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WATER VAPOR PROFILE RETRIEVALS FROM SATELLITE MICROWAVE SOUNDING INSTRUMENTS

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1. INTRODUCTION

Knowledge of the horizontal and vertical distribution of water vapor on the global scale is required for applications ranging from numerical weather forecasting to climate modeling and climate change studies. Because of their global clear and cloudy sky water vapor measurement ability, passive microwave satellite sensors, such as the Advanced Microwave Sounding Unit (AMSU), are a primary source of data for fulfilling this requirement. An optimal-estimation algorithm has therefore been developed for the retrieval of water vapor profiles from passive microwave observations (Mckague et al, 2003).

The algorithm uses the method of Engelen and Stephens (1999) to simultaneously retrieve profiles of temperature and water vapor as well as cloud water path and surface emissivity. It can be considered a 1-dimensional variational data assimilation retrieval, or 1DVAR. Because of the highly coupled nature of the atmosphere and the sensitivity of microwave measurements to the desired retrieval parameters, more accurate retrievals of each can be achieved through a simultaneous retrieval. Furthermore, the retrieval method is quite general, making it flexible in terms of data used and parameters retrieved. Explorations of the new SSMIS data are anticipated within the next year. The retrieval is structured in a modular fashion, so new data sources, updates on instrument noise and channel failures, and retrieval parameters can be added easily.

In this paper, the algorithm is demonstrated using data from AMSU with comparisons to a radiosonde matchup database over ocean. Performance tests of the algorithm obtained from brightness temperatures (TB's) simulated from the radiosonde data are also presented.

This work is closely related to Joint Center for Satellite Data Assimilation work to estimate microwave land surface emissivity and understand the performance of the NESDIS Microwave Emissivity Model (Jones, Poster 3.15). Retrieving the atmospheric overburden and allowing for its radiometric effect leads to a clearer estimate of emissivity.

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2. ALGORITHM DESCRIPTION

The 1DVAR retrieval is hosted within the Data Processing and Error Analysis System (DPEAS), a modular computing environment described in Jones and Vonder Haar (2002). The retrieval is currently installed at CIRA with a near-realtime capability. A major effort with this retrieval has been creating data feeds for first guess and constraining fields. Figure 1 shows the data flows going into the real time system. Current work focuses on obtaining and understanding the impact of an improved first guess water vapor profile.

The retrieval algorithm is a physically based iterative optimal-estimation scheme (OE algorithm) adapted from the method of Engelen and Stephens (1999). The algorithm can take data from AMSU-B and AMSU-A combined, from SSM/T-2 with a fixed temperature profile, or from the SSMIS instrument. Future sensors can be added with knowledge of their channelization and noise. A variety of parameters can be retrieved including profiles of water vapor mixing ratio, joint water vapor and temperature profiles (including surface temperature), and water vapor and temperature profiles along with microwave surface emissivities.

The retrieval scheme requires a first guess of the water vapor and temperature profiles as well surface emissivities at the relevant microwave frequencies. An a priori distribution of the retrieval parameters is used to constrain a non-linear iterative optimal-estimation scheme which minimizes the cost function Φ to find the optimal solution x, where:

$$\Phi = (x - x_a)^T S_a^{-1} (x - x_a) + \{y - F(x)\}^T S_y^{-1} \{y - F(x)\}$$

(Equation 1)

where x is the vector of parameters to be retrieved, x_a is the a priori vector, y is the set of observations (Tb's), F(x) is a forward radiative transfer model used to compute radiances given x, and S_a and S_y are the error covariance matrixes of the a priori data and the observations, respectively. The vector of retrieval parameters consists of the temperature and moisture profiles, surface emissivity in 6 bands from 23 to 183 GHz, and cloud liquid water in cloudy cases. For the initial test of the retrieval, we focus on clear cases. The presence of cloud as a constraint would best be added from another sensor, such as infrared or visible radiances. The a priori error covariance matrix includes the variances of and correlations between the retrieval parameters, thus providing a constraint on the solution from a priori knowledge. The formulation and sensitivity of the results to this matrix is currently under research. The error covariance matrix of the observations includes forward model errors and uncertainty in the observed radiances.

