

Article

Quantifying the Impact of Aerosols on Geostationary Satellite Infrared Radiance Simulations: A Study with Himawari-8 AHI

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Abstract: Aerosols exert a significant influence on the brightness temperature observed in the thermal infrared (IR) channels, yet the specific contributions of various aerosol types remain underexplored. This study integrated the Copernicus Atmosphere Monitoring Service (CAMS) atmospheric composition reanalysis data into the Radiative Transfer for TOVS (RTTOV) model to quantify the aerosol effects on brightness temperature (BT) simulations for the Advanced Himawari Imager (AHI) aboard the Himawari-8 geostationary satellite. Two distinct experiments were conducted: the aerosol-aware experiment (AER), which accounted for aerosol radiative effects, and the control experiment (CTL), in which aerosol radiative effects were omitted. The CTL experiment results reveal uniform negative bias (observation minus background (O-B)) across all six IR channels of the AHI, with a maximum deviation of approximately -1 K. Conversely, the AER experiment showed a pronounced reduction in innovation, which was especially notable in the $10.4\ \mu\text{m}$ channel, where the bias decreased by 0.7 K. The study evaluated the radiative effects of eleven aerosol species, all of which demonstrated cooling effects in the AHI's six IR channels, with dust aerosols contributing the most significantly (approximately 86%). In scenarios dominated by dust, incorporating the radiative effect of dust aerosols could correct the brightness temperature bias by up to 2 K, underscoring the substantial enhancement in the BT simulation for the $10.4\ \mu\text{m}$ channel during dust events. Jacobians were calculated to further examine the RTTOV simulations' sensitivity to aerosol presence. A clear temporal and spatial correlation between the dust concentration and BT simulation bias corroborated the critical role of the infrared channel data assimilation on geostationary satellites in capturing small-scale, rapidly developing pollution processes.

Keywords: aerosols; CAMS; RTTOV; Jacobian; Himawari-8 AHI; infrared channel



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1. Introduction

In recent decades, numerical weather prediction (NWP) has made great strides [1–5]. As the NWP system evolves, incorporating a broader range of factors has become essential, with aerosols being a particularly important element [6–8]. Aerosols can influence atmospheric radiative processes, thereby affecting the numerical forecasts' depiction of the entire atmospheric evolution process [9–12]. Accurate aerosol representation is crucial for reducing errors in key forecast variables, such as precipitation and wind, directly contributing to the overall enhancement of NWP performance [13]. Furthermore, coupling the numerical forecast of atmospheric components, including aerosols, in the numerical weather prediction system has become the development direction of Earth system numerical forecasting [14,15]. A comprehensive assessment of the radiative properties of aerosols and their impacts on weather patterns is a crucial first step for incorporating them into numerical weather prediction models [14,15].

Aerosols can impact numerical weather prediction systems through their influence on the assimilation of satellite data. Numerous studies demonstrated that aerosols significantly affect the brightness temperature in thermal infrared window channels (8–12 μm). For instance, Wei et al. [16] evaluated the impact of dust aerosol on the simulated brightness temperature of the CRTM radiative transfer model in the Atlantic and Sahara regions based on the Infrared Atmospheric Sounding Interferometer (IASI). They found a decrease of about 4 K in brightness temperature under dusty conditions. Similarly, Kim et al. [17] investigated the effects of different aerosol types—dust, carbonaceous (black carbon and organic carbon), sulfate, and sea salt—on a global scale, noting that dust exerted the most substantial cooling effect, approximately 1 K, followed by carbonates and sulfates, with sea salt having a minimal impact. Further acknowledging the role of aerosols in the infrared spectrum, research demonstrated that integrating these radiative effects can enhance the accuracy of retrieval processes within these channels. Merchant et al. [18] introduced an empirical correction scheme for sea surface temperature (SST) retrieval, enhancing SEVIRI's retrieval quality by accounting for Saharan dust aerosols. Pierangelo et al. [19] successfully retrieved the height of dust aerosols over the Atlantic Ocean using Advanced Infrared Radiation Sounder (AIRS) observations, showing good agreement with MODIS products. Despite such progress, comprehensive quantitative analyses of the specific contributions made by different types of aerosols in the infrared channels are still lacking. Moreover, previous works were mainly based on polar-orbiting satellites for tracking atmospheric pollution events, which may not promptly reflect the situation of rapidly developing atmospheric polluted weather due to temporal resolution limitations. In contrast, geostationary satellites have a high temporal resolution and can provide continuous, high-temporal-resolution observations of atmospheric pollution events.

In international operational numerical weather prediction (NWP) services, the traditional approach to satellite data assimilation has been to discard all cloud- and aerosol-contaminated fields of view (FOVs), retaining only clear-sky observations [20–23]. This method is straightforward but leads to substantial observational data loss. In reality, scenes completely free of clouds and aerosols represent a small fraction, accounting for approximately 10% of the observations. Moreover, due to varying accuracies, different cloud detection algorithms may classify aerosol-containing FOVs as cloudy, thus filtering them out. While clouds have a more pronounced effect on infrared channel radiances, aerosols also significantly impact temperature and humidity variations. Marquis et al. [24] demonstrated that dust aerosols significantly impact temperature and humidity analyses in numerical weather prediction. A unit dust aerosol optical depth (AOD) contamination at 550 nm can introduce biases of over 2.4 K and 8.6 K in the analyzed temperature and dewpoint, respectively. This highlights the importance of accounting for aerosol effects in infrared radiance assimilation. Thus, it is imperative to find ways to improve the utilization of this information [25]. Clarifying the radiative effects of aerosols can aid in developing improved cloud detection algorithms and, concurrently, assimilate previously wasted observational information into numerical models.

Despite extensive research demonstrating that aerosols significantly affect the simulation of infrared brightness temperatures, studies specifically examining the direct radiative effects of various aerosol types in the China region remain limited. Moreover, most domestic assimilation systems have yet to incorporate aerosol information. This study aimed to quantitatively assess the impact of various aerosols on brightness temperature simulations by integrating aerosol information into the RTTOV model. This endeavor lays the groundwork for a numerical forecasting system that includes atmospheric composition considerations. Section 2 provides a systematic description of the data, the methods, and the experimental design utilized in this study. Several cases of aerosol distributions are also briefly discussed in Section 3. Discussion of the experimental results and conclusions follow in Sections 4 and 5, respectively.

2. Data and Methods

2.1. The Advanced Himawari Imager

The Advanced Himawari Imager (AHI) is mounted on the new-generation geostationary meteorological satellite Himawari-8 with 16 spectral channels, covering wavelengths from 0.47 to 13.3 μm , including three visible light channels, three near-infrared channels, and ten infrared channels [26,27]. In addition to high-frequency routine Earth observations every ten minutes, the AHI supports fast scanning every 2.5 min for specific target areas. The spatial resolution of the AHI is 500 m in the visible light channel, 1 km in the near-infrared channel, and 2 km in the infrared channel. Detailed spectral channels and spatial resolution information for AHI are presented in Table 1.

