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Use of Total Precipitable Water Classification of A Priori Error and Quality Control in Atmospheric Temperature and Water Vapor Sounding Retrieval

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ABSTRACT

This study investigates the use of dynamic a priori error information according to atmospheric moistness and the use of quality controls in temperature and water vapor profile retrievals from hyperspectral infrared (IR) sounders. Temperature and water vapor profiles are retrieved from Atmospheric InfraRed Sounder (AIRS) radiance measurements by applying a physical iterative method using regression retrieval as the first guess. Based on the dependency of first-guess errors on the degree of atmospheric moistness, the a priori first-guess errors classified by total precipitable water (TPW) are applied in the AIRS physical retrieval procedure. Compared to the retrieval results from a fixed a priori error, boundary layer moisture retrievals appear to be improved via TPW classification of a priori first-guess errors. Six quality control (QC) tests, which check non-converged or bad retrievals, large residuals, high terrain and desert areas, and large temperature and moisture deviations from the first guess regression retrieval, are also applied in the AIRS physical retrievals. Significantly large errors are found for the retrievals rejected by these six QCs, and the retrieval errors are substantially reduced via QC over land, which suggest the usefulness and high impact of the QCs, especially over land. In conclusion, the use of dynamic a priori error information according to atmospheric moistness, and the use of appropriate QCs dealing with the geographical information and the deviation from the first-guess as well as the conventional inverse performance are suggested to improve temperature and moisture retrievals and their applications.

Key words: atmospheric sounding, AIRS, total precipitable water, a priori error, quality control

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1. Introduction

Atmospheric temperature and water vapor soundings from routinely observed satellite measurements both over land and ocean are critical in numerical weather prediction, as well as in other scientific researches. Given the importance of atmospheric sounding data, several multispectral and hyperspectral infrared (IR) instruments, such as the High-Resolution Infrared Sounder (HIRS), the Atmospheric InfraRed Sounder (AIRS), and the Interferometer Atmospheric Sounding Iinstrument (IASI), have been developed; their advancement will continue to be critical to improving atmospheric remote sensing techniques. A large number of algorithms (e.g., Eyre, 1989; Ma et al., 1999; Li et al., 2000; Susskind et al., 2003; Carissimo et al., 2005; Smith et al., 2005 among many others) have also been developed to retrieve atmospheric tem-

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perature and water vapor profiles from IR sounders.

Since the inversion from satellite-measured radiances to atmospheric state is a mathematically ill-posed problem that has no unique solution, typical retrieval methods take the form of constraining the ill-posed inverse problem (Rodgers, 2000). These constrained retrieval methods find the solution that is consistent with both satellite-measured radiances and a priori information. A priori information generally consists of a first-guess for the atmospheric state and an a priori error specifying the ranges within which the retrieved atmospheric state departs from the first-guess to match the satellite radiance observations. Many studies have investigated the role of a priori errors in the inverse problem, and the conclusions of these studies have pointed out that an incorrect error can constrain the solution inappropriately (Crosby and Weinreb, 1974; Ho et al., 2001; Prunet et al., 2001; Luo et al., 2007). If the a priori error is too small, the solution could be over-constrained and largely biased. Conversely, if the a priori error is too large, the solution could be under-constrained and unstable.

Considering the importance of a priori errors in the inverse problem, there is a question of whether the use of a fixed a priori error is appropriate for the retrieval of atmospheric temperature and water vapor profiles, which have significant seasonal and regional variation. Since atmospheric moistness differs according to weather, climate, and surface conditions (land/ocean), atmospheric moistness can be used as a proxy for the diverse atmospheric conditions. According to Kwon et al.[a], atmospheric temperature and moisture profiles, and those retrievals from satellite measurements, show different statistical behaviors depending on atmospheric moistness. Therefore, it is worthwhile to investigate the effect of a priori errors classified by atmospheric moistness as an alternative to a fixed a priori error in the temperature and water vapor profile retrievals.

It is also valuable to assign appropriate quality control (QC) flags in the retrieval process. Under some conditions, such as an incorrect specification of cloud, measurement error, surface information, etc., the inverse of satellite radiance measurements to the atmospheric state cannot be performed well and thus can result in divergence of the solution or convergence to an unrealistic solution. Also, poor performance of atmospheric temperature and moisture retrievals has been reported over high terrain (Jiang et al., 2005) and desert (Borbas et al., 2011). Since those poor retrievals can have a substantial negative impact on their applications, assigning QC flags is necessary so that users can appropriately select good retrievals, depending on their purpose. In the assimilation study of AIRS temperature profiles, the use of appropriate QC for sounding retrievals resulted in better forecasts (Susskind and Reale, 2009).

In this study, we apply a priori errors classified by atmospheric moistness in the temperature and water vapor retrievals from hyperspectral IR sounders, and we compare the result with those from a fixed a priori error. Various QC flags, which check inverse performance, geographical information, and deviation from the first-guess, are also examined in the temperature and moisture soundings. In doing so, temperature and water vapor profiles are retrieved from AIRS radiance measurements using the retrieval algorithm of Li et al. (2000) which is a physical iterative approach using the regression retrieval as the first-guess. This study intends to suggest a way to improve atmospheric temperature and water vapor retrievals by using dynamic a priori error information according to atmospheric conditions and to provide insights on QC that should be considered in the application of the retrievals.

