

Article

Impact of Assimilating Advanced Himawari Imager Channel 16 Data on Precipitation Prediction over the Haihe River Basin

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Abstract: Assimilation of high-resolution geostationary satellite data is of great value for precise precipitation prediction in regional basins. The operational geostationary satellite imager carried by the Himawari-8 satellite, Advanced Himawari Imager (AHI), has two additional water vapor channels and four other channels compared with its predecessor, MTSAT-2. However, due to the uncertainty in surface parameters, AHI surface-sensitive channels are usually not assimilated over land, except for the three water vapor channels. Previous research showed that the brightness temperature of AHI channel 16 is much more sensitive to the lower-tropospheric temperature than to surface emissivity, which is similar to the three water vapor channels 8–10. As a follow-up work, this paper evaluates the effectiveness of assimilating brightness temperature observations over land from both the three AHI water vapor channels and channel 16 to improve watershed precipitation forecasting through both case analysis (in the Haihe River basin, China) and batch tests. It is found that assimilating AHI channel 16 can improve the upstream near-surface atmospheric temperature forecast, which in turn affects the development of downstream weather systems. The precipitation forecasting test results indicate that adding the terrestrial observations of channel 16 to the assimilation of AHI data can improve short-term precipitation forecasting in the basin.

Keywords: AHI; Haihe River basin; rainfall; forecast



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1. Introduction

Reliable, timely, and accurate precipitation forecasts are essential for establishing flood forecasting and warning systems, and operational flood forecasting systems require precipitation forecasts several days in advance to predict flood risk [1]. Hydroelectric power generation requires accurate and reliable precipitation forecasts in order to predict flow changes in the rivers and tributaries where they are located for safe control of power generation. However, currently, basin rainfall forecast still has many shortcomings—for example, the National Centers for Environmental Prediction (NCEP) model forecast products, despite progress in the application of climate models at different spatial and temporal scales, are still prone to mean bias and under-propagation in forecasting [2,3]. The accuracy of model forecasts is also unevenly distributed spatially, especially in less developed regions such as Africa, where the lack of a sufficient number of observations is one of the important factors affecting the accuracy of basin precipitation forecasts [4].

Basin-scale precipitation is a complex dynamic process whose forecasting uses many conceptualized hydrological models and parameters that rely on the interpretation and judgment of the input and output information. Since a variety of hydrological and meteorological parameters are input into the forecast model, these parameters create uncertainty in the basin precipitation forecast at each step of the forecast. Therefore, a large number of accurate observations is an important condition to improve the accuracy of the initial field of the model. With the development of numerical weather prediction (NWP), more and more

observations can be added into data assimilation systems to obtain a more accurate initial field of the forecast. Among the many observations, satellite data account for about 98% [5], so the assimilation of satellite observations is particularly important for the improvement of NWP. For precipitation forecasting in small areas over the tropics and mid-latitudes, geostationary satellite observations with high spatial and temporal resolution perfectly meet the need for observations for basin precipitation forecasting. Meteorologists have attempted to use geostationary satellite observations to estimate basin precipitation in a way that provides stable estimates for areas where conventional observations are sparse [6,7], and meteorologists have also combined geostationary satellite precipitation estimates with basin precipitation models to predict basin floods [8].

In the 1990s, direct assimilation of satellite radiometric observations within the framework of variational data assimilation led to a new period in the application of satellite data in numerical forecasting [9,10]. Meteorological satellites can mainly be divided into polar-orbiting satellites and geostationary satellites, and the number of high-altitude channels is far less than that of polar-orbiting satellites. Geostationary satellites are capable of observing the observation area with high spatial and temporal resolution, thus providing more detailed information about weather systems at small and medium scales. The launch of geostationary satellites in Japan, the United States, and China has further promoted the research of geostationary satellite data assimilation. Following the successful launch of the second generation of meteorological satellites carrying the Spinning Enhanced Visible and Infrared Imager (SEVIRI) by the European Space Agency (ESA) and the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) [11], Japan's Himawari-8 and Himawari-9 satellites with the Advanced Himawari Imager (AHI) on board [12], the US GOES-R satellite with the Advanced Baseline Imager (ABI) on board [13], China's FY-4A (Feng Yun-4A) satellite with the Advanced Geostationary Radiation Imager (AGRI) on board [14], and Korea's GEO-KOMPSAT-2A satellite with the Advanced Meteorological Imager (AMI) on board [15], the assimilation of the infrared channels of these geostationary imagers will continue to make important contributions to the improvement of numerical forecasting accuracy.

