Improvement of the Temperature and Moisture Retrievals in the Lower Troposphere using AIRS and GPS Radio Occultation Measurements

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Abstract. Accurate temperature and water vapor profiles in the middle and lower troposphere (LT) are crucial for understanding the water cycle, cloud systems and energy balance. Global Positioning System (GPS) radio occultation (RO) is the first technique that can provide a high vertical resolution all-weather refractivity profile, which is a function of pressure, temperature and moisture. However, in the moist LT over the tropics, the refractivity retrievals from GPS RO data are often significantly negatively biased due to tracking errors and propagation effects related to sharp vertical moisture gradients that may result in super-refraction (SR). The Atmospheric InfraRed Sounder (AIRS) is a nadir viewing sounder that can measure vertical temperature and moisture profiles with about 1-2 km vertical resolution. However, AIRS observation cannot usually obtain accurate temperature and water vapor profiles in the Planetary Boundary Layer (PBL) due to the poor resolving power in the LT. In this study, we perform simulations based on radiosonde profiles by combining the AIRS and the GPS RO measurements to obtain the best temperature and moisture retrievals in the LT. Different approaches are used for the drier LT and for the moist LT, respectively. For the drier LT, where GPS RO data are not affected by SR errors, we use a multi-variable regression algorithm for inverting the combined AIRS and GPS RO measurements. In the moist LT (e.g., SR on top of PBL), we use the combined AIRS and GPS RO regression inversion above the LT as the first guess for AIRS-only physical retrieval, which we extend into the LT. The results show that combining AIRS and GPS RO data effectively constrains the individual solutions, and therefore, significantly improves inversion results. The algorithm is also applied for all available radiosonde profiles (19 profiles) over a one month period from the site characterized by strong SR on top of the PBL. Retrieved temperature and water vapor profiles yield unbiased low-resolution refractivity profiles in the PBL.
1. Introduction

Temperature and water vapor play a crucial role in weather and climate. Accurate global water vapor and temperature estimates, particularly in the middle and lower troposphere (LT), are extremely important for understanding the physics of convective cloud systems, precipitation, the hydrological cycle and the energy balance of the Earth (Crook 1996, Lee et al. 1991, Mueller et al. 1993, Weckwerth et al. 1996 and Webster and Stephens, 1984). To more accurately assess global sounding profiles from space, two very high vertical resolution atmospheric remote sensing instruments were recently put into orbit. The Global Positioning System (GPS) Radio Occultation (RO) is the first technique that can provide high vertical resolution all-weather refractivity (N) profiles, which depend on pressure, temperature and humidity (Yunck et al., 2000). By placing a GPS receiver on board a low Earth orbiting satellite, one can measure the bending of radio signals transmitted by GPS satellites as they set or rise behind the Earth. From the measurement of the bending angles, one can derive vertical profiles of atmospheric refractivity (Kuo et al., 2004). For the purpose of this study, we treat the GPS RO inverted refractivity as the observable, by not considering any modifications of the standard GPS RO inversion algorithms. By using active limb observations for retrieval of the atmospheric refractivity, GPS RO measurement has a vertical resolution ranging from ~100 m (from 0 to 18 Km) to ~1 km at 20 km, which is much higher than that of most other satellite data (Kursinski et al., 1997). In addition to GPS RO soundings, high vertical resolution temperature and moisture profiles can be obtained from Atmospheric Infrared Sounder (AIRS) measurements. With a very high spectral resolution ($\lambda / \Delta \lambda \approx 1200$), AIRS can measure vertical temperature and moisture profiles with about 1-2 km vertical resolution (Aumann et al., 2003). The temperature root mean square error (RMSET) is better than 1 K and the moisture RMSE (RMSEW) is less than 10%
compared to collocated radiosondes (Fetzer et al., 2003a). Nevertheless, even with high vertical resolution instruments, such as GPS RO and AIRS, it is still very difficult to obtain accurate global temperature and water vapor profiles in the free troposphere using a single observing system (Ho et al., 2002, Westwater and Grody, 1980; Westwater et al., 1984).