Table 1. Spectral channels and spatial resolutions of the Advanced Himawari Imager.

Channel Number	Central Wavelength (μm)	Band Width (μm)	Spatial Resolution (km)	Explanation
1	0.47	0.05	1	Visible
2	0.51	0.02	1	
3	0.64	0.03	0.5	
4	0.86	0.02	1	Near-infrared
5	1.61	0.02	2	
6	2.26	0.02	2	
7	3.89	0.22	2	Infrared
8	6.24	0.37	2	
9	6.94	0.12	2	
10	7.35	0.17	2	
11	8.60	0.32	2	
12	9.63	0.18	2	
13	10.45	0.30	2	
14	11.20	0.20	2	
15	12.35	0.30	2	
16	13.30	0.20	2	

In this study, the AHI Level-1 full-disk dataset (<https://www.eorc.jaxa.jp/ptree/index.html>, accessed on 2 June 2022) was used with a spatial resolution of 2 km. In addition, the official cloud mask (CLM) product *H8_L2_CLP* was also used in the research to divide clear-sky areas and cloudy areas. This product has an excellent spatial and temporal match with the MODIS official Collection-6 product, with a hit rate of 85% [28]. Since the official AHI CLM products are only available during the day, we selected the time of day (03:00 and 06:00 UTC) for simulation. Furthermore, since the spatial resolution of the CLM product and the AHI observation data in the infrared channel was inconsistent, we interpolated the CLM product to the AHI observation point based on the nearest-neighbor interpolation method to facilitate the subsequent simulation work.

In this study, we selected 03:00 UTC on 28 November 2018 as the specific time for analysis. Figure 1 illustrates the corresponding spatial distribution of the FY-4A AGRI Channel 6 (wavelength: 2.25 μm) brightness temperature and Himawari-8 Level-2 cloud mask products. The red solid lines in Figure 1 represent the aerosol optical depth (AOD) values at 550 nm, highlighting a significant aerosol event. The cloud detection algorithm of AHI identifies the central region with high AOD values as a cloudy area, while some surrounding regions were classified as clear sky areas. Despite the presence of clouds in the core high-AOD area, extensive clear-sky regions facilitated quantitative studies on the impact of aerosols on clear-sky radiative transfer simulations using RTTOV forward-modeling experiments.

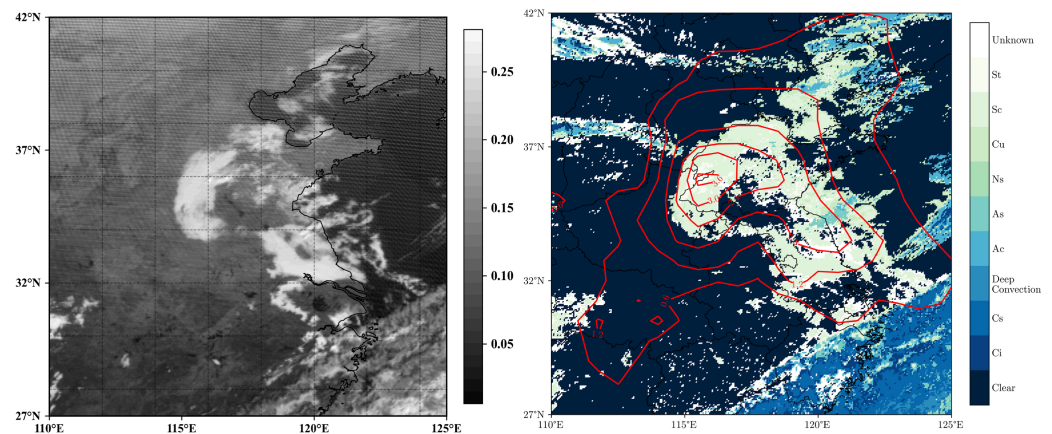


Figure 1. Spatial distribution of the FY-4A AGRI Channel 6 (wavelength: 2.25 μm) brightness temperature (**left**) and Himawari-8 Cloud Product (**right**) at 03:00 UTC on 28 November 2018. The red solid lines in the right image represent the aerosol optical depth (AOD) values at 550 nm.

The FY-4A Advanced Geostationary Radiation Imager (AGRI) is an advanced instrument onboard China's Fengyun-4A (FY-4A) satellite that is designed to enhance weather forecasting and environmental monitoring capabilities. The AGRI is equipped with 14 spectral channels spanning visible, near-infrared, and infrared wavelengths, enabling it to capture high-resolution images and perform various meteorological observations. The brightness temperature (BT) of FY-4A AGRI Channel 6 (2.25 μm) was particularly crucial in our analysis, as it helped to eliminate the potential contamination from thin cirrus clouds that could lead to negative BT differences, ensuring that the BT deviations were attributed to aerosols rather than thin cirrus clouds. This channel was chosen due to the presence of a water vapor absorption band near 2 μm , making it sensitive to cirrus clouds. This sensitivity helped to effectively exclude the influence of cirrus clouds from our aerosol analysis.

2.2. CAMS Reanalysis Data

This study used the CAMS (Copernicus Atmosphere Monitoring Service) reanalysis aerosol data to drive the RTTOV radiation simulations. The CAMS reanalysis data comprise the latest generation of the global atmospheric composition reanalysis dataset launched by the European Center for Medium-Range Weather Forecasts (ECMWF) (<https://www.ecmwf.int/en/forecasts/dataset/cams-global-reanalysis>, accessed on 2 June 2022). So far, the time range covers 2003 to 2022, with a temporal resolution of 3 h and a spatial resolution of $0.75^\circ \times 0.75^\circ$. The CAMS reanalysis data contain 60 model layers in the vertical direction, with the highest layer at 0.1 hPa.

Based on a variational bias correction scheme, the CAMS reanalysis data assimilated the total AOD data at 550 nm of the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the Aqua and Terra satellites, and the AOD retrieval data from the Advanced Along-Track Scanning Radiometer (AATSR) on Envisat from 2003 to March 2012 [29,30]. Based on the MODIS data from 2003 to 2018, Liu et al. [31] evaluated CAMS reanalysis data in the Sichuan Basin and found that although it was overestimated by about 20% across the study range, there was good agreement between the two on a given timescale, with correlation coefficients ranging between 0.89 and 0.97, depending on the season.

