

Article

An Optimization Approach for Specific Humidity Profiles Derived from FY-4B GIIRS

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Abstract

Specific humidity profile retrievals from the Geostationary Interferometric Infrared Sounder (GIIRS) onboard Fengyun-4B (FY-4B) are often degraded by cloud contamination, while strict quality control flags further limit data usability. To address these issues, an optimization framework for FY-4B GIIRS specific humidity profiles was developed using ERA5 reanalysis data spanning January 2023 to January 2024. Guangxi and the Beibu Gulf were selected as the study domain. Independent ERA5 datasets, not involved in model construction, were used as a benchmark to evaluate performance. The results indicate that the original FY-4B GIIRS specific humidity profiles tend to underestimate moisture relative to ERA5. For profiles with quality flags of 0 and 1, the Bias, Root Mean Square Error (RMSE), and Mean Relative Error (MRE) range of $-3\sim 0$ g/kg, $0\sim 4$ g/kg, and $17\sim 53\%$, respectively. After optimization, the bias is effectively reduced to 0 g/kg. RMSE shows an average reduction of 15% within the 700~300 hPa layer, while the most notable improvement in MRE occurs between 1000 and 920 hPa. For lower-quality data (Flags 2~3), the bias, RMSE, and MRE span $-12\sim 0$ g/kg, $0\sim 13$ g/kg, and $48\sim 140\%$, respectively. Following optimization, the bias range narrows to $-6\sim 0$ g/kg. RMSE decreases by 20~40% from the near-surface layer up to 400 hPa, and MRE is reduced by 40% below 300 hPa. A case study of Typhoon “Peipah” further demonstrates the model’s effectiveness. At stations experiencing intense rainfall, the optimized specific humidity profiles show markedly improved accuracy, and the Mean Absolute Errors (MAEs) of derived forecast-related physical variables are substantially reduced. Overall, the proposed optimization model significantly enhances both the accuracy and practical usability of FY-4B GIIRS specific humidity profiles, providing more reliable data support for monitoring severe weather events such as typhoons and heavy rainfall.

Keywords: FY-4B/GIIRS; specific humidity profile; ERA5 reanalysis; accuracy evaluation



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1. Introduction

Atmospheric temperature and specific humidity profiles describe the thermal and moisture structure of the atmosphere and are fundamental to weather analysis. Their vertical distribution plays a crucial role in numerical weather prediction, severe weather monitoring, and data assimilation processes [1,2]. Compared with conventional radiosonde observations, satellite-based remote sensing provides more continuous spatial and temporal coverage, making it possible to capture three-dimensional atmospheric variations that

are otherwise difficult to observe with sparse ground stations [3,4]. As the first operational satellite in the Fengyun-4 (FY-4) series, FY-4B carries the Geostationary Interferometric Infrared Sounder (GIIRS), a hyperspectral infrared instrument capable of retrieving atmospheric profiles with relatively high temporal frequency and broad spatial coverage. These characteristics make it particularly valuable for applications such as convective weather monitoring and nowcasting [5–7].

Advancing the quality assessment and application development of FY-4B products is essential for strengthening the research and operational use of geostationary hyperspectral satellite data in China. Previous studies have provided valuable insights into the performance of GIIRS-derived products. An analysis over the Eastern Tibetan Plateau by Wang et al. (2024) showed that FY-4B GIIRS temperature profiles are broadly consistent with ERA5 reanalysis, with high-quality retrievals (flags “best (0)” and “good (1)”) accounting for 68.45% under clear-sky conditions; however, this proportion drops markedly to 48.3% in the presence of clouds [8]. Using radiosonde observations, Chen et al. (2025) evaluated the retrieval capability of FY-4A/4B GIIRS temperature and specific humidity profiles, noting that while temperature profiles from both satellites exhibit comparable and relatively high accuracy, the specific humidity retrievals from FY-4B remain less reliable, with a relative humidity Root Mean Square Error (RMSE) of 15.42% [9]. A layer-by-layer comparison conducted by Zhang et al. (2025) further confirmed the strong agreement between GIIRS temperature profiles and radiosonde data, with FY-4B demonstrating superior performance to FY-4A under clear-sky conditions [10]. A more detailed assessment by Jin et al. (2024), focusing on profiles with quality flags of 0 and 1, revealed a substantial reduction in the availability of high-quality data under cloudy conditions [11]. Under clear skies, the temperature bias ranges from -0.3 to 1 K with RMSE below 2 K, while the specific humidity bias lies between 0 and 1.3 g/kg, and the near-surface RMSE reaches approximately 2.1 g/kg. Zhu et al. (2025), using ERA5 as a reference, found that FY-4B specific humidity profiles are systematically underestimated under both clear and cloudy conditions, with RMSE decreasing with altitude and consistently lower errors observed in clear-sky scenarios [12]. In terms of practical applications, Li et al. (2025) applied FY-4A/4B temperature and specific humidity profiles to three hail events in Guizhou Province [13]. Their results indicate that these profiles can effectively signal hail potential, although notable errors in near-surface thermodynamic fields can lead to discrepancies in hail size estimation. Ren et al. (2025) employed FY-4B temperature profiles to track cold vortices in Northeast China and reported a mean positional bias of 140.6 km when compared with ERA5 [14]. Yao et al. (2025) demonstrated that assimilating thinned FY-4B GIIRS observations can improve the prediction of heavy rainfall centers over the South China Sea and enhance the representation of typhoon rainbands [15]. Efforts to refine GIIRS profile products have also been explored. Jin et al. (2024) introduced a probability density matching approach to correct FY-4B temperature profiles under cloudy conditions, achieving a reduction in RMSE from 1.89 and 3.2 to 1.73 and 2.34 K for profiles with quality flags of 0 and 1, respectively [11]. Du et al. (2022) incorporated Global Navigation Satellite System (GNSS)-derived Precipitable Water Vapor (PWV) to update FY-4A specific humidity profiles, reducing the overall RMSE by 20% and achieving a 20~25% reduction from the near-surface layer up to 700 hPa, thereby substantially improving data usability [16].

