

Article ID: 1006-8775(2026)01-0019-14

Diurnal Bias Correction of FY-4B AGRI Water Vapor Channels with Time-Shifted Solar Elevation Angle

SONG Jia-yun (宋佳轡)¹, HAN Wei (韩 威)^{2,3}, SUN Hao-fei (孙昊飞)^{4,5}, YANG Yun-fan (杨云帆)^{4,5}

(1. Chinese Academy of Meteorological Sciences, China Meteorological Administration, Beijing 100081 China; 2. CMA Earth System Modeling and Prediction Centre (CEMC), China Meteorological Administration, Beijing 100081 China;

3. State Key Laboratory of Severe Weather, Chinese Academy of Meteorological Sciences, China Meteorological Administration, Beijing 100081 China; 4. State Key Laboratory of Atmospheric Boundary Layer Physics and Atmospheric Chemistry, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029 China; 5. University of Chinese Academy of Sciences, Beijing 100049 China)

Abstract: The infrared channels of the FY-4B advanced geosynchronous radiation imagers (AGRI) play a crucial role in temperature and humidity analyses for mesoscale numerical weather prediction, particularly in enhancing the initial field quality and the forecasting accuracy of the model. This study assimilated FY-4B AGRI data into the CMA-MESO model and analyzed the bias characteristics and correction methods. Analysis of the AGRI data revealed a clear diurnal variation in the bias, which was positively correlated with the solar elevation angle. However, the diurnal variation in the bias lagged behind the solar elevation angle, likely owing to temperature changes and delayed instrument responses resulting from solar radiation. To address this issue, we propose a correction method that utilizes the solar elevation angle after an optimal time shift. Using the time-shifted solar elevation angle as a predictor effectively reduces the diurnal variation in bias and significantly improves the correction effect. This approach provides theoretical support for the assimilation of FY-4B AGRI data into mesoscale numerical weather predictions, thereby enhancing the reliability of the assimilation results.

Key words: FY-4B AGRI; bias correction; diurnal variation; solar elevation angle

CLC number: P414

Document code: A

Citation: Song, J. Y., W. Han, H. F. Sun, and Y. F. Yang, 2026: Diurnal Bias Correction of FY-4B AGRI Water Vapor Channels with Time-Shifted Solar Elevation Angle. *J. Trop. Meteor.*, **32**, 19–32, <https://doi.org/10.3724/j.1006-8775.2025.036>.

1 INTRODUCTION

With the rapid advancement of numerical weather prediction (NWP) technology, satellite data have become an essential component that enhances forecast accuracy, particularly that derived from high spatial and temporal resolution imagery provided by geostationary satellites (Dong et al. 2008; Yang et al. 2017). In addition, with the evolution of fast radiative transfer models and their linearized versions, the assimilation of various satellite data is widely employed in global meteorological forecasting systems (McNally et al. 2006; Hilton et al. 2009; Bauer et al. 2011; Kazumori 2014). The advantages of data obtained from satellites, such as global coverage, frequent observation capabilities, and fewer constraints imposed by natural and geographic conditions, make them critical components of NWP systems (Bauer et al. 2010).

Geostationary satellites offer continuous high-

frequency observations (Obs); as such, they are playing an increasingly important role in short-term weather forecasts and extreme weather predictions (Ma et al. 2017; Montmerle et al. 2007; Qin et al. 2013; Stengel et al. 2009; Szyndel et al. 2005; Wang et al. 2018; Zou et al. 2011). The Fengyun-4 series (FY-4A and FY-4B) satellites are part of China's new generation of geostationary meteorological satellites; they are equipped with advanced geosynchronous radiation imagers (AGRI) and other sensors, which provide more accurate radiation data support for China's NWP (Yang et al. 2017). In this context, the assimilation of AGRI data has been instrumental in improving the forecast accuracy of extreme weather events such as precipitation and typhoons (Niu et al. 2022; Xu et al. 2023; Zhang et al. 2022). However, satellite data assimilation presents significant challenges. Systematic errors in satellite data resulting from factors such as sensor performance, observational conditions, and the meteorological context significantly compromise the accuracy of numerical weather forecasts (Dee 2005; Eyre 1992). Bias correction is known to play a critical role in enhancing assimilation efficiency and forecasting quality (Shi et al. 2023; Yang et al. 2017). The primary methods used for bias correction include offline correction, variational bias correction (VarBC), and dynamic correction techniques based on machine learning (Auligné et al. 2007; Harris and Kelly

Received 2025-04-17; **Revised** 2025-04-18; **Accepted** 2025-04-30

Funding: National Key Research and Development Program of China (2022YFC3004004); National Natural Science Foundation of China (42075155, 12241104); National Natural Science Foundation of China Joint Fund (U2342213)

Biography: SONG Jia-yun, primarily undertaking research on satellite data assimilation.

Corresponding author: HAN Wei, e-mail: hanwei@cma.gov.cn

2001; Jin et al. 2019). However, although previous studies have examined the bias characteristics and assimilation effects of the FY-4A AGRI (Geng et al. 2020), research on the FY-4B AGRI remains limited, particularly in relation to the diurnal bias characteristics of the AGRI radiative data.

This study aimed to provide a new approach for the assimilation of FY-4B AGRI data and offer more accurate radiation data support for future mesoscale weather forecasting. We employed the China Meteorological Administration Mesoscale Weather Forecast System (CMA-MESO) to assimilate FY-4B AGRI data, and analyzed the diurnal bias characteristics. The analysis results showed that AGRI data exhibited a distinct diurnal variation in bias, which was positively correlated with the solar elevation angle; however, the variation lagged behind the solar elevation angle. This lag may be attributed to the temperature changes and delayed responses to solar radiation. Based on these findings, the time-shifted solar elevation angle was used as a predictor for bias correction, effectively mitigating diurnal bias variations and substantially improving correction performance, and a bias-correction method was developed based on the solar elevation angle.

The remainder of this paper is structured as follows: Section 2 briefly introduces the assimilation system, data, and correction methods; Section 3 presents the diurnal variation characteristics of the bias and its associated factors; Section 4 discusses the correction results; Section 5 presents a case study; and the final section presents the conclusions and discussions.

2 MODEL, DATA, AND METHODOLOGY

2.1 CMA-MESO assimilation system and radiative transfer for TIROS operational vertical sounder (RTTOV) model

The CMA-MESO (formerly GRAPES-MESO) assimilation system (a regional rapid update cycle system developed independently by the Numerical Weather Prediction Center of the China Meteorological Administration (CMA)) was employed in this study. The system was built upon a regional GRAPES 3DVar analysis and a regional mesoscale NWP model, forming an intermittent rapid analysis and forecasting cycle system (Hao et al. 2011; Xu et al. 2013), and it features a regional horizontal resolution of 3 km and an observational data assimilation frequency of 3 h. The primary components of the CMA-MESO include the global forecast data preprocessing module, observation data preprocessing module, data assimilation module, and model forecasting module. The data assimilation module primarily encompasses large-scale information extraction, three-dimensional variational assimilation, cloud analysis, mixed-scale analysis, land surface assimilation, and analysis increment updates. The specific business process of the MESO assimilation forecasting can be found in Zhuang et al. (2023).

The RTTOV is a rapid radiative transfer model initially developed by the European Centre for Medium-Range Weather Forecasts to simulate TOVS instruments. This model was subsequently improved by Saunders et al. and Matricardi et al. to create a more advanced model for satellite radiative observation assimilation (Hocking et al. 2021; Zhu et al. 2023). The latest version, RTTOV V13.2, expands its simulation capabilities to encompass major satellite-based instruments, enabling the rapid simulation of radiative fluxes across the visible, infrared, and microwave bands. RTTOV currently serves as a vital tool for retrieving atmospheric parameters from satellite remote sensing and for directly assimilating satellite radiative data. It has been extensively applied to satellite product retrieval and NWP, yielding significant results (Hocking et al. 2021). This study employed the RTTOV V12.2 radiative transfer model to simulate FY-4B AGRI radiance data.