2. Retrieval method and data

2.1 *Retrieval method*

By letting $\boldsymbol{F}(\boldsymbol{X})$ be the forward model that maps the atmospheric state vector $\boldsymbol{X}$ to the upwelling spectral radiance vector $\boldsymbol{Y}$, satellite measured radiance vector $\boldsymbol{Y}_{\rm m}$ is given by

$$\boldsymbol{Y}_{\rm m} = \boldsymbol{F}(\boldsymbol{X}) + \sigma \ , \tag{1}$$

where σ includes the instrument noise and forward model error. State vector $\boldsymbol{X}$ contains atmospheric temperature, water vapor, and ozone profiles, surface skin temperature, and surface emissivity. For water vapor, the natural logarithm of mixing ratio is used in $\boldsymbol{X}$ because it is more linear with radiances compared to the mixing ratio itself. The surface emissivity spectrum is represented by six eigenvector coefficients as explained by Li et al. (2007). The linear form of Eq. (1) around a suitable first-guess $\boldsymbol{X}_0$ of the atmospheric state is

$$\delta \boldsymbol{Y} = \boldsymbol{K} \delta \boldsymbol{X} \ , \tag{2}$$

where $\delta \boldsymbol{Y} = \boldsymbol{Y}_{\rm m} - \boldsymbol{F}(\boldsymbol{X}_0)$, $\delta \boldsymbol{X} = \boldsymbol{X} - \boldsymbol{X}_0$, and $\boldsymbol{K}$ is the Jacobian matrix (weighting function matrix) of the forward model $\boldsymbol{F}$. A general constrained solution to this problem is that which minimizes a cost function

[a]Kwon, E. H., B. J. Sohn, W. L. Smith, and J. Li, 2011: Validating IASI Temperature and Moisture Retrievals over East Asia using Radiosonde Observations. *J. Atmos. Oceanic Technol.*, submitted.

$$\boldsymbol{J}(\boldsymbol{X}) = [\boldsymbol{Y}_{\rm m} - \boldsymbol{F}(\boldsymbol{X})]^{\rm T} \boldsymbol{E}^{-1} [\boldsymbol{Y}_{\rm m} - \boldsymbol{F}(\boldsymbol{X})] + [\boldsymbol{X} - \boldsymbol{X}_0]^{\rm T} \boldsymbol{H} [\boldsymbol{X} - \boldsymbol{X}_0] \ , \quad (3)$$

where $\boldsymbol{E}$ is a measurement error covariance matrix and $\boldsymbol{H}$ is the inverse a priori (background) matrix which constrains the solution. By following the Gauss-Newtonian iteration and neglecting the second derivative of $\boldsymbol{F}(\boldsymbol{X})$, the solution is given by

$$\boldsymbol{X}_{n+1} = \boldsymbol{X}_0 + \left[\boldsymbol{K}_n^{\rm T} \boldsymbol{E}^{-1} \boldsymbol{K}_n + \boldsymbol{H}\right]^{-1} \boldsymbol{K}_n^{\rm T} \boldsymbol{E}^{-1} \times [\boldsymbol{Y}_{\rm m} - \boldsymbol{F}(\boldsymbol{X}_n) + \boldsymbol{K}_n (\boldsymbol{X}_n - \boldsymbol{X}_0)] \ , \quad (4)$$

where $\boldsymbol{X}_n$ is the atmospheric state retrieved at the nth iteration and $\boldsymbol{K}_n$ is the Jacobian matrix evaluated at $\boldsymbol{X}_n$. Here, Jacobian matrix $\boldsymbol{K}$ is calculated by using an efficient analytical form of Li (1994). By letting $\boldsymbol{H}$ be the inverse of the a priori first-guess error covariance matrix $\boldsymbol{S}_a$, Eq. (4) becomes the minimum variance solution, which is also the maximum a posteriori solution in the case of Gaussian statistics (Rodgers, 2000). Here, $\boldsymbol{H}$ is set to be the inverse of the a priori first-guess error covariance matrix multiplied by smoothing factor γ (i.e., $\boldsymbol{H} = \gamma \boldsymbol{S}_{\boldsymbol{a}}^{-1}$) so that we can balance the fit to the measurement [the first term in Eq. (3)] and a priori [the second term in Eq. (3)]. This gives the iterative solution as follows

$$\boldsymbol{X}_{n+1} = \boldsymbol{X}_0 + \left[\boldsymbol{K}_n^{\rm T} \boldsymbol{E}^{-1} \boldsymbol{K}_n + \gamma \boldsymbol{S}_a^{-1}\right]^{-1} \boldsymbol{K}_n^{\rm T} \boldsymbol{E}^{-1} \times [\boldsymbol{Y}_{\rm m} - \boldsymbol{F}(\boldsymbol{X}_n) + \boldsymbol{K}_n (\boldsymbol{X}_n - \boldsymbol{X}_0)] \, . \quad (5)$$

A simple numerical approach is applied to determine the appropriate smoothing factor γ. Starting with γ_0=1, γ is updated at each iteration step by the following procedure:

• If $\|\boldsymbol{F}(\boldsymbol{X}_n) - \boldsymbol{Y}_{\rm m}\|$ decreases, then decrease γ by a factor of 0.8.

• If $\|\boldsymbol{F}(\boldsymbol{X}_n) - \boldsymbol{Y}_{\rm m}\|$ increases, then increase γ by a factor of 1.8 and keep the state vector retrieved in the previous iteration. If this happens three times, the iteration stops and the previously retrieved state vector is set as the final solution.

The initialization and update factors for smoothing factor γ have been determined from empirical experience. The maximum number of successful iterations (i.e., the first procedure above) is set to be six.

The first-guess $\boldsymbol{X}_0$ usually comes from climatology, linear regression retrieval, and numerical forecast data. This study wants the sounding retrievals to be independent of numerical weather prediction (NWP) models so that the models can potentially use the data; therefore, the first-guess $\boldsymbol{X}_0$ is retrieved from satellite-measured radiances using a linear regression method. The linear regression retrieval method is simple and fast, but it is not able to extract temperature and moisture profiles accurately due to the nonlinearity between atmospheric profiles and radiances. The nonlinearity can be taken into account through the physical iterative approach as explained above.