Although GPS RO data can produce accurate refractivity profiles in the middle atmosphere (Kuo et al. 2004), significant systematic negative bias related to the complicated structure of refractivity (vertical and horizontal) is usually found in the moist LT, particularly over the tropics (Rocken et al., 1997, Sokolovskiy, 2003a, Ao et al., 2003, Beyerle et al., 2004). Two kinds of errors are usually observed. The errors of the first kind are related to the incapability of a generic GPS receiver to correctly process and record tropospheric RO signals because of the strong phase and amplitude fluctuations, which, based on the current signal tracking algorithm (the phase-locked loop tracking), lead to larger uncertainty in the retrieved refractivity below 5 km, particularly over the tropics. This problem will be overcome in the future by applying open-loop tracking (Sokolovskiy, 2001) in the next generation GPS RO receivers, such as on the Constellation Observing System for Meteorology, Ionosphere and Climate (COSMIC) satellites (Kuo et al. 2004). Testing of the open-loop tracking algorithm on the SAC-C satellite has already demonstrated much improved penetration, and significantly reduced biases in the LT (Sokolovskiy et al., 2006). The errors of the second kind are fundamentally related to atmospheric propagation effects (e.g., such as the super refraction-SR) and may not be overcome unless applying additional constraints. (i) Vertical refractivity gradients < -157 N/km (SR) (Sokolovskiy, 2003a), commonly observed on top of the marine planetary boundary layer (PBL) in the tropics and sub-tropics, result in significant negative bias, up to several percent, in retrieved refractivity below the top of the PBL. (ii) In addition, there is
evidence that elongated (layered) irregularities of refractivity with small vertical scales may result in inversion errors with significantly larger vertical scales and magnitudes up to several percent (Sokolovskiy, 2003b). This degraded quality of GPS RO data in the moist lower troposphere significantly limits their usage in data assimilation and numerical weather prediction (Healy et al. 2005). Similarly, although with excellent vertical and moderate horizontal resolution (15 km × 15 km) compared to other nadir viewing sounders, AIRS observation alone cannot usually obtain accurate temperature and water vapor profiles in the PBL due to the poor resolving power in the LT. The water vapor uncertainty for AIRS is ~15% in the bottom 2 km over oceans (Validation of AIRS/AMSU/HSB Core Products for Data Release Version 4.0). Large uncertainties over land are found, especially in the bottom 2 km of the profile. The total water vapor uncertainties can be as large as 30-45% over land. Extra information is still needed to reduce the effect of these errors on GPS RO refractivity retrievals and compensate for the deficiency of the respective GPS RO and AIRS sounding systems. Although it was demonstrated that better temperature and moisture profiles can be obtained in the tropopause (for temperature) and in the mid-troposphere when GPS RO data are used together with other nadir sounding measurements (Collard and Healy, 2003, and Borbas et al., 2003), the improvement of temperature and moisture profiles in the lower troposphere, particularly under the SR condition, has not been demonstrated yet by using combined retrievals from GPS RO data and data from nadir viewing sounders.

The purpose of this study is to demonstrate that, by combining atmospheric thermal information observed from AIRS with GPS RO refractivity soundings, improved temperature and moisture profiles can be obtained, not only in the middle troposphere, but also in the lower troposphere. In this paper, AIRS measurements are simulated and used together with GPS RO
refractivity for retrieval of the temperature and moisture profiles. The unbiased AIRS retrievals shall provide extra temperature and water vapor information in the LT where GPS RO inversions are affected by the propagation effects discussed above. The accurate GPS RO refractivity shall impose a strong constraint on AIRS measurements in the middle atmosphere and improve AIRS retrievals in the LT. In this study, a multi-variable regression algorithm is developed to invert the combined AIRS and GPS RO measurements above the LT. Under the assumption that the GPS RO data are affected by the LT errors (e.g., SR on top of the PBL), we use the combined AIRS and GPS RO regression results above the LT as the first guess for AIRS-only physical retrieval which we extend into the LT. The improved temperature and moisture information from AIRS and GPS RO data in the middle troposphere shall strongly constrain AIRS physical retrieval by improving its quality in the LT. For additional demonstration of the performance of this approach for cases with complicated atmospheric structures, we apply the algorithm to radiosonde profiles collected within a month from the site characterized by strong SR on top of the PBL (19 profiles).

In Section 2 we describe the AIRS and GPS RO data characteristics and global sounding database used in the simulation analysis. The AIRS physical retrieval method and the simultaneous AIRS and GPS RO temperature and water vapor retrieval method are introduced in Section 3. The general simulation analysis results, including information content analysis, are shown in Section 4 while the simulation results, in the case of SR, are presented in Section 5. We conclude this study in Section 6.

2. Data Sources
Launched in 2002 on board the NASA Aqua satellite, AIRS is the first of a new generation of operational remote sensors for upwelling atmospheric emission (Aumann et al., 2003). With more than 2000 channels covering 3.74-4.61 μm, 6.2-8.22 μm and 8.8 –15.4 μm in infrared wavebands (Fig. 1a), AIRS is able to sense atmospheric temperature, water vapor, trace gases and surface skin temperature with a very high accuracy. The mean instrument noise is about 0.5 K (Fig. 1b). The nadir field of view (FOV) of AIRS is around 15x15 km. The GPS RO limb sounding technique measures the phase and amplitude of radio signals propagated through the atmosphere between GPS satellites (~20200 km orbit height) and GPS receivers on low Earth orbiting (LEO) satellites (Melbourne et al., 1994; Hocke, 1997; Kursinski et al., 1997; Rocken et al., 1997; Steiner et al., 1999; Feng and Herman, 1999, Hajj et al., 2002, Kuo et al., 2004). Over the past few years, three RO missions have been placed into orbit: CHAMP (Germany) and SAC-C (Argentine) both launched in 2000 and GRACE (Germany) launched in 2004. Of those missions, CHAMP is the one regularly providing openly available RO data, about 250 occultations per day (the data from other missions are less regular). With knowledge of the exact positions and velocities of GPS and LEO satellites, and the phase and amplitude of the RO signals, an accurate atmospheric bending angle and refractivity profile can be determined. The details of inversions of radio occultation signals can be found in the above referenced publications. In a neutral atmosphere, the refractivity (N) is related to the pressure (P), the temperature (T) and the partial pressure of water vapor (P_W) by the following equation (Bean and Dutton, 1966):

