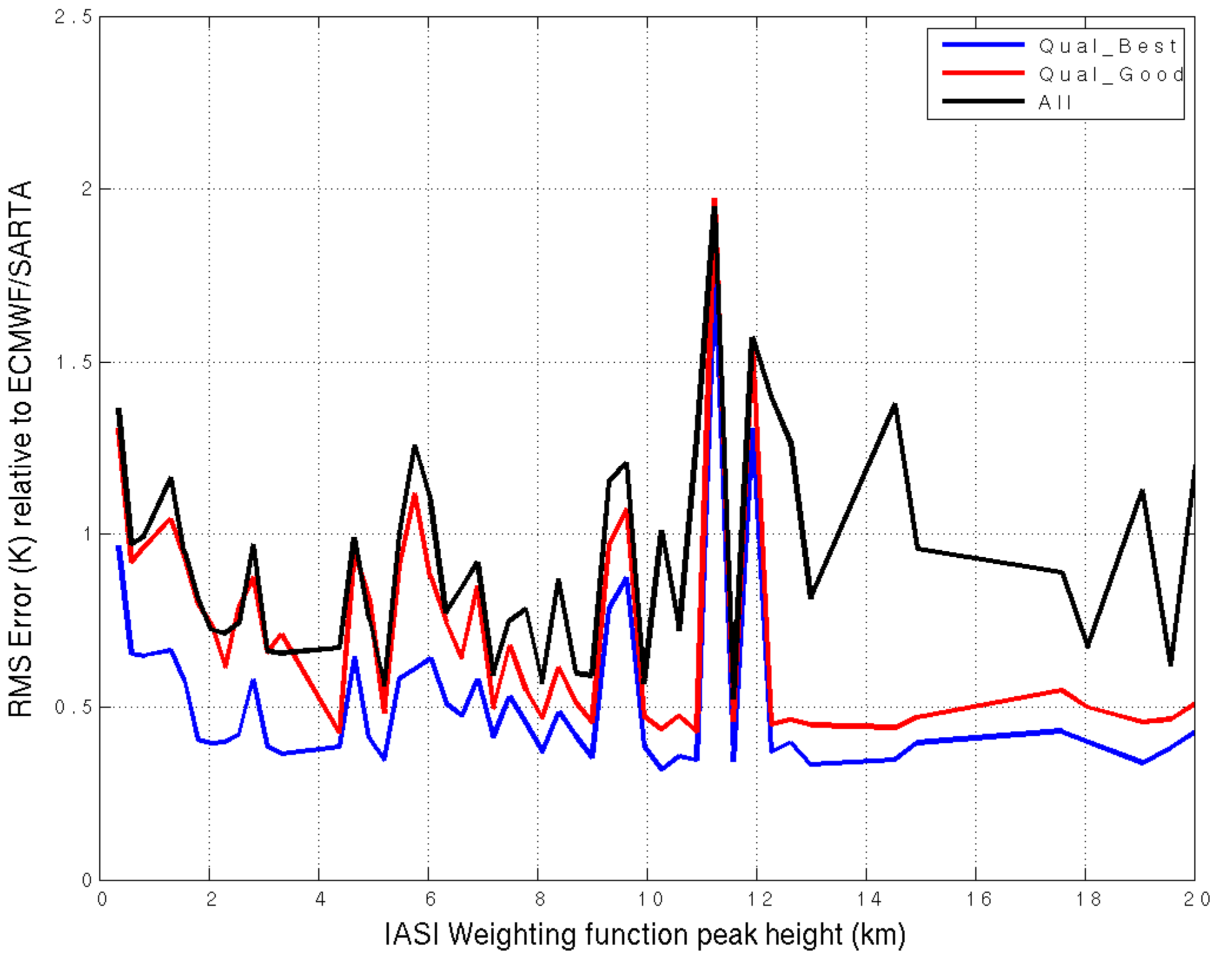


(b) Eigenvector set #2



(c) Eigenvector set #3

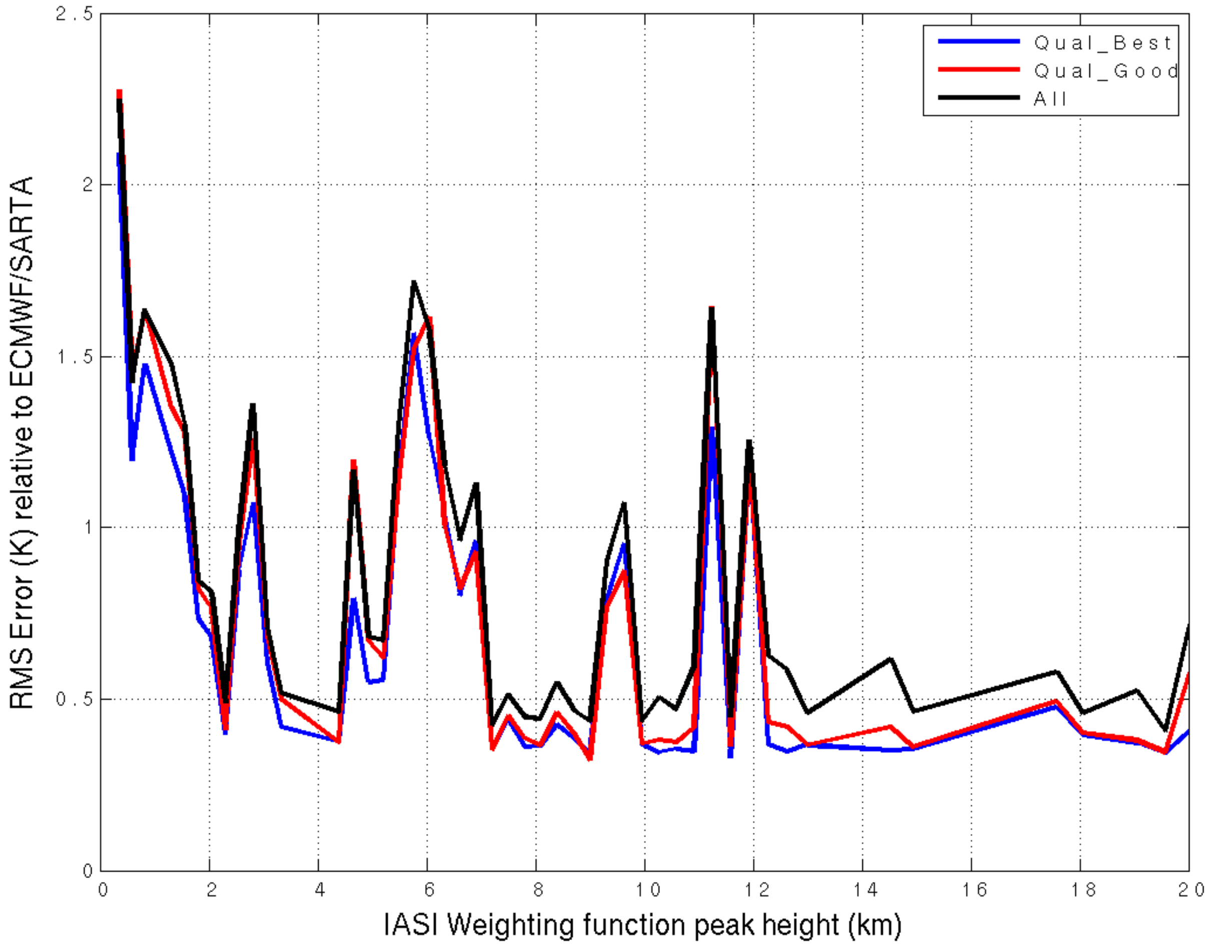
Stochastic Cloud Clearing of IASI



473 IASI channels were cleared
Descending orbits within ±60° latitude, ocean

ECMWF is “truth”