In this study, the first-guess $\boldsymbol{X}_0$ comes from a linear regression method (Weisz et al., 2007) based on a global training data set that consists of 15 704 atmospheric profiles and their corresponding simulated AIRS radiances. A total number of 1450 AIRS channels are used in a principal component regression method in which principal component scores of the channel radiances are regressed against the atmospheric state to obtain the regression coefficients. Predictors consisting of 30 principal component scores, surface pressure, and solar zenith angle are used to estimate atmospheric temperature, water vapor, and ozone profiles in addition to surface skin temperature and surface emissivities. The regression coefficients are classified by 6 ranges of brightness temperature in the window region and also by 11 ranges of AIRS scanning angle. A priori first-guess error covariance matrix $\boldsymbol{S}_a$ is calculated using the difference between the regression retrieval that corresponds to the first-guess and the true atmospheric state in the global training data set. The Stand-alone AIRS Radiative Transfer Algorithm (SARTA) is used as the radiative transfer model (RTM) in the construction of the training data set and in the retrieval process (Strow et al., 2003). In the radiative transfer calculation of physical iterative retrieval, gas concentrations are fixed except for water vapor and ozone. To take into account the increase of CO_2 concentration with time, a global average CO_2 value that varies with time is used based on the linear fit of Maddy et al. (2008). Other gases, such as CO, CH_4, SO_2, HNO_3, and N_2O are fixed in the retrieval algorithm; however, the errors coming from these gases should have negligible impact on the retrieval results because the absorption lines of the gases are avoided in the channel selection for the temperature and water vapor retrieval.

2.2 *Data*

AIRS is a hyperspectral IR instrument on board the Aqua satellite, launched on 04 May 2002 (Chahine et al., 2006). AIRS provides measurements at 2378 channels over the IR spectral regions of 3.74–4.61 μm, 6.20–8.22 μm, and 8.8–15.4 μm, with a spatial resolution of 13.5 km at nadir. Due to its high spectral resolution over the IR region, atmospheric temperature and moisture profiles with a very high vertical resolution can be retrieved from AIRS radiance measurements. The retrieval method noted in section 2.1

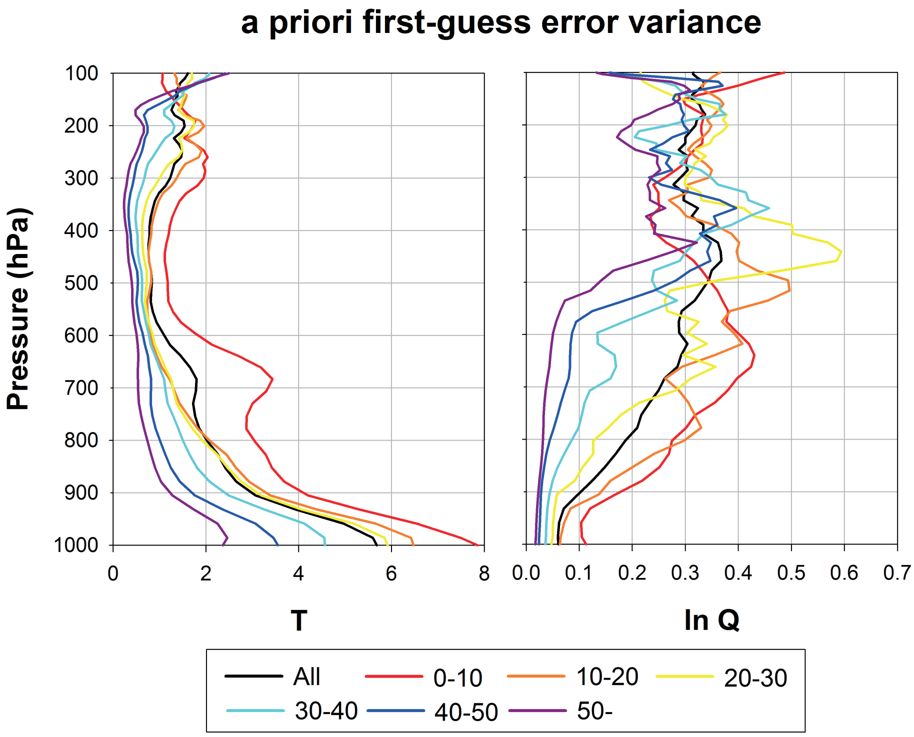

Fig. 1. A priori first-guess error variances (diagonal values of the a priori first-guess error covariance matrix $\boldsymbol{S}_{\rm a}$) for temperature (left) and water vapor (right) profiles classified by TPW. For water vapor, the natural logarithm is used for the calculation.

is applied to AIRS clear-sky measurements over East Asia (0°–55°N, 90°–150°E) from 20 July to 24 July 2009. To identify the AIRS clear pixels, Moderate Resolution Imaging Spectrometer (MODIS) level 2 cloud mask data are used (Li et al., 2004).

To evaluate temperature and moisture retrievals from AIRS, the European Centre for Medium-Range Weather Forecasting (ECMWF) reanalysis data (spatial resolution 0.25°×0.25°) is used as a reference. Only the AIRS data whose observation times are within 1 h of the ECMWF reanalysis time are collocated. The closest ECMWF data are matched to an AIRS pixel, and 91-level ECMWF temperature and moisture profiles are interpolated to 101 AIRS pressure levels.