\[
N = 77.6 \frac{P}{T} + 3.73 \times 10^5 \frac{P_W}{T^2}
\] (1)
Due to the propagation effects mentioned in section 1, the estimated GPS RO refractivity inversion errors depend significantly on global moisture distribution in the atmosphere. As shown by Kuo et al. (2004) and reproduced in Fig. 2, from about 5 km to 25 km, the GPS RO observation errors range from 0.3% to 0.5% in refractivity when compared to refractivity profiles derived from NCEP AVN and ECMWF analyses. However, below 5 km, the observation errors in the tropical lower troposphere increase toward the surface, and reach about 3% near the surface (Fig. 2a). The observation errors in the LT decrease toward higher latitudes. At high latitude regions, north of 60° N and south of 60° S, the GPS RO observation errors in the LT range from 0.5% to 0.7% in refractivity. Due to the signal tracking problems mentioned in section 1, after quality control procedures, the numbers of GPS RO samples in the LT are significantly reduced (Fig. 2c). The GPS RO data are significantly negatively biased below 700 mb over the tropics (Fig. 2b). In this study, we use the mean global refractivity error estimates provided by Kuo et al. (2004) in our inversion procedures. Since the error statistics are based on the comparison between GPS RO observations and NCEP and ECMWF analyses, the noise estimates used in this study shall be considered the upper limit of GPS RO sounding uncertainties.

For use in the simulation analysis, the NOAA-88b clear sky radiosonde temperature and water vapor and ozone profiles are used to represent the global sounding data. This NOAA-88b dataset, created and distributed by NOAA–National Environmental Satellite, Data, and Information Service (NESDIS), contains 2584 clear sky radiosonde temperature and water vapor profiles collected from globally distributed stations over land, including coasts, and islands in 1988. Ozone was derived from solar backscatter ultraviolet (SBUV) collocated profiles. For
simulation purposes in this study, we interpolate and extrapolate all NOAA-88b profiles to 100-level fixed AIRS pressure grids from surface to 0.005 hPa (see Section 3.b).

3. Retrieval Methods

a. AIRS Retrieval Method

By giving the AIRS measurements \( Y \) and the uncertainties of instrument and background profiles, the desired state parameter \( X \), which contains temperature \( T \) and water vapor profile \( W \), can be determined by minimizing the cost function

\[
J(X) = \{Y - F(X)\}^T E^{-1} \{Y - F(X)\} + \gamma (X - X_0)^T C^{-1} (X - X_0),
\]

(2)

where \( C \) is the a priori background covariance matrix; instrument noises and the forward model error are described by the covariance matrix \( E \); \( X_0 \) is the a priori state vector; \( F(X) \) is the AIRS forward model applied to \( X \). \( \gamma \) is a smoothing parameter, that balances the fit to the observations and the fit to the background of state parameters. The optimal state \( X \) is found by using the following iteration method:

\[
X_{n+1} = X_0 + (K_n^T E^{-1} K_n + \gamma C^{-1})^{-1} K_n^T C^{-1} \{\delta Y_n + K_n (X_n - X_0)\}.
\]

(3)

Here \( n \) is the iteration index, \( \delta Y_n \) is the difference between the observed and the calculated brightness temperatures; \( K \) is the weighting function (matrix) defined by
where \( l \) and \( m \) are, respectively, the channel index of AIRS measurement \( Y \) and the index of the corresponding vertical level of the state vector \( X \) in \( \delta X_m \) is the perturbation of the state vector, \( \delta Y_l \) indicates the radiance perturbation in response to \( \delta X_m \). \( X_0 \) is the initial temperature and moisture profile for the iteration procedure (Eq.(3)). In the current AIRS operational product, the regressed temperature and moisture profiles from the measurements of the Advanced Microwave Sounding Unit (AMSU) are used to provide the initial temperature and moisture profiles for AIRS retrievals. Here we use AIRS regressed profiles (see below) as initial profiles. In each iteration step, the smoothing parameter \( \gamma \) is determined by using the discrepancy principle (Morozov 1966), which has been proven as an efficient method to choose the optimal smoothing parameter (Wahba 1975, Craven and Wahba, 1979). The optimal smoothing parameter is found by minimizing the differences between brightness temperature residuals and instrument errors plus forward model errors. The details of implementation of the discrepancy principle in the retrieval algorithm can be found in Ho et al., (2002).

The retrieved state vector \( (X_{\text{ret}}) \) from the AIRS measurements may be represented as the weighted mean of the true state \( (X_{\text{true}}) \) and the a priori state \( (X_0) \). By assigning \( \gamma \) equal to 1, where we assume that we have perfect knowledge of the background of state parameters, the retrieved state vector can be written as

\[
X_{\text{ret}} \approx A_{\text{avg}} X_{\text{true}} + (I - A_{\text{avg}}) X_0
\]

\( (5) \)
where $I$ is the identity matrix and $A_{\text{avg}}$ is the averaging kernel matrix. $A_{\text{avg}}$ provides a measure of the vertical resolution of the retrievals and is defined as

$$A_{\text{avg}} = \frac{\delta X_{\text{rel}}}{\delta X_{\text{True}}} = (K^T E^{-1} K + C^{-1})^{-1} K^T E^{-1} K,$$

(6)

where $\delta X_{\text{True}}$ and $\delta X_{\text{rel}}$ are the true and retrieved temperature and water vapor vertical profile deviations from the *a priori* profiles, respectively. The Degrees of Freedom for Signal (DFS) is the trace of the averaging kernel matrix and is a measure of how much independent information is presented in the measurements (Rodgers, 2000).

