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Postprint: Retrieval of Clear-Sky Atmospheric Temperature and Humidity Profiles over Land from FY-3C MWHTS Data

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Date: 2017-03-10T00:00:00+00:00

Abstract

A one-dimensional variational retrieval system was established for the clear-sky observations over land from the FY-3C Microwave Humidity and Temperature Sounder (MWHTS) to retrieve atmospheric temperature and humidity profiles. To better characterize the correlation between temperature and humidity profiles while reducing error propagation between temperature and humidity during the retrieval process, a method using a combination of joint and separate background covariance matrices for combined retrieval was proposed. For biases between MWHTS simulated and observed brightness temperatures, a scan-point-by-scan-point statistical regression method was used for correction. Clear-sky brightness temperature observations over certain land regions in China were selected to retrieve temperature and humidity profiles, and ECMWF reanalysis data, NCEP analysis data, and radiosonde observation (RAOB) data were used to validate the retrieval results. The maximum root-mean-square errors of the retrieved temperature and humidity profiles validated against ECMWF reanalysis data were 2.59 K and 11.87%, respectively, those against NCEP analysis data were 1.88 K and 21.50%, respectively, and those against RAOB data were 3.43 K and 25.48%, respectively. The validation results demonstrate the reliability of the retrieval results. Additionally, a comparison was conducted with the retrieval accuracy of physical and statistical methods using observations from the foreign counterpart instrument AMSU. The results indicate that MWHTS has strong capability for humidity profiling and upper-level temperature profiling, and the one-dimensional variational retrieval system established for MWHTS observations achieves high retrieval accuracy. Validation results against NCEP 6-hour forecast profiles indicate that the retrieved humidity profiles can improve the accuracy of forecast profiles.

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Full Text

Retrieval of Clear-Sky Temperature and Humidity Profiles over Land Using FY-3C/MWHTS Data

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Abstract

A one-dimensional variational retrieval system has been developed to retrieve atmospheric temperature and humidity profiles from clear-sky observations over land by the Microwave Humidity and Temperature Sounder onboard the Fengyun-3C satellite (FY-3C/MWHTS). To better characterize the correlation between temperature and humidity profiles and to reduce error propagation between these parameters during retrieval, a hybrid approach combining the united matrix and individual matrix of the background covariance matrix is proposed. The bias between simulated and observed brightness temperatures is corrected using a scan-point-by-scan-point statistical regression method. Clear-sky observations over selected land regions in China are used to retrieve temperature and humidity profiles, with validation performed against European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data, National Centers for Environmental Prediction (NCEP) analysis data, and Radiosonde Observation (RAOB) data. The maximum root-mean-square errors are 2.59 K and 11.87% for temperature and humidity, respectively, when validated against ECMWF reanalysis; 1.88 K and 21.50% against NCEP analysis; and 3.43 K and 25.48% against RAOB data. These results demonstrate the reliability of the retrieval products. Comparison with retrieval accuracies from similar instruments such as AMSU using both physical and statistical methods indicates that MWHTS possesses strong capabilities for humidity profiling and upper-level temperature sounding, and that the one-dimensional variational retrieval system developed for MWHTS observations achieves high retrieval accuracy. Validation against NCEP 6-hour forecast profiles shows that the retrieved humidity profiles can improve forecast accuracy.

Keywords: MWHTS, one-dimensional variational retrieval, temperature and humidity profiles, pixel-by-pixel correction, forecast profiles