3. A priori error classified by TPW

In the retrieval method explained in section 2.1, smoothing factor γ is used to allow a dynamic balance between the satellite measurement and the a priori error. However, the smoothing factor γ starts and increases with the same value for all cases and for all levels in the inversion procedure, and thus smoothing factor γ alone may not fully represent dynamic a priori error information with a fixed error covariance matrix $\boldsymbol{S}_{\rm a}$. To better handle the a priori error, we incorporate a priori first-guess error covariance matrix $\boldsymbol{S}_{\rm a}$ classified by precipitable water (PW) up to the 300 hPa level (referred to as total precipitable water: TPW) instead of a fixed error.

Figure 1 shows the a priori first-guess error variances (i.e., diagonal values of $\boldsymbol{S}_{\rm a}$) of the training data classified by TPW for the ranges of <10, 10–20, 20–30, 30–40, 40–50, and >50 kg m^{-2}. The percentage of samples used for each class are 31.64%, 22.26%, 15.07%, 11.71%, 10.21%, and 9.11%, respectively. The a priori first-guess error variances for all samples are also shown in a black line in Fig. 1. For water vapor, error variances are plotted in natural logarithm form, since the natural logarithm of the mixing ratio is used in the retrieval procedure rather than the mixing ratio itself. Figure 1 shows the a priori first-guess error variances for each TPW class are significantly different, indicating that the first-guess errors coming from the regression retrieval depend on the atmospheric moistness. The first-guess errors generally decrease with increasing moistness both for temperatures below 200 hPa and for water vapor below 500 hPa. A smaller a priori first-guess error has the impact of more greatly constraining the retrieval increments in Eq. (5) and thus makes the solution's departure from the first-

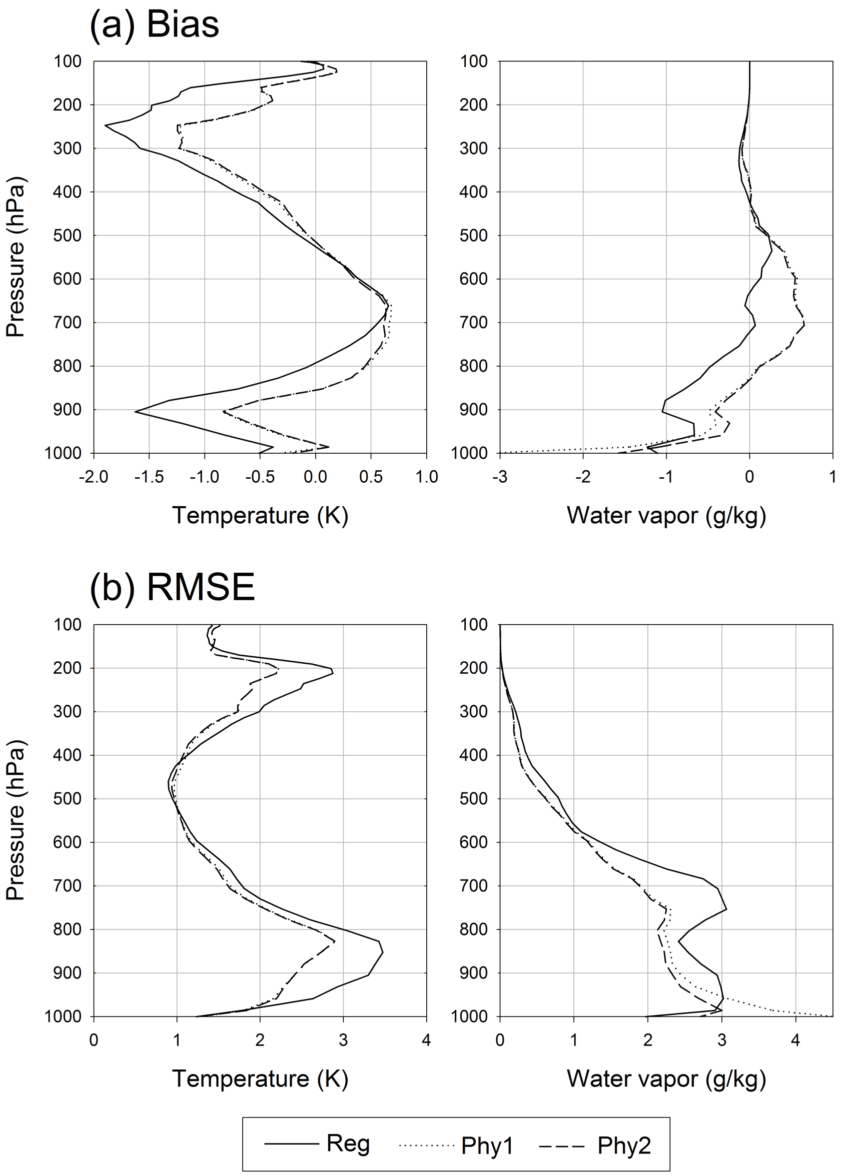

Fig. 2. (a) Bias and (b) RMSE of AIRS temperature and water vapor retrievals over East Asia from 20 July to 24 July 2009. Statistics are calculated for regression retrieval (Reg), physical retrieval using a fixed a priori first-guess error (Phy1), and physical retrieval using a priori first-guess errors classified by TPW (Phy2). ECMWF reanalysis data is used as a reference for the statistics.

guess smaller. Therefore, applying the a priori first-guess error values classified by TPW in the physical inverse procedure will result in more weight to the first-guess for moist cases and less weight to the first-guess for dry cases, compared to applying the total mean error values of the black line in Fig. 1. Since the a priori first-guess error is used in the form of the inverse in the solution of Eq. (5), the classification will have more impact on the moist cases that have smaller a priori first-guess error values, as well as larger deviations of the first-guess error from the total mean error.