**b. The Simultaneous AIRS and GPS RO Retrieval Method**

Here we use a multi-variable regression method to retrieve atmospheric $T$ and $W$ profiles from simultaneous AIRS and GPS RO data. The regression equation is the following:

$$\delta X = \sum_{i=1}^{4} \sum_{j=1}^{n} a_{ij} \delta f_i(N_j) + \sum_{k=1}^{m} b_k \delta B_k,$$

(7)

where $f_i(N_j)$ is a linear, quadratic, logarithmic and the inverse function of $N_i$ respectively; $\delta f_i(N_j)$ is the departure of $f_i(N_j)$ from its mean, and $a_{ij}$ is the corresponding regression coefficient and $j$ is the index of pressure level; $k$ is the index of AIRS brightness temperature ($B$), $\delta B$ is the departure of $B$ from its mean, $b_k$ is the corresponding regression coefficient for AIRS brightness temperature, and $n$ is the total number of AIRS channels used and $m$ is equal to 100 to
represent 100-fixed AIRS pressure grids. $X$ is the combination of retrieved $T$ and $W$ profiles. $\delta X$ is the departure of $X$ from its mean. The mean of $X$ and $f_i(N_j)$ is computed from the training set. In this study, the training set is composed of 2179 profiles randomly selected from 2584 clear sky NOAA88b profiles. The fast and accurate AIRS transmittance model (Standard Alone AIRS-Radiance Transfer Algorithm package – SARTA) from University of Maryland Baltimore County (UMBC) AIRS team (Strow et al., 2003) is used to simulate AIRS brightness temperatures. It has 100 vertical levels from 0.01 mb to 1085 mb. Nominal AIRS instrument noise (Fig. 1b) and 0.2 K forward model errors are randomly added to the simulated brightness temperature. We use AIRS channels with instrument noise less than 0.4 K in this retrieval algorithm. About 2000 AIRS channels are used. The GPS RO refractivities are also simulated using these NOAA 88b radiosonde sounding profiles. The global mean RO observation errors (Fig. 2) are randomly added to the corresponding RO signals. Regression coefficients are generated using simulated $N$ and AIRS brightness temperatures and 2179 NOAA88b training profiles. For GPS RO only retrieval, $b_i$ are equal to zero, where for AIRS only retrievals, $a_{ij}$ are all set to zero.

4. Retrieval Results

a. Information Content and Retrieval Sensitivity Analysis

The DFS is the trace of the averaging kernel matrix (Eq. (6)) and is a measure of how much independent information is contained in the measurement (Rodgers, 2000). This is a measure of the number of components of the retrieved variable that are not constrained by the $a_{priori}$. To explicitly demonstrate the DFS of AIRS measurements, we generate the eigenvalue sequences of the $K^T E^{-1}K$ term in Eq. (6) for temperature and water vapor in Fig. 3a and b,
respectively. Since AIRS measurements are highly correlated, the first few eigenvalues of $K^TE^{-1}K$ for both AIRS temperature and water vapor channels represent more than 99% of AIRS information. By using the NOAA88b global temperature and moisture sounding data, we can generate the background covariance matrix $C$ in Eq. (6). Then DFS can be calculated from trace $(A_{avg})$. Results show that AIRS measurements provide about 16 and 10 independent pieces of information for temperature and water vapor profiles, respectively, in the entire atmosphere (Table 1).

Compared with AIRS measurements, the GPS RO measurements are less correlated because the GPS RO measurement corresponding to a given ray depends on the atmospheric state only above the tangent point of that ray (Ahmad and Tyler 1998). However, since GPS RO refractivity is a function of both temperature and moisture (Eq. (1)), it is important to distinguish the relative sensitivity of refractivity to temperature and water vapor at different vertical levels. To consider the combined impacts of both GPS RO noise and GPS RO signal sensitivity to the state parameters at different vertical levels, we define noise-equivalent change ($NE\Delta X$) of the state vector $X$

$$NE\Delta X = \left| \frac{NER}{\Delta(N)/\Delta X} \right|,$$

where $N$ is refractivity profile, $NER$ is defined as noise-equivalent refractivity at a different vertical level, which is computed from the global mean $N$ profile times percentage $N$ errors in Fig. 2. $NE\Delta X$ is a measurement of the smallest change in the state vector $X$ ($T$ and $W$) that can be detected by each GPS RO signal at each vertical level. Figs. 4a and b show the GPS RO noise-
equivalent change for temperature (in K) and percentage water vapor (in % of mixing ratio) variation, respectively. It is shown in Fig. 4b that GPS RO signals can sense as small as a 4% variation in the water vapor mixing ratio below 500 mb, which is consistent with statistical comparisons between GPS-derived moistures and forecast moistures from the European Center for Medium-Range Weather Forecasts (ECMWF) (Kursinski et al., 2000). The corresponding noise-equivalent change of moisture in mixing ratio is shown in Fig. 4c. Note that the above plots are assuming all refractivity information is used for either $T$ or $W$ retrieval. In the troposphere, since $N$ is more sensitive to $W$ than to $T$ (Ware et al., 1996), GPS RO refractivity is used more for moisture retrievals than for temperature retrievals (as demonstrated in next Section).