The CAMS reanalysis data contain 11 aerosol species: three bins for sea salt (0.03–0.5, 0.5–5, 5–20 μm) and dust (0.030–0.55, 0.55–0.9, 0.9–20 μm), hydrophilic and hydrophobic organics/black carbon, and sulfate aerosol. The standard Lorentz–Mie algorithm calculates each aerosol species, and the different aerosol species are treated as external mixing, i.e., a single aerosol species is assumed to coexist in the considered air volume and maintain their respective optical and chemical properties, corrected for their relative contributions to the total aerosols [32,33]. Referring to the practice of the AHI CLM product above, the

CAMS reanalysis product was also interpolated to the observation point of the AHI infrared channel based on the nearest-neighbor interpolation method.

2.3. RTTOV

The RTTOV (Radiative Transfer for TOVS) is a speedy one-dimensional radiative transfer model. In 1991, the European Center for Medium-Range Numerical Weather Prediction (ECMWF) developed the radiative transfer model to simulate TOVS satellite observations, and the RTTOV model was born based on this model. Over the past two decades, the RTTOV model has been continuously improved and optimized to meet the main requirements of the variational assimilation system for observation operators [34].

The RTTOV model can quickly and accurately simulate the radiation value of various satellite instruments (such as satellite radiometers in the infrared, visible, microwave bands, spectrophotometers, and interferometers) for given atmospheric state parameters. The core of RTTOV is to simulate the radiance of clear skies. For channels with a significant thermal radiation contribution at frequency ν and zenith angle θ , the top-of-atmosphere clear-sky radiance $L^{Cr}(\nu, \theta)$ can be calculated using

$$L^{Cr}(\nu, \theta) = \tau_s(\nu, \theta) \varepsilon_s(\nu, \theta) B(\nu, T_s) + \int_{\tau_s}^1 B(\nu, T) d\tau + (1 - \varepsilon_s(\nu, \theta)) \tau_s^2(\nu, \theta) \int_{\tau_s}^1 \frac{B(\nu, T)}{\tau^2} d\tau \quad (1)$$

where τ_s is the surface-to-space transmittance, ε_s is the surface emissivity, and $B(\nu, T)$ is the Planck function for the defined frequency and temperature.

The most significant advantage of this software is that in addition to very accurately simulating the brightness temperature of the satellite sensor at a exceptionally rapid speed, it can also perform an analysis of the partial derivative of the observed radiation of the temperature of each layer of the atmosphere/absorbed gas fast, namely, the Jacobian matrix [35,36].

Given a state vector $\mathbf{x}$, a radiance vector $\mathbf{y}$ is computed:

$$\mathbf{y} = H(\mathbf{x}) \quad (2)$$

where $\mathbf{x}$ represents the atmospheric state, including parameters such as the temperature, relative humidity, wind speed/direction, aerosol concentration, and aerosol properties (e.g., species and particle sizes). $\mathbf{y}$ represents the radiance vector, which indicates the brightness temperatures (BTs) in the channels of the Advanced Himawari Imager (AHI).

In this study, $\mathbf{y}$ specifically comprises the BTs in the AHI's long-wave infrared channels (channels 11 to 16), as this research investigates the impact of aerosols on long-wave infrared brightness temperature (BT) simulation.

Then the Jacobian matrix of the function H is denoted by $\mathbf{H}$, which is defined to be an $m \times n$ matrix:

$$\mathbf{H} = \begin{bmatrix} \frac{\partial y}{\partial x_1} & \cdots & \frac{\partial y}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_m}{\partial x_1} & \cdots & \frac{\partial y_m}{\partial x_n} \end{bmatrix} \quad (3)$$

For a single component $H_{ij} = \partial y_i / \partial x_j$, the subscript i refers to the channel number and j refers to the position in the state vector. Given a perturbation in any element of the state vector $\delta \mathbf{x}$, the Jacobian matrix $\mathbf{H}$ gives the change in radiance $\delta \mathbf{y}$ for each channel. It clearly shows how each layer of the atmosphere is affected by changes in the temperature and variable gas concentrations for the given profile [37].

In this specific research focused on the impact of aerosols on infrared brightness temperature (BT) simulation, we concentrated on a subset of the information in the $\mathbf{H}$ matrix. Specifically, we analyzed a selection of the information within the state vector $\mathbf{x}$, namely, the profiles of nine aerosol types. These nine aerosol types were derived by

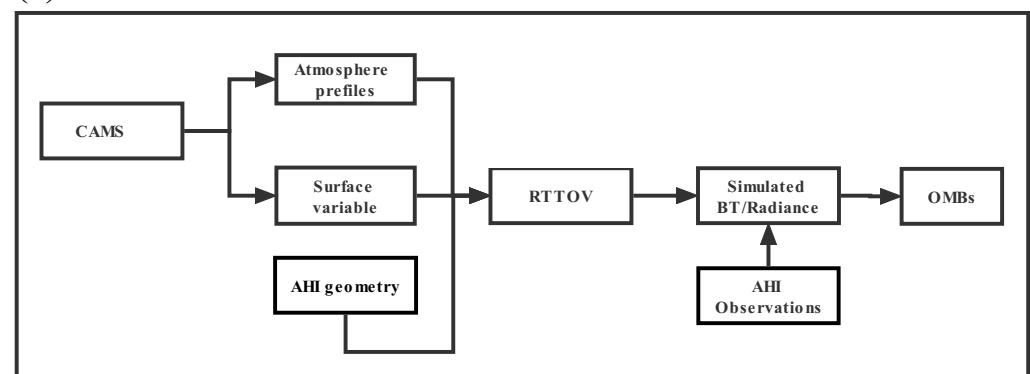
merging the 11 aerosol species provided by CAMS, without distinguishing between the hydrophilic and hydrophobic properties for each aerosol type.

In this study, the 13th version of the RTTOV was adopted. RTTOV-13 provides pre-defined optical coefficient files for the OPAC (Optical Properties of Aerosols and Clouds) and CAMS datasets and supports user-defined aerosol types.

2.4. Experimental Setup

The experimental design for the brightness temperature simulation based on the RTTOV model and CAMS reanalysis data is shown in Figure 2. We read the atmospheric state parameters, such as temperature, pressure, and specific humidity, from the CAMS reanalysis data and obtained the geometric parameters, such as latitude, longitude, Sun/satellite azimuth, and zenith angle, from the AHI data. Based on the given atmospheric variables and geometric parameters, the RTTOV was used for brightness temperature simulation. The study area was 22–45° N and 100–125° E, and the study period was 28 November 2018. The aerosol distribution of the selected case is introduced in Section 3.