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1. Introduction

Temperature and humidity profiles are two crucial parameters for describing atmospheric conditions, with wide applications in atmospheric science, including initialization of numerical weather prediction models, climate change research, and real-time forecasting of severe convective weather (Zavodsky et al., 2012; Araki et al., 2015; Chan et al., 2015). Satellite remote sensing of atmospheric temperature and humidity information has a history spanning over 50 years, during which sensor hardware has advanced considerably and numerous retrieval algorithms have been developed for various instruments. For microwave radiometers, Wang et al. (2010) used statistical regression to retrieve atmospheric humidity profiles over clear-sky oceans from Advanced Microwave Sounding Unit (AMSU) observations, demonstrating good consistency with NCEP forecast profiles through case studies. Mathur et al. (2013) similarly employed statistical regression to retrieve humidity profiles from Microwave Humidity Sounder (SAPHIR) observations over both ocean and land, validating the accuracy against ECMWF reanalysis and RAOB data. Karbou et al. (2005) used neural networks to retrieve clear-sky atmospheric temperature and humidity profiles over land from AMSU data, achieving high accuracy through classification based on land surface types and seasonal variations of atmospheric parameters. Gangwar et al. (2014) applied the same method to retrieve clear-sky temperature profiles over both ocean and land from AMSU observations, performing classified retrievals for tropical and subtropical regions according to surface type characteristics and spatiotemporal distributions of atmospheric parameters, with detailed error analysis. Li et al. (2000) developed the International ATOVS Processing Package (IAPP) for retrieving atmospheric parameters under both cloudy and clear-sky conditions from AMSU and High-resolution Infrared Radiation Sounder (HIRS) observations, with detailed descriptions of cloud detection and brightness temperature bias correction. Boukabara et al. (2011) developed the Microwave Integrated Retrieval System (MIRS), which uses a physical-statistical method to retrieve global atmospheric parameters from AMSU, Microwave Humidity Sounder (MHS), and Special Sensor Microwave Imager/Sounder (SSMI/S) observations, with all-weather retrieval capability.

However, previous retrieval results demonstrate that different prior information leads to different retrieval accuracies. For temperature profile retrieval, accuracy over land is significantly lower than over ocean, with the poorest performance in the near-surface layer. This is largely related to the complexity of land surface types and the characteristic variations of temperature and humidity parameters above land surfaces (Karbou et al., 2005; Gangwar et al., 2014). The channel configuration of FY-3C/MWHTS enables independent retrieval of temperature and humidity profiles. While literature exists on the hardware design and data calibration/validation of FY-3C/MWHTS (Guo et al., 2015), no studies have described retrieval methods specifically for this instrument. Among various atmospheric profile retrieval methods, physical retrieval—achieved through modeling of the atmospheric radiative transfer process and inversion of the radiative transfer equation—represents the fundamental approach for improving retrieval accuracy. This study therefore employs a physical retrieval method to investigate retrievals from MWHTS clear-sky observations over land. However, due to the difficulty and poor accuracy of land surface emissivity calculations in atmospheric radiative transfer modeling (Karbou et al., 2005; Gangwar et al., 2014), this study does not perform detailed classification of land surface types to reduce retrieval complexity, but instead improves retrieval accuracy from the perspective of prior information.

This paper first establishes a physically iterative one-dimensional variational retrieval system for MWHTS observed brightness temperatures to retrieve atmospheric temperature and humidity profiles under clear-sky conditions over selected land regions in China. Brightness temperature data from April and May 2015 are used for retrieval, with validation performed against ECMWF reanalysis data, NCEP analysis data, and RAOB data. The retrieval accuracy is also compared with that from similar instruments such as AMSU.

2. Data and Methodology

2.1 MWHTS Instrument MWHTS is a total-power microwave radiometer with a superheterodyne receiver. It has eight atmospheric temperature sounding channels near the 118.75 GHz oxygen absorption line, five atmospheric humidity sounding channels near the 183.31 GHz water vapor absorption line, and two window channels at 89 GHz and 150 GHz. The 118.75 GHz channels represent the first operational use of such atmospheric sounding channels on a satellite, enabling simultaneous sounding of atmospheric temperature and humidity parameters in conjunction with the 183.31 GHz channels. MWHTS has a scanning swath of approximately 2700 km, a nadir spatial resolution of about 15 km, 98 scan points per scan line (each corresponding to a satellite zenith angle), and a scan period of 2.667 seconds. Bao (2014) provides a detailed analysis of the channel weighting functions and their vertical distribution characteristics.