Although substantial progress has been made in evaluating the quality of GIIRS profile products, comparatively limited attention has been given to improving their retrieval accuracy. Existing studies have also highlighted several issues that remain unresolved. One major challenge arises from cloud contamination. Owing to the strong sensitivity of hyperspectral infrared observations to clouds, cloud-related processes such as emission, absorption, and scattering can significantly degrade both the accuracy and usability of the

retrieved profiles [17–19]. Another limiting factor lies in the use of quality flags. While these flags are effective in distinguishing retrieval reliability [20], profiles labeled as “not good (2)” and “not use (3)” still exhibit pronounced systematic biases. Consequently, most studies retain only data with quality flags of 0 and 1, leading to considerable data loss and incomplete vertical structures, which in turn restricts their practical application [11,21,22]. Some attempts have been made to address these issues. Kuo et al. (1993) and Du et al. (2022) adjusted layer-wise specific humidity using the ratio between GNSS-derived PWV and profile-integrated PWV [16,23]. This approach enables rapid integration of GNSS observations with specific humidity profiles and contributes to improving three-dimensional moisture fields. However, its applicability depends on the availability of GNSS stations. Moreover, since PWV represents the total column water vapor, its direct use in profile correction does not adequately capture variability at individual pressure levels. To overcome these limitations, the present study develops an optimization framework based on ERA5 reanalysis data and the water vapor density at each pressure level derived from FY-4B Atmospheric Vertical Profile (AVP) products. The specific humidity profiles are iteratively updated, and an adjustment factor—defined by the differences before and after correction—is further described using a periodic function. On this basis, an optimization model for FY-4B GIIRS atmospheric specific humidity profiles is constructed. In addition, given the distinct error characteristics associated with different quality flags, two separate sets of model coefficients are derived for profiles with quality flags of 0–1 and 2–3, respectively.

Operational forecasting requires timely information on the three-dimensional structure of the atmosphere. Conventional radiosonde observations are generally available only at 00:00 and 12:00 UTC, so supplementary products are needed to provide greater temporal continuity. The ECMWF forecast system is widely used in operational forecasting, and ERA5 reanalysis often supplements the limited temporal coverage of radiosonde observations. However, the 5-day latency of ERA5 restricts its operational utility. FY-4B GIIRS atmospheric specific humidity profile products offer broad spatial coverage, high spatiotemporal resolution, and a shorter latency of 2–3 days. Improving the accuracy of these profiles is therefore important for short-term weather forecasting and climate research.

2. Materials and Methods

The datasets were obtained from the Fengyun Satellite Remote Sensing Data Service Network and the official website of the European Centre for Medium-Range Weather Forecasts. Data from 16 January 2023 to 16 January 2024 were used to construct the model, whereas data from July through September 2024 were reserved for accuracy evaluation. The data sources and methodology are described below.

2.1. FY-4B Atmospheric Temperature and Specific Humidity Profiles

The FY-4B AVP product is derived from GIIRS channel-matched observations and is obtained from the FY satellite data service platform. The GIIRS instrument onboard FY-4B employs a 16×8 detector array and operates based on Michelson interferometry, measuring infrared radiation across multiple spectral bands to retrieve vertical distributions of atmospheric temperature and specific humidity [24]. The product provides observations with a spatial resolution of approximately 12 km and a temporal interval of 45 min. The radiometric calibration accuracy is about 0.7 K, while the spectral calibration accuracy is better than 10 ppm. Each field of view includes geolocation information (longitude and latitude), surface pressure, surface temperature, and atmospheric temperature and specific humidity profiles divided into 101 pressure levels ranging from 0.005 to 1100 hPa [10]. Observations are available 12 times per day (0103, 0303, 0503, 0703, 0903, 1103, 1303, 1503, 1703, 1903, 2103, and 2303 UTC). To account for cloud contamination and calibration

uncertainty, quality flags are assigned by the National Satellite Meteorological Center, where 0, 1, 2, 3, and 4 correspond to “best”, “good”, “not good”, “not use”, and “L1 data bad”, respectively.

2.2. ERA5 Reanalysis Data

ERA5, released by the European Centre for Medium-Range Weather Forecasts (ECMWF), is a fifth-generation global reanalysis dataset, providing atmospheric, land, and oceanic variables from 1950 to the present with a latency of 5 days [25]. In this study, ERA5 data with a spatial resolution of $0.25^\circ \times 0.25^\circ$ and a temporal resolution of 2 h are used. The dataset includes temperature, relative humidity, and specific humidity distributed over 37 pressure levels from 1000 to 1 hPa, allowing direct comparison with FY-4B AVPs.

2.3. Methodology for Specific Humidity Profile Optimization

The study focused on the Guangxi region and the Beibu Gulf ($103\text{--}113^\circ \text{E}$, $18\text{--}27^\circ \text{N}$), an area that plays a key role in moisture transport toward South China. Improved monitoring of atmospheric moisture in this region is particularly relevant for understanding precipitation processes associated with landfalling typhoons and for enhancing heavy rainfall forecasts during the flood season. The modeling workflow is shown in Figure 1. The methodology is described below with reference to this workflow:

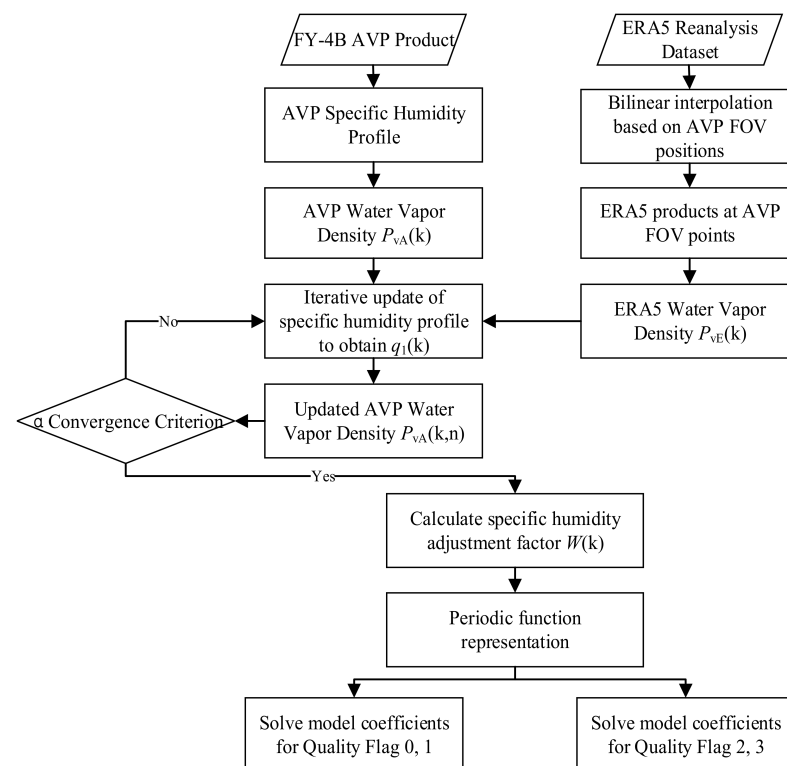


Figure 1. Modeling workflow.

(1) FY-4B AVP data and ERA5 reanalysis data from 16 January 2023 to 16 January 2024 were collected.

(2) For each AVP field of view, the four nearest ERA5 grid points were identified, and bilinear interpolation was applied to estimate pressure, temperature, and specific humidity at the AVP location.

(3) Based on these variables, water vapor density at each pressure level was calculated for both ERA5 and AVP datasets using [26]:

$$P_v = \frac{e}{R_v T} \quad (1)$$

$$e = \frac{P \cdot q}{622} \quad (2)$$

$$P_v = \frac{P \cdot q}{622 R_v (T + 273.15)} \quad (3)$$

where R_v denotes the specific gas constant for water vapor (461.5 J/(kg·K)); P_v denotes the water vapor density (kg/m³); e denotes the vapor pressure (hPa); T denotes the temperature (°C); and q denotes the specific humidity (g/kg).

(4) The AVP specific humidity profiles were then iteratively refined as follows:

$$q_1(k) = q_0(k) \cdot P_{vE}(k) / P_{vA}(k) \quad (4)$$

where $q_1(k)$ denotes the updated AVP specific humidity (g/kg); $q_0(k)$ denotes the original AVP specific humidity (g/kg); k denotes the k th pressure level of AVP; $P_{vE}(k)$ denotes the water vapor density of ERA5 (g/m³); $P_{vE}(k)$ denotes the mean water vapor density of the two ERA5 pressure levels adjacent to the pressure of the k th AVP layer through Equation (3); and $P_{vA}(k)$ denotes the water vapor density of AVP (g/m³). When deriving the AVP water vapor density from Equation (3), if the temperature quality flag at the k th AVP pressure level is 2 or 3, the ERA5 temperature is used in place of the AVP temperature, and the ERA5 temperature can be interpolated from

$$T_E = T_{2E} + (T_{1E} - T_{2E}) \frac{P_k - P_2}{P_1 - P_2} \quad (5)$$

where T_E denotes the ERA5 temperature at the k th pressure level of AVP; T_{1E} and T_{2E} denote the temperatures at the two ERA5 pressure levels adjacent to the pressure of the k th AVP layer, respectively; P_k denotes the pressure at the k th AVP layer; while P_1 and P_2 denote the pressures at the two ERA5 levels adjacent to the pressure of the k th AVP layer, respectively.

(5) Using the updated AVP specific humidity profiles, the updated AVP water vapor density $P_{vA}(k, n)$ (n denotes the n th iteration) was calculated according to Equation (3), and a convergence criterion was imposed to terminate the iterative updating procedure:

$$|P_{vA}(k, n) - P_{vE}(k)| < \alpha \quad (6)$$

where α denotes the convergence factor, which was set to 1×10^{-8} g/m³ for all profiles.

(6) Once the iterative procedure is completed, the specific humidity adjustment factor was derived using

$$w(k) = q_1(k) / q_0(k) \quad (7)$$

where $w(k)$ denotes the specific humidity adjustment factor at the k th pressure level.

(7) A grid resolution of $0.25^\circ \times 0.25^\circ$ was adopted, resulting in a total of 1440 grid cells. In previous studies, temporal variations in atmospheric parameters have often been represented using empirical periodic functions that incorporate annual and semiannual cycles, which have been shown to achieve satisfactory accuracy [27,28]. Following this idea, the $w(k)$ is expressed using a similar functional form in this study. Considering the pronounced diurnal variability of atmospheric moisture, an additional diurnal term is introduced into the original formulation:

$$w(k) = A_0(k) + A_1(k) \sin(2\pi \frac{doy}{365.25}) + A_2(k) \cos(2\pi \frac{doy}{365.25}) + A_3(k) \sin(4\pi \frac{doy}{365.25}) + A_4(k) \cos(4\pi \frac{doy}{365.25}) + A_5(k) \sin(2\pi \frac{hour}{24}) + A_6(k) \cos(2\pi \frac{hour}{24}) \quad (8)$$

where A_0 denotes the constant term; A_1 and A_2 denote the annual cycle coefficients; A_3 and A_4 denote the semiannual cycle coefficients; A_5 and A_6 denote the diurnal cycle coefficients; day denotes the day of year; and $hour$ denotes the duration (h). Using the procedures described in Steps (3–6), specific humidity adjustment factors are calculated separately for profiles with quality flags 0–1 and 2–3. The model coefficients in Equation (8) are then estimated for each grid cell using the least squares method. As a result, two sets of coefficients are obtained, corresponding to high-quality (flags 0–1) and lower-quality (flags 2–3) profiles, respectively.