The iterative inversion procedure explained in section 2.1 is performed using a priori first-guess errors classified by TPW and using a fixed a priori first-guess error. To assign the class of the a priori first-guess error, the TPW value is calculated from the regression-retrieved moisture profile, which is used as the first-guess in the physical retrieval procedure. We applied only diagonal values of the a priori first-guess error matrix in the inversion process. Figure 2 shows the bias and RMSE of AIRS temperature and water vapor profiles taken from the regression retrieval (Reg), physical retrieval using a fixed a priori first-guess error (Phy1), and physical retrieval using a priori first-guess errors classified by TPW (Phy2) over East Asia from 20 July to 24 July 2009. ECMWF reanalysis data is used as a reference; the number of AIRS-ECMWF collocated profiles used in this case is 22 689.

Temperature regression retrievals show a large negative bias and large RMSE in the upper-tropospheric layer above 400 hPa and in the boundary layer below 800 hPa. The large error in the temperature regression retrieval is substantially reduced via a physical iterative process, although the gross aspect of the regression error remains similar. Temperature statistics for Phy2 are very similar to that for Phy1, suggesting that the TPW classification of a priori first-guess error does not have significant impact on the temperature retrievals. For water vapor, regression retrievals show a dry bias in the upper-tropospheric layer and in the boundary layer where a cold temperature bias is found. The physical retrieval Phy1 substantially reduces the dry bias of the regression retrieval, while it increases the moist bias in the mid-tropospheric layer between 500 hPa and 800 hPa and sharpens the dry bias near the surface. For water vapor RMSE, the physical retrieval Phy1 shows significantly reduced values except at the surface boundary layer below 950 hPa. The degraded water-vapor retrieval performance of Phy1 near the surface is substantially overcome by the physical retrieval Phy2 using the a priori first-guess errors classified by TPW. The result indicates that the use of a priori first-guess errors classified by TPW has a positive impact on water vapor retrievals, especially in the boundary layer. The larger water vapor RMSEs from physical retrievals than that from regression retrieval near the surface suggest that water vapor profile solutions obtained from physical iterative process are unstable near the surface probably due to the lower sensitivity of AIRS radiances to lower-level water vapor. To prevent the unstable solutions, the use of additional information is suggested, such as temporally and spatially collocated surface temperature and moisture observations, constraining the physical retrieval near the surface.

To compare the retrieval outputs in terms of horizontal distribution, the AIRS granule 178 on 20 July 2009 is selected. Most clear pixels of this granule are located over the ocean, and most TPW values for clear pixels are >40 kg m^{-2}; therefore, the TPW classification of an a priori first-guess error can have significant impact on the physical retrieval results as expected from Fig. 1. For the selected granule, the water vapor mixing ratio from ECMWF analysis and the water vapor mixing ratio differences between three AIRS retrievals (Reg, Phy1, and Phy2) and ECMWF analysis at 904.87 hPa are plotted (Fig. 3). Water vapor regression retrieval tends to show a dry bias for the pixels with relatively moist ECMWF values, while a moist bias tends to be found for the pixels with dry ECMWF values. Although physical retrieval Phy1 reduces some moist biases of the regression retrieval, it more obviously increases dry biases. In contrast to Phy1, Phy2 reduces both dry and moist biases of the regression and shows better agreement with ECMWF analysis than other two retrievals, confirming the improvement of boundary layer moisture retrievals via TPW classification of a priori first-guess errors.

4. Quality control

Due to many factors, such as incorrect specification of cloud, surface, and a priori and measurement errors, atmospheric soundings from satellite radiance measurements can sometimes be very poor, and thus their quality needs to be controlled. In this study, we test six quality controls, which are related to inverse performance, geographical information, and deviation from the first-guess. We also discuss whether the quality controls can be used appropriately to rule out the retrievals with large errors.

The first quality control (QC1) identifies non-converged and bad physical retrievals. In the physical iterative process described in section 2.1, the first-guess coming from the regression retrieval is kept as the final retrieval if the iterative solution has never been updated due to the increasing residual of $\|\boldsymbol{F}(\boldsymbol{X}_n) - \boldsymbol{Y}_{\rm m}\|$ (i.e., non-convergence) and if the retrieved solution is out of a physically reasonable boundary (i.e., bad physical retrieval). Therefore, those final retrievals are the same as the regression retrieval and have no improvement via the physical inverse procedure. Since the physical iterative process tries to fit the radiances calculated from the retrieved atmospheric state to the observed radiances, the large difference between observed and calculated radiances indicates that the physical retrieval performance has not been successful. The second quality control (QC2) rejects those physical retrievals with a large residual between observed and calculated brightness temperatures. A threshold of 1 K is used to determine the large residual of $\|\boldsymbol{F}(\boldsymbol{X}_n) - \boldsymbol{Y}_{\rm m}\|$. For the East Asia case over the period of 20–24 July 2009, 4.9% and 0.8% of the total clear-sky retrievals are rejected by QC1 and QC2. Temperature and water vapor RMSEs of the rejected retrievals are much larger than those of all retrievals, as shown in Fig. 4a. Temperature retrievals with large residuals, moreover, show obvious degradation of the physical retrievals compared to the regression retrievals. These results suggest that assigning