2.2 Research Data and Models The datasets used in this study include: (1) FY-3C/MWHTS brightness temperature data (Level 1 product) from the China Meteorological Administration website for February 2014 to May 2015; (2) NOAA-18 AMSU-A and AMSU-B brightness temperature data (Level 1c product) from the China Meteorological Administration website for February 2014 to May 2015; (3) ECMWF reanalysis data (ERA-Interim), including temperature and humidity profiles and surface parameters. The profiles extend from the surface to the upper atmosphere in 37 levels: 1000, 975, 950, 925, 900, 875, 850, 825, 800, 775, 750, 700, 650, 600, 550, 500, 450, 400, 350, 300, 250, 225, 200, 175, 150, 125, 100, 70, 50, 30, 20, 10, 7, 5, 3, 2, and 1 hPa, with a horizontal resolution of 0.25°×0.25°, obtained from the ECMWF website (http://apps.ecmwf.int/datasets) for February 2014 to May 2015; (4) NCEP Global Forecast System (GFS) 6-hour forecast and analysis data, including temperature and humidity profiles and surface parameters. The profiles have 26 levels from surface to upper atmosphere: 1000, 975, 950, 925, 900, 850, 800, 750, 700, 650, 600, 550, 500, 450, 400, 350, 300, 250, 200, 150, 100, 70, 50, 30, 20, and 10 hPa, with 0.25°×0.25° resolution, obtained from the NCEP website (http://rda.ucar.edu/datasets/ds084.1) for January to May 2015. To match the ECMWF profile levels, NCEP profiles are interpolated using cubic splines; (5) RAOB data from the RAOB website (http://www.esrl.noaa.gov/raobs) for April to May 2015. Quality control is applied to RAOB data, requiring total pressure levels greater than 20 and minimum pressure greater than 200 hPa for valid temperature and humidity soundings, and interpolated to 37 levels.

Since this study focuses on atmospheric parameter retrieval over selected land regions in China, all datasets are confined to the geographic domain (25°N–45°N, 90°E–120°E). For simulated brightness temperature calculations, this study uses the Radiative Transfer for TOVS (RTTOV) version 11.2 developed by ECMWF (Hocking et al., 2014).

2.3 Clear-Sky Data Selection Numerous studies have addressed clear-sky data selection. Karstens et al. (1994) used relative humidity thresholds for clear-sky determination, but water vapor parameters vary significantly in time and space, making such thresholds subjective and requiring statistical analysis based on local meteorological conditions for specific applications. Ishimoto et al. (2014) matched infrared cloud products with microwave brightness temperatures for clear-sky selection, but this method heavily depends on infrared cloud products. Buehler et al. (2007) used inter-channel brightness temperature relationships from microwave sensors to identify cloudy and rainy data, but could not effectively detect thin cloud regions. To more accurately characterize clear-sky atmospheres and avoid cloud effects on emission, absorption, and scattering, this study selects clear-sky atmospheric parameters based on cloud water path equal to zero in ECMWF reanalysis data, then matches these with MWHTS and AMSU brightness temperature data temporally and spatially to select clear-sky observations.

3. Retrieval Methodology

3.1 One-Dimensional Variational Retrieval Algorithm The radiative transfer equation is nonlinear, and atmospheric parameters are obtained through its inversion, which is an underdetermined process. The one-dimensional variational retrieval algorithm is a typical physical retrieval method consisting of two main components: a radiative transfer model that calculates forward brightness temperatures and their gradients, and a minimization cost function that balances contributions from prior information and satellite observations to the final solution. Assuming observation errors and prior information errors are unbiased, uncorrelated, and Gaussian-distributed, the optimal estimate of atmospheric parameters **x** can be obtained by minimizing the cost function (Boukabara et al., 2011):

$$J(\mathbf{x}) = (\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + [\mathbf{I}-\mathbf{H}(\mathbf{x})]^T\mathbf{R}^{-1}[\mathbf{I}-\mathbf{H}(\mathbf{x})]$$

where **x**_b is the background profile, **B** is the background covariance matrix, **R** is the measurement error covariance matrix (including observation error covariance matrix $\mathbf{E}$ and forward model error covariance matrix $\mathbf{F}$), $\mathbf{I}$ is the observed brightness temperature, and $\mathbf{H(x)}$ is the forward model simulating brightness temperatures from atmospheric parameters $\mathbf{x}$.