The impact of assimilating imager data from geostationary satellite on weather forecasting at global and regional scales has been studied extensively [16–19], and it has been found that assimilating this information can have a positive impact on short- and medium-term water vapor forecasts, effectively improving precipitation forecasts. For strong-impact weather such as typhoons, assimilation of the observations of geostationary satellite imagers can likewise yield improvements in the analyzed typhoon structure and onset development process, thus improving forecasting accuracy [20–23]. Nowadays, observations from geostationary satellite imagers are already assimilated in many operational assimilation systems [24–28]. The AHI has 16 channels, of which 10 (channels 7–16) are infrared channels that can be used for assimilation studies and applications. Compared to the previous-generation geostationary satellite imager, AHI has two high-altitude water vapor channels and four near-surface channels added. The Himawari-8 satellite is located at 140° E above the equator and has an observation range of 120° of latitude and longitude. The AHI has 16 channels, including 3 visible channels, 3 near-infrared channels, and 10 infrared channels. Channel 7 has a frequency of 3.85 μm ; channels 8–10 are water vapor channels with frequencies of 6.2, 6.9, 7.3 μm and weight functions peaking at 377, 457, and 587 hPa; and channels 11–16 have frequencies of 8.60, 9.63, 10.45, 11.20, 12.35, and 13.3 μm . However, most geostationary satellite data assimilation studies have focused on the three high-altitude vapor channels of the AHI, i.e., channels 8–10. Wang et al. [29] analyzed the improvement in forecasting strong storms in North China on 19 July 2016 stemming from assimilating data from these three channels and found that the assimilation resulted in better humidity and wind fields and had a significant positive impact on the precipitation forecast for the first 6 h. Jones et al. [30] studied the impact of assimilating channel 3 of GOES-13 on high-impact weather forecasts and found that the assimilation had a neutral-to-positive impact on the model analysis. Lee et al. [31] conducted assimilation tests on the

water vapor channels of the ABI carried by GOES-16 and found that the ground surface had a significantly bad impact on the assimilation of the three water vapor absorption bands of the instrument, but this bad impact could be eliminated by quality control, and the proposed method could be applied to the infrared and microwave channels of polar and geostationary satellites. Wang et al. [32] intercalibrated the water vapor channels of GOES-11 and GOES-12 with the Infrared Atmospheric Sounding Interferometer (IASI) hyperspectral instrument of MetOp-A, demonstrating the technique of using hyperspectral radiometry from polar-orbiting satellites to accurately assess the calibration of the GOES imager broadband radiometer.

Great progress has been made in the area of AHI all-sky data assimilation. Many meteorologists have tried to assimilate AHI data in cloudy areas. Stengel et al. [33] improved the assimilation of geostationary satellite data in cloudy areas by introducing a simplified cloud diagnosis algorithm. Zhang et al. [34] and Honda et al. [35] introduced more observation data in cloudy areas by adaptively adjusting the observation error. However, there are still many challenges in all-sky data assimilation. At present, the cloud simulation accuracy of the numerical model is relatively poor, so it is difficult to provide accurate cloud information for the data assimilation system [36]. At the same time, the mismatch between the observed cloud and the cloud in the simulation results also causes great difficulties in cloudy data assimilation. The radiative transfer model is also imperfect. As an observation operator of data assimilation, the radiative transfer model still has great uncertainty in the simulation of strong nonlinear processes such as scattering and absorption of radiation by clouds [37–40]. These uncertainties further aggravate the non-Gaussian characteristics of O-B probability distribution [41] and affect the final assimilation effect.

Basin precipitation forecasting is also limited by the accuracy of the initial conditions of the numerical model, since basin precipitation is mainly located in inland areas and the small-scale characteristics of basin precipitation are obvious. In particular, it is necessary to assimilate data from near-surface channels that can reflect the characteristics of small-scale weather changes near the surface. Although some scientists have also assimilated AHI data from terrestrial areas, they mainly focused on the three high-altitude water vapor channels; and even though some studies have focused on assimilation techniques for the surface channel, these mostly concentrated on oceanic areas. This is mainly due to the influence of surface emissivity. The brightness temperature of the surface and near-surface channels is more influenced by the surface emissivity and surface temperature; and for marine areas, the surface emissivity is relatively homogeneous and the simulation error is small, so the bias and observation error of the observations can be estimated relatively accurately. However, for terrestrial areas, the complexity and variable types of terrestrial vegetation and the large simulation errors of surface emissivity and surface air temperature make it difficult to estimate the observation errors of the surface and near-surface channels in these areas.

While the assimilation of the observations of geostationary satellite imagers for observations over the sea surface has been extensively studied, until recently, observations over land were assimilated only at wavelengths that are insensitive to the surface [42]. Assimilation of land-surface-sensitive channels faces many difficulties due to large uncertainties in the description of surface emissivity and surface temperature [43]. Zheng et al. [44] tested new vegetation-dependent momentum and thermal roughness length formulations in the NCEP's Global Forecast System (GFS) that greatly reduced the large-value region of cold deviation in daytime surface temperature in the arid western continental United States during the warm season, which in turn improved the simulation of infrared and microwave channels in the window and near-window regions. Although meteorologists have made some improvements in the simulation and assimilation of surface-sensitive channels, the accuracy of surface emissivity datasets remains a challenging issue. Qin's [45] study found that the observation error of AHI channel 16 is basically the same in the marine and land areas, while the observation errors of other near-surface channels, 7 and 11–15, are much greater than those of the corresponding ocean areas. From the perspective of

adjoint sensitivity, it is further proved that this characteristic of this observation error is because the sensitivity of AHI channel 16 to the surface emissivity is much less than that of other near-surface channels. Therefore, we are confident to improve the precipitation forecast of the watershed mainly located on land by assimilating the observation data of AHI channel 16.

Previous studies have shown that the brightness temperature of AHI channel 16 is mainly influenced by the lower-tropospheric atmospheric temperature, and its sensitivity to the temperature of the lower atmosphere is greater than that to the surface emissivity [45], indicating the possibility of assimilating AHI channel 16 observations over land. This paper explores the improvement effect of AHI channel 16 assimilation on watershed precipitation forecasting, because the watershed is mainly located in inland areas, and the small-area precipitation of the watershed also needs more accurate initial conditions. We hope that this work can show the application prospect of AHI channel 16 data assimilation over land in improving various hydrological forecasts of the watershed. Considering many difficulties in cloud data assimilation, especially the strong uncertainty of O-B characteristics for cloudy data in the land area, this study focuses on the impact of AHI channel 16 assimilation on watershed precipitation in a clear sky.