(a) CTL



(b) AER

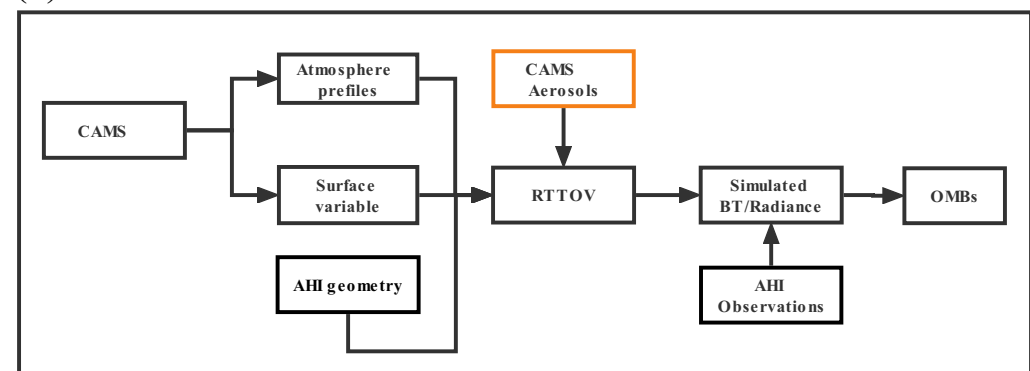


Figure 2. Diagram for the aerosol-blind experiment (CTL) and the aerosol-aware experiment (AER). The orange box indicates whether the impact of aerosols is considered in RTTOV. In the CTL experiment (a), aerosols are not considered, while in the AER experiment (b), aerosols from CAMS are included in RTTOV.

Two experiments were set up: the aerosol-aware experiment (AER), in which nine species of aerosols in the CAMS reanalysis were included in the simulation process, and the aerosol-blind experiment (CTL), in which the radiation effects of aerosols were not considered. As mentioned above, the CAMS reanalysis data and AHI CLM products were interpolated to the AHI observation points by the nearest-neighbor interpolation method. It should be noted that the RTTOV adopts different cloud schemes for pixels with and without aerosol. In order to avoid additional errors caused by different cloud schemes, in the CTL experiment, the “*addaerosol*” flag in the RTTOV was set to TRUE, as well as

in the AER experiment, but all nine species of aerosol profiles were set to zero. Based on this design, it is believed that the difference between the AER and CTL experiments was entirely due to the radiation effect of the aerosol. Therefore, the impact of aerosols could be evaluated by comparing the difference between the brightness temperature simulated by the CTL/AER experiments and the AHI-observed value.

It should be noted that the CAMS reanalysis data provided three bins of dust aerosols (0.03–0.55, 0.55–0.9, 0.9–20 μm) and sea salt aerosols (0.03–0.5, 0.5–5, 5–20 μm), respectively. In this study, different particle sizes of dust and sea salt were combined, and the combined profiles were used to calculate the brightness temperature using the RTTOV.

3. Aerosol Distribution

Figure 3 shows the spatial distribution of the column mass concentration (cMass) of the 550 nm AOD and five species of aerosols in the study area at 03:00 UTC on 28 November 2018. Regarding the AOD distribution of 550 nm, the large AOD value areas were mainly concentrated in western Shandong, northeastern Henan, and northern Jiangsu. The spatial distributions of sulfate, black carbon, and organic matter aerosols were well in agreement with the AOD distributions. Strong dust could be seen over the Bohai Sea, and some areas, such as Beijing, Tianjin, Hebei, and Liaoning were also affected by dust. Sea salt aerosols had high values in the East China Sea. From the perspective of column mass concentration, the concentration of dust aerosol in its active area was the highest, and its cMass value was more than ten times that of the other aerosols in their respective active areas. Sulfate and organic aerosols were next, and the black carbon concentration was the lowest, which was about 1–2 orders of magnitude less than the other aerosols. Figure 4 illustrates the vertical distribution of five types of aerosols from 600 to 1000 hPa. A large portion of black carbon was deposited in the atmosphere's boundary layer, where its concentration was orders of magnitude lower than that of other types of aerosols. Similar distributions of organic matter and sulfate could be found in the vertical direction, concentrated in 950 hPa to 1000 hPa. The dust had a wide vertical distribution, with high concentrations in the middle and lower tropospheres (below 850 hPa), which explains why they had the greatest column mass concentration among all aerosols.

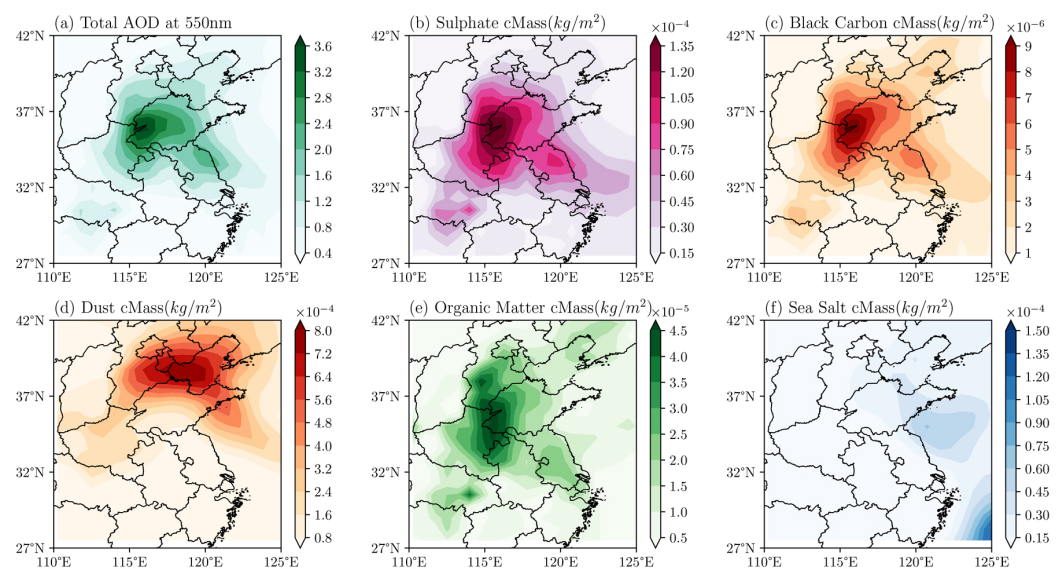


Figure 3. Spatial distribution of the column mass concentration (cMass) of the 550 nm AOD and 5 species of aerosols in the study area at 03:00 UTC on 28 November 2018.