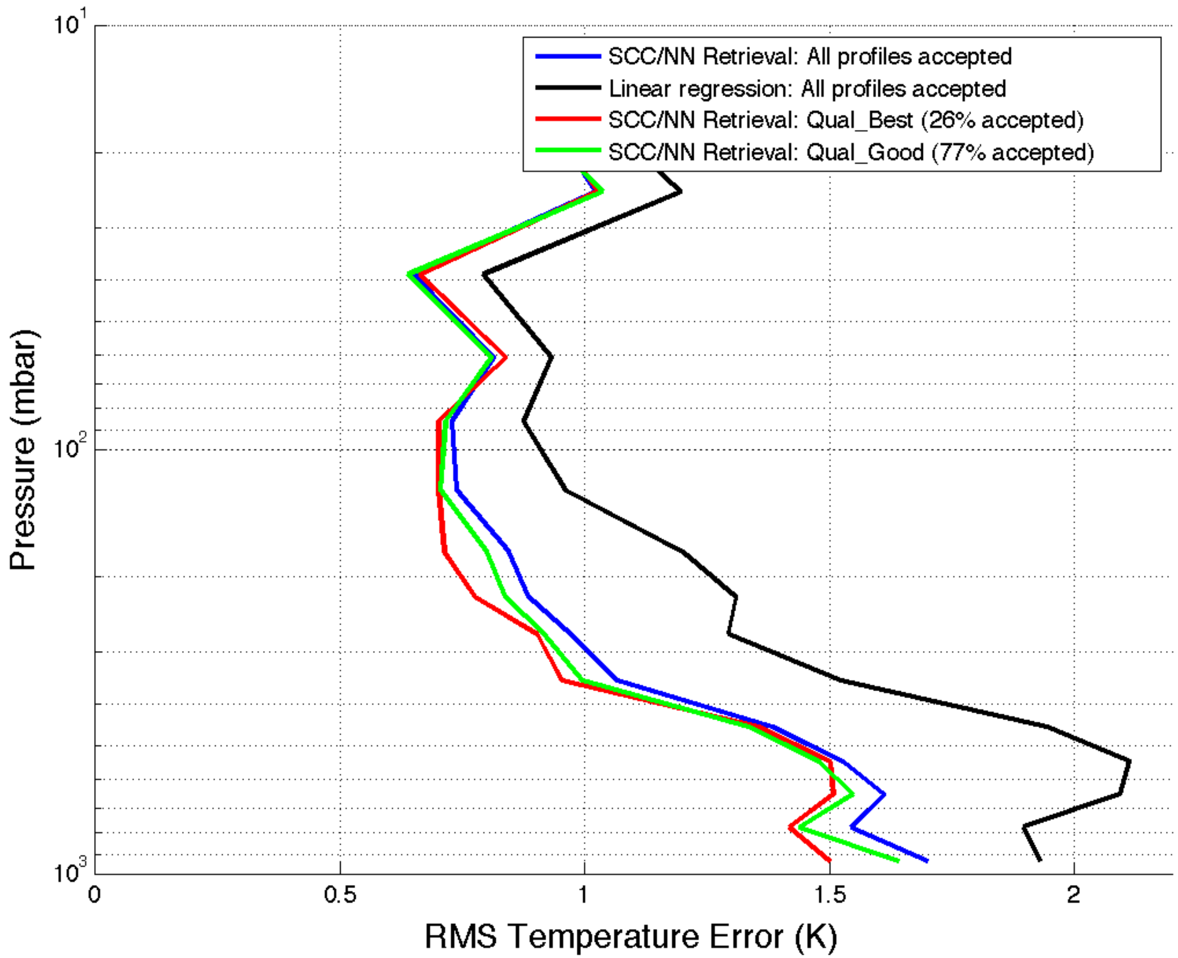
Stochastic Cloud Clearing of IASI



473 IASI channels were cleared
Descending orbits within ±60° latitude, land

ECMWF is “truth”