After introducing the data and experimental design in Section 2, Section 3 presents the precipitation processes of the selected individual cases and analyzes the effects of assimilating AHI channels 8–10 and adding channel 16, as well as the differences in forecasts. A summary and some further discussion are provided in Section 4.

2. Data and Experimental Design

This paper uses AHI observations from Japan's Himawari-8 satellite assimilated into the 3 water vapor detection channels (8–10) and the temperature-sensitive channel (16). The Advanced Research version of the Weather Research and Forecasting model (WRF-ARW) and the Gridpoint Spectral Interpolation (GSI) assimilation system were selected for the model and assimilation system [46]. The fast-radiative-transfer model is the Community Radiative Transfer Model (CRTM) v2.1.3. Figure 1 illustrates the model range with a horizontal resolution of 6 km and a total number of 600×600 model grid points. The top of the model layer was set at 1 hPa, with 61 vertical layers. The WRF-ARW model uses the WRF single-moment three-class microphysical scheme [47] and the Yonsei University planetary boundary layer scheme [48]. Quality control in the GSI assimilation system is based on a number of parameters related to clouds, water vapor and temperature, surface emissivity, and observation errors [49], and bias revisions include static bias revisions and air mass bias revisions [50,51]. We focused on analyzing the effects of the assimilation of channel 16 on the geopotential height, temperature, and humidity fields. The verification data of precipitation is from the CMORPH dataset, which integrates the grid data with horizontal resolution of 0.05° obtained from nearly 30,000 stations' rain gauge observation data in China through optimal linear interpolation [52].

The initial condition of the WRF model was generated by FNL data. To avoid the influence of double assimilation, FNL data 6 h before the start of the assimilation experiment were used as the initial field and the 6 h forecast was performed. This 6 h forecast result was used as the initial field at the beginning of the experiment.

To more clearly show the effect of AHI channel 16 data assimilation, we only assimilated AHI data and conventional observations, including radiosonde data, aircraft observations, and surface observations, but observations of other satellites were not included in the experiment.

To carefully analyze the impact of assimilating AHI channel 16 on precipitation in the basin, we first selected two individual cases of precipitation in the Haihe River basin for analysis, which occurred at 0000–2300 on July 11 2016, and 0000–2300 on July 24 2016, respectively. Figure 1 shows the spatial distribution of the 500 hPa height and humidity fields at the beginning of the two cases' forecasts, and Figure 2 shows the spatial distribution of the 24 h cumulative precipitation for the two cases. Case 1 is a weak precipitation process

occurring in the western part of the Haihe River basin. As the trough moves eastward and deepens, cold air from the north moves southward and meets with warm and humid air to produce precipitation. The precipitation falls in the western periphery of the Haihe River basin and then gradually moves into the Haihe River basin with the weather system. Case 2 is a heavy precipitation process covering most of the Haihe River basin. The precipitation is mainly distributed in the central and northern parts of the Haihe River basin, and the heavy precipitation falls in the central part of the basin, which is related to the weakening of the northern low-pressure trough and strengthening of the subtropical high pressure.

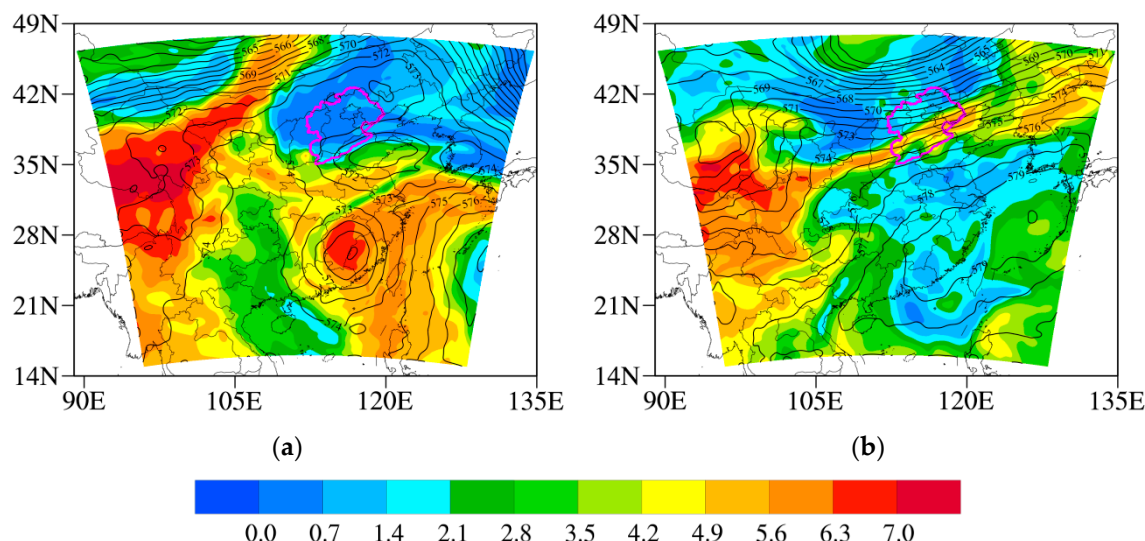


Figure 1. Superimposed plot of the height forecast field (contours, hPa) and specific humidity forecast field (color shading, g/kg) of FNL data at (a) 0000 on July 10 and (b) 0000 on July 23. The magenta line marks the extent of the Hai River basin obtained from geographic survey data.