For the forward radiative transfer, monochromatic microwave brightness temperatures are computed using numerical integration of the radiative transfer equation for a plane parallel, absorbing atmosphere together with Liebe's MPM92 (Liebe and Hufford 1993) model of microwave atmospheric attenuation. Only liquid clouds are currently included. An analytic Jacobian is used in the radiative transfer model (RTM) for speed. The method is modular so that an alternative RTM can be added if desired.

3. RETRIEVAL RESULTS

The channel characteristics used in this study for the NOAA-15 AMSU are shown in Table 1. Note that that AMSU-B data were prescribed a noise value of 2 K, due to the residual error from the radio frequency interference correction used only on NOAA-15. As a radiosonde simulation and validation dataset, we are using the Comprehensive Aerological Reference Data Set (CARDS) radiosonde collection (Eskridge et al, 1995). This is a quality controlled sounding dataset. An example of NOAA-15 AMSU and CARDS matchups for January 2000 is shown in Figure 2.

The antenna pattern correction (APC) has a significant effect on the results. The AMSU-B APC is discussed in more detail in Poster 2.17 (Nielsen et al). Figure 3 shows retrieval results with and without the NESDIS AMSU-A APC applied. The antenna temperatures were simulated by forward model calculations from the radiosonde data. The atmospheric temperature retrievals are warmed by about 2 K by using brightness temperatures instead of antenna temperatures. This effect feeds back into water vapor retrievals and may introduce error, since saturation vapor pressure is a nonlinear function of temperature.

A goal of this research is to understand how the terms in the cost function interact and drive the solution. The cost function in Equation 1 consists of two terms which are added. The first is the fit of the retrieval to what we would consider a realistic atmosphere. The second term is the penalty incurred for how well the simulated radiances match the satellite observations. This term can be visualized by summing the absolute value of the differences of the simulated minus retrieved brightness temperatures for all channels used in the retrieval. A map of this difference can then be displayed. We use 13 channels, the AMSU-A channels closer to 60 GHz are not used. Figure 4 shows such a map for two AMSU passes on August 3, 2003. Note that the retrieval does a good job in reducing the modeled minus observed TB differences over land. This indicates that the radiative transfer model is working properly. The differences are larger over ocean in this case due to use of a fixed SST of 293 K, the use of dynamic realtime SST should reduce the ocean difference greatly.

	Channel	Frequency (GHz)	NEDT (K)
AMSU-A	1	23.8	0.3
	2	31.4	0.3
	3	50.3	0.4
	4	52.8	0.25
	5	$53.596 \pm .115$	0.25
	6	54.4	0.25
	7	54.94	0.25
	8	55.5	0.25
	9	$57.290344 = f_0$	0.25
	10	$f_0 \pm .217$	0.4
	11	$f_0 \pm .3222 \pm .048$	0.4
	12	$F_0 \pm .3222 \pm .022$	0.6
	13	$f_0 \pm .3222 \pm .010$	0.8
	14	$F_0 \pm .3222 \pm .0045$	1.2
	15	89.0	0.5
AMSU-B	1	89.0	2.0
	2	150.0	2.0
	3	183.31 ± 1.0	2.0
	4	183.31 ± 3.0	2.0
	5	183.31 ± 7.0	2.0

Table 1. AMSU characteristics used in retrievals.

A test of the effect of the assumed error of the a priori data is shown in Figure 5. Simulated radiance data created from CARDS data. An unrealistically low standard deviation of 0.1 K error was specified for the first guess temperature. The retrieval is unable to move away from the first guess at levels above 1000 mb. At 1000 mb however, the retrieval does begin to perturb the temperature. This indicates that the surface emissivity is not properly specified, and the retrieval attempts to compensate by adjusting the surface temperature. This is a good check that the retrieval behaves as expected.

The comparison of a preliminary version of the retrieval with global island and coastal radiosonde data for all of 2000 is shown in Figure 6. There were 13289 matchups. Temperature and moisture are shown. The retrievals are over ocean only in this case. For temperature, the first guess (Mitch Goldberg's NESDIS statistical method) performs better than the retrieval above 500 mb. The top of the model atmosphere used here was 100 mb, this may not be enough. In general, the moisture retrieval is too moist below 805 mb, and too dry above.