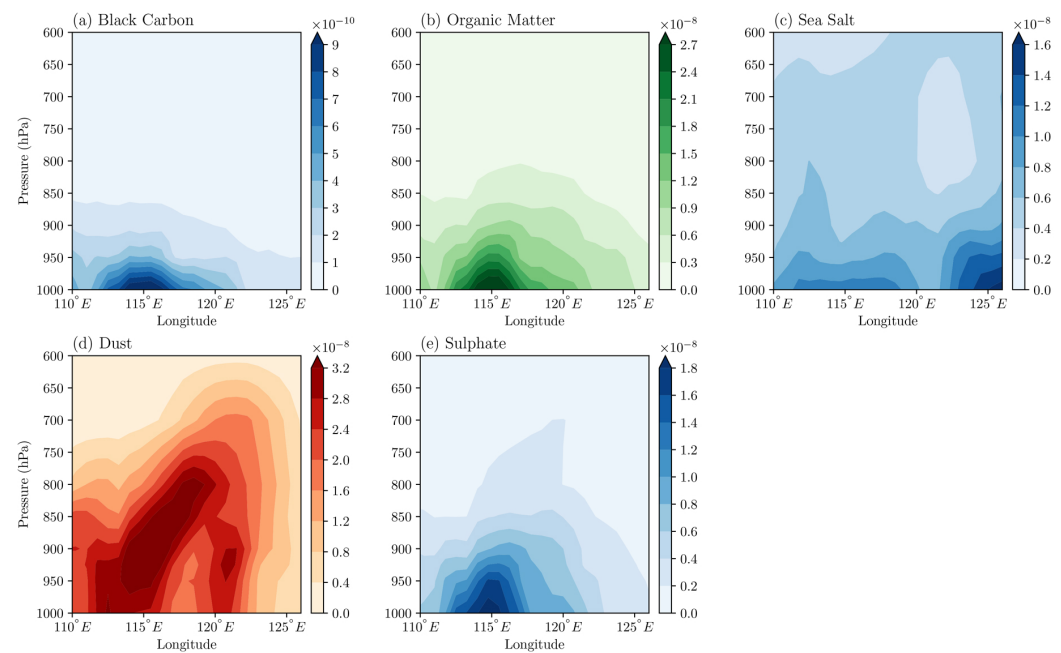


Figure 4. Mixing ratio vertical distribution of 5 species of aerosols in the study area at 03:00 UTC on 28 November 2018.

4. Results

This section presents a comparative analysis of the AHI observational data, results from the AER experiment, and findings from the CTL experiment. The focus was on evaluating the innovation, defined as the discrepancy between the observed and simulated brightness temperatures (O-B). This analysis aimed to ascertain whether the integration of aerosol information into the RTTOV simulation yielded brightness temperature values that were more closely aligned with the observations. Additionally, we explored the variances between the AER and CTL experiments by delving into how different aerosol types influenced the simulated brightness temperature.

4.1. Brightness Temperature

To isolate the radiative effects of aerosols, our examination was restricted to clear-sky regions significantly affected by aerosols, specifically those with an aerosol optical depth (AOD) at 550 nm equal to or exceeding 0.6. Within these regions, we compared the differences between the AHI observations and the simulated brightness temperatures from both the CTL and AER experiments. Figure 5 illustrates the statistical distribution of the innovations (observed minus simulated values) for both experiments using data captured at 03:00 UTC on 28 November 2018.

As shown in Figure 5a, the CTL experiment (blue curve) showed negative innovations in all long-wave infrared channels of the AHI. The average value of the innovation in the infrared window region channel (8–12 μm) exceeded 0.5 K, and the maximum innovation was -1 K. After considering the radiation effect of aerosol, the innovation of the AER experiment (red curve) was significantly improved compared with the CTL experiment, which indicates that the aerosol exhibited a cooling effect in the long-wave infrared channel. In the 10.4 μm channel, the aerosol cooling effect was notably evident, reducing the average innovation by 0.7 K. These pronounced discrepancies were primarily attributed to the single-scattering albedo (SSA) of dust aerosols. At 10.4 microns, a high imaginary part of the refractive index in dust aerosols results in increased absorption and a correspondingly lower SSA. The standard deviation (STD) and root mean square error (RMSE) of the AER experiment were also significantly lower than those of the CTL experiment in the infrared window channel (8–12 μm), and the RMSE in the 10.4 μm channel was reduced from 2.38 to 1.9. The above results show that compared with the CTL experiment's consistent negative

innovations, the aerosol's cooling effect in the long-wave infrared band caused the brightness temperature value calculated by the RTTOV to be closer to the AHI observation value.

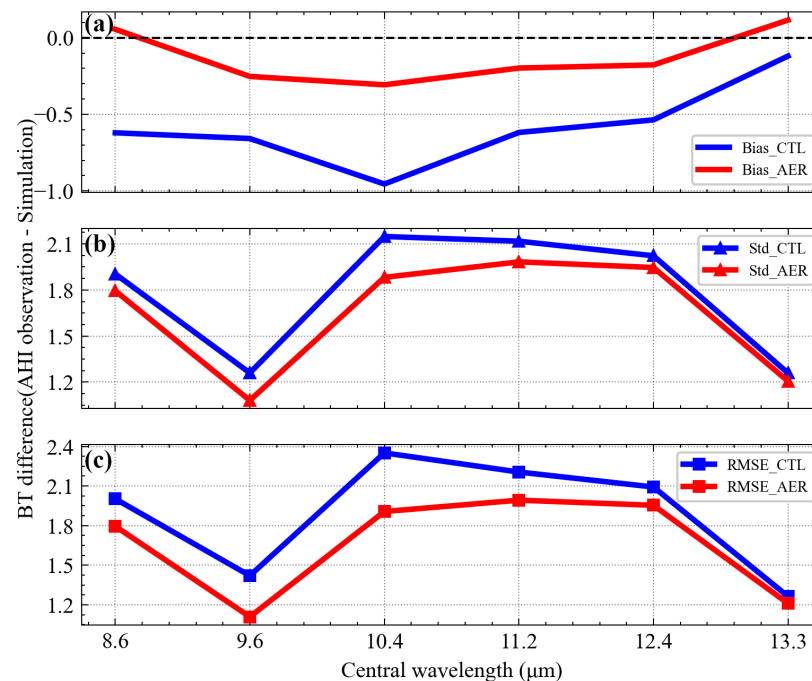


Figure 5. Statistics of innovations of the CTL and AER experiments at 03:00 UTC. The blue line represents the CTL experiment results, and the red line represents the AER experiment results. Subfigure (a) shows the bias (difference between simulation and observation), subfigure (b) shows the standard deviation (STD) of the brightness temperature (BT) difference from AHI observations, and subfigure (c) shows the root mean square error (RMSE) of the BT difference.

4.2. Radiation Effects of Different Aerosol Species

In order to link the above innovation (O-B) results with aerosol species and investigate the radiation effects of different aerosol species, five experiments were set up. In each experiment, one single aerosol type was separately considered in the RTTOV13 (i.e., *aerosol-only* experiment), and the difference in brightness temperature between the CTL and *aerosol-only* experiments was analyzed. The results are as follows.