The specific application procedure of the model is outlined as follows:

- 1 Based on the input specific humidity profile, including its longitude, latitude, and quality flag, the corresponding grid cell is identified, and the associated model coefficients are retrieved.
- 2 Using the coefficients of the identified grid, together with the day of year and hour information of the profile, the specific humidity adjustment factor is calculated through Equation (8).
- 3 The optimized specific humidity is obtained by applying the adjustment factor to the original specific humidity profile.

2.4. Evaluation Metrics

Bias, root mean square error (RMSE), and mean relative error (MRE) are used to assess the specific humidity profiles before and after optimization. Bias quantifies systematic deviation from the reference, RMSE reflects the overall magnitude of the error, and MRE expresses the error relative to the reference values.

$$\text{Bias} = \frac{1}{m} \sum_{i=1}^m (S_i - R_i) \quad (9)$$

$$\text{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^m (S_i - R_i)^2} \quad (10)$$

$$\text{MRE} = \frac{1}{m} \sum_{i=1}^m \frac{|S_i - R_i|}{R_i} \quad (11)$$

where S denotes the specific humidity before and after optimization, R denotes the specific humidity from ERA5, and m denotes the number of samples.

3. Results and Discussion

3.1. Accuracy Evaluation

To evaluate the performance of the proposed model, independent ERA5 reanalysis data (not used in model construction) are taken as a reference. The accuracy of FY-4B specific humidity profiles before and after optimization is analyzed for the period from July to September 2024. The number of FY-4B product samples used in this study is shown in Figure 2. In Figure 2, “q-ERA5” represents the mean specific humidity profile from ERA5 at each pressure level over the study period, and this curve is used for the subsequent accuracy analysis of the product. “Num (21)” and “Num (05)” denote the number of FY-4B samples at each pressure level at 21:00 and 05:00 UTC, respectively. The vertical distributions of sample counts exhibit a similar pattern for daytime (05:00 UTC) and nighttime (21:00 UTC). However, the total number of samples is consistently higher at night (1.36×10^5) than during the day (1.30×10^5), particularly within the 1000–400 hPa layer. This difference is likely related to cloud conditions. Since the performance of FY-4B GIIRS retrievals is strongly influenced by cloud coverage, the larger number of valid samples at night suggests relatively clearer conditions over Guangxi and the Beibu Gulf during the study period. As

a result, the capability of GIIRS to retrieve specific humidity profiles appears to be slightly better at night than during the day.

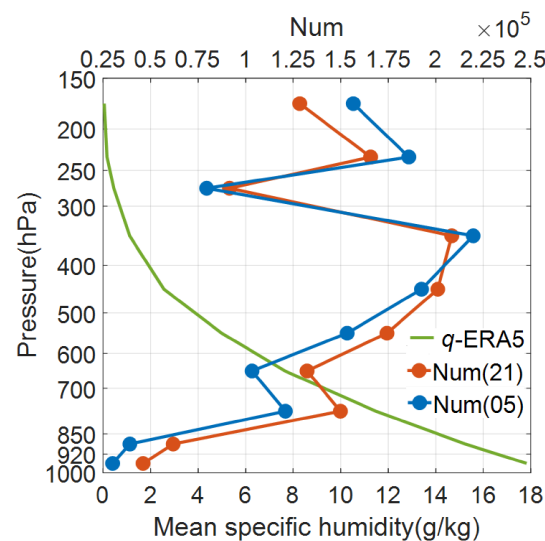


Figure 2. Sample counts for specific humidity profiles (Num (21) and Num (05) denote the numbers of FY-4B specific humidity profile samples at 21:00 and 05:00 UTC, respectively).

Figure 3 illustrates the bias characteristics of FY-4B GIIRS specific humidity profiles relative to ERA5. Overall, the retrieved profiles tend to underestimate atmospheric moisture, with the discrepancy being more pronounced for lower-quality data (flags 2–3). In particular, within the 1000–850 hPa layer, the bias for these profiles exceeds -10 g/kg. For profiles with higher quality (flags 0–1), a clear diurnal difference can be observed in the 850–500 hPa layer, where daytime biases are generally larger than those at night. In contrast, for lower-quality profiles (flags 2–3), the difference between daytime and nighttime remains relatively small. After optimization, the bias was reduced across most atmospheric layers, indicating a clear overall improvement. In Figure 3a, the bias for profiles with flags 0–1 is largely centered around 0 g/kg, with the variation range narrowed to approximately -0.5 to 1 g/kg. For profiles with flags 2–3 (Figure 3b), the optimized results still exhibit a slight underestimation compared to ERA5; however, the magnitude of the bias is substantially reduced. The most notable improvement occurs in the lower troposphere up to 850 hPa, where the bias decreases by approximately 6 g/kg.

From the perspective of RMSE, the profiles with quality flags 0–1 before optimization (Figure 4a) exhibit values of approximately 3.5 g/kg from the near-surface layer up to 700 hPa. Within the 1000–400 hPa range, RMSE is slightly higher during daytime than at night. After optimization, RMSE is reduced across most pressure levels below 300 hPa. Except for the 850–700 hPa layer, nighttime RMSE remains generally below 3 g/kg at all levels, indicating a consistent improvement. For lower-quality profiles (flags 2–3, Figure 4b), the difference between daytime and nighttime RMSE is relatively small. Nevertheless, a clear reduction is observed after optimization, particularly below 400 hPa, with the most pronounced improvement occurring below 850 hPa.

In terms of Mean Relative Error (MRE), the profiles with quality flags 0–1 before optimization (Figure 5a) show values of about 15–20% in the lower atmosphere. With increasing altitude, MRE rises gradually, exceeding 50% within the 850–150 hPa layer. After optimization, improvements are mainly observed below 300 hPa. In contrast, at higher levels, the optimized MRE exhibits a slight increase at certain pressure layers. For profiles with quality flags 2–3 (Figure 5b), the initial MRE is substantially larger, generally ranging between 50 and 60% throughout the atmosphere, and exceeding 100% above 200 hPa.