2.2 AGRI observation data

The FY-4B AGRI data and its formatted description are available on the official website of the National Satellite Meteorological Center (<http://satellite.nsmc.org.cn>). This study focused on full-disk Level-1 (L1) data from the AGRI instrument, with a spatial resolution of 4 km at the nadir, along with geographic information data in the HDF5 format. As this study focused solely on AGRI clear-sky observation data, cloud detection was conducted using the AGRI L2 Cloud Mask product with native resolution. The cloud mask data were categorized into four classes: cloud, probably cloud, clear, and probably clear. Additionally, a 4 km resolution full-disk cloud-type product was utilized for cloud-type identification. The data, also in netCDF format, included cloud types, such as clear clouds, liquid water clouds, supercooled water clouds, mixed clouds, opaque ice clouds, cirrus (semi-transparent ice clouds), and multilayer clouds (upper semi-transparent layer, lower opaque layer).

The number of channels in the FY-4A AGRI increased from 5 in the visible infrared spin-scan radiometer of the FY-2 satellite to 14, spanning wavelengths from the visible (0.47 μm) to the longwave infrared (13.5 μm). As the successor to the FY-4A AGRI, the FY-4B AGRI introduces a 7.42 μm channel for detecting low-level water vapor, with an adjusted spectral range including 1.379, 6.95, 8.55, and 13.3 μm . It has a total of 15 channels: three visible, three near-infrared, two midwave infrared, three water vapor, and four longwave infrared. This expansion enhances the observational capabilities for data assimilation and weather monitoring (Zhu et al. 2023).

Based on data obtained from <http://www.nsmc.org.cn/nsmc/cn/instrument/AGRI.html>, the performance parameters of the AGRI channels are summarized in Table 1. The spatial resolution of AGRI/FY-4B reaches 0.5 km for visible and near-infrared channels, 2 km for mid-wave infrared channels, and 4 km for long-wave infrared channels (Dong 2016; Zhang et al. 2017).

Table 1. Performance parameters of AGRI channels

Band	Central wavelength (μm)	Bandwidth (μm)	Spatial resolution (km)	Primary applications
1	0.47	0.45–0.49	1	Fine aerosol particles, true-color synthesis
2	0.65	0.55–0.75	0.5	Vegetation, image navigation and registration, stellar observation
3	0.825	0.75–0.9	1	Vegetation, aerosols over water surfaces
4	1.379	1.371–1.386	2	Cirrus clouds
5	1.61	1.58–1.64	2	Low cloud/snow identification, water cloud/ice cloud discrimination
6	2.25	2.10–2.35	2	Cirrus clouds, aerosols, particle size
7	3.75	3.5–4 (High)	2	High-albedo targets such as clouds, fire points
8	3.75	3.5–4 (Low)	4	Low-albedo targets, surface features
9	6.25	5.8–6.7	4	Upper-level water vapor
10	6.95	6.75–7.15	4	Mid-level water vapor
11	7.42	7.24–7.6	4	Lower-level water vapor
12	8.55	8.3–8.8	4	Clouds
13	10.80	10.3–11.3	4	Cloud and surface temperature, etc.
14	12.00	11.5–12.5	4	Clouds, total precipitable water, surface temperature
15	13.3	13–13.6	4	Clouds, water vapor

Channels 1 to 6 cover the visible and near-infrared bands, primarily detecting the reflection or scattering of solar energy by the Earth's surface or atmosphere during the daytime. Channels 7 and 8 cover the midwave infrared band and detect both incident solar radiation and radiation emitted from the Earth's surface and clouds. In relation to the significant variations in radiative energy, AGRI channels 7 and 8 are designated for detecting high- and low-temperature targets, respectively, enabling the simultaneous detection of both. Channels 9 to 11 cover the water vapor absorption band, exhibit strong water vapor absorption, and reflect the distribution of water vapor in the upper, middle, and lower troposphere. Channels 12 to 14 cover the infrared window band, are characterized by relatively high atmospheric transmissivity, and are employed for cloud pixel identification. Channel 15 covers the carbon dioxide absorption band (Lu et al. 2017).

The RTTOV radiative transfer model was employed, utilizing the U.S. standard atmospheric profile to compute the weighting function for AGRI Infrared bands. The peak height of the weighting function for channel 8 (3.5–4 μm) is relatively low. The peak heights of the weighting functions for channels 9 (5.8–6.7 μm), 10 (6.75–7.15 μm), and 11 (7.24–7.6 μm), which are water vapor absorption channels, are 378, 458, and 588 hPa, respectively, and they enable detection of water vapor in the middle and upper troposphere. The peak heights of the weighting functions for channels 12 (8.3–8.8 μm), 13 (10.3–11.3 μm), and 14 (11.5–12.5 μm) are near the surface and are primarily used to detect surface and cloud information. The peak of the weighting function for channel 15 (13–13.6 μm) is at approximately 900 hPa; information about clouds, the lower troposphere, and the surface are obtained, and it serves as a detection channel for low atmospheric

temperatures (Lu et al. 2017).

Among these, the observation minus background (OMB) biases of channels 12–15 exhibit significant spatial differences between land and sea, whereas the biases in channels 8 and 12 are strongly influenced by the satellite zenith angle (Zhu et al. 2023). Consequently, we focused on the water vapor channels that have fewer influencing factors, specifically channels 9 to 11, to conduct our analysis and bias correction.

Figure 1 illustrates the sensitivity distributions of the Jacobian matrices for the temperature and humidity corresponding to channels 9–11. The left panel shows the sensitivity of the Jacobian matrix to temperature changes, whereas the right panel shows its sensitivity to humidity changes. The results revealed significant variations in the sensitivity of the three channels to temperature and humidity across different atmospheric layers. In the Jacobian temperature matrix, channel 9 demonstrated greater sensitivity to temperature changes in the middle to upper troposphere (approximately 500–200 hPa), channel 10 exhibited a strong response in the middle troposphere (600–300 hPa), and channel 11 was the most sensitive to changes in the lower troposphere (850–500 hPa). The positive regions in the Jacobian matrix indicate that an increase in temperature corresponds to an increase in the brightness temperature, reflecting a positive correlation between atmospheric temperature variations and the radiative brightness temperature. In the humidity Jacobian matrix, channel 9 was sensitive to humidity changes in the middle to upper layers, channel 10 demonstrated greater sensitivity in the middle layers, and channel 11 exhibited the strongest response in the lower layers. Negative regions in the humidity Jacobian matrix indicate that an increase in water vapor corresponds to a decrease in the brightness temperature, demonstrating a negative correlation. This

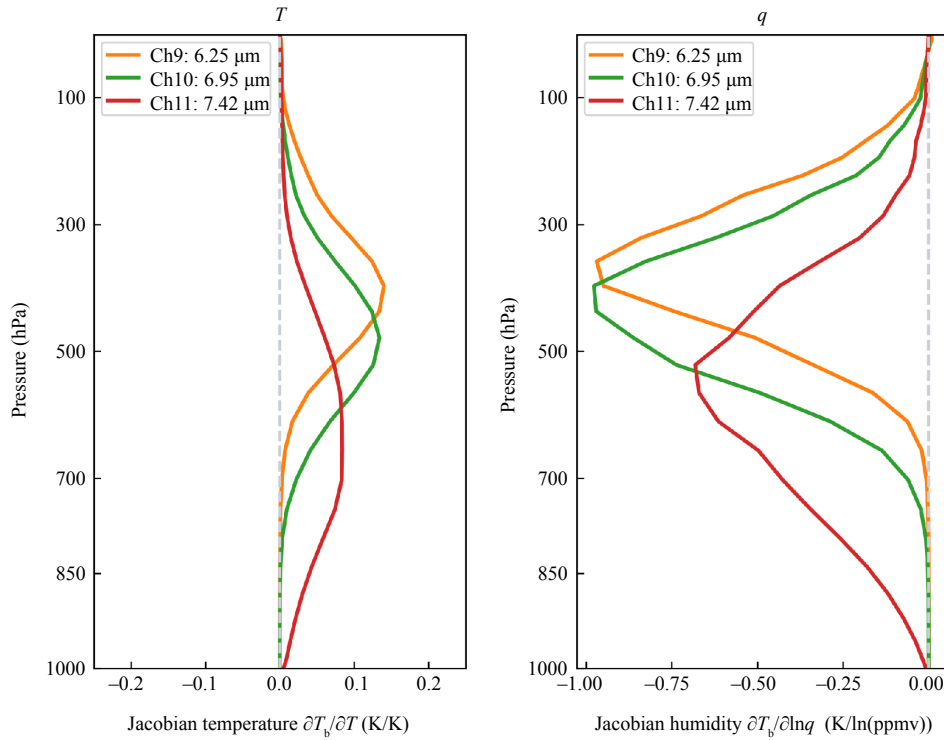


Figure 1. Sensitivity distribution of the Jacobian matrix of FY-4B AGRI instrument channels 9 to 11 to temperature (left figure) and humidity (right figure).

phenomenon occurred because the increased water vapor enhanced the absorption of radiation.