A summary of our findings about the performance of the retrieval is shown below:

- (Ocean) The retrieval gives too much moisture at low levels (< 850 mb), and too little at high levels.
- The number of iterations rarely exceeds 5
- The radiative transfer model, adjoint and minimization function well
- The emissivity solution is sensitive to the apriori noise in the temperature and moisture
- Lapse rates are sometimes superadiabatic over land
- The top of the model atmosphere is 100 mb, needs to be higher
- Errors are not dependent on zenith angle or CLW (ocean)

4. CONCLUSIONS AND FUTURE WORK

An algorithm for the retrieval of water vapor profiles from passive microwave satellite observations has been presented. A variety of tests with expected results have been applied to the algorithm. It performs as expected. A comparison to one year of rawinsonde data indicates some biases in the results. Work is in progress on these items. The algorithm holds great promise both for real time product generation within DPEAS, and as a testbed for new and upcoming sensors such as SSMIS. The fusion of microwave data with cloud information from infrared and visible sensors holds great promise. The performance of the retrieval over land surfaces is currently being investigated. Microwave water vapor profile retrievals over land, or even TPW retrievals, have been hindered by poor knowledge of land emissivity. Related work at CIRA (see Jones, Poster 3.15) aims to address this issue and unlock more potential from passive microwave measurements.

5. ACKNOWLEDGMENTS

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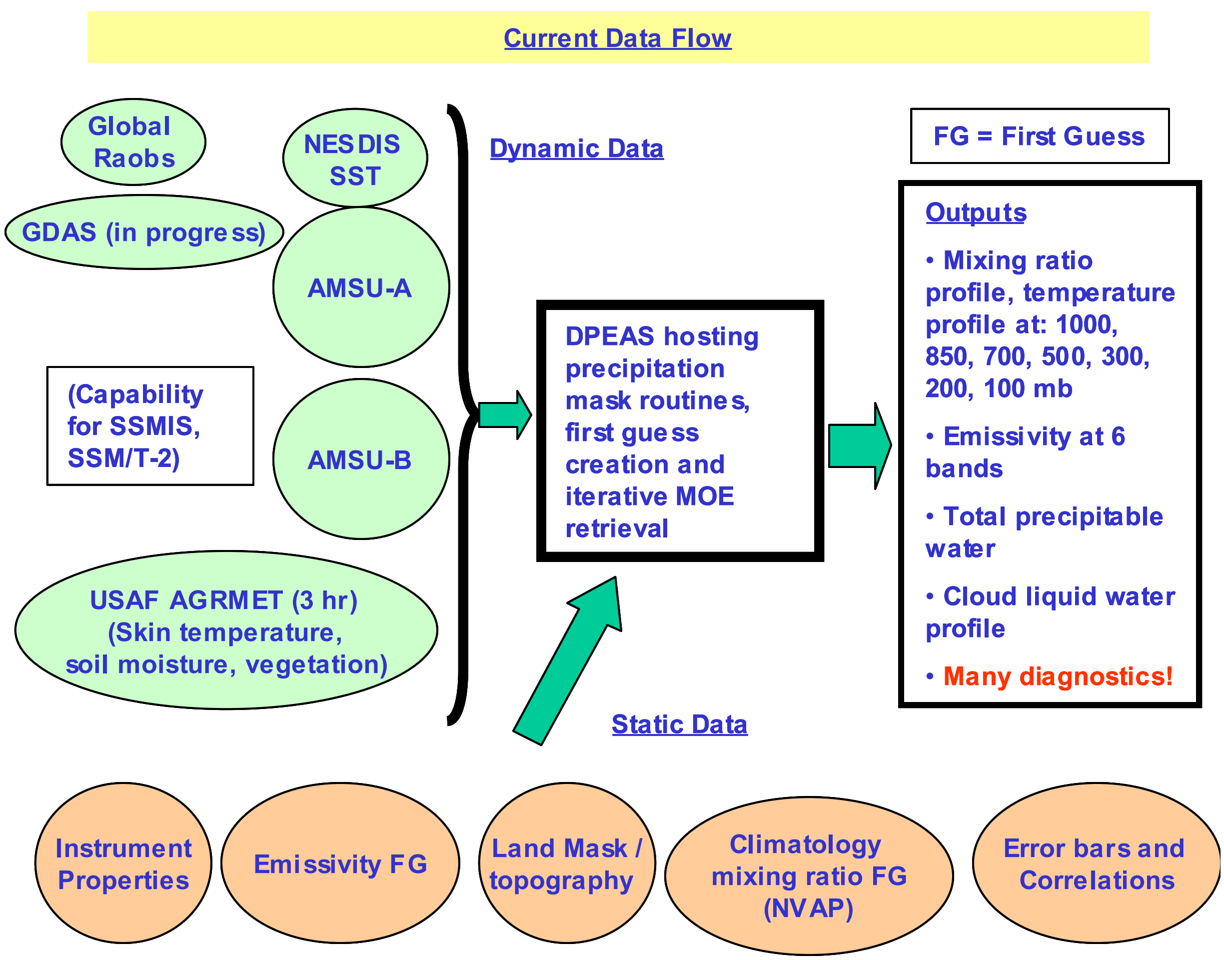