Following optimization, the overall pattern of improvement is similar to that of higher-quality profiles, with more noticeable reductions below 300 hPa, where MRE decreases to approximately 30–40%. However, in the upper atmosphere (above 200 hPa), MRE increases further and can exceed 150%, indicating that the optimization is less effective at higher altitudes.

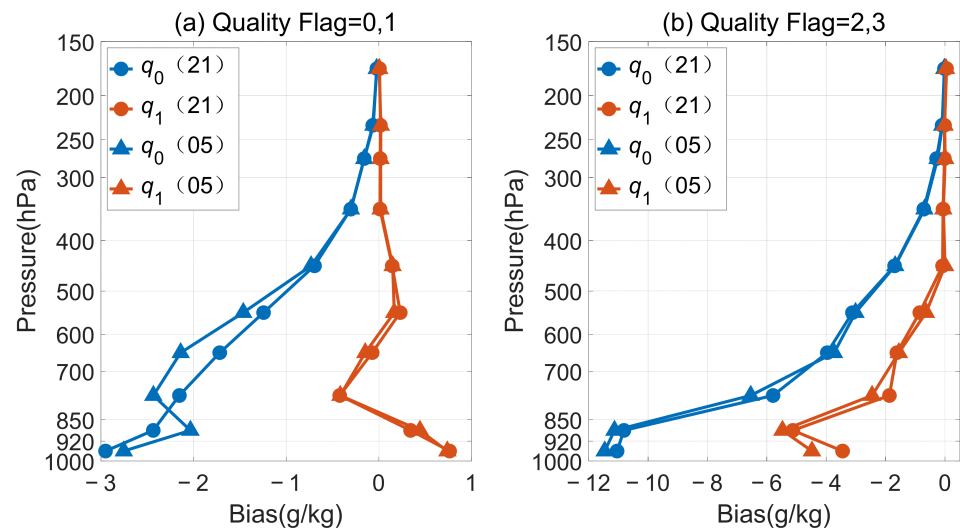


Figure 3. Bias of specific humidity profiles before and after optimization (note: 0 = before optimization; 1 = after optimization; 21 and 05 = UTC time). (a) Quality Flag = 0, 1. (b) Quality Flag = 2, 3.

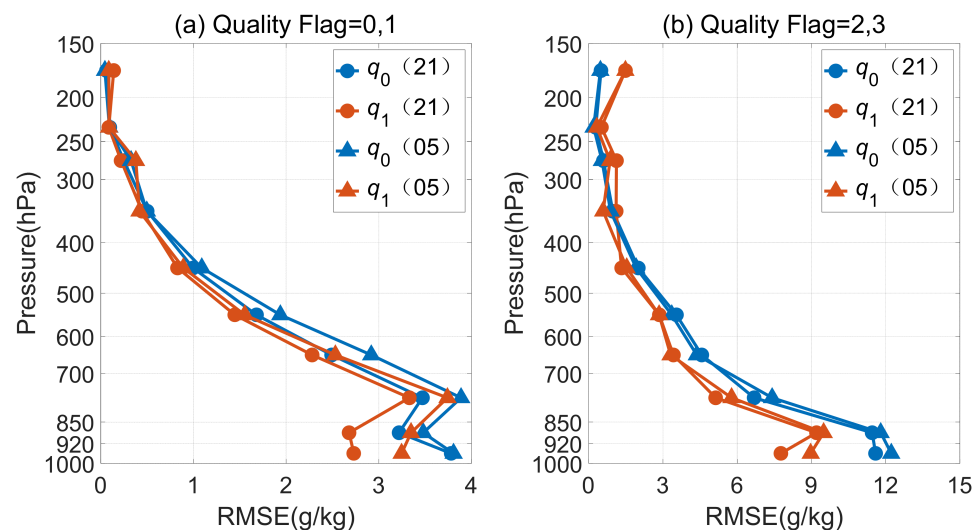


Figure 4. RMSE of specific humidity profiles before and after optimization (note: 0 = before optimization; 1 = after optimization; 21 and 05 = UTC time). (a) Quality Flag = 0, 1. (b) Quality Flag = 2, 3.

The reduction ratios of RMSE and MRE provide a direct indication of the effectiveness of the proposed optimization (Figure 6). In Figure 6a, for profiles with quality flags 0–1, the improvement in RMSE is more pronounced at night from the near-surface layer up to 700 hPa. In particular, within the 1000–920 hPa layer, the nighttime reduction reaches nearly 30%. Between 700 and 300 hPa, the reduction rates during daytime and nighttime are comparable, with an average decrease of about 15%. At higher levels (300–200 hPa), nighttime improvements remain slightly better; however, above 200 hPa, RMSE increases significantly for both day and night, exceeding 50% in the 200–150 hPa layer. For lower-quality profiles (flags 2–3), RMSE reductions range from 20% to 40% below 400 hPa.

Above this level, RMSE begins to increase, with values exceeding 50% above 300 hPa. In Figure 6b, the reduction in MRE is mainly concentrated below 300 hPa. At higher altitudes, the optimized MRE increases at certain pressure levels, particularly for lower-quality profiles (flags 2–3), where increases exceeding 50% are observed in the 200–150 hPa layer. For higher-quality profiles (flags 0–1), the reduction in MRE becomes more pronounced closer to the surface. The largest decreases occur within the 1000–920 hPa layer, reaching approximately 22% during daytime and approximately 30% at night. For lower-quality profiles, the average MRE reduction below 300 hPa is approximately 40%. Overall, the optimization substantially improves the accuracy of FY-4B GIIRS specific humidity profiles, especially in the lower and middle troposphere, thereby significantly enhancing their practical usability.