Overall, there were notable differences between the sensitivities of the three channels to temperature and humidity variations across the different atmospheric layers. Channel 9 was best suited for detecting temperature and humidity variations in the middle to upper troposphere, channel 10 exhibited heightened sensitivity to changes in the middle troposphere, and channel 11 demonstrated the highest sensitivity to variations in the lower troposphere. The positive and negative values in the temperature and humidity Jacobian matrices indicate the distinct contributions of temperature and humidity variations at different atmospheric levels to changes in the brightness temperature. This sensitivity differentiation offers a multichannel advantage for layered atmospheric observations, facilitating the precise detection of temperature and humidity variations across different atmospheric layers.

2.3 Quality control

To ensure the validity and reliability of the radiative data, quality control was conducted prior to bias correction, eliminating anomalous observation biases and performing cloud detection to exclude cloud-affected areas. Considering the complex environment of the cloud and precipitation regions and the limitations of the current model in accurately representing these conditions, incorporating such regions into the bias correction would introduce considerable uncertainty, potentially resulting in larger errors. The following observations were excluded: observations in which the satellite zenith angle exceeded

60°; observations in which the absolute value of the OMB brightness temperature difference exceeded 3 K; and for cloud detection, cloudy pixels were excluded based on the FY-4B AGRI full-disk cloud detection product, and only clear-sky observations were retained.

2.4 Offline correction method for Bias correction

Offline bias correction employs a linear combination of forecast factors to represent bias, which is expressed as follows:

$$\tilde{H}(x, \beta) = H(x) + \sum_{i=1}^{N_p} \beta_i p_i \quad (1)$$

where $\tilde{H}(x, \beta)$ represents the observation operator after bias correction, $H(x)$ denotes the observation operator in the radiative transfer model, x is the background state vector, β_i and p_i represent the i -th forecast factor and its corresponding coefficient, and N_p represents the total number of forecast factors.

2.5 Method used to calculate solar elevation angle

The solar elevation angle is defined as the angle between the incoming solar radiation and the horizontal plane. When the solar elevation angle is 90°, the solar radiation intensity reaches its maximum value. As the zenith angle decreases, the solar radiation intensity diminishes, and the solar elevation angle varies depending on the local time and solar declination. The solar elevation angle H is calculated as follows:

$$\sin H = \sin \phi \sin \delta + \cos \phi \cos \delta \cos t \quad (2)$$

where δ denotes the solar declination, corresponding to the

latitude of the point of direct sunlight; ϕ represents the geographical latitude of the observation location, where both solar declination and geographical latitude are positive in the Northern Hemisphere and negative in the Southern Hemisphere; and t denotes the local time (hour angle).

2.6 Method used to calculate the Pearson correlation coefficient

The value of the Pearson correlation coefficient, a statistical measure employed to quantify the linear relationship between two variables, ranges from -1 to 1 , where 1 indicates a perfect positive correlation, -1 represents a perfect negative correlation, and 0 signifies no linear correlation. Given the observed values of variables X and Y , denoted as $(x_1, x_2, \dots, x_n)$ and $(y_1, y_2, \dots, y_n)$, the Pearson correlation coefficient r was calculated using the following formula:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3)$$

where $\bar{x}$ and $\bar{y}$ are the mean values of X and Y , respectively.

3 AGRI BIAS ANALYSIS

3.1 Diurnal variation characteristics of bias

We conducted a statistical analysis of biases in FY-4B AGRI radiance data from 00:00 UTC on July 22, 2023, to 00:00 UTC on July 29, 2023, using the MESO regional rapid update cycle system. To conduct a detailed bias analysis, we focused on channels 9 to 11 and three water vapor channels. Fig. 2 shows the statistical results of the mean and standard deviation of the OMB bias for each channel as a function of time. As shown in Fig. 2, the OMB bias for all three channels exhibited diurnal variations, with channels 9 and 10 displaying more pronounced changes. Between 07:00 and 15:00, the OMB bias for all three channels demonstrated an apparent “warming” trend, whereas between 15:00 and 07:00 (the next day), the bias exhibited a “cooling” phenomenon.

3.2 Relationship between bias and solar elevation angle

As described in Section 3.1, the mean OMB bias exhibited significant diurnal variation. Fig. 3 illustrates

that this diurnal variation closely resembled changes in the solar elevation angle (black line). In this context, the solar elevation angle was computed for the subsatellite point of the FY-4B satellite. It was hypothesized that the satellite instrument was influenced by solar radiation, suggesting a potential correlation with the solar elevation angle. The solar elevation angle was computed using the formula in Section 2.5, with the latitude and longitude set to the subsatellite points of the FY-4B satellite (0°E , 133°E). The correlation coefficient between the OMB bias and the solar elevation angle was calculated using the formula presented in Section 2.6, and Figs. 4a–4c demonstrate that the correlation between the mean OMB bias and the solar elevation angle was positive, with a correlation coefficient of approximately 0.5 . Furthermore, Fig. 3 indicates that the diurnal variation in the mean OMB bias exhibited a delayed response compared to the periodic changes in the solar elevation angle. This delay was likely attributable to the thermal response characteristics of the satellite instruments to solar radiation. Specifically, when instruments are exposed to solar radiation, the absorbed energy increases their temperatures. However, the temperature changes did not occur instantaneously. Owing to the thermal inertia of satellite instruments, a time lag exists between the radiation absorption and the resulting temperature adjustment. Consequently, the variation in the mean OMB bias exhibited a corresponding delay. To determine the optimal lag time, correlation coefficients between the mean OMB bias and solar elevation angle were computed at 0.5 h intervals over a 24 h period. The optimal lag time was defined as the time corresponding to the highest correlation coefficient. Fig. 3 demonstrates that, after applying the optimal time shift, the diurnal variation in the mean OMB bias aligned more closely with the solar elevation angle (red line). Further statistical analysis of the correlation coefficients between the mean OMB bias and the optimal time-shifted solar elevation angle, as shown in Figs. 4d–4f demonstrated a clear positive linear relationship. The positive correlation between the optimally time-shifted solar elevation angle and the mean OMB bias was enhanced, with the correlation coefficient reaching approximately 0.7 and a maximum value of 0.788 .

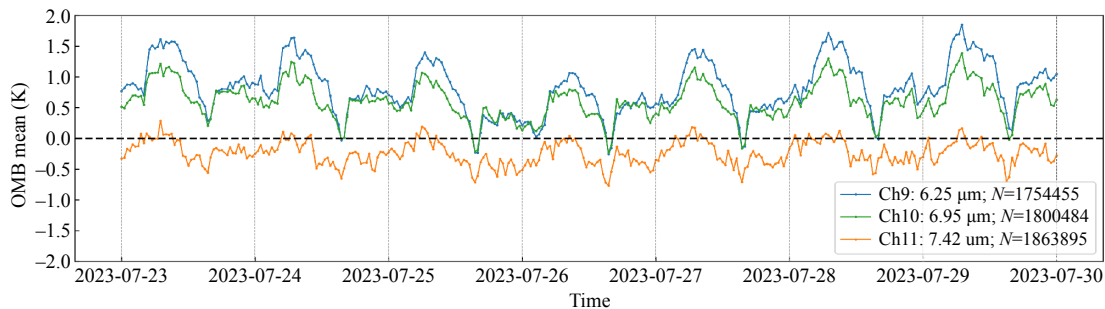


Figure 2. Time series of the mean OMB bias from 00:00 UTC on July 23, 2023, to 00:00 UTC on July 30, 2023.