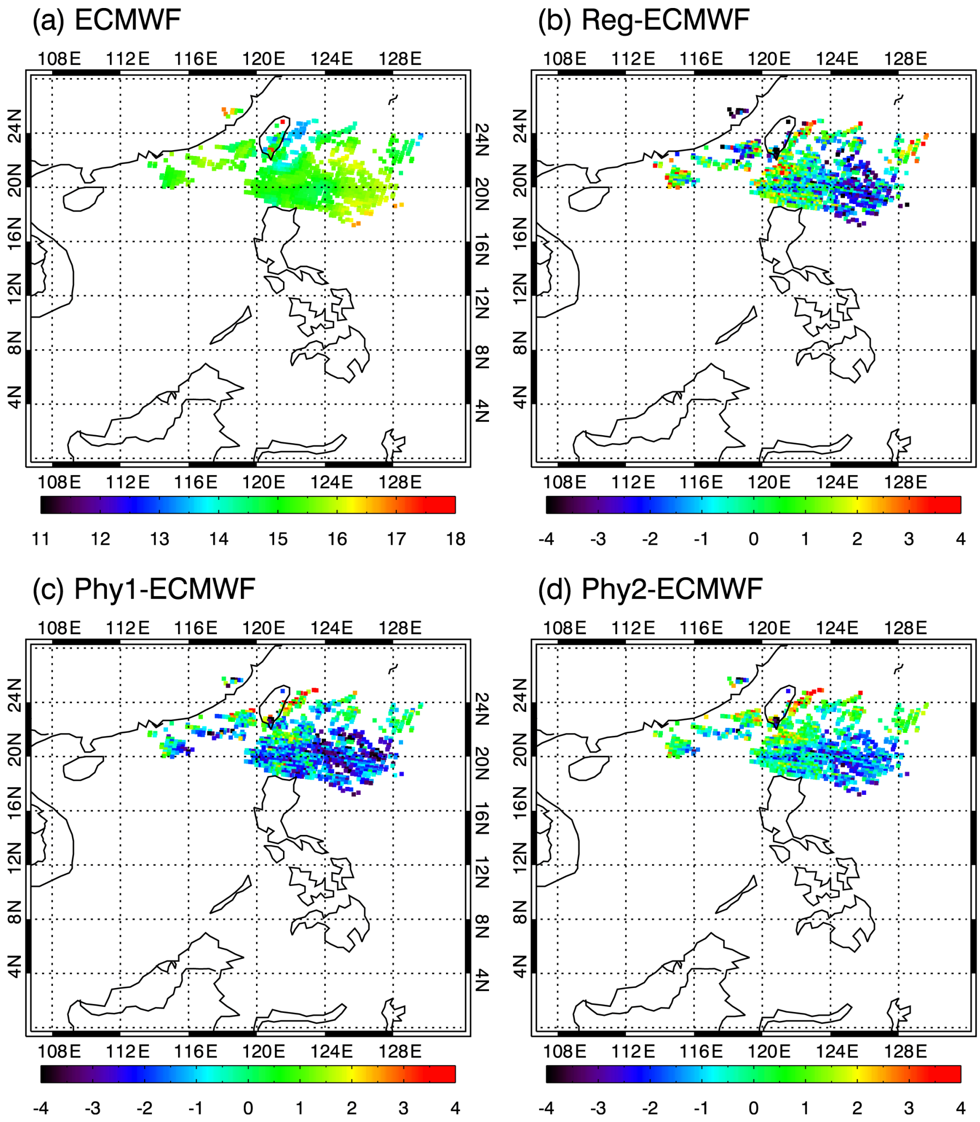

Fig. 3. Distributions of (a) water vapor mixing ratio (g kg^{-1}) of ECMWF analysis, and the differences between ECMWF and AIRS water vapor mixing ratio (g kg^{-1}) taken from (b) Reg, (c) Phy1, and (d) Phy2 retrievals at 904.87 hPa for granule 178 on 20 July 2009.

QC flags related to the physical iteration performance is very important in the retrieval procedure.

Over complex and high terrain areas, it is difficult to get exact surface pressure and emissivity information, and thus the accuracy of temperature and moisture retrievals could be poorer in these areas than that over flat areas (Jiang et al., 2005). Over the desert, there are known difficulties in retrieving surface skin temperature and emissivity, and the difficulties significantly affect the corresponding atmospheric profile retrievals (Borbas et al., 2011). The third (QC3) and fourth (QC4) quality controls separate those retrievals over high terrain areas and over desert. High terrain areas are identified by surface pressure based on the surface altitude by applying a threshold of 750 hPa. To identify desert, an ecosystem land surface type map from the International Geosphere-Biosphere Program (IGBP) is used (Loveland et al., 2000). Over East Asia, the case used in this study, 1.2% and 6.0% of the total clear-sky retrievals are rejected by QC3 and QC4, respectively. The temperature and water vapor RMSEs of the rejected retrievals are shown in Fig. 4b; over high terrain and desert areas, both regression and physical retrievals show significantly large errors, and the physical retrievals show even degradation for temperature compared to the regression retrievals. These results suggest that the retrievals over high terrain and desert should be used with caution unless additional