Using an approach similar to that used for AIRS, the GPS RO information content analysis is also conducted. GPS RO $K^TE^{-1}K$ eigenvalue sequences for temperature and moisture are shown in Fig. 3. The eigenvalue sequences of the GPS RO are flatter compared to those of AIRS. This is related to the fact that in the nadir-viewing observation geometry all measurements related to one vertical profile contain information about all atmospheric layers, while in the limb-viewing (occultation) geometry each measurement contains information about an atmospheric layer that does not affect the measurements obtained above that layer. The DFS for GPS RO and combined AIRS and GPS RO data are listed in Table 1. It is shown in Table 1 that moisture information content increases from 10.2 (using AIRS alone) to 23.6 (AIRS+GPS RO); temperature information content increases from 12.4 (using GPS RO alone and assuming GPS RO N is only used for temperature retrieval) to 17.9 (AIRS+GPS RO).

b. Simultaneous inversion of GPS RO and AIRS data
A total of 405 profiles randomly picked from 2584 NOAA 88b global profiles are used as an independent dataset to test the accuracy of the temperature and water vapor profiles retrieved from the simulated AIRS and GPS RO data, separately and concurrently. This independent dataset contains widely distributed temperature and water vapor profiles, which are characterized by very large standard deviations in temperature (Fig. 5a) and moisture mixing ratio (Fig. 5b) profiles.

The root mean square errors of temperature (RMSET), water vapor mixing ratio (RMSEW) and refractivity (RMSEN) retrieved from AIRS (A), GPS RO (G) and concurrently from AIRS and GPS RO observations (A,G) using the statistical regression solution (described in Section 3.b) are shown in Fig. 6. The vertical resolution of AIRS is about 1-2 km (Aumann et al., 2003), where the vertical resolution for GPS RO data is confined in the AIRS 100-level fixed pressure grids, which varies from about 200 m in the LT to 500 m in the free troposphere. The small RMSET$_A$ and RMSEW$_A$ demonstrate the feasibility of the regression algorithm and the internal consistency of the SARTA. The RMSET$_A$ is less than 1 K almost at all levels, which is about 1 to 1.5 K smaller than retrieval results from GOES and HIRS (not shown). The reason that RMSET$_A$ is large near the surface (about 1.9 K) is due to lack of resolving power in the PBL. The RMSET$_A$ is about 1.2 K at 200mb due to the sharp temperature inversion at that region (not shown). Although AIRS has very sharp water vapor weighting functions near the surface, RMSEW$_A$ is still large (about 1.5 g/kg). The dependence of the water vapor weighting function on the temperature makes AIRS moisture inversion in the lower troposphere very difficult. The highly variable moisture structure (Fig. 5b) near the surface also leads to larger moisture retrieval errors.
Although these results are only from the regression retrieval algorithm, the internal consistency of the SARTA and the high spectral resolution radiance from AIRS provide detailed atmospheric thermal structure. These regression results are consistent with the global AIRS validation results (Fetzer et al., 2003a) retrieved using an iterative physical retrieval algorithm (Susskind et al. 2003).

For GPS RO alone retrieval, since both temperature and water vapor are sharing the same $N$ information (which in the middle and lower troposphere is more sensitive to moisture than to temperature (Fig. 4)), most of $N$ information is used for moisture retrieval in the simultaneous $T$ and $W$ inversion procedure. The RMSET$_G$ is large at all levels (Fig. 6a).

When AIRS and GPS RO measurements are used concurrently, the retrieval results are better than those from individual retrievals. For the combined AIRS and GPS RO retrieval, the AIRS data provide extra atmospheric thermal information that dramatically improves GPS RO retrieval, not only in temperature but also in water vapor. For the middle and lower troposphere, the RMSET$_{A,G}$ shows improvement over the results achieved by either instrument alone due to the increased independent information obtained from the combined observations (Table 1). The mean RMSET$_{A,G}$ of all layers is 0.67 K, which approaches the uncertainty of radiosondes. The RMSEW$_{A,G}$ shows even more significant improvements on the RMSEW$_A$ and the RMSEW$_G$ (Fig. 6b). The mean RMSEW$_A$ and the mean RMSEW$_G$ of all layers are 0.87 g/kg and 0.72 g/kg, respectively, while the mean RMSEW$_{A,G}$ of all layers is only 0.43 g/kg (Table 2). To demonstrate how much the combined GPS RO and AIRS data can improve $N$ observations, the retrieved $T$ and $W$ were converted to $N$ using Eq. (1). The RMSEN for the combined AIRS and GPS RO data (RMSEN$_{A,G}$) is shown in Fig. 6c. The RMSEN$_{A,G}$ is improved mainly in the LT.
compared to the current GPS RO refractivity inversion errors in Fig. 2. In the free troposphere, concurrently accounting for both $T$ and $W$ retrieval errors, the forward calculated $N$ actually contains slightly larger retrieval errors ($\text{RMSEN}_G$) than the GPS RO refractivity inversion errors in Fig. 2. The reason that $\text{RMSEN}_G$ is better than $\text{RMSEN}_A$ is due to the fact that both GPS RO temperature and moisture retrievals are constrained by the corresponding refractivities, which is not the case for AIRS temperature and moisture retrievals.

c. Simulation Results: discarding GPS RO data in the Lower Troposphere

Simultaneous inversion of GPS RO and AIRS data mentioned in the previous section shall work well under drier LT condition. However, in the moist LT GPS RO data are often affected by tracking errors and wave propagation effects, such as the SR. Under such conditions, a possible approach is to discard the GPS RO data from inversion in the LT, but to use them as a strong constraint for AIRS inversion above the LT, thus preserving the information content (DFS) of AIRS for mainly LT inversion. For GPS RO receivers operating in phase-locked loop mode it is feasible to discard all tropical and sub-tropical data, while for the open-loop receivers it is sufficient to discard RO data in the SR regions where the GPS RO retrieved $N$-gradient substantially exceeds its mean value $\sim$50 N/km (Sokolovskiy et al., 2006). To demonstrate how the GPS RO data can improve AIRS inversion performance under such conditions, a two-step strategy is implemented.