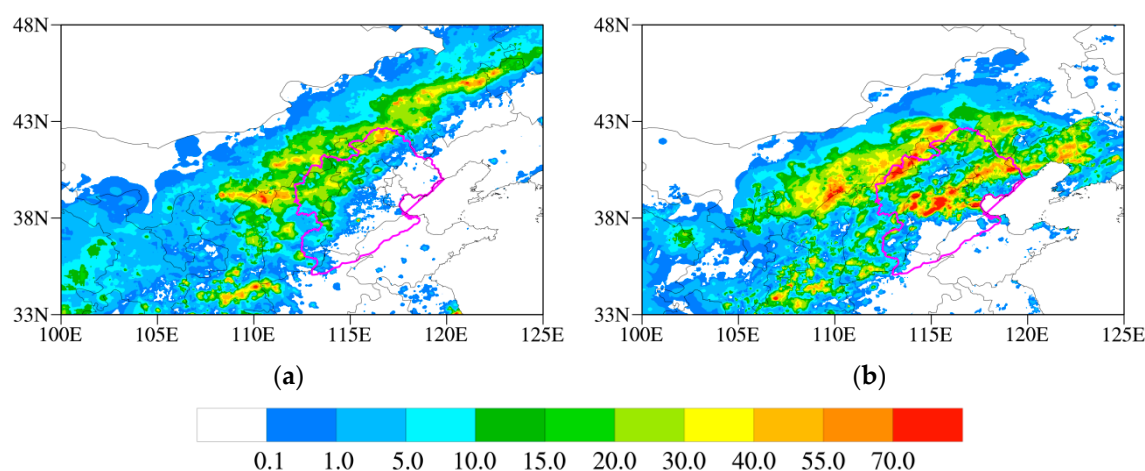


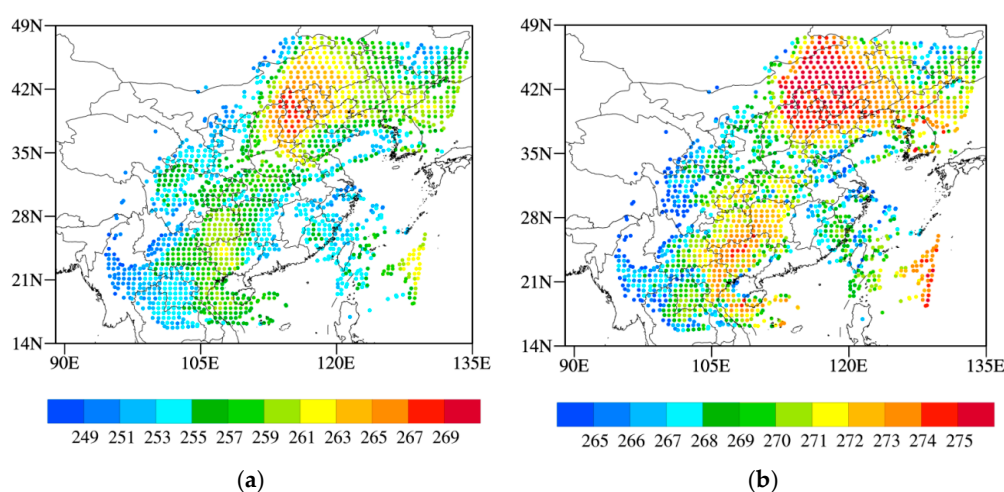
Figure 2. The 24 h observed accumulated precipitation distribution on (a) July 11 and (b) 24 July.

To evaluate the effect on the 24 h model forecast of assimilating AHI channel 16, we designed two sets of experiments—one in which only channels 8–10 (VAPOR) were assimilated and the other in which the assimilation of channel 16 (SURF) was added to the previous set. Each set of trials was initialized with a 6 h forecast of the FNL analysis data 6 h before the start of the data assimilation cycle. The assimilation cycle was 1 day, and a total of five assimilations were made during each 6 h assimilation window. Specific assimilation information regarding the experiments is shown in Table 1.

Table 1. Details of the two assimilation experiments.

	VAPOR	SURF
Observations	AHI channels 8–10	AHI channels 8–10, 16
Initialization	FNL 6 h forecast	FNL 6 h forecast
Assimilation time	0000, 0600, 1200, 1800, 2400 UTC	0000, 0600, 1200, 1800, 2400 UTC
Forecast time	24 h forecast with 3 h interval	24 h forecast with 3 h interval

The two experiments assimilated only clear scenes of AHI data, and the cloud detection method proposed by Zhuge and Zou [53], which relies only on the infrared channel, was used to reject cloudy data. Figure 3 gives the spatial distribution of the assimilated data of AHI channel 10 at the initial moments of the two cases, where the blank areas are cloudy. The observations were mainly distributed over the land in the central-eastern region of China and Southeast Asia, while the information over the ocean was sparse.

**Figure 3.** Distribution of brightness temperature at 0000 UTC on July 10, 2016, for (a) channel 10 and (b) channel 16.

Observations over ice, snow, and mixed surfaces were excluded; observations were also rejected from assimilation if their $|O-B|$ was larger than 2 K or three times the observation errors. The data biases and observation error statistics required by the AHI data assimilation were calculated following the same method as Zou et al. [54].