Figure 1: Current dataflow into the 1DVAR retrieval. The retrieval can be run in near realtime, or retrospectively. The GDAS fields work in progress provides an improved first guess moisture profile over climatology which is currently used.

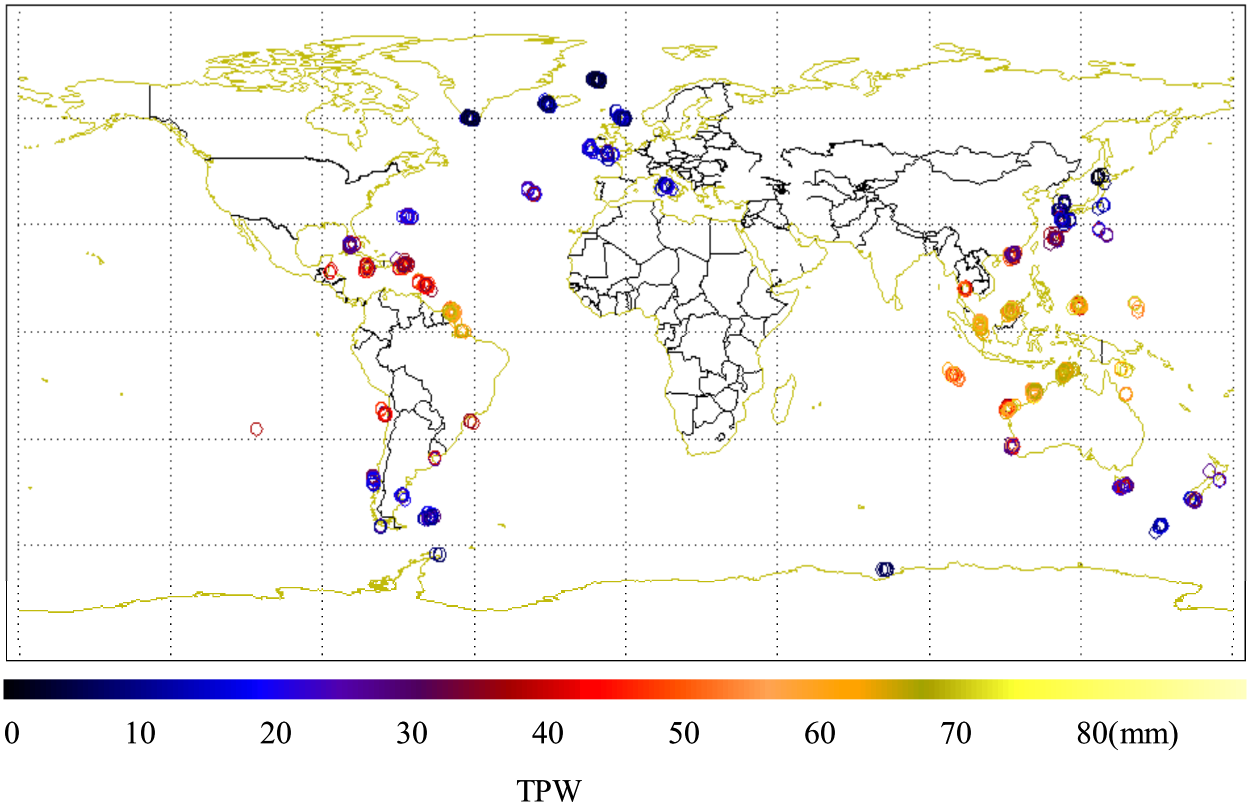

Figure 2: Matching NOAA-15 and radiosonde sites for January, 2000. A matchup criteria of 2 degrees radius and 2 hours was used. Total precipitable water (TPW) of the radiosondes is shown in color, indicating a large range of TPW was sampled.