Step 1: Assuming GPS RO data are affected by tracking errors and wave propagation effects below 700 mb, in the dependent dataset, we replace $N$ below 700 mb by the mean $N$ profile from the same dataset. The new regression coefficients for the combined AIRS and GPS RO inversions are generated from the new dependent GPS RO $N$ profiles and AIRS simulated
brightness temperatures. The independent dataset remains unchanged. In this case, the best retrieval results above 700 mb are mainly from the combined AIRS and GPS RO data as demonstrated in Figs. 6a and b. The information below 700 mb is mainly from AIRS data.

Step 2: Under the condition that we are confident in retrieval results above 700mb, we use the $T$ and $W$ profiles retrieved by the combined regression inversion as the first guess for AIRS physical retrieval algorithm (Eq. (3)) and strongly constrain its variation by reducing the corresponding variance value above 700 mb in the background covariance matrix. The diagonal term in the background covariance above 700 mb is set to 0.01K for temperature and 0.0001 g/kg for moisture for the AIRS alone physical retrieval algorithm described in Section 3.a. Thus constrained sounding profiles for the entire atmosphere, including the LT, are retrieved.

To demonstrate how the information content of AIRS observations can be utilized mainly in the LT, the temperature and water vapor averaging kernels for AIRS only ($A_{\text{avg}_{\text{noconstr}}}$) and AIRS with strong constraint above the LT ($A_{\text{avg}_{\text{constr}}}$) are shown in Fig. 7a and b, respectively. As indicated in Eq. (5), the accuracy of the retrieved profiles closely corresponds to the shape and magnitude of its averaging kernel. A higher averaging kernel value indicates that the retrieval results are mainly from the information of measurements and less from a priori. It is clearly seen in Fig. 7 that the magnitude of $A_{\text{avg}_{\text{constr}}}$ is larger than that from $A_{\text{avg}_{\text{noconstr}}}$ at almost all levels, particularly at levels near 700 mb. A relatively small increase in averaging kernel near the surface, compared to that above 850 mb, indicates that GPS RO data above 700 mb still has impact on $T$ and $W$ retrievals below 700 mb through the correlation in the background error covariance matrix.

The temperature, water vapor and refractivity RMSE for GPS RO, AIRS and GPS RO combined with AIRS, in which GPS RO data are discarded below 700 mb, are shown in Figs. 8a,
b and c, respectively. As shown in Fig. 8, the RMSET\textsubscript{G} and RMSEW\textsubscript{G} below 700 mb are worse than retrievals shown in Fig. 6. This reflects the impact of discarding GPS RO \textit{N} information below 700 mb. When we strongly constrain AIRS data in the middle atmosphere by using the GPS RO and AIRS information above the LT, more AIRS information is utilized for \textit{T/W} retrievals in the LT. RMSET\textsubscript{A,G} and RMSEW\textsubscript{A,G} are still smaller than those from AIRS and GPS RO alone. To quantify the improvement of the AIRS constrained moisture retrievals relative to those from AIRS only retrievals, we define the percentage improvement of RMSEW\textsubscript{A,G} from RMSEW\textsubscript{A} as

$$\text{RMSEW}_{\text{IMP}} = 100 \times \frac{(\text{RMSEW}_A - \text{RMSEW}_{A,G})}{\text{RMSEW}_A} \%.$$  \hspace{1cm} (9)

The RMSEW\textsubscript{IMP} for the Tropics (30° N to 30° S), the Southern Hemisphere (30° S to 90° S) and the Northern Hemisphere (30° N to 90° N) are shown in Fig. 9. The same global mean GPS RO noise estimates are used for all three cases. As shown in Fig. 9, the global mean RMSEW\textsubscript{IMP} is about 80% above 700 mb and decreases to about 20% below 700 mb. Although RMSEW\textsubscript{IMP} is only about 20% between 800 mb and the surface, the improvement is significant since the uncertainty of AIRS moisture retrievals is high in the LT due to the high variability of moisture. In addition, since AIRS weighting functions are larger over regions with stronger surface thermal contrast (Ho et al., 2002), more AIRS moisture information is used for retrievals in the LT in the tropical regions than in the mid- and high-latitudes. The RMSEN\textsubscript{A,G} is significantly improved compared to RMSEN\textsubscript{G} (Fig. 8c). The retrieved biases for temperature, water vapor and refractivity are all close to zero at all levels (not shown).
5. Simulation Results: a special case of super-refraction