Bias correction of the observations was carried out through two steps. First, static bias correction and then airmass bias correction were applied to further eliminate the systematic bias of the observations. For each channel, four bias correction predictors are used in the airmass bias correction. The first predictor $p_{1,i}$ is 1.0; the second predictor $p_{2,i}$ is calculated as $\left(\frac{1}{\cos(\alpha)} - 1\right)^2$, where α is the satellite zenith angle; and the third predictor $p_{3,i}$ and fourth predictor $p_{4,i}$ are related to the lapse rate of transmittance:

$$\tau_i^\tau = \sum_{k=2}^{lev-1} \left(\tau_i^{k+1} - \tau_i^k \right) \times \left(T^{k-1} - T^{k+1} \right) \quad (1)$$

Here, lev is the number of model level; T^k is the temperature of model level “ k ”; on the lowest level, the surface temperature is used to replace the temperature at that level; and the fourth predictor $p_{3,i}$ is $(\tau_i^\tau - \bar{\tau}_i^\tau)^2$ and is the mean lapse rate of transmittance.

Here, the airmass correction coefficients were the stable correction coefficients determined after 50 round-robin tests, which were then used for subsequent airmass bias correction. No additional consideration was made for the channel correlation of the AHI data. To reduce the potential influence of the spatial correlation of the observation errors, the observations were thinned to 60 km, and GSI established an equally spaced grid of

60 km in the model region and selected the AHI data closest to the center of any grid as the observation at that point.

3. Analysis of Results

Figure 4 shows the spatial distribution of O-B and O-A for AHI channels 10 and 16 in the SURF test at the analysis time of 0000 UTC on July 10. The major magnitudes of O-B ranged from -1.5 to 1.5 , and the large-value area of O-B for channel 10 was concentrated over mainland Southeast Asia and Southwest China, while the small-value area was concentrated in northern and northeastern China. Channel 16 O-B large-value areas were concentrated over mainland Southeast Asia and northern China, while small-value areas were concentrated around Northeast China. The different colors represent the O-B values, where gray is the observations rejected using the quality control method applied by Zou et al. [54]. A comparison of the O-B and O-A fields reveals that the vast majority of $|O-A|$ was significantly smaller than $|O-B|$, indicating that the AHI data assimilate with good convergence.

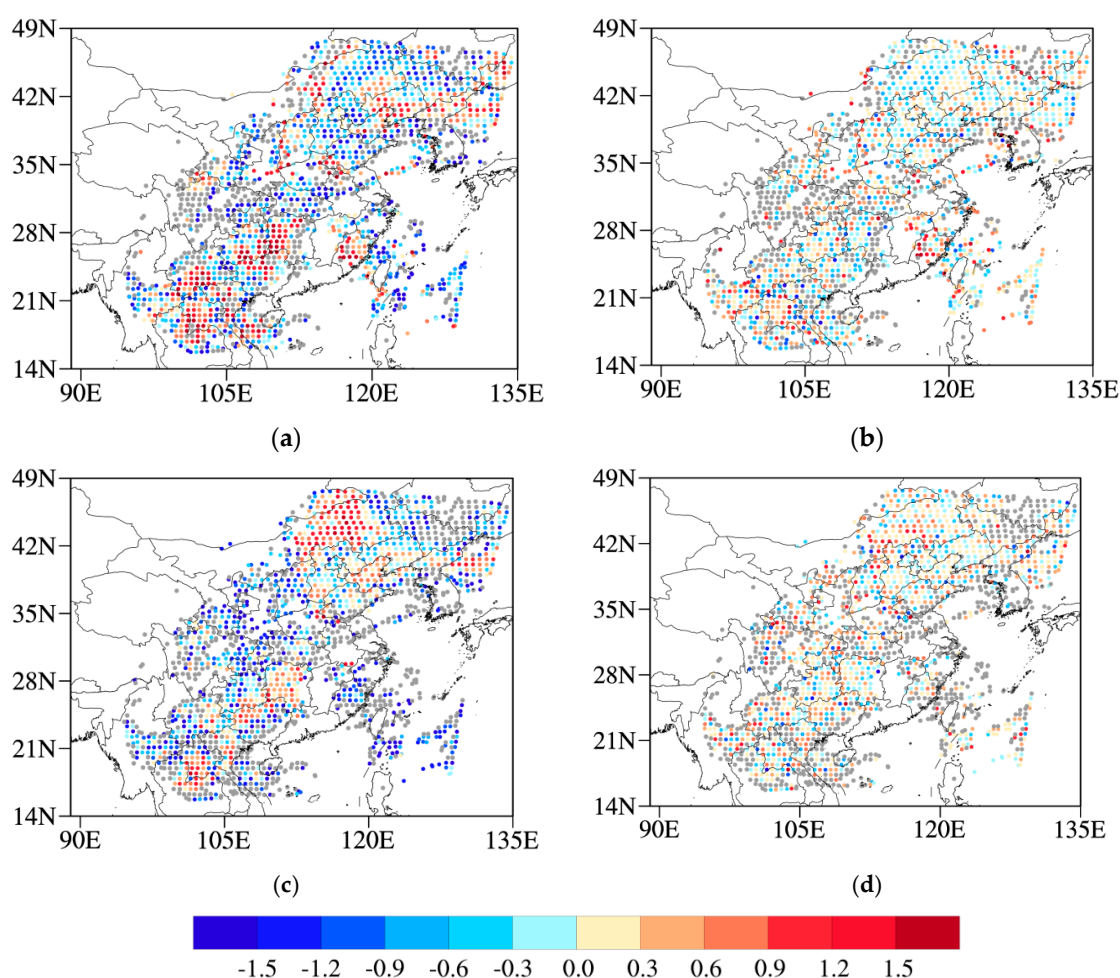


Figure 4. Distribution of (a,c) O-B and (b,d) O-A of the SURF test at 00:00 on July 10 for (a,b) channel 10 and (c,d) channel 16.