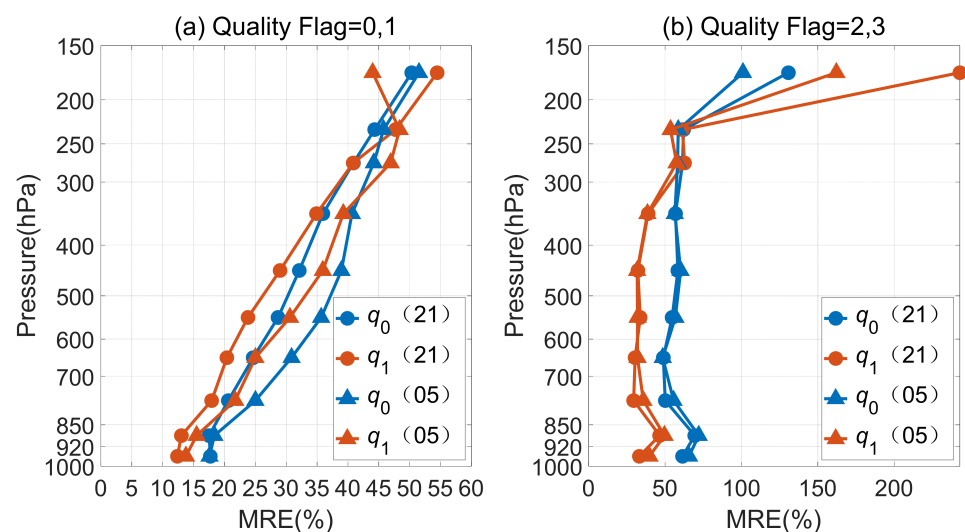


Figure 5. MRE of specific humidity profiles before and after optimization (note: 0 = before optimization; 1 = after optimization; 21 and 05 = UTC time). (a) Quality Flag = 0, 1. (b) Quality Flag = 2, 3.

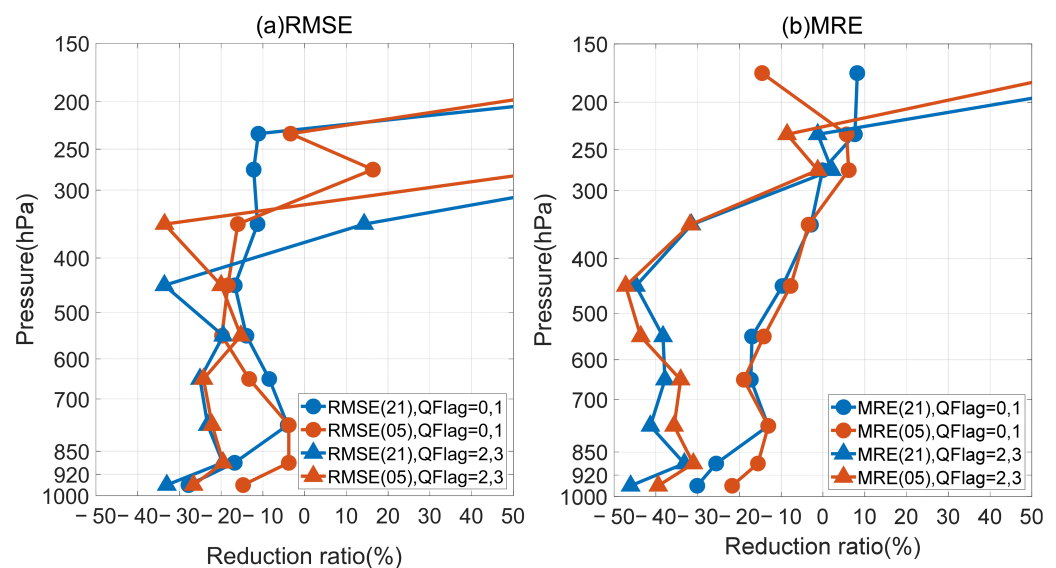


Figure 6. Reduction ratios of errors in specific humidity profiles after optimization (0–1 and 2–3 = quality flag groups; 21 and 05 = UTC time). (a) RMSE. (b) MRE.

From a vertically integrated perspective, the improvement introduced by the optimization is more pronounced in pressure layers below 400 hPa, where atmospheric moisture

content remains relatively high, particularly from the near-surface layer up to 850 hPa. In contrast, above 400 hPa, both RMSE and MRE tend to increase after optimization. This behavior can be explained by the vertical distribution of atmospheric moisture. Based on ERA5 statistics (Figure 2), the average specific humidity in the lower troposphere (1000~850 hPa) is about 16.53 g/kg. In the mid-troposphere (850~400 hPa), it decreases from 11.48 to 2.56 g/kg, corresponding to a reduction of approximately 78%. From 400 to 200 hPa, the average value further drops from 1.12 to 0.17 g/kg, indicating an additional decrease of approximately 85%. Due to the extremely low moisture content in the upper troposphere, even small variations in specific humidity can lead to disproportionately large changes in RMSE and MRE (Figure 6). This effect is particularly evident for profiles with quality flags 2–3, where both RMSE and MRE increase most significantly in the 200~150 hPa layer (Figures 4b and 5b), with MRE exceeding 150% in certain cases. In the upper atmosphere, cirrus clouds and convective cloud tops markedly reduce the sensitivity of FY-4B GIIRS infrared observations, leaving too little effective information for reliable retrieval. Consequently, the optimization model cannot consistently resolve the differences between the water vapor density derived from ERA5 and those derived from the FY-4B specific humidity profiles, and RMSE and MRE may consequently increase rather than decrease. This behavior indicates that the performance of the optimization is highly sensitive to the FY-4B specific humidity profile used as a key input. The optimization is generally more effective at night, particularly for reducing near-surface RMSE, which is consistent with the lower cloud cover and more favorable detection conditions at night. Greater confidence can therefore be placed in nighttime profiles in applications such as data assimilation. For profiles with quality flags 2 and 3, the optimization substantially reduces lower-tropospheric errors, whereas errors in the upper levels remain pronounced. The model can therefore partly compensate for retrieval deficiencies caused by cloud contamination and other factors, but it cannot reliably reconstruct upper-level water vapor information that is fully obscured by clouds.