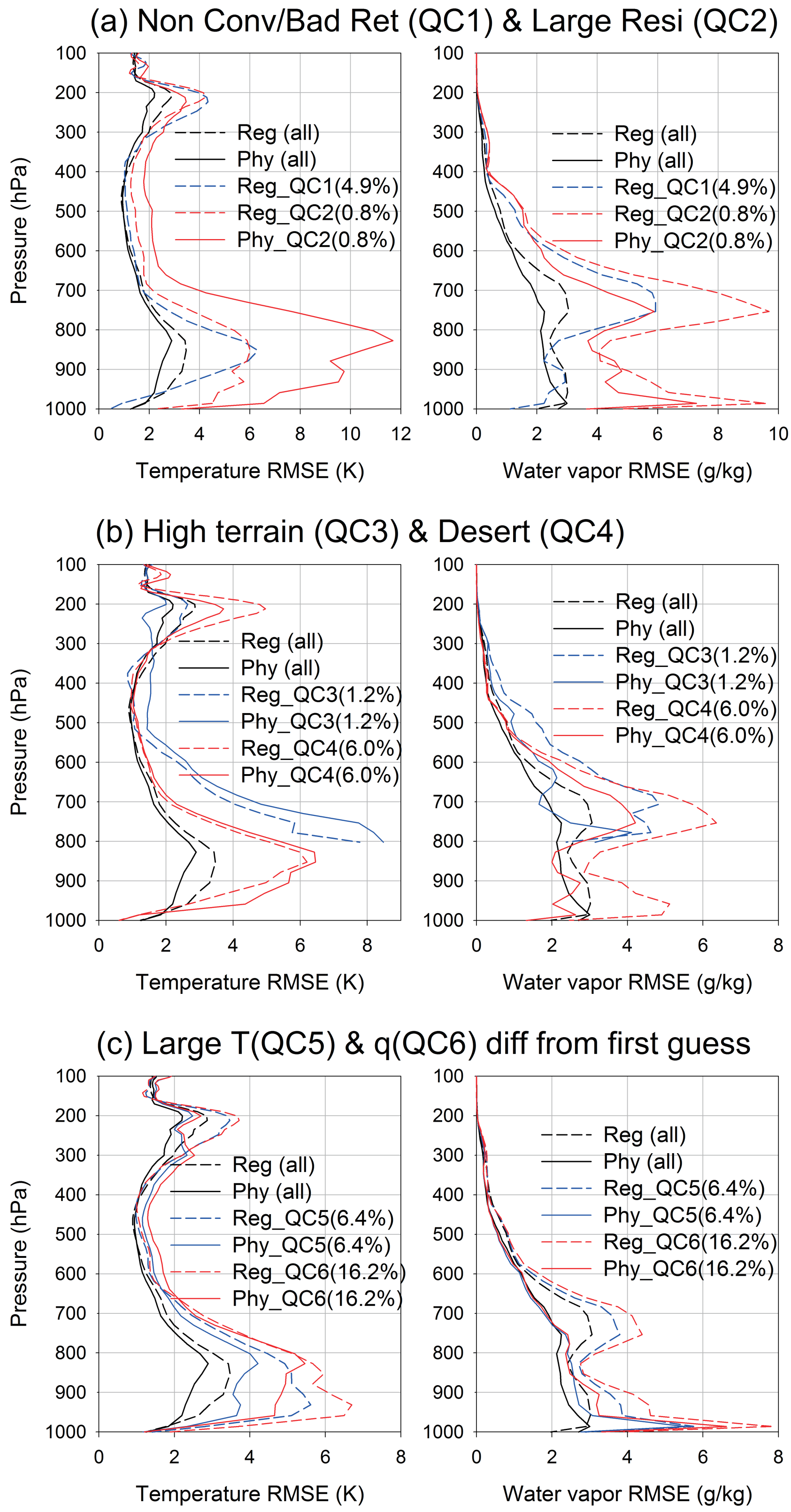

Fig. 4. RMSE of AIRS temperature and water vapor retrievals rejected by six quality controls of (a) QC1 and QC2, (b) QC3 and QC4, and (c) QC5 and QC6 over East Asia from 20 July 2009 to 24 July 2009. RMSEs of all retrievals are shown in black lines for reference.

procedures to manage retrieval problems over high terrain and desert are implemented.

The inverse problem discussed in section 2.1 can be highly nonlinear if the first-guess profile is quite apart from its true profile. For these retrievals, QC is also applied based on the temperature and water vapor differences between the first-guess (regression retrieval; $T_{\rm g}$ and $q_{\rm g}$) and the final physical retrieval ($T_{\rm r}$ and $q_{\rm r}$). The fifth quality control (QC5) identifies the retrievals with large temperature differences, $|T_{\rm g} - T_{\rm r}| > 5$ K at any level below 100 hPa. The threshold of 5 K was determined in experiments by finding the appropriate value which gives sufficient yields and some improvement in statistics. The sixth quality control (QC6) separates the retrievals with large water vapor difference ratio, $|q_{\rm g} - q_{\rm r}|/q_{\rm g} > \alpha$ at any level below 100 hPa. The value of α varies depending on the magnitude of $q_{\rm g}$ and the sign of $q_{\rm g} - q_{\rm r}$ based on the maximum adjustment allowance calculated for Geostationary Operational Environmental Satellite (GOES) soundings by Li (2009). Since the maximum adjustment allowance was used for the moisture update in each iteration by Li (2009), the values need to be tuned in this study for the total adjustment allowance between the first-guess and final physical retrieval. After several experiments, the appropriate threshold for water vapor