Since the assimilation of satellite observations of brightness temperature data first affects the temperature and water vapor in the background field, the impact of the assimilation of AHI data is shown here first in terms of the analysis increments of the temperature field. Figure 5 shows the 500 hPa temperature analysis field of the SURF test and the temperature difference field of the two tests (SURF-VAPOR); the shading is the temperature field difference, and the contour is the temperature field after assimilation of channel 16. The dashed rectangle indicates the key areas of assimilation impact. At the beginning of the

assimilation, there was a low-value center in the eastern part of the basin in the temperature, and the temperature in the area where the low-value center was located was lower than the surrounding area, with a warm area in the west. From the differential of temperature, a negative zone was found near 103° E and 36° N (marked by the dashed rectangle) after assimilation of channel 16, which was stable and moved gradually to the northeast as the assimilation progressed, reaching the western edge of the Haihe River basin at 1800 UTC. Whether the generation and movement of this negative zone are the reason for the change in the precipitation forecast needs to be further analyzed by combining the geopotential height and humidity fields.

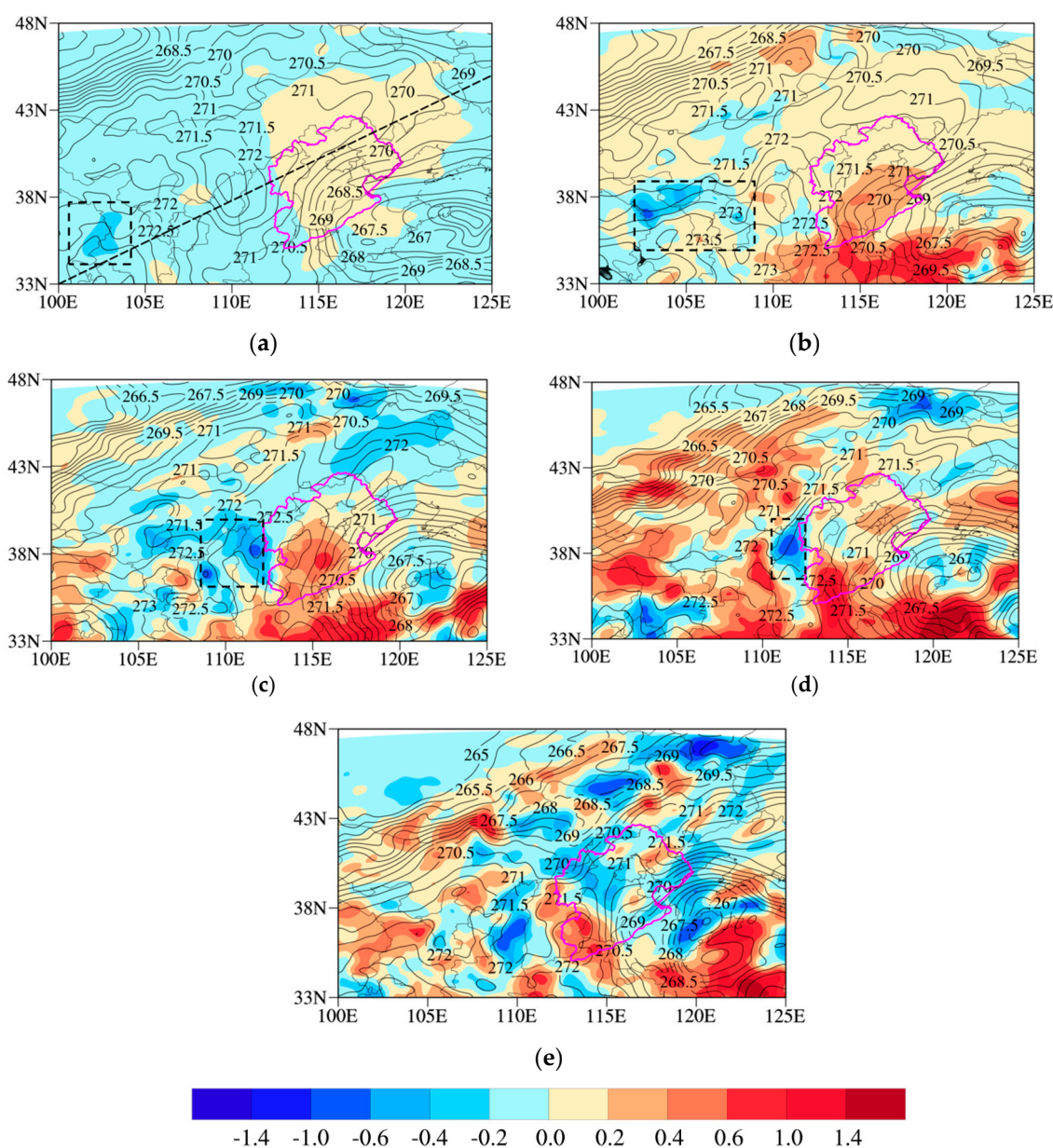


Figure 5. The 500 hPa temperature difference in analysis fields shown as SURF–VAPOR, where the color shading is the temperature difference field and the contours denote the temperature field after assimilating channel 16 on July 10 at (a) 0000 UTC, (b) 0600 UTC, (c) 1200 UTC, (d) 1800 UTC, and (e) 2400 UTC, and the dotted line in (a) represents the position of the profile in Figure 8. The dashed rectangle indicates the key areas of assimilation impact.