Differentiating the cost function yields:

$$\nabla J(\mathbf{x}) = \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) - \mathbf{H}^T\mathbf{R}^{-1}[\mathbf{I} - \mathbf{H}(\mathbf{x})]$$

where $\mathbf{H}$ is the Jacobian matrix of the forward model, representing the sensitivity of simulated brightness temperatures to changes in atmospheric parameters $\mathbf{x}$. The optimal solution is obtained by setting this expression to zero, with the Newtonian iteration scheme given by:

$$\mathbf{x}_{n+1} = \mathbf{x}_n + (\mathbf{B}^{-1} + \mathbf{H}_n^T\mathbf{R}^{-1}\mathbf{H}_n)^{-1}\mathbf{H}_n^T\mathbf{R}^{-1}[\mathbf{I} - \mathbf{H}(\mathbf{x}_n)]$$

where n denotes the iteration number and **x**_{n+1} represents the optimal solution (retrieved profile). Equation (3) shows that prior information (**B** and **x**_b) and the difference between observed and simulated brightness temperatures directly affect retrieval accuracy.

3.2 Prior Information Solving an underdetermined nonlinear equation requires finding an optimal solution among infinite possibilities that has physical meaning, necessitating constraints from prior information that directly determines solution existence and accuracy. The background covariance matrix $\mathbf{B}$ is generated from climatological datasets including RAOB data and reanalysis data from assimilation systems (Rodgers, 2000). This study uses 111,069 temperature and humidity profiles under clear-sky conditions from ECMWF reanalysis data in 2014 to generate $\mathbf{B}$:

$$\mathbf{B}_{ij} = \frac{1}{N}\sum_{n=1}^{N}(x_{i,n} - \bar{x}_i)(x_{j,n} - \bar{x}_j)$$

where **B**_{ij} is the element at row i and column j of the background covariance matrix, $\bar{x}$ is the mean profile, and N is the number of profile samples.

When $\mathbf{x}$ represents temperature and humidity profiles separately, the resulting covariance matrices describe only the auto-correlation of temperature or humidity profiles individually, referred to as "individual matrices." When $\mathbf{x}$ simultaneously represents both temperature and humidity profiles, the resulting matrix can describe cross-correlations between temperature and humidity, referred to as the "united matrix." These matrices are more intuitively represented using correlation coefficient matrices, as shown in [Figure 1: see original paper].

In [Figure 1: see original paper], levels 1–37 represent temperature profile correlation coefficients from upper atmosphere to surface, while levels 38–74 represent humidity profile correlation coefficients from upper atmosphere to surface.

[FIGURE:1(a)] shows strong auto-correlation within temperature and humidity levels individually, but no cross-correlation between them. [FIGURE:1(b)] reveals strong cross-correlation between temperature and humidity in addition to their individual auto-correlations, particularly in the upper atmosphere where cross-correlation coefficients exceed 0.8. Under natural conditions, temperature and humidity profiles are inherently correlated and contribute radiatively to each other' s sounding channels. Therefore, using the united matrix for temperature and humidity retrieval more accurately describes natural atmospheric variability and helps improve retrieval accuracy. However, uncertainties in these parameters during retrieval can affect each other, particularly for humidity retrieval, where insufficiently accurate prior temperature profiles can significantly degrade humidity retrieval accuracy (Aires et al., 2015).

Previous one-dimensional variational retrieval systems have used either individual or united background covariance matrices, but none have employed both simultaneously (Boukabara et al., 2011; Li et al., 2000). This study proposes a hybrid retrieval approach using both united and individual matrices for MWHTS clear-sky observations over land: the united matrix is used for temperature retrieval (with the resulting humidity profile discarded), while the individual matrix is used for humidity retrieval (with the resulting temperature profile discarded). This approach fully utilizes the correlation between temperature and humidity profiles while simultaneously reducing error propagation during retrieval.

For the background profile **x**_b, Equation (3) shows it directly influences retrieval results—the closer it is to the true profile, the higher the retrieval accuracy. Potential data sources for **x**_b include: (1) mean profiles from climatological datasets; (2) output profiles from statistical retrievals; and (3) spatiotemporally matched forecast profiles. Since climatological mean profiles only represent historical averages and deviate significantly from actual atmospheric states, and statistical retrieval methods require sample selection and regression coefficient calculation (increasing computational load), this study selects NCEP 6-hour forecast profiles as background profiles. Retrieval accuracy is also compared with forecast profile accuracy to demonstrate the value of MWHTS observations for numerical weather prediction assimilation systems. The initial guess profile (**x**_0 in Equation 3) must be conceptually distinguished from the background profile—a good initial guess accelerates convergence but does not affect retrieval accuracy. In this retrieval system, the background profile is used as the initial guess.