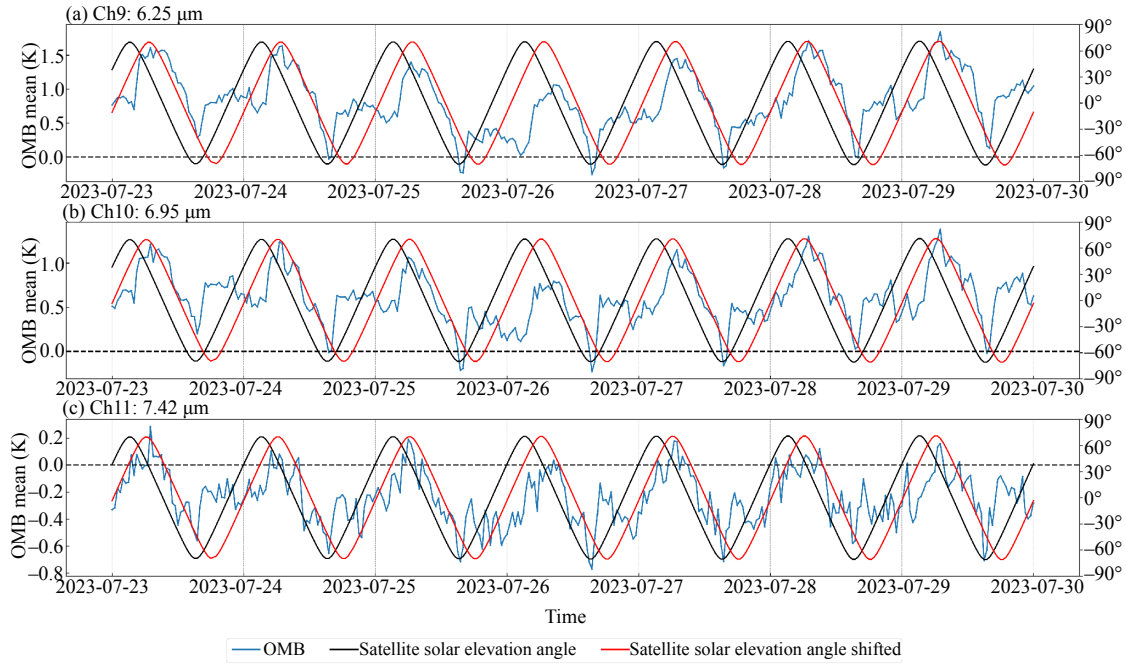


Figure 3. Time series of observed and simulated brightness temperature biases (OMB; units: K; blue line), solar elevation angle (units: °; black line), and optimal time-shifted solar elevation angle (units: °; red line) for FY-4B AGRI channels (a) 9, (b) 10, and (c) 11, spanning from 00:00 UTC on July 23, 2023 to 00:00 UTC on July 30, 2023.

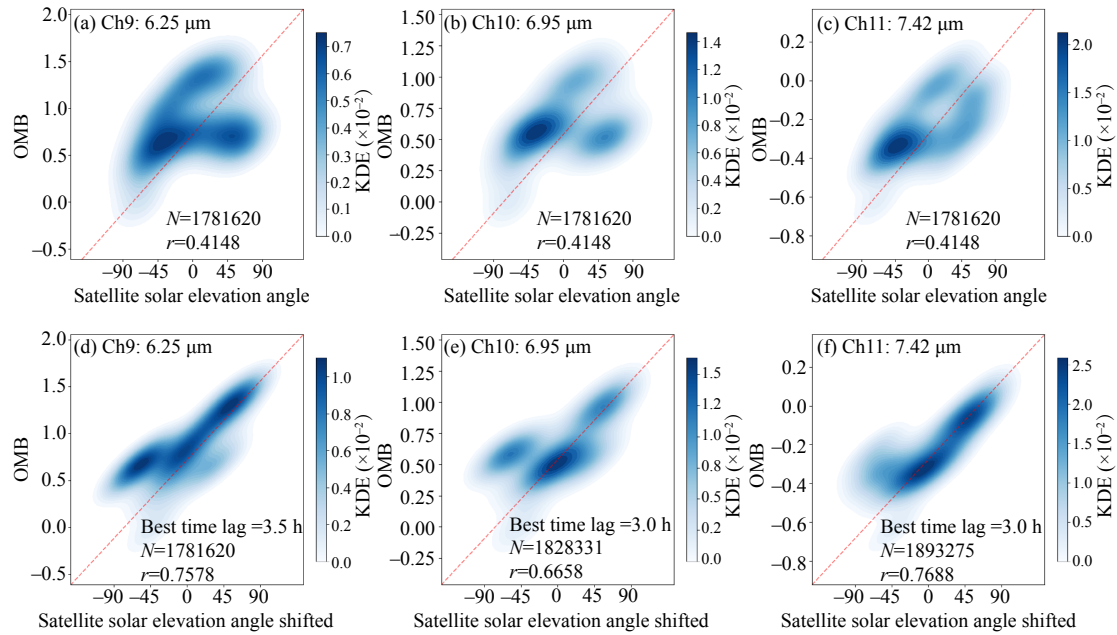


Figure 4. Relationship between observed and simulated brightness temperature bias (OMB; units: K) and solar elevation angle (units: °) for FY-4B AGRI channels 9 to 11 from 00:00 UTC on July 23, 2023, to 00:00 UTC on July 30, 2023, including the relationship after applying the optimal time shift. Panels (a)–(c) illustrate the relationship between channels 9 and 11 and the solar elevation angle, and panels (d)–(f) show this relationship after applying the time shift. The kernel density map illustrates that areas with darker colors correspond to higher densities, whereas areas with lighter colors correspond to lower densities.

4 BIAS CORRECTION TEST AND RESULT ANALYSIS

4.1 Experimental setup

Based on a previous analysis of the AGRI radiance bias characteristics, a significant positive correlation was

observed between the diurnal variation in the mean OMB bias and the optimally time-shifted solar elevation angle. We employed an offline bias correction method (described in Section 2.3) to adjust the OMB bias and used the quality control method from Section 2.4 to process the data. Two comparative experiments were conducted: no-satellite

solar elevation angle (CTRL) and satellite solar elevation angle (EXP), with the experimental period spanning from 00:00 UTC on July 23, 2023, to 00:00 UTC on July 30, 2023. For simplicity, the terms CTRL and EXP are used hereafter to refer to these two experiments. The most commonly used and effective predictors currently include surface temperature, precipitable water, 850–300 hPa thickness, and 200–50 hPa thickness. When combined linearly, these four predictors produce effective bias-correction results. Consequently, these four predictors were employed in the CTRL experiment. The EXP experiment accounts for the influence of the solar elevation angle by including the first- and second-order terms of the optimal time-shifted solar elevation angle in addition to the four predictors used in the CTRL experiment (Table 2).

4.2 Analysis of bias correction results

Channels 9 to 11 correspond to the upper, middle, and lower water-vapor layers, respectively. Bias-correction experiments were conducted for these three channels, and the observational data used in the analysis were subjected to quality control. Fig. 5 illustrates the temporal variation in the mean OMB bias and corrected mean OMB bias from the CTRL and EXP experiments for channels 9 to 11. Before correction, the mean OMB bias for all three channels exhibited significant diurnal variations. The mean OMB bias ranged from 0 to 1 K for channels 9 and 10 and from -0.3 to 0 K for channel 11. After bias correction, the mean OMB bias was reduced in both experiments. In the CTRL experiment, although the mean OMB bias decreased, the pattern of diurnal variation remained consistent with the original OMB mean bias. In the EXP experiment, the corrected mean OMB bias approached 0, with the mean bias for channels 9 and 10 reduced to within ± 0.2 K and for channel 11 to within ± 0.1 K. Furthermore, the dominant diurnal variation characteristics were effectively corrected.

Overall, the offline bias-correction experiments exhibited a strong performance. As shown in Fig. 5, the bias correction results of the EXP experiment surpassed those of the CTRL experiment, indicating that the solar elevation angle significantly affected the systematic bias of the AGRI data. Therefore, the influence of the solar elevation angle should be incorporated into future bias-correction experiments for AGRI data.