As shown in Figure 6, the Haihe River basin is controlled by a low-pressure trough in the west and a low-value center in the east. Trough lines are marked out with thick black curves. The low-pressure trough in the west was flatter at the beginning moment

of assimilation, and since the temperature trough lagged behind the height trough, the low-pressure trough gradually moved eastward and deepened to the south, eventually producing pre-trough precipitation near the Haihe River basin. As the negative temperature difference field near 103° E and 36° N was initially born, the height field after assimilation of channel 16 decreased near the negative temperature difference field and increased near the positive field. The low-pressure trough after assimilation of channel 16 was deeper than the VAPOR test because of this effect.

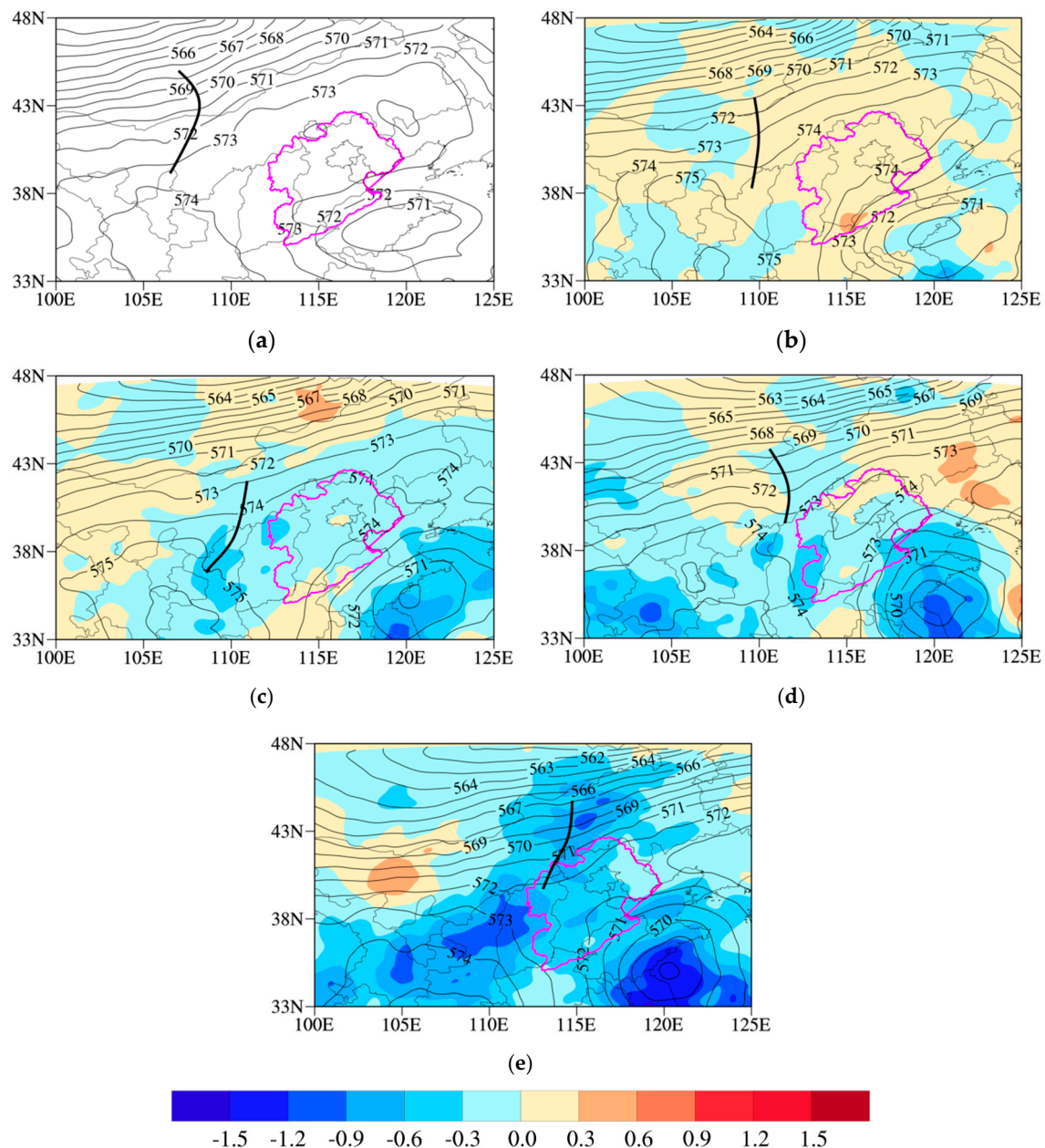


Figure 6. The 500 hPa height difference in analysis fields shown as SURF–VAPOR, where the color shading is the height difference field and contours denote the height field after assimilating channel 16 on July 10 at (a) 0000 UTC, (b) 0600 UTC, (c) 1200 UTC, (d) 1800 UTC, and (e) 2400 UTC. Trough lines are marked out with thick black curves.