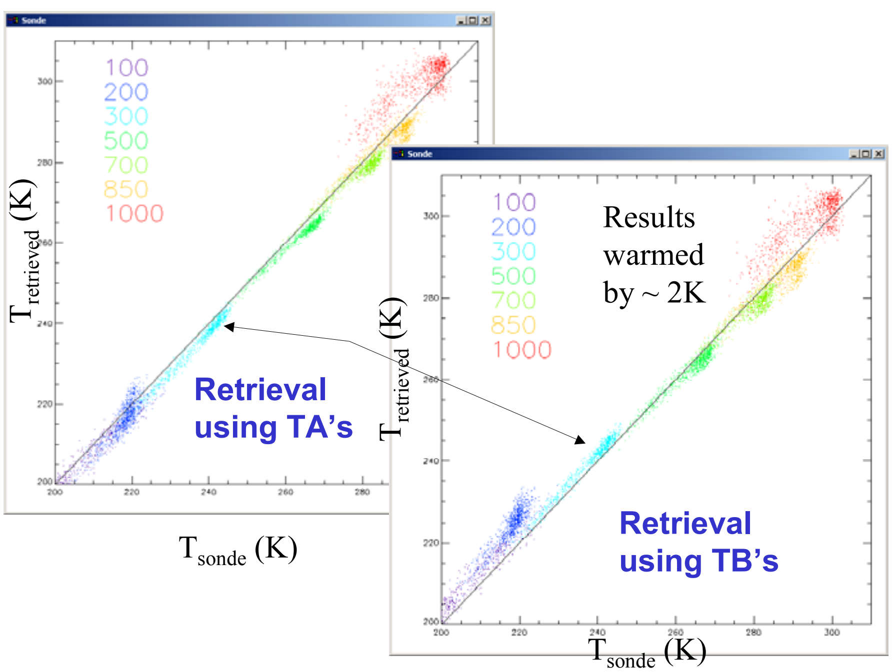

Figure 3: Demonstrating the effect of the antenna pattern correction on AMSU-A radiances. A roughly 2 K bias occurs in the temperature profile retrieval.