5 CASE APPLICATION ANALYSIS

5.1 Case overview

In this case study, the heavy rainfall event that occurred in the Beijing–Tianjin–Hebei region from July 29 to August 2, 2023, was studied. This heavy rainfall event, also referred to as the “23·7” Haihe Basin catastrophic flood, was influenced by the residual circulation of Typhoon Doksuri, the subtropical high, moisture transport from Typhoon Khanun, and topographic effects. The region has experienced widespread heavy to torrential rainfall, with localized areas of extremely heavy rainfall exceeding historical records. The total precipitation in some parts of the Beijing–Tianjin–Hebei region ranged from 200 to 450 mm, with local totals exceeding 600 mm, and the maximum hourly rainfall ranged from 30 to 60 mm, with localized maxima exceeding 80 mm (Yang et al. 2023); this heavy rainfall triggered widespread flooding, leading to casualties and substantial economic losses.

5.2 Analysis of case synoptic patterns

This heavy rainfall event in the Beijing–Tianjin–Hebei region was driven by multiple factors. Typhoon Doksuri made landfall in Fujian on July 28 and subsequently tracked northward. Owing to land friction, it gradually weakened to a tropical depression, but its residual circulation persisted and reached the southern side of the Beijing–Tianjin–Hebei region on July 29. In eastern North China, the subtropical high extended westward, whereas the high-pressure ridge moved eastward from the west. By the night of July 29, the high-pressure systems from the east and west were connected, forming a high-pressure dam in northern North China. At 12:00 UTC on July 30, 2023, in the 500 hPa pressure field, the “588 line” spanned the eastern and northern sides of the Beijing–Tianjin–Hebei region, signifying that the subtropical high to the east and the high-pressure ridge to the north had merged to form a high-pressure dam. This slowed the northward progression of Typhoon Doksuri’s circulation, prolonging its retention over North China and the Huang–Huai region, and resulting in extended rainfall and significant cumulative precipitation.

Typhoon Doksuri transported a substantial amount of moisture. At 12:00 UTC on July 30, 2023, humidity levels in central and eastern China were high, reaching $16\text{--}18\text{ g kg}^{-1}$ in the 850 hPa pressure field. Meanwhile, Typhoon Khanun, which had developed in the western Pacific, transported substantial moisture northwestward,

Table 2. AGRI bias-correction test plan

Experiment name	Predictors				Optimally time-shifted solar elevation angle	(Optimally time-shifted solar elevation angle) ²
	850–300 hPa thickness	200–50 hPa thickness	Model surface temperature	Total water vapor in the initial field		
CTRL	√	√	√	√	×	×
EXP	√	√	√	√	√	√

Note: In the table, √ indicates that the forecasting factor was selected for the experiment, while × denotes that the forecasting factor was not included.

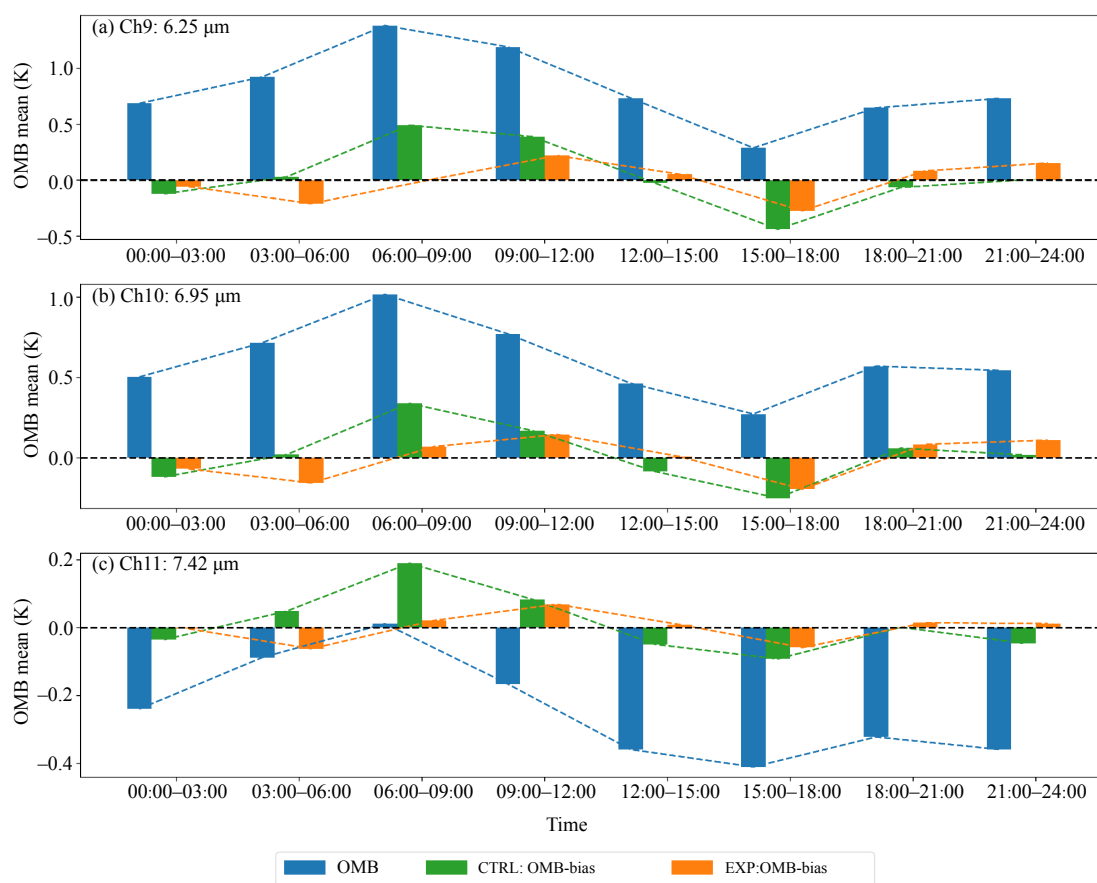


Figure 5. AGRI channels (a) 9, (b) 10, and (c) 11 spanning from 00:00 UTC on July 23, 2023, to 00:00 UTC on July 30, 2023.

causing humidity levels at 850 hPa in the eastern seas to reach $14\text{--}16\text{ g kg}^{-1}$. A subtropical high was located on the eastern side of the Beijing–Tianjin–Hebei region. A significant pressure gradient along its periphery generated strong southerly and southeasterly winds over the southern and eastern parts of the region.

Typhoon Doksuri transported substantial moisture, which remained concentrated south of the Beijing–Tianjin–Hebei region. Persistent southeasterly winds transported moisture from Typhoon Khanun over long distances to the North China Plain. These two channels delivered exceptionally abundant moisture to North China. Furthermore, the easterly and southeasterly winds carrying moisture intersected with the Taihang Mountains to the west and the Yanshan Mountains to the north of the Beijing–Tianjin–Hebei region. This interaction uplifted moisture over the terrain, leading to extremely heavy and concentrated rainfall along the mountain fronts.

In summary, prolonged and abundant moisture transport, combined with the orographic blocking effect of the terrain, contributed to extreme precipitation events in the Beijing–Tianjin–Hebei region.

5.3 OMB Bias and incremental results analysis

Figure 6 illustrates the horizontal distribution of FY-4B AGRI channel 11 at 12:00 UTC on July 30, 2023. Figs. 6a–6c show the original OMB bias, the OMB bias from the CTRL experiment, and the OMB bias from the EXP

experiment. As shown in Fig. 6, the distributions of both the positive and negative OMB biases were remarkably similar between the two experiments. In Fig. 6a, the OMB bias for channel 11 was predominantly positive in the region ($30^{\circ}\text{--}40^{\circ}\text{N}$, $120^{\circ}\text{--}130^{\circ}\text{E}$), which encompassed the Yellow Sea and the eastern coastal areas. Figs. 6b and 6c show a reduction in the OMB bias in both experiments, with a decrease in the area of positive values and an expansion in the region of negative values. Compared with the CTRL experiment, the negative bias region in the EXP experiment was more expansive, and the magnitude of the negative bias was amplified.