As mentioned earlier, the CAMS reanalysis data contained 11 aerosol species. In this study, we did not consider the difference in particle sizes under the same aerosol type and summarize the above 11 aerosol species into the following five types: dust, black carbon, sulfate, organic matter, and sea salt. For each aerosol type i , only the observation points that satisfied $cMass_{(point,i)} > cThreshold_i$ were counted, where point means all observation points of the AHI in the clear-sky area. We set a concentration threshold ($cThreshold$) for each aerosol type, specifically, black carbon: $1.5 \times 10^{-0.6}$ kg/m², dust: $1.5 \times 10^{-0.4}$ kg/m², sulfate: $2.5 \times 10^{-0.5}$ kg/m², organic matter: $8 \times 10^{-0.6}$ kg/m², and sea salt: $0.2 \times 10^{-0.4}$ kg/m². It should be noted that the thresholds here were set according to the cMasses of the various aerosols in Figure 3. The size of the threshold did not affect the conclusion, but only affected the number of observed profiles input into RTTOV13. The smaller the threshold, the more profiles were sampled.

Figure 6 illustrates the difference in the simulated brightness temperature between the CTL experiment results and *aerosol-only* experiments, in which the five aerosol species were considered individually. At the same time, Figure 7 more intuitively quantifies the contribution of different aerosol types in each channel. The results are in good agreement with the innovation results of the AER experiment shown in Figure 5. Foremost, all five aerosol species exhibited cooling effects in the long-wave infrared channel. Among them, the cooling contribution of dust was the largest, and the difference in brightness

temperature of the 10.4 μm channel was reduced by 0.7 K, accounting for about 91.2% of the five species of aerosols. In the 8.6 μm channel, sulfate and organic matter reached the most cooling effect, and the brightness temperature bias decreased by about 0.25 K and 0.1 K, respectively. Sea salt exhibited a strong cooling effect for the infrared channels with longer wavelengths (channels 15 and 16), with relative contribution rates reaching 9.2% and 8.8%, respectively. While black carbon had a small impact on calculating the brightness temperatures in each long-wave infrared channel, it also exhibited a cooling effect.

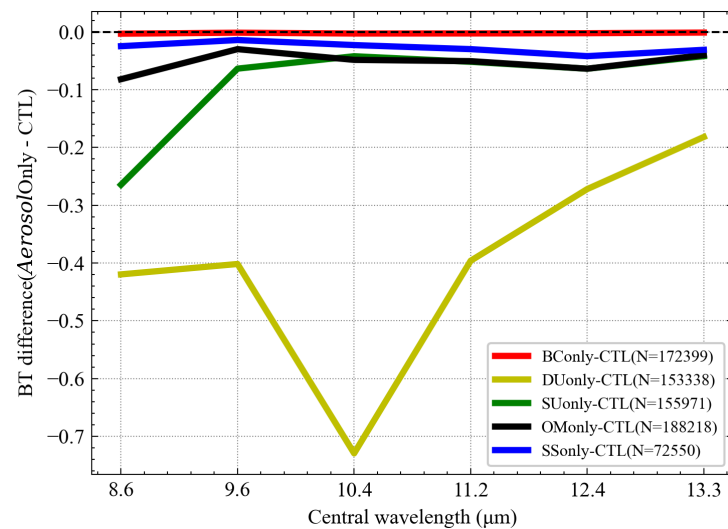


Figure 6. The difference in the simulated brightness temperature values between the CTL experiment and the *aerosol-only* experiments.

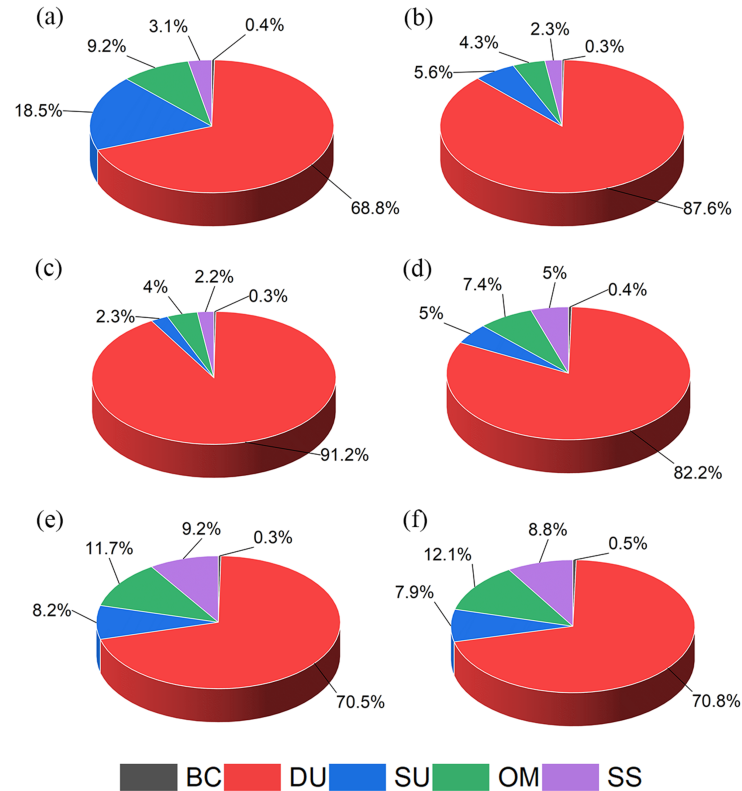


Figure 7. Contributions of different aerosol types in each infrared channel in the *aerosol-only*-CTL experiments. Subfigures (a–f) correspond to the six AHF infrared channels at wavelengths of 8.6 μm , 9.6 μm , 10.4 μm , 11.2 μm , 12.4 μm , and 13.3 μm , respectively. The aerosol types are color-coded as follows: black carbon (BC), dust (DU), sulfate (SU), organic matter (OM), and sea salt (SS).

4.3. Jacobians

In order to further explore the response of the RTTOV simulations to the presence of aerosols, the Jacobians were calculated for the above five types of aerosols. As shown in Figure 8, the Jacobian results could well explain the results of the five *aerosol-only* experiments in Figure 6: First, the Jacobian values of the five types of aerosols were all negative in six infrared channels, which explains why the aerosols produced a “cooling” effect in the RTTOV simulation. For dust, its Jacobian satisfied $CH13 > CH11 > CH12 > CH14 > CH15 > CH16$, consistent with the brightness temperature differences in each IR channel in the *dust-only* experiment (the yellow solid line in Figure 6). Its highest sensitivity in the 10.4 μm channel justified the importance of the 10.4 μm channel in the study of dust events.