IASI Temperature Retrievals Over Land

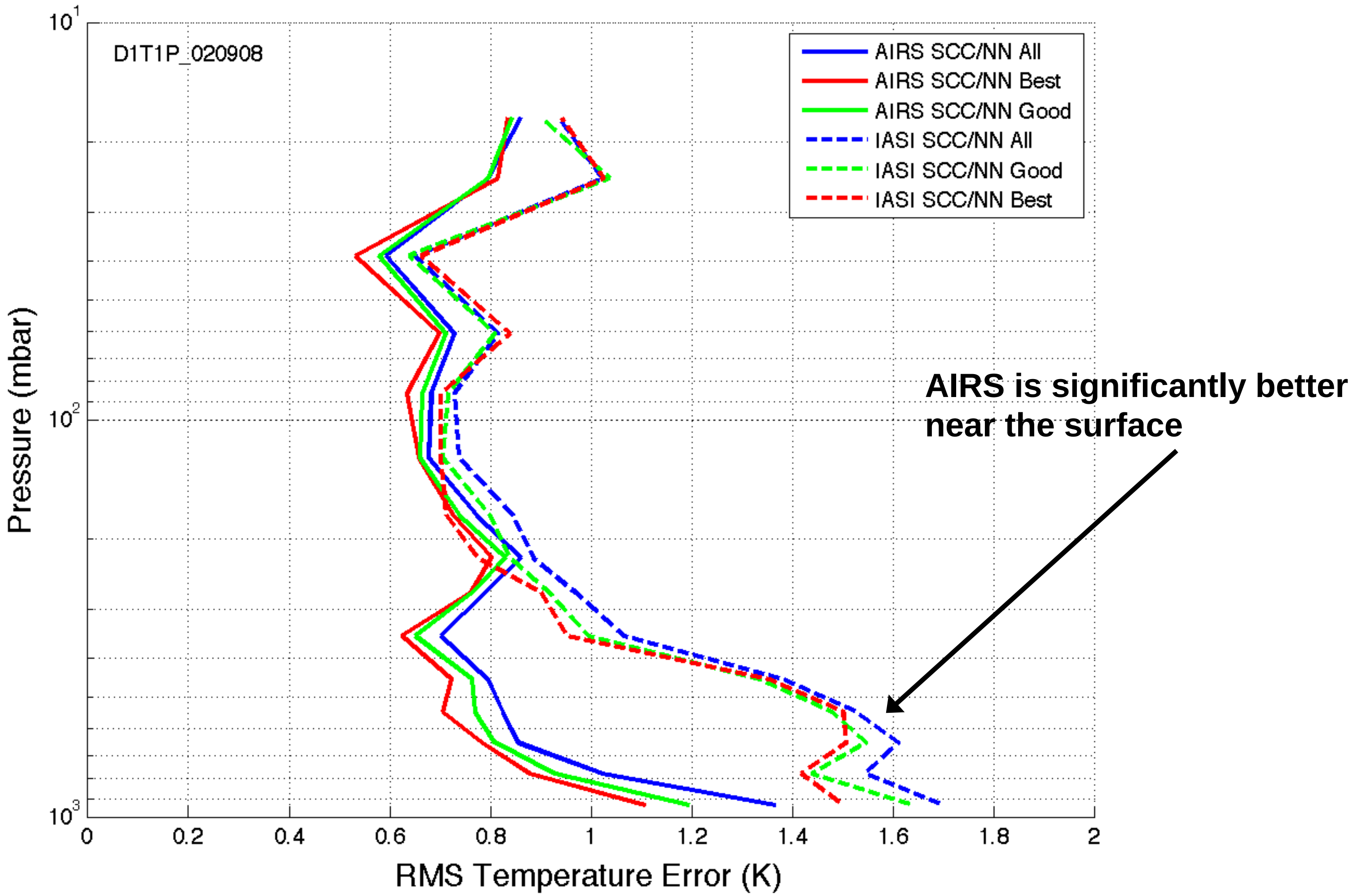


~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”