The negative values in the humidity Jacobian matrix, evident in the Jacobian distribution in Fig. 1, represent a negative correlation between atmospheric temperature changes and the radiative brightness temperature, as increased water vapor enhanced the absorption of radiation. In the Yellow Sea and the eastern coastal areas, the OMB bias for Channel 11 was predominantly negative. This indicated that both experiments showed a positive increment in lower atmospheric humidity, resulting in a moisture bias in the humidity field.

Figure 7 shows the horizontal distribution of the humidity field at the 700 hPa level at 12:00 UTC on July 30, 2023. Fig. 7a presents the humidity increments determined from the analysis of the EXP experiment, Fig. 7b presents the increments from the CTRL

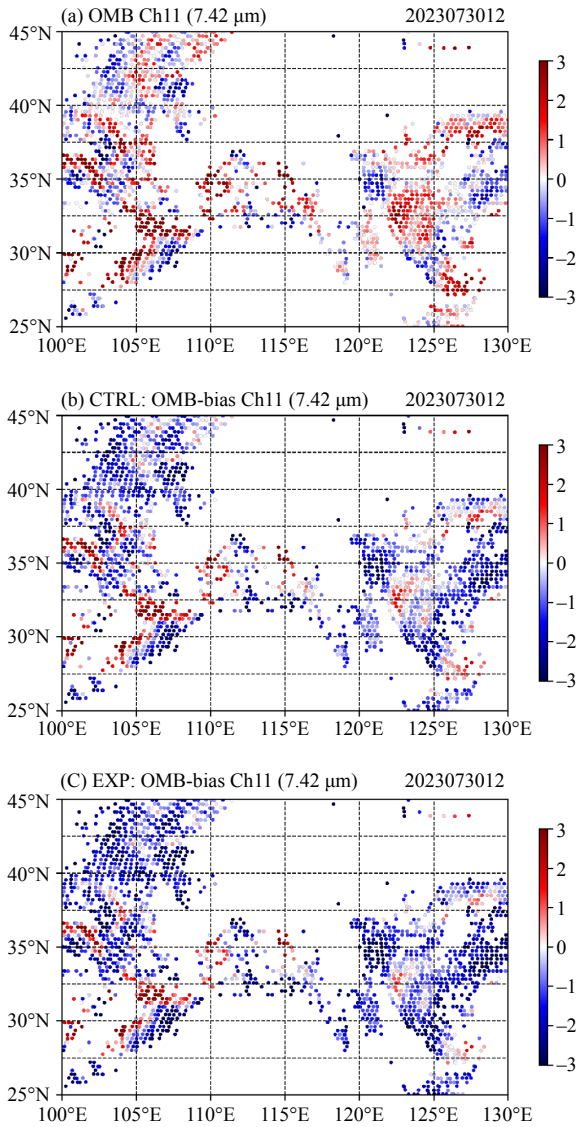


Figure 6. Horizontal distribution of OMB bias for channel 11 at 12:00 UTC on July 30, 2023. Panels (a), (b), and (c) show the original OMB bias, the OMB bias from the CTRL experiment, and the OMB bias from the EXP experiment, respectively.

experiment, Fig. 7c shows the difference between the background field and ERA5 humidity, and Fig. 7d presents the difference in humidity increments between the EXP and CTRL experiments. As shown in Fig. 7c, the background field was drier than the ERA5 humidity field in the Yellow Sea and eastern coastal regions (30° – 40° N, 120° – 127° E) as well as in the boundary area between the Zhejiang, Jiangxi, and Fujian provinces (27° – 32° N, 116° – 119° E), indicating that humidity was underestimated in these regions by the background field. Figs. 7a and 7b demonstrate that in these aforementioned regions, both the EXP and CTRL experiments exhibited positive humidity increments, suggesting that the analysis fields in both experiments positively adjusted background humidity, aligning it more closely with the true field. Fig. 7d further illustrates that the positive humidity increment in the EXP experiment exceeded that of the CTRL

experiment, suggesting that the humidity correction in the EXP experiment aligned more closely with the ERA5 true humidity field, thereby improving the accuracy of the humidity field. Overall, the correction capability when analyzing the 700 hPa humidity field was superior in the EXP experiment, particularly in drier regions, where larger positive humidity analysis increments lead to a humidity distribution in the analysis field that was more consistent with the true field.

Figure 8 shows the vertical humidity profile along 35° N and 115° – 135° E at 12:00 UTC on July 30, 2023. Fig. 8a represents the humidity increments from the EXP experiment, Fig. 8b represents the humidity increments from the CTRL experiment, Fig. 8c shows the difference between the humidity background field and ERA5, and Fig. 8d illustrates the difference in humidity increments between the EXP and CTRL experiments. As shown in Fig. 8c, the background field exhibits a noticeable dry bias between 850 and 500 hPa compared with the true ERA5 field. Figs. 8a and 8b show that the methods used in both the EXP and CTRL experiments effectively corrected the background field. Positive humidity increments were observed between 850 and 500 hPa, suggesting that the methods used in both experiments made positive adjustments to the background humidity. Fig. 8d illustrates that the method used in the EXP experiment provided stronger corrections between 850 and 700 hPa than the CTRL experiment, resulting in a humidity distribution that was closer to the true field.

The results of the humidity analysis show that under the influence of Typhoons Doksuri and Kanun, the humidity field in the EXP experiment over the East China Sea and the boundary regions of Zhejiang, Jiangxi, and Fujian provinces was more closely aligned with the true ERA5 field, offering more accurate humidity data for precipitation forecasting.

5.4 Analysis of precipitation forecast results

The accuracy of precipitation forecasts is a crucial indicator for evaluating forecast performance. Figs. 9A–9C present the horizontal distribution of 12, 24, and 36 h accumulated precipitation forecasts issued at 12:00 UTC on July 30, 2023. Panels (a)–(d) correspond to precipitation observations for different cumulative time periods, precipitation forecasts from the CTRL experiment, precipitation forecasts from the EXP experiment, and the differences between the precipitation forecasts of the EXP and CTRL experiments, respectively. The precipitation observations were retrieved products obtained through the fusion of multi-source precipitation data.

Based on the results shown in Fig. 9, the method used in the EXP experiment demonstrated significant improvements in forecasting heavy precipitation areas (>250 mm) compared to the CTRL experiment, particularly in the 36 h accumulated precipitation forecast. As shown in Fig. 9C, the accuracy of prediction of a heavy precipitation area (>250 mm) near the region

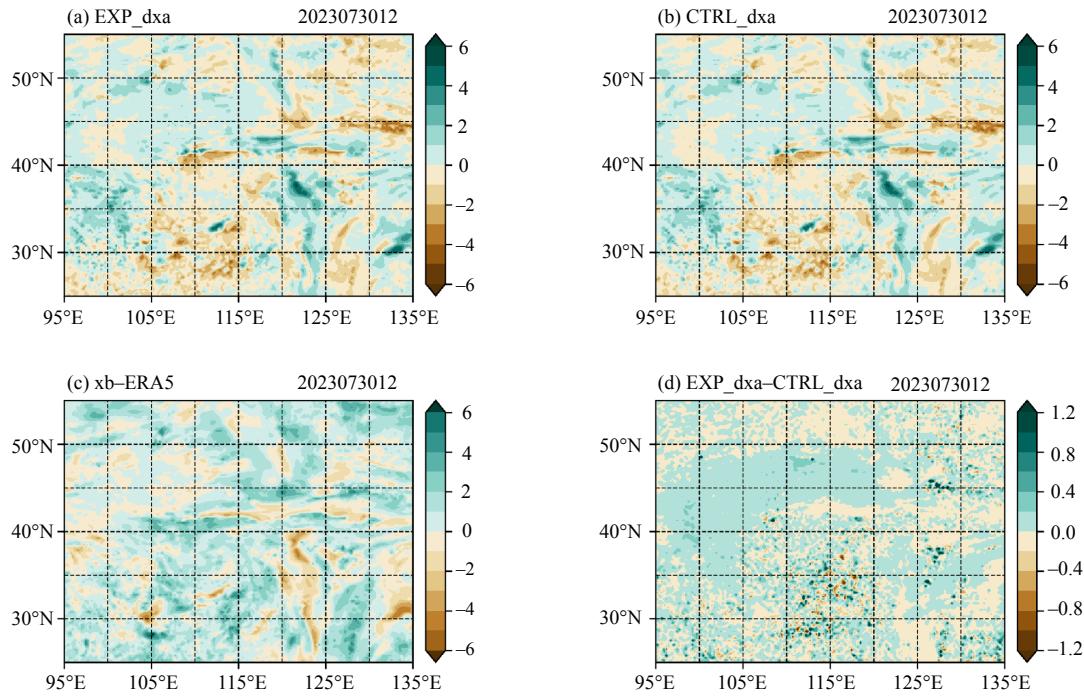


Figure 7. Horizontal distribution of the humidity field at 700 hPa level at 12:00 UTC on July 30, 2023. Panels (a), (b), (c), and (d) illustrate the humidity (units: g kg^{-1}) analysis increment from the EXP experiment, the humidity analysis increment from the CTRL experiment, the difference between the background field and ERA5 humidity, and the difference in humidity analysis increments between the EXP and CTRL experiments, respectively.