3.3 FY-3C/MWHTS Channel Bias Correction Compared with ocean surface emissivity calculations, land surface emissivity calculations have larger errors, leading to systematic biases in simulated brightness temperatures that directly affect retrieval accuracy. This study uses 14 months (February 2014 to March 2015) of clear-sky ECMWF reanalysis data for forward brightness temperature simulation, with surface emissivity calculated using the Fast Emissivity Model version 5 (FASTEM-5). To analyze the statistical characteristics of all MWHTS scan points, the matching criteria between reanalysis data and MWHTS observations are set to time differences less than 2 hours and latitude/longitude differences less than 0.05°, yielding over 100,000 matched pairs. Statistical analysis reveals linear relationships between simulated and observed brightness temperatures for most channels. The correlation coefficients for each channel vary with scan point, as shown in [Figure 2: see original paper].

[Figure 2: see original paper] shows that window channels 1 and 10 have large errors between simulated and observed brightness temperatures due to surface emissivity calculation uncertainties, with most scan points having low correlation coefficients below 0.85. Channel 2 maintains low correlation coefficients below 0.75 at all scan points, possibly due to insufficient accuracy of ECMWF temperature profiles at high altitudes. For other temperature channels, channels 4, 5, 6, and 7 have high correlation coefficients near 0.95, while channels 3, 8, and 9 have slightly lower coefficients but mostly above 0.90. Humidity channels all have correlation coefficients above 0.80, with substantial variation across satellite zenith angles—coefficients near 0.90 at large zenith angles and near 0.80 at small zenith angles. Overall, each channel' s correlation coefficient varies with scan point, which, apart from spatiotemporal matching errors, reflects characteristics of cross-track scanning sensors whose observations depend on satellite zenith angle.

The average bias between simulated and observed brightness temperatures for MWHTS' s fifteen channels varies with satellite zenith angle, as shown in [Figure 3: see original paper]. Each channel exhibits some zenith-angle dependence in average brightness temperature bias, particularly for window channels which show large biases with substantial angular variation. For temperature channels, channels 2–6 show modest angular variation, while channels 7, 8, and 9 exhibit clear angular trends. For humidity channels, channels 11–13 show modest angular dependence, while channels 14 and 15 display more pronounced trends. Bias correction is crucial in physical retrieval systems, as uncorrected systematic biases can cause iteration divergence or yield incorrect results. This study proposes a scan-point-by-scan-point statistical regression method to correct biases in MWHTS observed brightness temperatures. To fully utilize MWHTS data, bias correction is applied to scan points where the correlation coefficient between simulated and observed brightness temperatures exceeds 0.80 (Li et al., 2000):

$$T_{ij}^{*} = a_{ij} T_{ij} + b_{ij}$$

where T_{ij}^{*} is the corrected brightness temperature, T_{ij} is the uncorrected brightness temperature, a_{ij} is the slope, and b_{ij} is the intercept. Here, i represents the MWHTS channel (1–15) and j represents the scan point (1–98).

Assuming no inter-channel correlation, the diagonal elements of matrix $\mathbf{R}$ can be used as the measurement error covariance matrix. The diagonal elements of forward model error covariance matrix **E** are obtained from squared differences between corrected observed brightness temperatures and simulated brightness temperatures for each channel. The diagonal elements of observation error covariance matrix **F** are generated using the square of channel sensitivity values (Ishimoto et al., 2014); this study uses average sensitivity values calculated by Bao (2014) for FY-3C/MWHTS operational data. Forward model errors and channel sensitivities are listed in .

3.4 Quality Control Quality control of retrieval results is performed through iteration convergence criteria and observed brightness temperature quality control. The iteration convergence criterion stops the iteration when the relative change in cost function value falls within 0.01, with a maximum of 10 iterations. If iteration stops due to exceeding 10 iterations, the background profile is used as the retrieval profile. Quality control of input background profiles and observed brightness temperatures uses differences between simulated brightness temperatures from background profiles and observed brightness temperatures—any channel with differences exceeding 20 K leads to rejection of that brightness temperature dataset.