3.2. Application During a Typhoon Event

To further assess the practical applicability of the proposed model, a case study is conducted during Typhoon “Peipah”. Three stations located closest to the FY-4B specific humidity profiles and experiencing heavy rainfall are selected for analysis. The accuracy of the profiles before and after optimization is compared. From 20 to 23 July 2024, Typhoon “Peipah” affected Beihai and the Beibu Gulf, bringing intense rainfall and strong winds. The system formed over the South China Sea at 05:00 UTC on 21 July, approximately 135 km southeast of Lingshui, Hainan Province. It then moved northwestward at a speed of approximately 15 km/h, gradually intensifying into a severe tropical storm by 20:00 UTC. The typhoon made landfall near Wanning, Hainan, around 01:30 UTC on 22 July, weakened temporarily, and re-intensified after entering the Beibu Gulf later that morning. Figures 7 and 8 depict the comparisons between FY-4B specific humidity profiles and ERA5 data during the typhoon event. The RMSE distribution shows a pattern similar to Figure 4, with reductions observed at all three stations after optimization. The improvement is most evident below 850 hPa and within the 600~250 hPa layer. In terms of MRE, the profiles before optimization exhibit a clear increase with altitude. Below 400 hPa, MRE generally remains below 40%, while above 300 hPa it exceeds 60%, with peak values approaching 80%. After optimization, MRE decreases throughout the atmospheric column, with notable improvements in the 600~400 hPa and upper-level regions. For stations N9024 and N9213, the optimized MRE remains approximately 40% above 400 hPa. At station N9200, a more pronounced improvement is observed between 250 and 150 hPa, where MRE is reduced to approximately 30%. Compared with the overall results in Figure 5, the improvement at

station locations is more evident in the upper atmosphere, without the increase in MRE observed in the general statistics. This difference is likely related to the abundant moisture associated with the typhoon, which reduces the sensitivity of MRE to small variations in specific humidity. It is also worth noting that the station-based profiles include all quality categories. In comparison of Figures 4 and 5, the pre-optimization accuracy lies between high-quality (flags 0–1) and lower-quality (flags 2–3) profiles, while being closer to the former. This suggests that FY-4B GIIRS maintains relatively strong detection capability even under typhoon conditions. Overall, both RMSE and MRE are reduced after optimization, demonstrating that the proposed model performs effectively in real-case applications and significantly improves the usability of FY-4B specific humidity profiles.

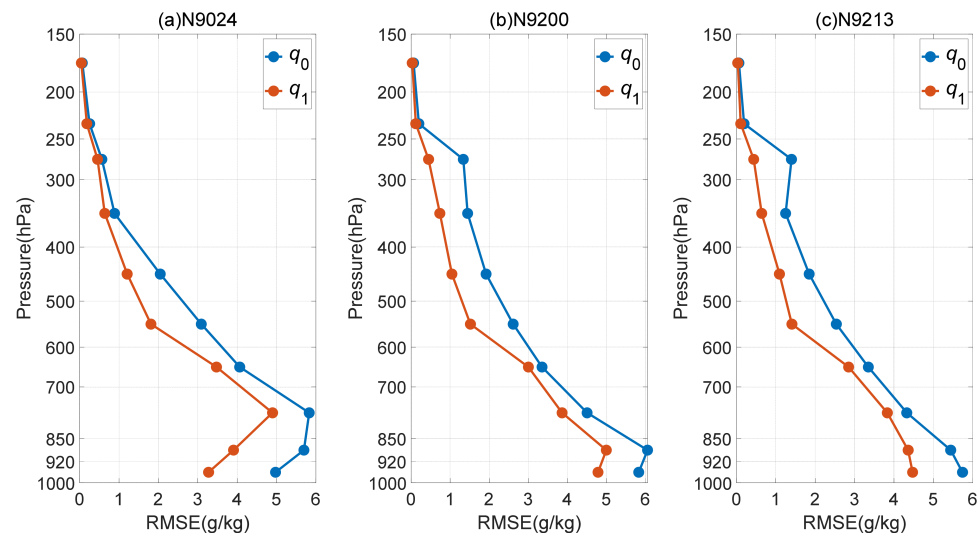


Figure 7. RMSE of specific humidity profiles at station locations before and after optimization (note: 0 = before optimization; 1 = after optimization).

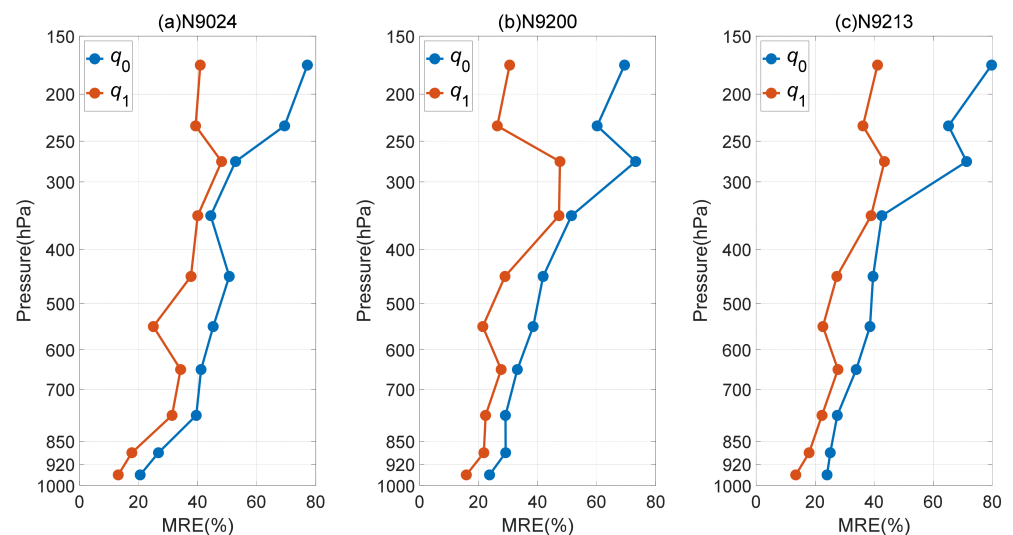


Figure 8. MRE of specific humidity profiles at station locations before and after optimization (note: 0 = before optimization; 1 = after optimization).