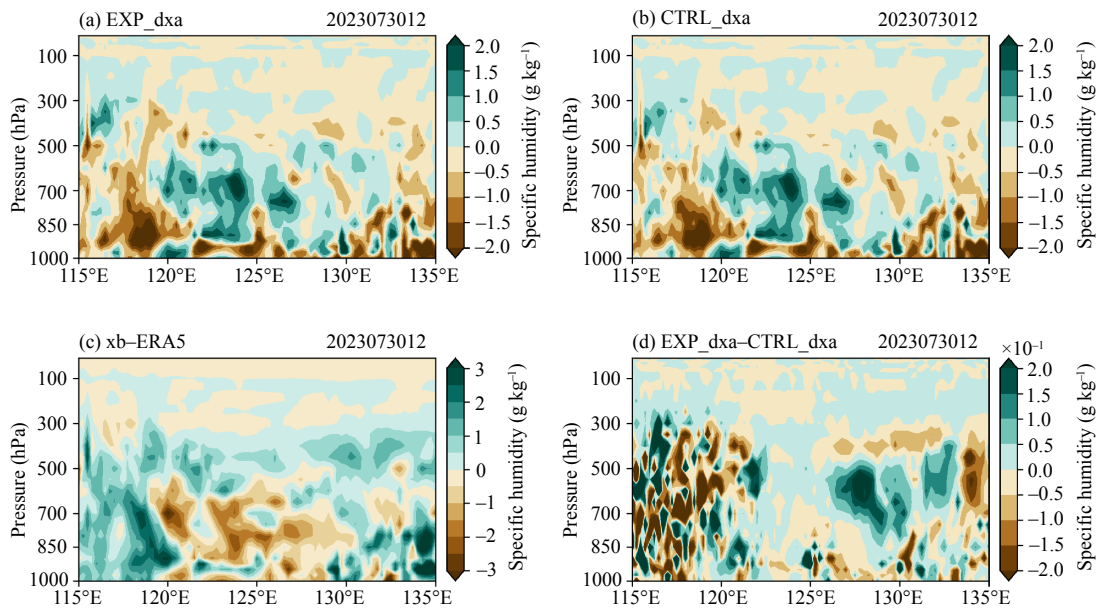


Figure 8. Vertical profile of humidity at 12:00 UTC on July 30, 2023, along 35°N and 115° – 135°E . Panels (a) and (b) show humidity increments for the EXP and CTRL experiments, respectively. Panel (c) displays the difference between the humidity background field and ERA5, and panel (d) illustrates the difference in humidity increments between the two experiments.

(39°N , 115°E) in the EXP experiment was comparatively greater because the forecast precipitation location aligned more closely with the observations, whereas the CTRL experiment exhibited a displacement in the predicted precipitation location.

Overall, although the precipitation location and

intensity forecasts from the EXP and CTRL experiments were similar, the method employed in the EXP experiment exhibited a distinct advantage in forecasting extreme precipitation events exceeding 250 mm within 36 h.

We also validated the accuracy of precipitation forecasts by employing the threat score (TS) as a

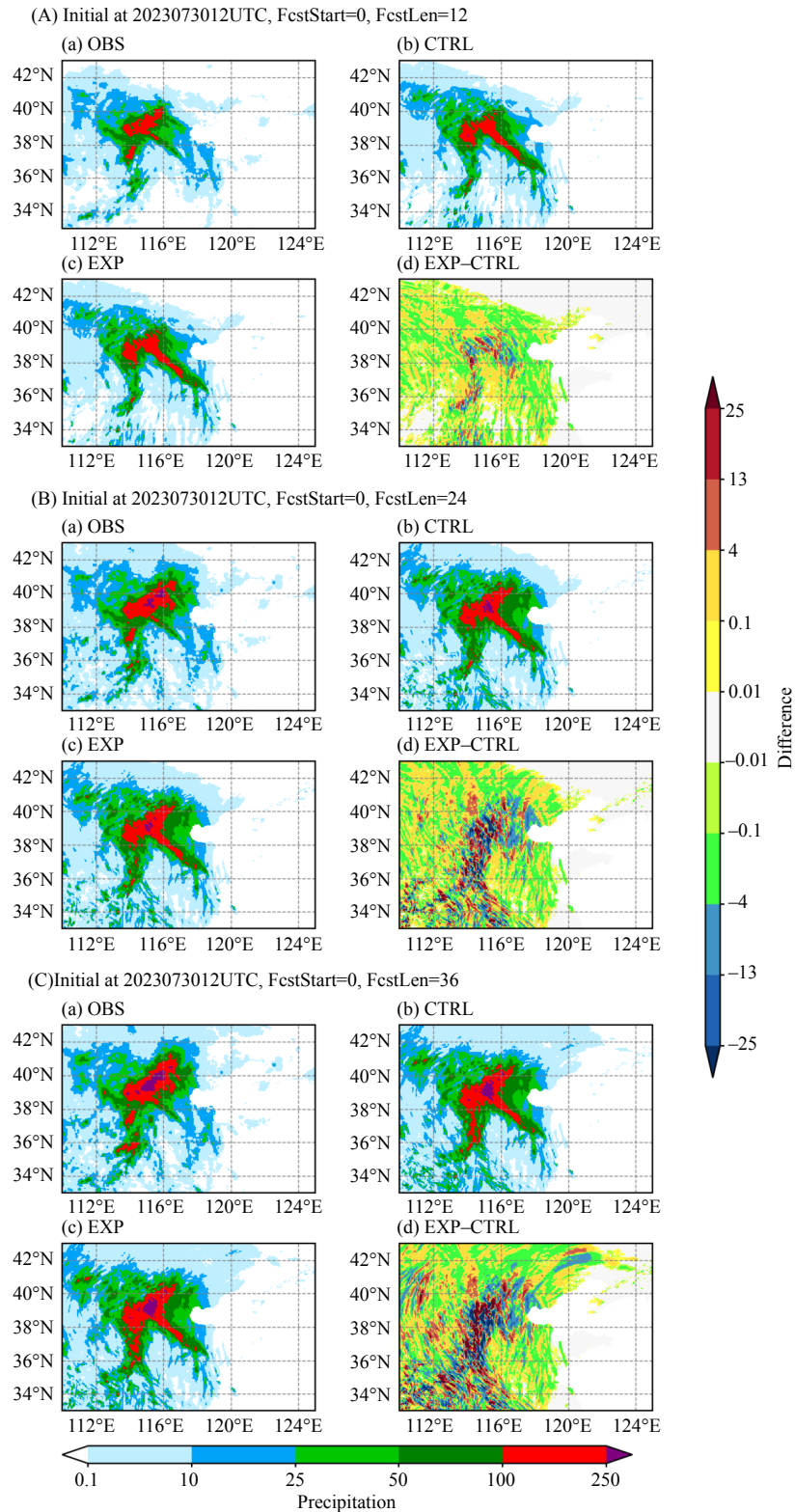


Figure 9. Horizontal distribution maps of accumulated precipitation (units: mm) starting from 12:00 UTC on July 30, 2023, for (A) 12, (B) 24, and (C) 36 h. Panels (a)–(d) represent the observed values (Obs), the forecast values from the CTRL experiment, the forecast values from the EXP experiment, and the difference between the forecast values of the EXP and CTRL experiments, respectively.