4. Retrieval Results and Validation

4.1 Retrieval Procedure The basic steps of the one-dimensional variational retrieval system developed in this study are:

1) Select clear-sky brightness temperature data from FY-3C/MWHTS and apply the scan-point-by-scan-point statistical regression correction method for bias correction.
2) Match the corrected brightness temperature data with ECMWF reanalysis data, NCEP forecast and analysis data, and RAOB data in space and time. Matching criteria are: time difference less than 0.5 hours and latitude/longitude differences less than 0.05° for MWHTS with ECMWF, NCEP forecast, and analysis data; time difference less than 3 hours and latitude/longitude differences less than 1° for RAOB data.
3) Input the matched NCEP 6-hour forecast profiles as background profiles, along with measurement error covariance matrix **R** and both individual and united background covariance matrices **B** established in Section 3, into the one-dimensional variational retrieval system.
4) Perform retrieval calculations using both individual and united background covariance matrices with corrected clear-sky brightness temperatures. The final retrieval uses the temperature profile from the united matrix retrieval and the humidity profile from the individual matrix retrieval. Retrieval accuracy is validated against matched ECMWF reanalysis, NCEP analysis, and RAOB data.

This study uses two months (April–May 2015) of FY-3C/MWHTS clear-sky brightness temperature data over land for retrieval calculations.

4.2 Scan-Point-by-Scan-Point Bias Correction Effects To evaluate bias correction across all scan points, FY-3C/MWHTS clear-sky brightness temperatures are matched with ECMWF reanalysis data using criteria of time difference less than 2 hours and latitude/longitude differences less than 0.05°, yielding 10,078 matched pairs. Brightness temperature bias correction is applied to these matched pairs, with results shown in [Figure 4: see original paper].

[Figure 4: see original paper] shows that bias correction is applied to only some scan points for window channels 1 and 10, while channel 2 is not corrected due to low correlation coefficients. For other temperature channels, correction effects are evident, though channels 7, 8, and 9 still exhibit large biases at individual scan points. For humidity channels, channels 12, 14, and 15 show good correction effects, while channel 11 performs poorly at nadir and channel 13 performs well at large zenith angles but poorly at small zenith angles. Overall, the effectiveness of scan-point-by-scan-point statistical regression correction depends on the correlation coefficient between simulated and observed brightness temperatures, indicating certain limitations in practical applications.

4.3 Retrieval Validation and Analysis Based on MWHTS channel weighting function characteristics (Bao, 2014), the retrieval pressure range is 10–1000 hPa for temperature and 250–1000 hPa for humidity. Mean bias and root-mean-square error are used as quantitative validation metrics (Mathur et al., 2013).

4.3.1 Impact of Background Covariance Matrix on Retrieval Results Corrected brightness temperatures from the 10,078 matched pairs are retrieved using both united and individual background covariance matrices. After rejecting 595 cases where differences between observed and background-simulated brightness temperatures exceed 20 K, 9,483 temperature and humidity profiles are obtained. Statistical validation against ECMWF reanalysis data is shown in [Figure 5: see original paper].

[FIGURE:5(a)] shows that temperature retrieval mean biases remain within 0.9 K for both matrices, with maximum root-mean-square errors of 3.9 K near the surface. United matrix retrievals show higher accuracy than individual matrix retrievals in the 300–1000 hPa range, but lower accuracy in the 200–300 hPa range. [FIGURE:5(b)] shows that humidity retrieval mean biases remain within 10% and root-mean-square errors within 17% for both matrices, with individual matrix retrievals showing higher accuracy than united matrix retrievals at all pressure levels. The hybrid approach improves retrieval accuracy, particularly for humidity near the surface (4.3% improvement), demonstrating that the proposed combination method enhances overall performance.

4.3.2 Retrieval Validation Analysis A single-point retrieval example at geographic coordinates (90.54°E, 43.03°N) for 26 April 2015 05:45 UTC is compared with ECMWF ERA-Interim profiles at (90.50°E, 43.00°N) for 26 April 2015 06:00 UTC in [Figure 6: see original paper]. The retrieved temperature and humidity profiles show high structural consistency with ECMWF profiles, capturing small structural variations. Retrieval biases and background biases exhibit similar pressure-dependent variations, suggesting background bias may be a source of retrieval error.