The Abel retrieved $N$-profile is negatively biased below the height where the negative $N$-gradient exceeds the critical value, $-157$ N/km (SR) that often happens on top of the tropical marine PBL. To evaluate the combined AIRS and GPS RO retrieval algorithm under the condition of SR, we apply it for all available radiosonde $N$-profiles (19 profiles) over St. Helena island ($15.97^\circ$ S, $5.7^\circ$ W) during January 2002. For all of these 19 cases, their critical $N$-gradients are exceeded at a height of about $\sim 1.8$ km ($\sim 800$ mb). Since there are no AIRS data available before May 2002, we simulated the collocated AIRS observation using the radiosondes. Temperature and moisture only above 944 mb are available from the radiosondes. The instrument noises and forward model noises are randomly added to the simulated AIRS brightness temperatures. Even with 1-2 km vertical resolution and large averaging kernels in the PBL (Fig. 7), it is still difficult to use AIRS measurements to resolve the very sharp temperature and water vapor mixing ratio changes under SR conditions without providing a reasonable initial temperature and moisture profile for the physical iterative procedure (Eq. (3)). Therefore, for the experiment in this section, we include radiosonde $N$-profiles over St. Helena island for two different months (December 2001 and February 2002) in the dependent set (NOAA 88) for regression retrieval in Step 1 of our two-step approach (see Section 4.c). In these retrievals we use GPS RO data only above 700 mb. The temperature and moisture profiles from the combined AIRS and GPS RO retrieval are used as the first guess to constrain the AIRS physical retrieval above the SR level. The mean temperature and moisture mixing ratio biases compared to the radiosonde profiles are within $\pm 1.3$ K and $\pm 1.2$ g/kg for levels below 700 mb, respectively (not shown). The mean $N$ biases from constraint, no constraint and the Abel retrieved $N$-profiles from GPS RO are plotted in Fig. 10. This result demonstrates that AIRS measurements, being
constrained by GPS RO above PBL, provide generally unbiased temperature and moisture retrievals in the PBL, which yield unbiased refractivity profiles in the LT.

6. Conclusions and Future Work

In this study, we performed simulations based on radiosonde profiles by combining the AIRS and the GPS RO measurements to obtain the improved temperature and moisture retrievals for both the drier LT and the moist LT under SR conditions, and compared them to separate AIRS and GPS RO retrievals. Our analysis led to the following conclusions:

1. In the information content analysis, we show that, although AIRS measurements can provide 16 and 10 independent pieces of information about temperature and water vapor profiles, respectively, the eigenvalue sequences of the GPS RO are flatter compared to those of AIRS, since each GPS RO measurement contains information about an atmospheric layer that does not affect the measurements obtained above that layer. Using the background covariance matrix generated from global NOAA88b profiles to constrain GPS RO data for information content calculation, we show that GPS RO data provide more than 20 independent pieces of information for vertical moisture profiles when we used GPS RO refractivity for 100 fixed AIRS pressure levels. The moisture information content increases from 10.2 (AIRS alone) to 23.6 (AIRS+GPS RO); AIRS information helps to partition GPS RO refractivity into moisture and temperature, and temperature information content increases from 12.4 (for the GPS RO only case, when assuming GPS RO N is only used for the temperature retrieval) to 17.9 (AIRS+GPS RO). It is expected that the increased information content from the concurrent inversion of AIRS and GPS data can benefit numerical weather prediction systems through assimilation of the inversion results.
2. The accuracy of the AIRS simulated retrievals using the multi-variable regression algorithm is very close to that of the global AIRS validation results (Fetzer et al., 2003a), which are retrieved using a physical algorithm (Susskind et al. 2003). The AIRS temperature RMSE is within 1 K above 900 mb and 1.8 K in the PBL while the moisture RMSE is less than 0.45 g/kg above 500 mb and less than 1.8 g/kg below 500 mb. These results give confidence in the internal consistency of SARTA and demonstrate the feasibility of the regression algorithm. When both AIRS and GPS RO measurements are used simultaneously, they constrain each other and provide better accuracy of retrieved temperature and moisture profiles than when the AIRS and the GPS RO measurements are used independently. The mean RMSET$_{A,G}$ of all layers is 0.67 K. The RMSEW$_{A,G}$ are even more significantly improved on the RMSEW$_{A}$ and the RMSEW$_{G}$ since GPS RO affects mainly moisture retrievals in the troposphere. The mean RMSEW$_{A,G}$ of all layers is 0.43 g/kg. Note that the GPS RO retrieval results shown here are based on the regression algorithm. An alternative method of utilizing GPS RO refractivity alone, which is used by the COSMIC Data Analysis and Archive Center (CDAAC), is to combine the GPS RO observation with NCEP AVN analysis profiles to find optimal temperature and moisture profiles (Kuo et al., 2004). Its equivalent temperature accuracy in dry atmosphere is about 1 K and water vapor pressure accuracy is about 0.5 mb from the middle troposphere up to 40 km, which is comparable to or better than the radiosonde (Rocken et al., 1997; Kuo et al. 2005) for non-SR conditions.

3. In this study, we have demonstrated that AIRS retrievals can provide unbiased temperature and moisture. Additionally, since we are confident in the combined AIRS and GPS RO retrievals above the LT, we strongly constrain AIRS inversion above the LT and improve AIRS retrieval in the LT (which otherwise suffers from strong correlation of AIRS
measurements). The water vapor uncertainty from the constrained AIRS retrieval is improved by about 80% above the LT compared to AIRS only retrievals. The improvement is decreased to about 20% in the LT. For cases with SR, while AIRS may not resolve sharp humidity gradients on top of the PBL, the GPS RO data above the SR level strongly constrain AIRS observations and help resolve the temperature and moisture structures better than would be possible by AIRS alone, by providing unbiased temperature and moisture information in the PBL through the correlation in the background error covariance matrix.