AIRS versus IASI: Land

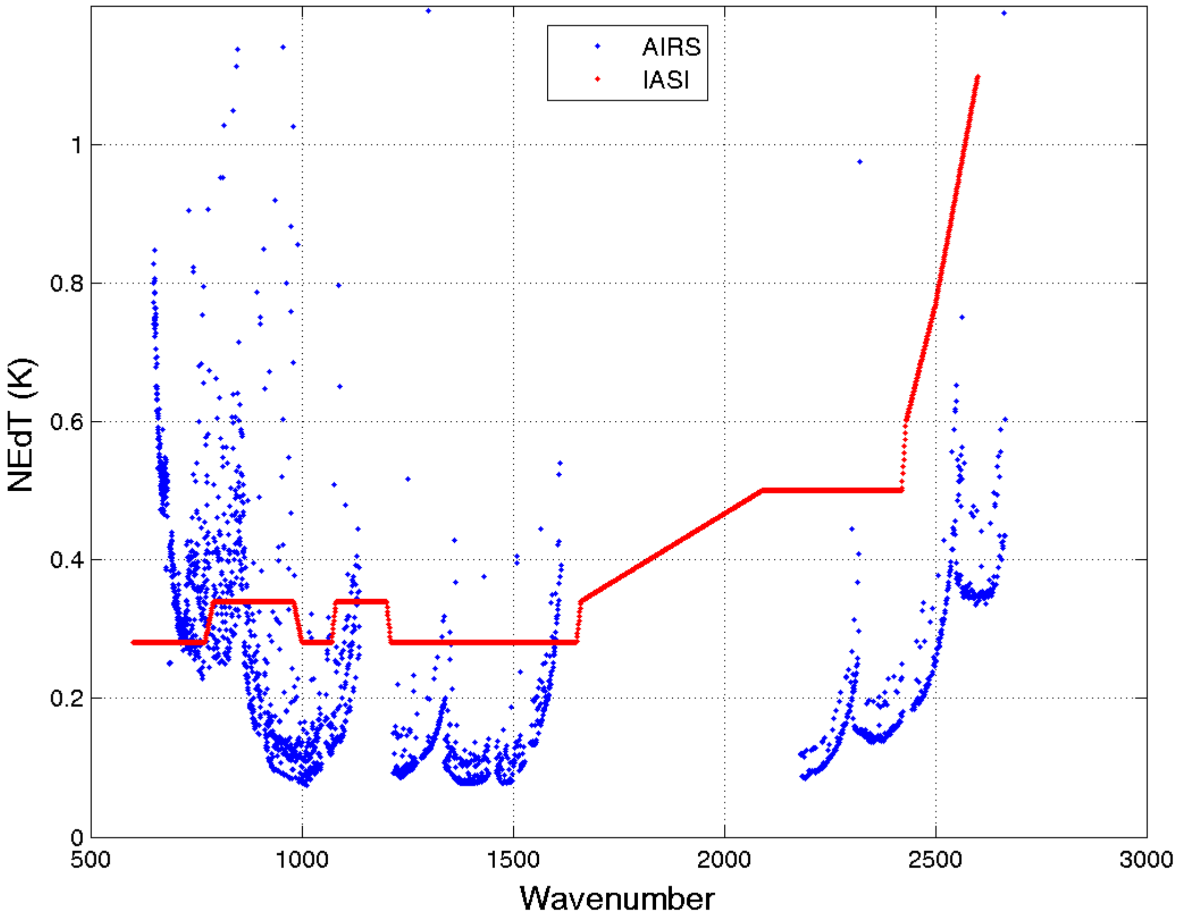


~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”