To minimize temporal matching errors, the time difference criterion is reduced to 0.5 hours, yielding 105 brightness temperature cases. Retrievals are performed using both uncorrected and corrected brightness temperatures. After quality control (rejecting cases with channel differences >20 K), 96 and 104 retrieval profiles are obtained, respectively, with statistical validation shown in [Figure 7: see original paper].

[FIGURE:7(a)] shows that bias-corrected temperature retrievals exhibit substantially reduced mean bias (up to 2 K reduction). Root-mean-square errors increase by about 0.1 K in the 500-600 hPa range, directly related to correction effects for temperature channels 7, 8, and 9. Near 1000 hPa, corrected and uncorrected retrievals show similar accuracy, largely due to poor correction of window channels, while other pressure levels show improved accuracy after correction, with a maximum root-mean-square error of 2.59 K. [FIGURE:7(b)] shows reduced mean bias for humidity retrievals after bias correction. Despite poor correction effects for channels 11 and 13, root-mean-square errors show clear reduction in the 400–750 hPa range where humidity channels contribute most. In the 250–400 hPa range, bias correction has minimal impact on humidity retrieval accuracy, with a maximum root-mean-square error of 11.87%.

Single-point and statistical validation of 104 retrieval profiles reveal that background profile errors and retrieval errors show high consistency, indicating that background profile accuracy significantly influences retrieval quality.

4.3.3 Validation Against NCEP Analysis and RAOB Data To ensure retrieval reliability, validation is performed against NCEP analysis and RAOB data. Following the matching procedures in Section 4.1, 104 and 1,068 retrieval profiles are obtained, respectively, with validation results shown in [Figure 8: see original paper].

For NCEP analysis validation, temperature mean bias is similar to ECMWF reanalysis validation, with root-mean-square errors below 1.88 K. Accuracy is better than ECMWF validation in the 800–1000 hPa range and comparable elsewhere. Humidity mean bias is larger than in ECMWF validation, with maximum root-mean-square error of 21.50% at 250 hPa and values within 16% for 350–1000 hPa. Errors exceed ECMWF validation in the 250–500 hPa range.

RAOB validation shows poorer accuracy for both temperature and humidity retrievals compared to the other datasets. Temperature retrieval accuracy is worst near the surface (3.43 K), remains at 2–3 K in the 600–800 hPa range, and stays within 1-2 K at other levels. Humidity retrieval accuracy is worst near 850 hPa (25.48%). Temporal matching errors likely contribute significantly to poorer RAOB validation accuracy. Additionally, complex land surface types mean that 1° latitude/longitude matching errors can cause large surface emissivity calculation errors, making spatial matching errors another important source.

4.3.4 Comparison with NCEP Forecast Profiles To demonstrate the importance of MWHTS observations for numerical weather prediction assimilation systems, retrieval accuracy is compared with NCEP 6-hour forecast profiles. Since NCEP GFS data archiving began in January 2015, the retrieval system is reconfigured using January–March 2015 clear-sky NCEP analysis data (instead of ECMWF reanalysis) to generate background covariance matrix $\mathbf{B}$, forward error covariance matrix $\mathbf{E}$, and scan-point bias correction coefficients using the same methods. Background profiles remain NCEP 6-hour forecasts. MWHTS brightness temperatures from April–May 2015 are matched with NCEP analysis and 6-hour forecast data using 0.5-hour time differences and 0.05° latitude/longitude differences, yielding 102 retrieval profiles for comparison with forecast profiles, as shown in [Figure 9: see original paper].

[FIGURE:9(a)] shows retrieval temperature mean bias is only smaller than forecast bias near 200 hPa, with root-mean-square errors better than forecast accuracy only in the 170–230 hPa range where temperature channels 4 and 5 contribute most. Retrieval accuracy is worse than forecast accuracy at other pressure levels. For humidity retrieval, [FIGURE:9(b)] shows substantially reduced mean bias compared to forecast profiles (up to 15% reduction). In the 250–750 hPa range where humidity channels contribute most, retrieval results significantly improve forecast profile accuracy (up to 18% improvement). This analysis indicates that the one-dimensional variational system developed for FY-3C/MWHTS clear-sky observations over land provides limited improvement to temperature forecast accuracy but substantial improvement to humidity forecast accuracy, demonstrating the value of MWHTS observations for numerical weather prediction assimilation systems.