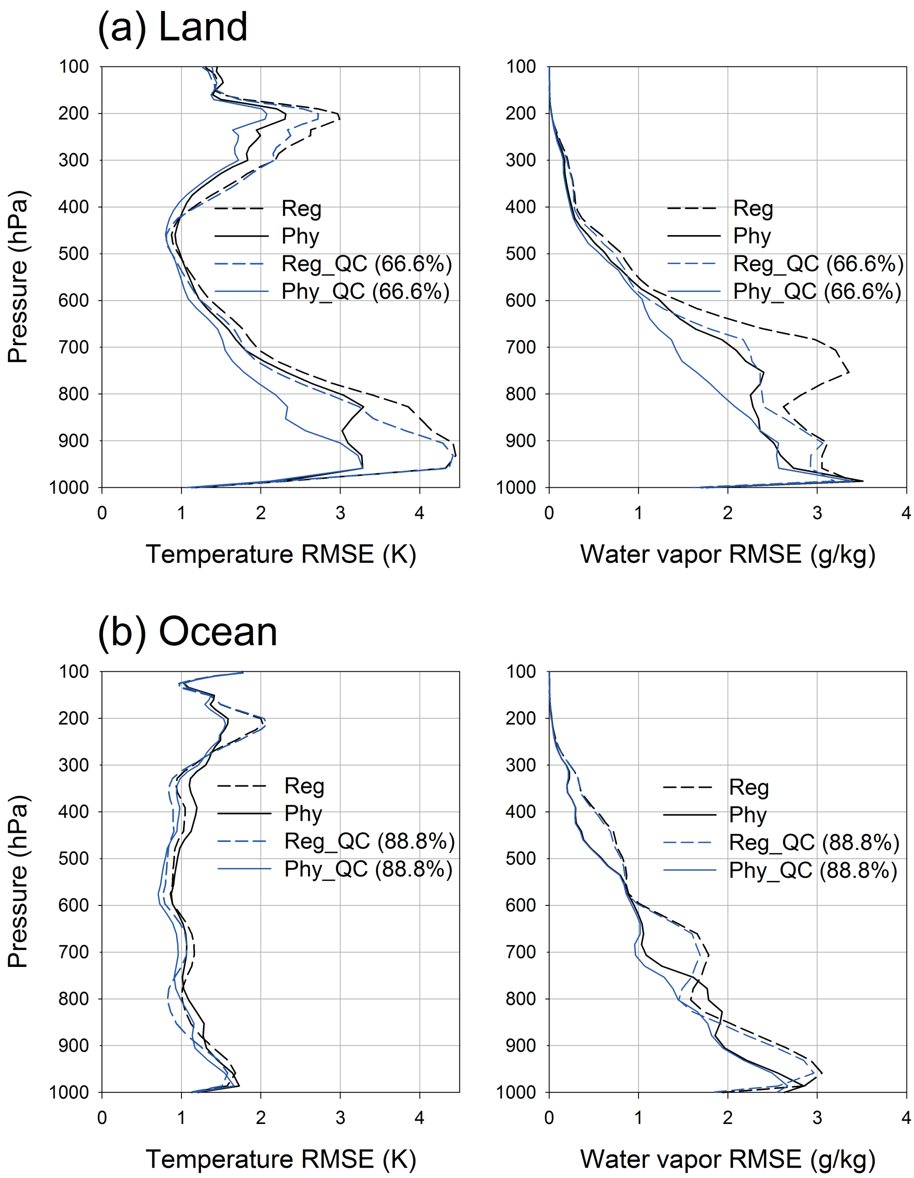

Fig. 5. RMSE of AIRS temperature and water vapor retrievals over (a) land and (b) ocean for the East Asia case of 20–24 July 2009. Accepted retrievals (Reg_QC and Phy_QC) by six quality control tests are compared with all retrievals (Reg and Phy).

difference ratio α was found to be two times the maximum adjustment allowance. QC5 and QC6 reject 6.4% and 16.2% of the total clear-sky retrievals for the East Asia case, respectively. The temperature and water vapor RMSEs of the rejected retrievals are shown in Fig. 4c. Although temperature and moisture errors of the first-guess are substantially reduced by the iterative inverse process, RMSEs for the rejected profiles are significantly larger than those of all retrievals in the lower troposphere for temperature and near the surface for moisture, which suggests the usefulness of QC5 and QC6.

RMSEs of the retrievals accepted by six quality control tests (QC1-6) are compared with those of all retrievals in Fig. 5 over land and over ocean. Over land, both temperature and moisture retrievals show much larger errors, especially for lower-tropospheric temperature. The percentage of the land retrievals that passed the six QC tests is also only 66.6%, which is 22.2% lower than that of ocean retrievals. Over the ocean, there is only a little room for improvement by the physical process and by QC because the regression itself shows very good agreement with the ECMWF analysis; therefore, the degree of improvement over ocean is not as significant as compared to that over land. In contrast to retrieval errors over the ocean, retrieval errors over land are substantially reduced by QC as well as by the physical process both for temperature and water vapor. These results imply that appropriate QC can have considerable impact on the application of temperature and water vapor retrievals, and the impact would be more significant over land.

5. Summary

This study examined the effect of TPW classification of a priori errors in temperature and water vapor profile retrievals from IR sounders. Since the errors of the first-guess coming from the regression retrieval show significant dependence on the atmospheric moistness, a fixed a priori error is not considered an appropriate representation of atmospheric temperature and moisture constraints in the inverse procedure. In the physical retrieval results from AIRS measurements over East Asia, the use of a priori first-guess errors classified by TPW, rather than fixed a priori errors, appears to improve water vapor retrievals in the boundary layer. This indicates that the use of dynamic a priori error information according to atmospheric conditions can be suggested as a way to improve atmospheric temperature and water vapor retrievals.

This study also tested six QCs, which check nonconverged or bad retrievals, large residuals, high terrain and desert areas, and large deviations from the first-guess for temperature and moisture, in the AIRS retrievals. The large retrieval errors for the rejected profiles by each QC indicate that the six QCs tested can be appropriately used to rule out poor retrievals which can have a negative impact on their applications. Also, based on the percentage of the retrievals rejected and the reduced amount of retrieval error by QCs, the use of QCs for the temperature and water vapor soundings seems to have more impact over land than over ocean, where regression and physical retrievals show good performance. These results provide some insights on the use of QCs dealing with geographical information and the deviation from the first-guess as well as the conventional inverse performance for better application of temperature and water vapor retrievals from IR sounders.

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