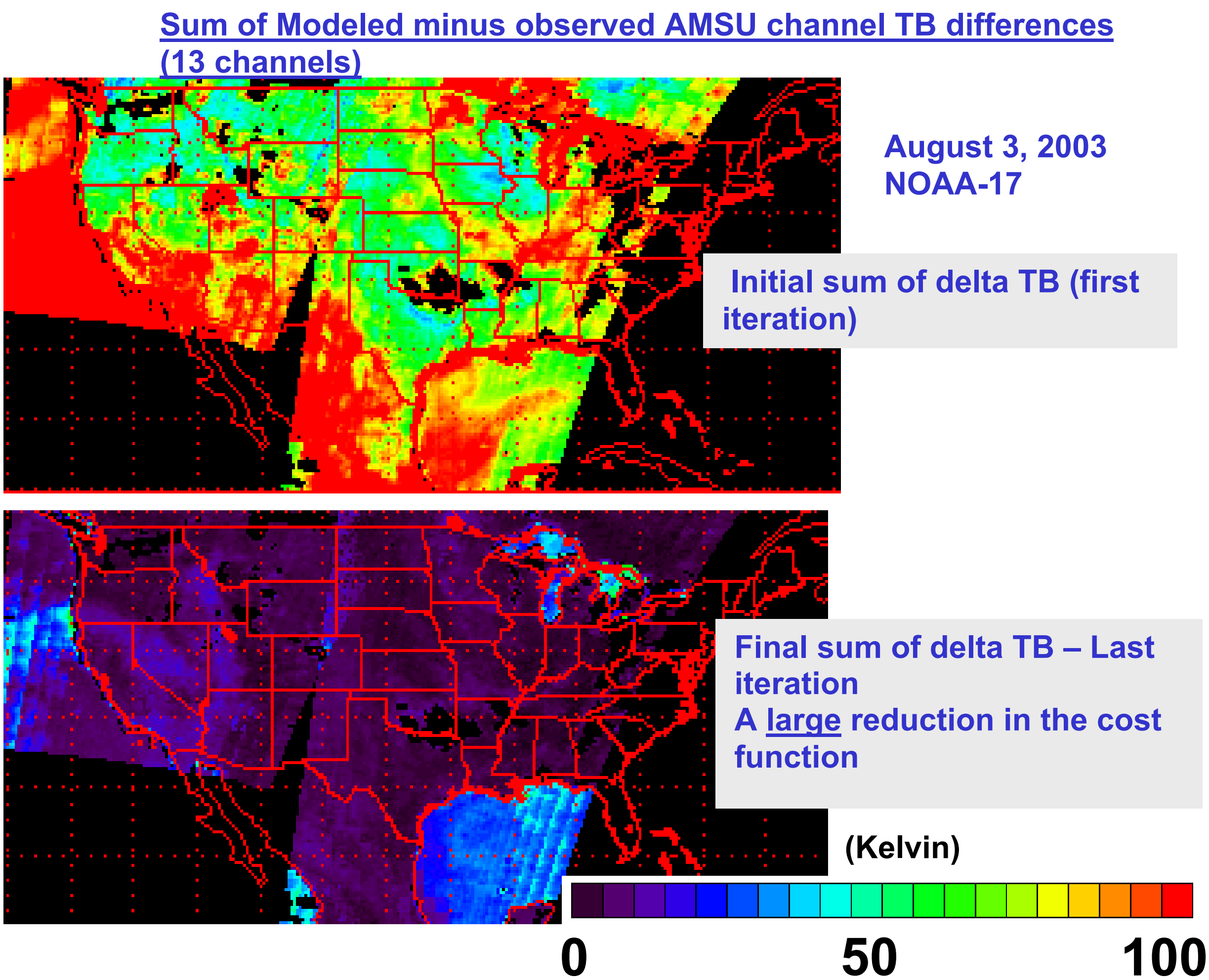

Figure 4: Map of the initial and final sum of modeled brightness temperatures minus observations for the 13 AMSU channels used in the retrieval. Note how initial differences of 50 to 100 K over land have been reduced to 10 to 20 K. A reduction to 0 K is not possible (or desirable) because of instrument noise. The greater differences over water, such as the Gulf of Mexico, are due to use of a fixed sea surface temperature first guess of 293 K which will be made dynamic in future work.