verification metric. TS scores were calculated for the 12, 24, and 36 h accumulated precipitation forecasts issued at 12:00 UTC on July 30, 2023. Figs. 10a–10c depict the TS scores for the three periods. As shown in Fig. 10, for the

50 mm precipitation level, the EXP experiment provided a slightly better result than the CTRL experiment, as reflected in the higher TS score. For the 250 mm precipitation level in the 24 and 36 h accumulated

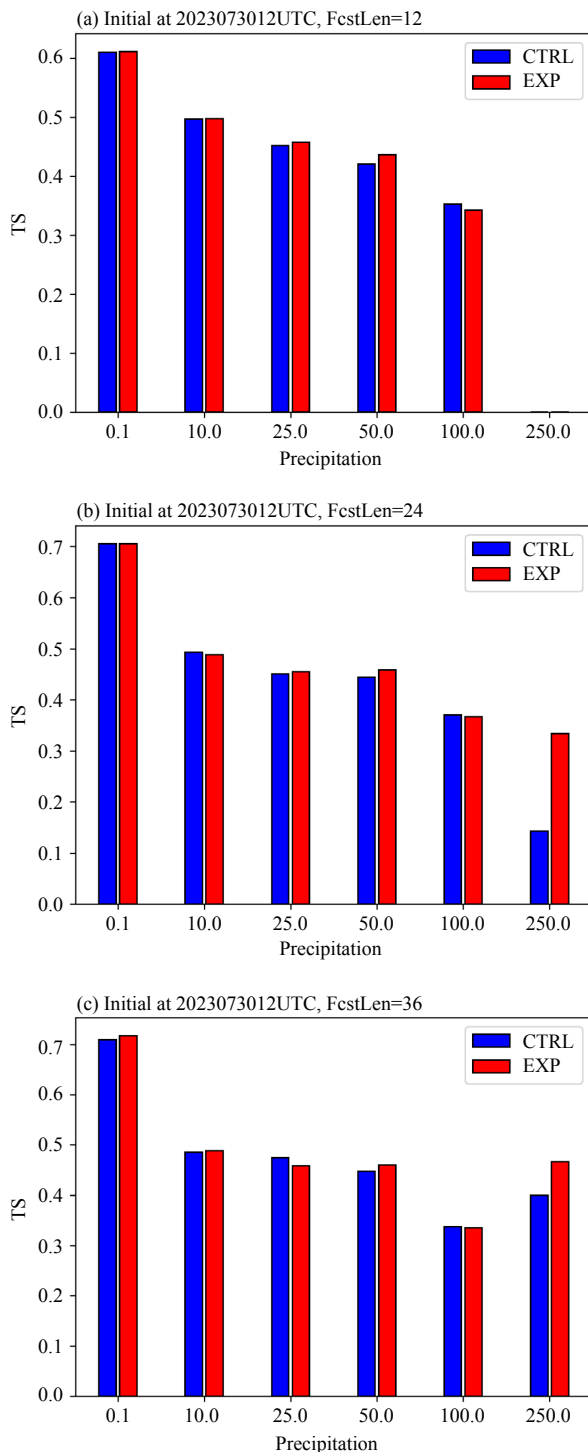


Figure 10. TS score plots of accumulated precipitation (units: mm) starting from 12:00 UTC on July 30, 2023, for (a) 12, (b) 24, and (c) 36 h. The blue bars represent the CTRL (control) experiment, and the red bars represent the EXP experiment.

forecasts, the TS scores of the EXP experiment were significantly higher than those of the CTRL experiment, highlighting a substantial improvement in the forecast accuracy for these precipitation levels. For other precipitation levels, the TS scores of the two experiments were comparable, reflecting similar

forecasting capabilities for smaller amounts of precipitation.

In summary, the performance of the EXP experiment was superior overall compared to that of the CTRL experiment, particularly in predicting larger precipitation amounts with enhanced accuracy and reliability. This further highlights the potential of using the method employed in the EXP experiment for enhancing forecasts of heavy rainfall intensities.

Overall, the performance of the EXP experiment was superior to that of the CTRL experiment for this extreme precipitation event, particularly with respect to the significant improvements in assimilating lower-level humidity and forecasting heavy precipitation. This suggests that following the method used in the EXP experiment has substantial potential and application value in forecasting extreme weather events, offering strong support for enhancing the precipitation forecast accuracy in the future.

6 CONCLUSION AND PROSPECT

6.1 Summary

As a key instrument onboard China's latest-generation geostationary meteorological satellite, FY-4B, AGRI holds significant potential for use in a wide range of applications. This study integrated AGRI radiance data into the CMA-MESO 3D-Var system, utilizing the RTTOV V12.2 radiative transfer model, and the CMA-MESO regional rapid update cycle analysis field to examine the diurnal variations in clear-sky radiance biases in the FY-4B AGRI infrared water vapor channels 9 to 11. A comparative bias correction experiment was performed to assess the impact of solar elevation angle on AGRI data correction, establishing a foundation for the future assimilation of AGRI infrared channel radiance data into mesoscale models.

The OMB biases for channels 9 and 10 were positive, whereas the OMB bias for channel 11 fluctuated by approximately 0. The bias exhibited a clear diurnal variation and demonstrated a significant positive correlation with the solar elevation angle. The slope of the fitted line between the bias and the optimally shifted solar elevation angle exceeded 0.7. Comparing the results of the CTRL and EXP experiments, the EXP experiment demonstrated better bias correction, effectively mitigating prominent diurnal variation. Therefore, the impact of solar elevation angle should be considered as a forecasting factor. The case analysis of heavy rainfall in the Beijing–Tianjin–Hebei region showed that, compared to the CTRL experiment, the method employed in the EXP experiment improved both the humidity and temperature fields, as well as the location and intensity of heavy rainfall forecasts. This demonstrates that incorporating the optimally shifted solar elevation angle as a forecasting factor results in better bias correction, facilitating more accurate predictions of extreme weather events, and highlighting its strong potential for application.

6.2 Limitations and prospects

This study conducted a preliminary investigation of employing FY-4B AGRI data by analyzing and correcting its bias characteristics. However, the study has several limitations that suggest that further exploration and analysis of the bias correction scheme for the AGRI radiance data are required. For example, (1) this study focused solely on the analysis and correction of bias in the three infrared water vapor channels of the AGRI. The diurnal variation characteristics of the bias were found to be influenced by solar radiation, and similar variations are likely present in the biases of other infrared channels. Therefore, further analyses and corrections of these channels are required.

(2) The solar elevation angle varies seasonally, resulting in changes in the intensity and duration of solar radiation received by the instrument. Therefore, further evaluation is required to assess whether the optimal lag time of the diurnal variation in the OMB bias relative to the diurnal variation in the solar elevation angle exhibits seasonal variability. If such variability is observed, a year-round bias correction should be implemented.

Future studies are required to investigate the assimilation effect of the data, its impact on the initial conditions of the numerical models, and its improvement in the numerical forecast performance. These studies provide crucial support for improving the accuracy and reliability of the FY-4B AGRI radiance data for practical applications.

Acknowledgements: We are grateful to the European Centre for Medium-Range Weather Forecasts for providing ERA5 data and the Numerical Weather Prediction Satellite Application Facility for providing the RTTOV code. We also thank James Hocking and Hejun Xie for helping us understand the internal computational processes of the RTTOV-SCATT. We are also grateful to the editors and two anonymous reviewers for their valuable comments that helped to improve the manuscript.

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Citation: Song, J. Y., W. Han, H. F. Sun, and Y. F. Yang, 2026: Diurnal Bias Correction of FY-4B AGRI Water Vapor Channels with Time-Shifted Solar Elevation Angle. *J. Trop. Meteor.*, **32**, 19–32, <https://doi.org/10.3724/j.1006-8775.2025.036>.