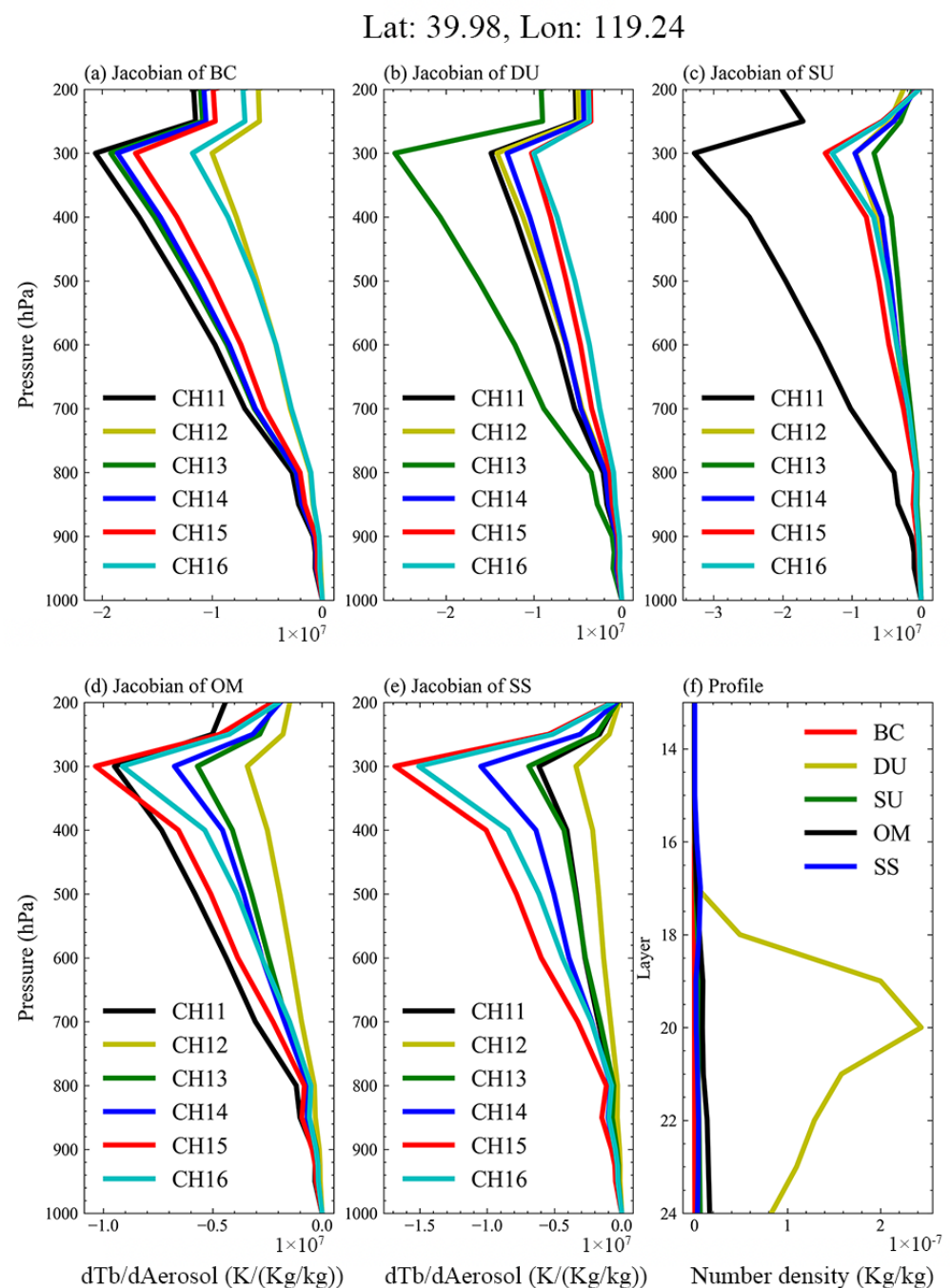


Figure 8. (a–e) The aerosol Jacobians of 6 channels, and (f) the number density profiles of 5 aerosols at point (39.98°N, 119.24°E).

For sulfate, it had the highest sensitivity in channel 11, which was much greater than those in the other infrared channels, as well as the sensitivity of dust in channel 13. It is worth noting that the change in brightness temperature was determined by the Jacobian and the concentration profile together. In channel 11, the Jacobians of sulfate and BC were significantly higher than those of dust, but the concentration of dust was much higher than that of the other aerosols (Figure 8), and thus, in the AER experiment, it still showed that dust had the strongest cooling effect. For organic matter and black carbon, the Jacobian reached the maximum value in channel 11 (corresponding to the green solid line and black solid in Figure 8).

4.4. Dust

As the cooling effect of the AER experiment mainly came from dust, we conducted a separate study (i.e., *dust-only* experiment) on the radiative effect of the dust profiles. At the observation points in the dust area ($cMass_{(point,i)} > cThreshold_i$), the simulated brightness temperature values of the CTL experiment and *dust-only* experiment were directly compared with the observation value of the AHI.

Figure 9d,e illustrate the innovations of the CTL experiment and the *dust-only* experiment, respectively. The simulated brightness temperature values of the two experiments were typically larger than the observed values in most dust activity areas. The maximum value of the innovation was about -4 K, and the maximum innovation was located in the large value area of dust. The results on land and sea were not the same. At all the observation points on the ocean, the innovations were negative, but not for all the observations on the land. In the fringes of the dust aerosol large value area, such as Hebei, Liaoning, and the southwest of Henan, the innovations were positive. This may be related to the surface emissivity.