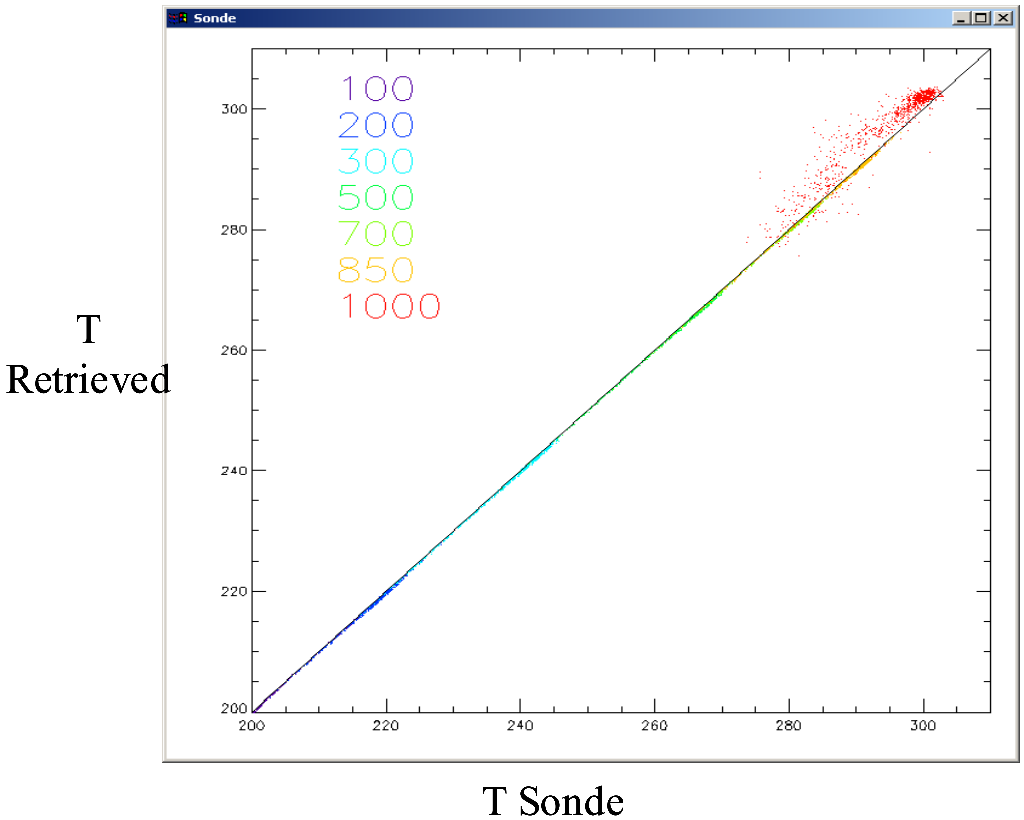

Figure 5: Test of the sensitivity of the retrieval to error estimate of first guess fields. The temperature was given an unrealistically tight constraint of 0.1 K standard deviation. Note that all pressure levels fall back to the first guess (the sonde value), except the 1000 mb layer. Error in surface emissivity are converted to temperature profile errors.

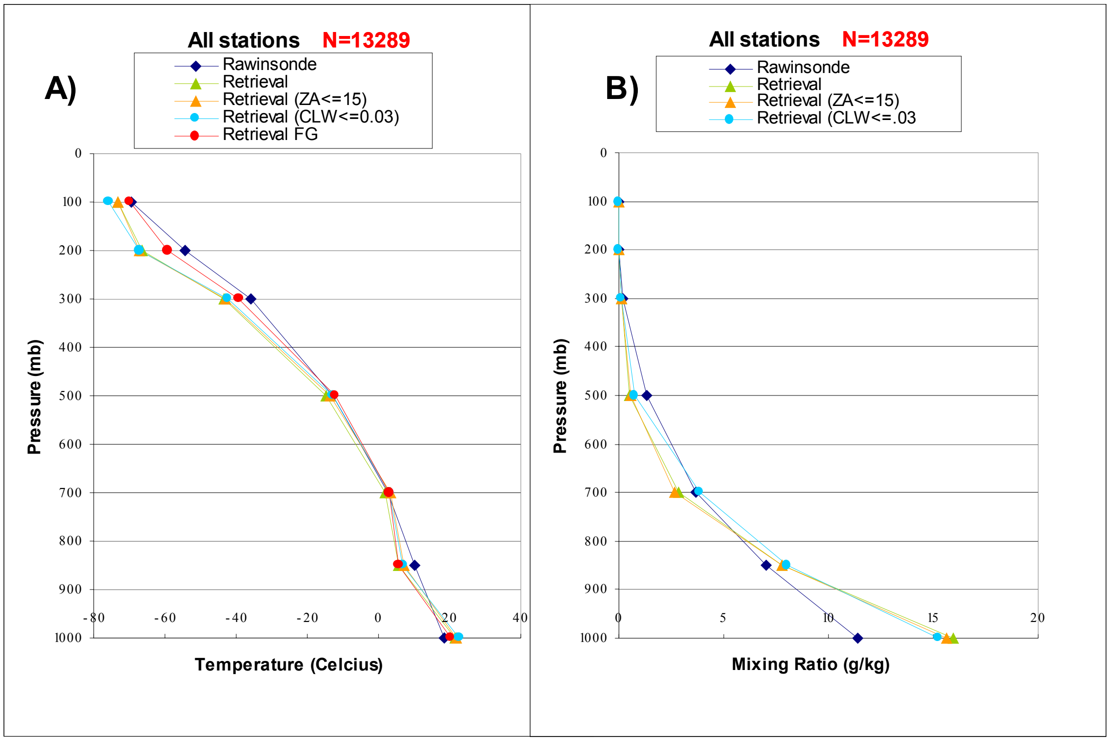

Figure 6: Comparison of rawinsonde and NOAA-15 AMSU retrievals for 2000. 13289 matchups. A) Temperature and (B) Mixing ratio. Different colored lines indicate rawinsonde, retrieval, retrieval with zenith angle less than 15 degrees, and retrieval with cloud liquid water less than 0.03 mm, respectively. Temperature tetrieval first guess error from the NESDIS statistical algorithm also shown.