AIRS versus IASI NEdT



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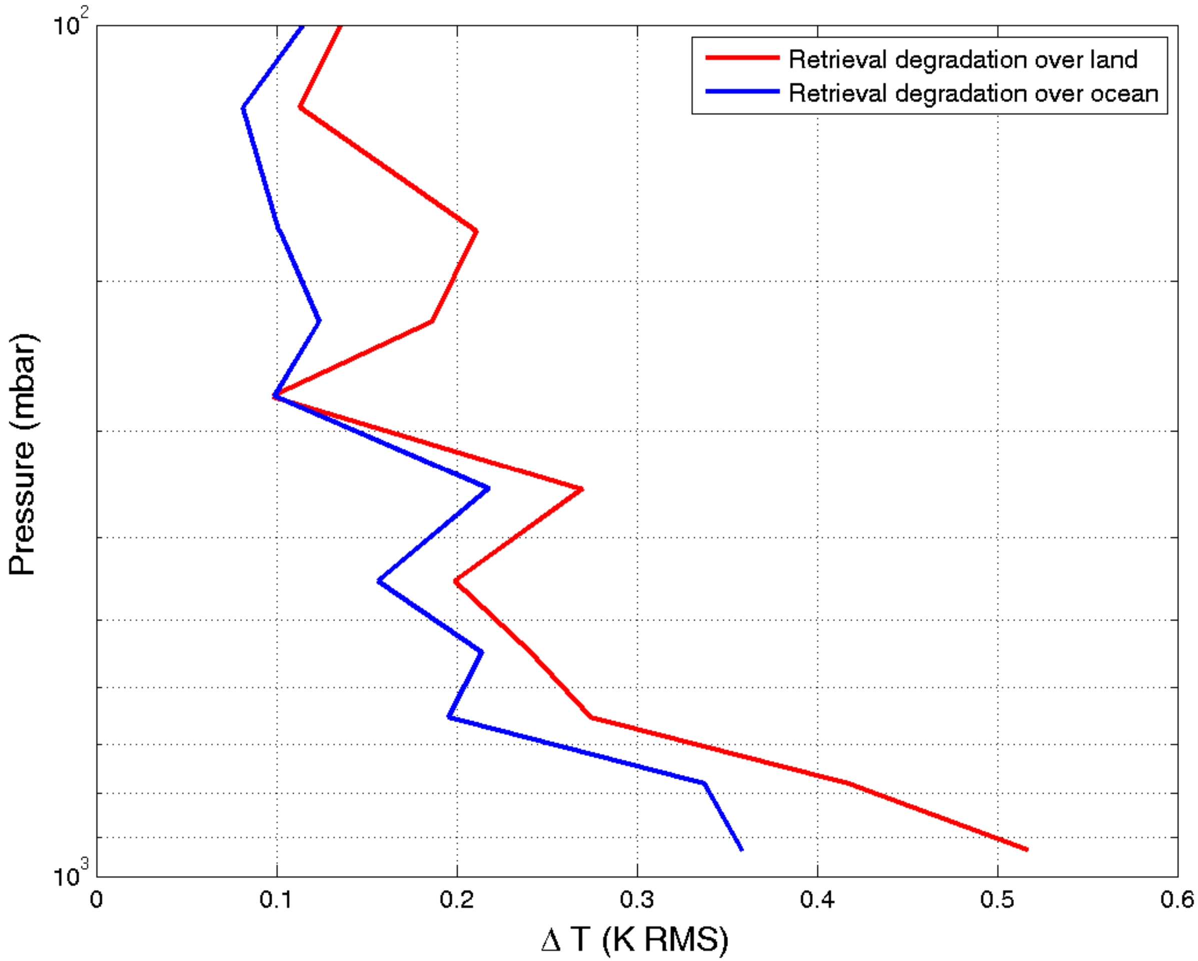
AIRS Retrieval Degradation After Adding Noise to Shortwave Channels



~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is "truth"

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