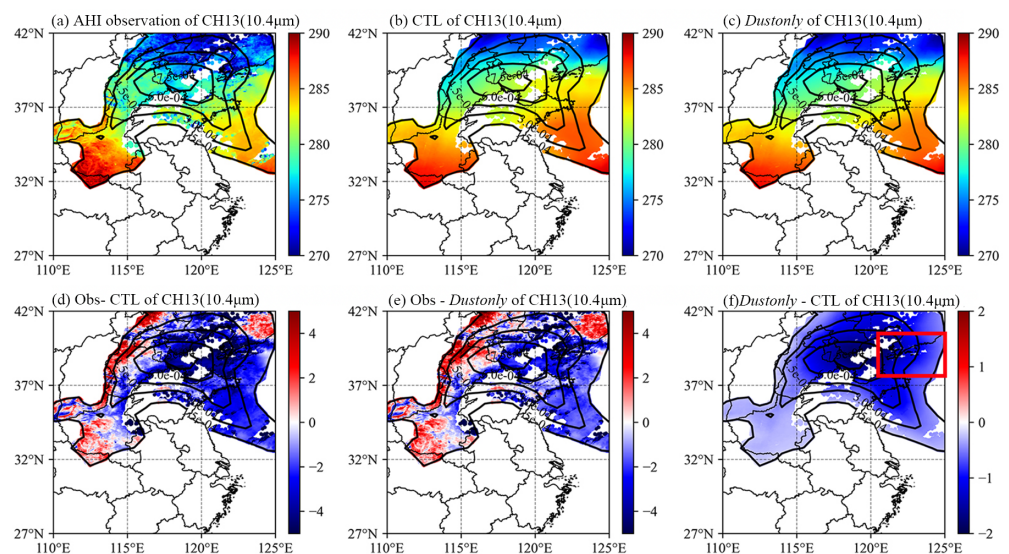


Figure 9. At 03:00 UTC, (a) the observed value of AHI in the $10.4\ \mu\text{m}$ wavelength channel, (b) the simulated brightness temperature value of the CTL experiment, (c) the simulated brightness temperature value of the *dust-only* experiment, (d) the observed value minus the CTL experiment value, (e) the observed value minus the *dust-only* experiment value, and (f) the *dust-only* experiment value minus the CTL experiment value. The solid black line represents the concentration distribution of dust aerosol.

Figure 9f shows the simulated brightness temperature bias between the CTL experiment and the *dust-only* experiment. At all observation points in the dust activity area, dust behaved as a cooling effect and showed a strong consistency with the dust concentration distribution (solid black line). The maximum brightness temperature bias reached 2 K, i.e., the simulated brightness temperature deviation could be improved by 50% , which

indicates that considering the dust aerosol data of 10.4 μm channel in the dust event could effectively improve the brightness temperature simulation.

In order to investigate the relationship between the simulated brightness temperature and the change in the pollutant intensity, the simulated brightness temperatures at 06:00 UTC were also calculated, and the results are shown in Figure 1. Comparing Figures 9f and 10f, we can see that from 03:00 UTC to 06:00 UTC, the dust concentration center moved from west to east, and the brightness temperature deviation of *dust-only* minus CTL also shifted accordingly. Focusing on the red box area in the two figures, as the dust aerosol concentration increased, the brightness temperature deviation of *dust-only*-CTL also increased accordingly. The consistent relationship between the simulated brightness temperature and the change in pollutant intensity further confirmed the correctness of considering the radiation effect of pollutants in the model.

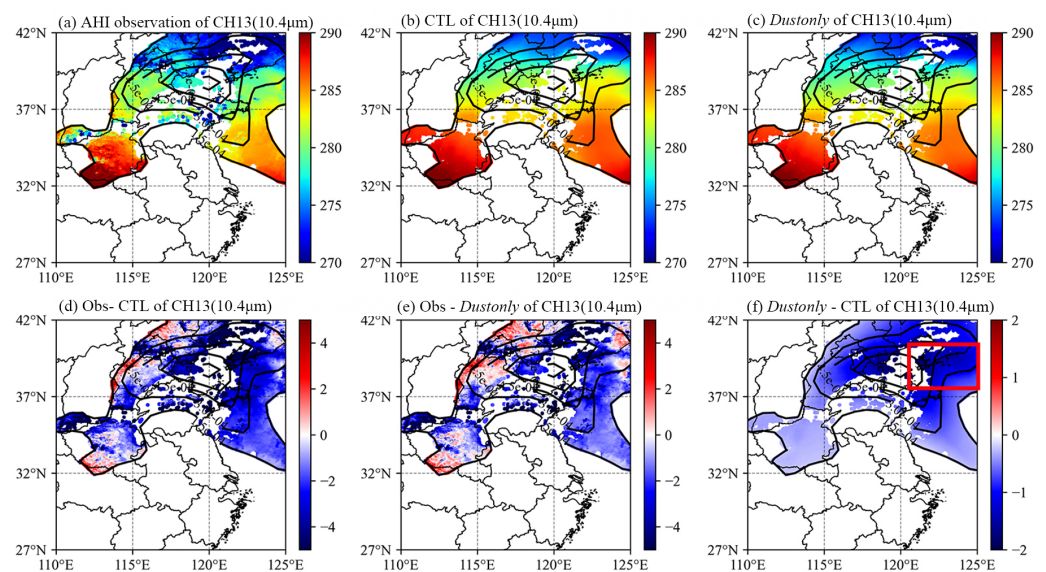


Figure 10. Same as in Figure 9, but for the spatial distribution at 06:00 UTC.

5. Discussion and Conclusions

In this study, we quantitatively investigated the effects of different aerosols on infrared channel brightness temperature simulations by inputting three-dimensional aerosol profile data into the RTTOV model, where the aerosol profile data came from the latest atmospheric composition dataset of the CAMS. Two experiments were conducted on 28 November 2018: the aerosol-aware experiment (AER), in which nine species of aerosols in the CAMS reanalysis were included in the simulation, and the aerosol-blind experiment (CTL), in which the radiation effect of aerosols was not considered. The effect of aerosols was evaluated by comparing the difference between the brightness temperature simulated by the CTL and AER experiments and the observed brightness temperature value of the AHI. Our results indicate that incorporating aerosol information in the RTTOV could reduce the difference between the simulated and AHI-observed brightness temperatures. In the six long-wave infrared channels of the AHI, the CTL experiments all showed negative innovation (O-B), and the maximum innovation was -1 K. However, in the AER experiment, the innovation was significantly reduced due to the cooling effect of the aerosol. The 10.4 μm channel had the most pronounced improvement, and the average brightness temperature deviation was reduced by 0.7 K.

To stratify the radiative effects of different aerosol species, we classified nine aerosol species into five, input the profile data for each aerosol type into the RTTOV model, and compared the simulated brightness temperature deviation between the CTL and AER experiments. The results show that the five species of aerosols all exhibited cooling effects. Dust aerosols had the most substantial cooling effect, and the average brightness

temperature deviation of the CTL-AER experiment in the 10.4 μm channel reached 1 K, accounting for about 86% of the five species of aerosols. Sulfate and organic matter aerosols reached the highest cooling effects in the 8.6 μm channel, while the brightness temperature bias decreased by about 0.25 K and 0.1 K, respectively.

Given that the cooling effect of the AER experiment mainly came from dust, we further analyzed the temporal and spatial relationships between the aerosol concentration and the simulation brightness temperature in the area where dust is the primary pollution. We found that as the dust concentration center moved from west to east, the brightness temperature deviation of the *dust-only*-CTL also shifted accordingly. As the dust aerosol concentration increased, the brightness temperature deviation of the *dust-only*-CTL also increased. The consistent relationship between the brightness temperature simulation deviation and the change in the pollutant intensity further confirmed the correctness of considering the radiation effect of pollutants in the model.

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