Monitoring and forecasting heavy rainfall during typhoon events rely heavily on accurate assessments of atmospheric moisture and thermodynamic conditions. To evaluate the impact of the optimized specific humidity profiles, the Mean Absolute Errors (MAEs) of several humidity-related variables are calculated for each station during the typhoon period, including relative humidity at 500 hPa (RH_{500}), specific humidity at 850 hPa (q_{850}),

surface dew point temperature (T_{do}), PWV, equivalent potential temperature at 850 hPa (θ_{se850}) and 500 hPa (θ_{se500}), as well as the K index (Table 1). The results show a consistent reduction in errors across all variables after optimization. In terms of moisture-related parameters, the error in RH500 decreases by 29% at station N9024 and by more than 40% at stations N9200 and N9213. The error in q_{850} is reduced to approximately 3 g/kg at all stations, while the dew point temperature error is limited to within 2.6 °C. For PWV, the mean error is reduced by 5.24 mm, with a decrease of 44% at station N9024, where value declines from 13.61 to 7.66 mm. Improvements are also evident in thermodynamic variables. The errors in θ_{se850} and θ_{se500} decrease substantially. For example, at station N9024, the error in θ_{se850} is reduced from 15.65 to 9.35 K, corresponding to a decrease of more than 40%. In addition, the K index error at all stations is reduced to below 7.5 °C after optimization. Overall, the optimized specific humidity profiles provide a more accurate representation of atmospheric moisture distribution and thermodynamic structure.

Table 1. MAE of humidity-related variables.

Station		Moisture Condition				Thermodynamic Condition		
		RH ₅₀₀ (%)	q_{850} (g/kg)	T_{do} (°C)	PWV (mm)	θ_{se850} (K)	θ_{se500} (K)	K Index (°C)
N9024	Before optimization	33.91	5.14	5.69	13.61	15.65	7.67	10.72
	After optimization	24.04	3.06	2.54	7.66	9.35	5.31	7.31
N9200	Before optimization	27.87	5.18	4.62	10.76	15.84	6.36	8.62
	After optimization	16.33	3.45	2.12	5.94	10.67	3.60	5.91
N9213	Before optimization	26.53	4.50	4.14	11.41	13.73	5.96	8.56
	After optimization	14.34	2.94	1.69	6.45	9.08	3.13	6.18

The typhoon case further confirms the generalization capability of the model under extreme rainfall and high-moisture conditions. The model substantially reduces systematic bias in the specific humidity profiles and prevents the amplification of relative errors in the upper atmosphere. This performance is likely attributable to the abundant water vapor throughout the atmospheric column under typhoon conditions, which provides rich and stable information for the model. Errors in thermodynamic diagnostic variables derived from the optimized profiles are also substantially reduced, indicating more reliable estimates of atmospheric convective instability and water vapor convergence. These improvements can strengthen the ability of forecasters to diagnose the location and intensity of typhoon-induced heavy rainfall, demonstrating clear operational value. The optimization model could also be incorporated into an FY-4B GIIRS data assimilation system to provide more accurate initial water vapor fields for numerical weather prediction, potentially improving forecasts of typhoon tracks and precipitation.

4. Conclusions

This study develops an optimization approach for FY-4B GIIRS atmospheric specific humidity profiles using ERA5 reanalysis data, with separate treatment of profiles according to data quality flags. The model is evaluated over Guangxi and the Beibu Gulf against independent ERA5 data, and its applicability is further examined during Typhoon “Peipah.” The principal findings are as follows:

- (1) Overall, FY-4B GIIRS atmospheric specific humidity profiles underestimate specific humidity relative to ERA5. Bias and RMSE decrease with altitude, whereas MRE increases. For profiles with quality flags 0 and 1, accuracy is higher at night (21:00 UTC) than during the day (05:00 UTC). For profiles with quality flags 2 and 3, no clear difference in accuracy is observed between daytime and nighttime.
- (2) The optimization model improves product accuracy and usability by effectively reducing systematic bias. By using separate coefficient sets for profiles with quality flags 0–1 and 2–3, the model markedly improves the accuracy of lower-quality profiles after optimization. This improvement gives previously discarded data practical value and substantially increases overall product usability.
- (3) During Typhoon “Peipah,” RMSE and MRE decrease throughout the atmospheric column at all station locations after optimization, with no deterioration in the upper atmosphere. Errors in several humidity-related physical variables derived from the optimized specific humidity profiles also decrease significantly. These results demonstrate the practical value of the model for monitoring heavy rainfall and show that it can provide forecasters with more detailed and reliable information for assessing rainfall intensity and affected areas.

Overall, the proposed optimization model is simple and efficient and effectively improves the accuracy and usability of FY-4B specific humidity profiles. The model therefore offers a feasible approach to operational quality enhancement of these profiles. However, its capacity to improve upper-level water vapor estimates remains limited. For profiles with quality flags 2 and 3, the post-optimization bias still spans a relatively wide range, and the causes of this residual error require further investigation. The optimization concept could also be extended to profiles of other meteorological variables, such as temperature and dew point. Future work should integrate additional data sources to improve performance in the upper atmosphere and further explore applications in numerical data assimilation and studies of extreme precipitation mechanisms.

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