4.3.5 Comparison with AMSU Retrieval Results AMSU has similar channel configuration and capabilities for temperature and humidity profiling, with operational applications. NOAA-18 AMSU-A and AMSU-B land observations matching the geographic domain and time period of MWHTS data are retrieved following Section 4.1 procedures. To simultaneously evaluate background profile effects, ECMWF ERA-Interim mean profiles (instead of NCEP 6-hour forecasts) are used as background profiles, yielding 90, 93, and 484 retrieval profiles for MWHTS, AMSU-A, and AMSU-B, respectively. Validation against ECMWF reanalysis is shown in [Figure 10: see original paper].

Compared to [Figure 7: see original paper], using climatological mean profiles as background substantially increases background root-mean-square errors, significantly degrading temperature and humidity retrieval accuracy. This further demonstrates the critical importance of background profile selection in this retrieval system. In [Figure 10: see original paper], MWHTS temperature retrieval accuracy is better than AMSU-A in the upper atmosphere (10–200 hPa), while

AMSU-A shows greater improvement to background profiles at other pressure levels. For humidity retrieval root-mean-square errors, MWHTS and AMSU-B show similar background improvement in the 750–1000 hPa and 450 hPa ranges, but MWHTS provides greater background improvement than AMSU-B at other pressure levels.

Additionally, neural network and physical retrieval results based on AMSU-A and AMSU-B clear-sky land observations are compared with this study's results. The statistical method uses neural network retrieval (Karbou et al., 2005) and the physical method uses the MIRS retrieval system (Boukabara et al., 2011). Both methods differ from this study by including detailed surface classification. AMSU-A and AMSU-B data are from NOAA-15 and NOAA-18, respectively. Validation against RAOB data compares temperature root-mean-square errors at 100, 300, 500, 800, and 950 hPa, and humidity root-mean-square errors at 300, 500, 800, and 950 hPa, as shown in and .

shows this study' s temperature retrieval accuracy is significantly better than neural network and MIRS results for AMSU in the upper atmosphere, comparable to MIRS at lower levels, and better than neural networks at lower levels. shows humidity retrieval accuracy is better than neural networks at lower levels but worse at upper levels. MIRS humidity retrieval accuracy is poorer, though MIRS has all-weather capability not present in this system. Despite not performing detailed surface classification to reduce computational complexity, this retrieval system achieves high accuracy for MWHTS clear-sky observations.

5. Conclusion

This study developed a one-dimensional variational retrieval system based on MWHTS observations to retrieve atmospheric temperature and humidity profiles under clear-sky conditions over land. To address the high complexity and poor accuracy of land surface emissivity calculations, this study approached the problem from the perspective of prior information, proposing for the first time a hybrid retrieval method using both united and individual background covariance matrices. This approach effectively reduces retrieval complexity while outperforming methods that classify surface types. Validation against multiple data sources confirms the reliability of retrieval results.

Retrievals using both MWHTS and AMSU brightness temperature data show that MWHTS temperature retrieval accuracy is better than AMSU in the upper atmosphere (10–200 hPa), while MWHTS humidity retrieval accuracy is better than AMSU across most pressure levels except near 750–1000 hPa and 450 hPa where they are comparable. These comparisons demonstrate MWHTS' s strong temperature sounding capability in the upper atmosphere and strong water vapor sounding capability throughout the atmospheric column, confirming the high quality of MWHTS observations. Furthermore, the improvement of MWHTS retrieval results over NCEP 6-hour forecast profiles demonstrates the important value of MWHTS data for numerical weather prediction radiance assimilation.

However, validation against various datasets reveals high consistency between background profile errors and retrieval errors, indicating that background profile accuracy is a significant error source. Future work to further improve retrieval accuracy should focus on identifying higher-accuracy background profile data sources and optimizing bias correction methods, which also critically affect retrieval precision.

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