Although in this study we used simulated data based on global soundings from radiosondes, the observed GPS RO refractivities are highly accurate and biases between AIRS observations and the forward calculated brightness temperatures using radiosonde soundings (Fetzer et al., 2003a) are around 0.5K. Therefore, when reasonable refractivity errors and AIRS instrument noises are used and when the biases between AIRS observations and the forward calculated brightness temperature are corrected, the results shall be very close to the retrievals from real GPS RO and AIRS observations. In the near future, we will apply the retrieval strategy introduced in this study to global collocated GPS RO and AIRS data to provide the possibly best temperature and moisture sounding data. Additionally, in this paper the combined AIRS and GPS RO inversion was performed by simply discarding GPS RO data in the PBL. In the future, a more advanced approach may involve the use of another GPS RO observable, such as the bending angle, which shall be not biased. And, although in the current study we focus on the GPS RO and AIRS combined retrievals in the troposphere, the accurate GPS RO refractivity information shall also help to improve AIRS temperature retrieval in the upper troposphere and lower stratosphere (UTLS), and shall dramatically improve the accuracy of water vapor retrieval in the UTLS, which is still a key uncertainty for global radiation balance and climate (Oltmans et
al., 2000). This subject is left for a future study. In addition, for the cloudy skies, we can use microwave sounders (e.g., Microwave Sounding Unit and Advance Microwave Sounding Unit), whose brightness temperatures in the oxygen band will not be affected by clouds, to provide temperature information for inverting GPS RO data. Better moisture profile retrievals within and below clouds can also be expected. This is also for a future study.

The first GPS RO constellation of satellites, COSMIC, was launched in April 2006. It will provide about 2,500 GPS RO profiles per day, which is about 10 times more than the currently available GPS RO soundings from CHAMP and SAC-C. It is anticipated that the new open-loop signal tracking technique implemented on COSMIC GPS receivers will significantly reduce the GPS RO inversion biases by eliminating tracking errors. Accurate temperature and moisture profiles from combined GPS RO data and future high resolution instruments like IASI (Infrared Atmospheric Sounding Interferometer) on METOP (Meteorological Operational Polar satellites of EUMETSAT), CrIS (Cross-track Infrared Sounder) on the NPOESS (National Polar-orbiting Operational Environmental Satellite System), and GIFTS (Geostationary Imagery Fourier Transform Spectrometer) (Smith et al., 2000) on the geostationary satellite, shall dramatically improve numerical weather prediction and allow us to better understand the water cycle and energy balance of the globe.
Acknowledgments

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References


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Figure Captions

Fig. 1. (a) Brightness temperature (K) in mid-latitude summer and (b) instrument noise for each AIRS channel for the 250 K scene temperature.

Fig. 2. GPS radio occultation observation uncertainties when compared to ECMWF and NCEP AVN analysis for (1) Southern Hemisphere (30° S to 90°S), (2) for Tropics (30° S to 30° N), and (3) for Northern Hemisphere (30° N to 90° N). (a) The standard deviations. (b) The mean fractional differences in refraction. (c) The total number of RO soundings used in these calculations as a function of height. The solid lines are comparisons with ECMWF analysis.

Fig. 3. Eigenvalue sequence plots of $K^T E^{-1} K$ for AIRS, GPS and AIRS combined with GPS measurements for (a) temperature and (b) water vapor mixing ratio.

Fig. 4. GPS noise equivalent change for (a) temperature, (b) percentage water vapor mixing ratio, and (c) water vapor mixing ratio.

Fig. 5. Standard deviation of 405 independent vertical profiles from NOAA88b for (a) temperature (K) and (b) water vapor (g/kg).

Fig. 6. Root Mean Square Errors (RMSE) for AIRS, GPS and AIRS combined with GPS for (a) temperature (K), (b) water vapor (g/kg), and (c) fractional refractivity (%).

Fig. 7. (a) AIRS temperature averaging kernel and (b) water vapor averaging kernel for no constraint condition and constraint condition.

Fig. 8. Root Mean Square Errors (RMSE) for AIRS, GPS and AIRS combined with GPS measurements for super-refraction and/or multi-path condition occurred below 700 mb for (a) temperature, (b) water vapor mixing ratio (g/kg), and (c) fractional refractivity (%). For AIRS combined with GPS retrievals, AIRS and GPS regressed profiles above 700 mb are used as the first guess for AIRS only physical retrieval.

Fig. 9. The percentage improvement of RMSE$_{WG}$ from RMSE$_{A}$ over Tropics (30° N to 30° S), Southern Hemisphere (30° S to 90° S) and Northern Hemisphere (30° N to 90° N).

Fig. 10. The mean $N$ bias of 19 profiles between the constraint, no constraint $N$ profiles and Abel retrieved $N$ profiles from GPS RO and radiosonde derived $N$ profiles. These 19 profiles were collected in January 2002 over Helena Island.
Table 1. Degrees of freedom for signal (DFS) for AIRS, GPS and AIRS combined with GPS measurements for temperature and water vapor.

<table>
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<th>AIRS</th>
<th>GPS</th>
<th>AIRS+GPS</th>
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<tr>
<td>DFS for Water Vapor</td>
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Table 2. The mean root square deviation of temperature and water vapor of all vertical layers for AIRS, GPS and AIRS combined with GPS. The root mean square deviation of all other quantities is from 1000 mb to 300 mb.

<table>
<thead>
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<th>AIRS</th>
<th>GPS</th>
<th>AIRS+GPS</th>
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<td>Temperature (K)</td>
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<td>Water Vapor (g/kg)</td>
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</table>
AIRS Temperature Averaging Kernels

AIRS Water Vapor Averaging Kernels
Improve of Moisture RMSE for SR below 700mb

AIRS+GPS 30N-30S
AIRS+GPS 30N-90N
AIRS+GPS 30S-90S

Pressure (mb)

Improvement of RMSE Mixing Ratio (%)