Water vapor is also necessary for the occurrence of precipitation, so Figure 7 gives the differential characteristics of the 500 hPa humidity fields of the two experiments. At the beginning of assimilation, the water vapor content is low over the Haihe River basin and high in the western part of the basin. It can be seen from the position of the trough marked by the thick black curve that the area with large specific humidity moves eastward along

with the trough and the area with specific humidity higher than 0.4 g/kg moved toward the Haihe River basin and reached the western edge of the Haihe River basin at 1800 UTC, thus favoring the occurrence of precipitation in this region. After assimilation, the humidity in the SURF test was higher than that in the VAPOR test in the western part of the basin, but over the Haihe River basin, the humidity in the SURF test was lower than that in the VAPOR test. Over time, the effects of assimilation at 1800 UTC gradually accumulated around the basin, eventually leading to an increase in humidity at its periphery and a decrease in humidity at the interior of its western part. It is inferred that in this case, the increase in channel 16 assimilation resulted in an increase in external precipitation and a decrease in internal precipitation over the Haihe River basin.

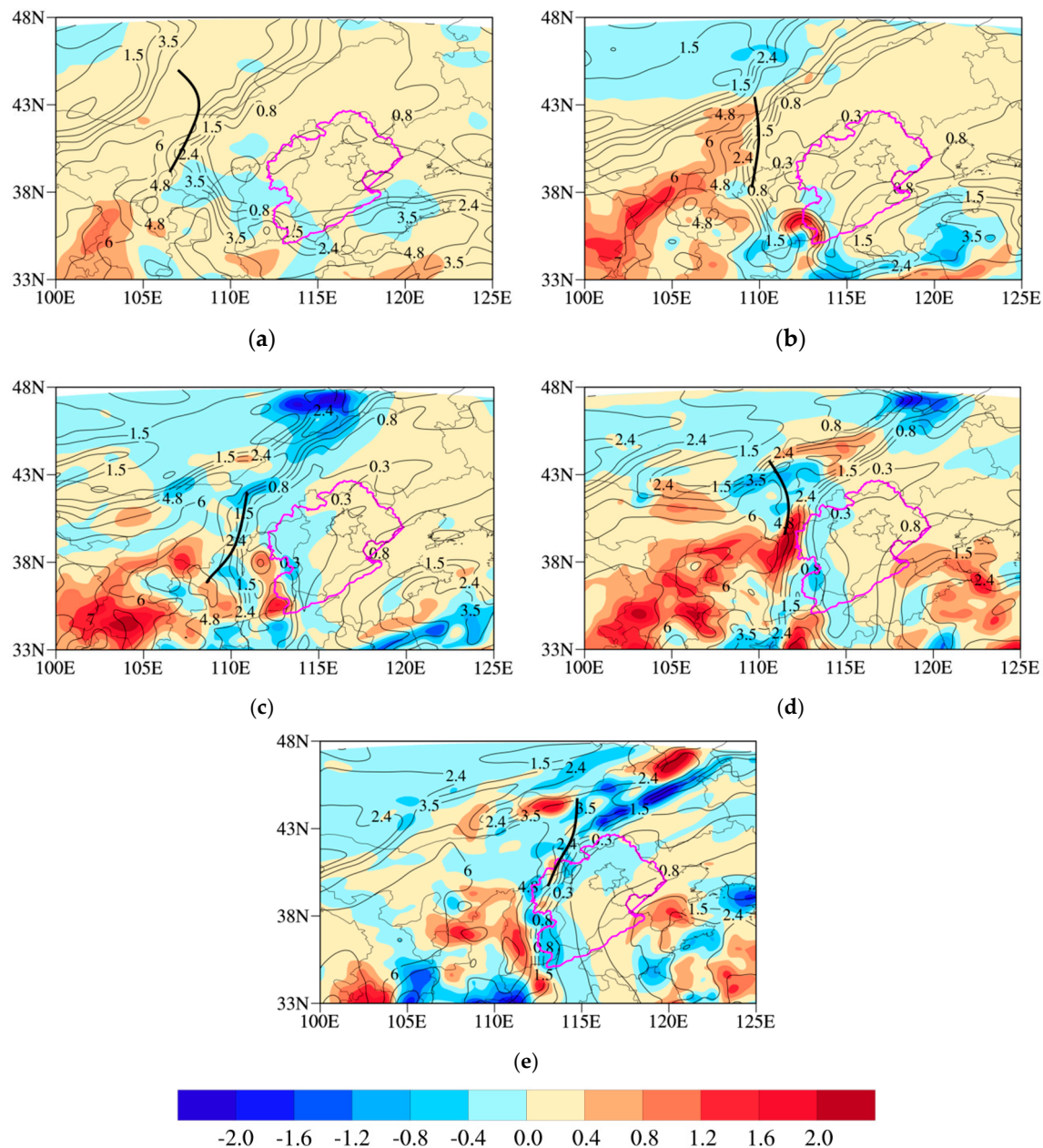


Figure 7. The 500 hPa specific humidity difference in analysis fields shown as SURF–VAPOR, where the color shading is the specific humidity difference field and the contours denote the humidity field after assimilating channel 16 on July 10 at (a) 0000 UTC, (b) 0600 UTC, (c) 1200 UTC, (d) 1800 UTC, and (e) 2400 UTC. Trough lines are marked out with thick black curves.

To see more clearly the development of the impact of increasing the assimilation of channel 16, the dashed line (100° E, 33° N– 125° E, 45° N) in Figure 5 was selected to plot the temperature and geopotential height difference field profiles, which shows in Figure 8; the shading is the temperature field difference, and the contour is the temperature field after assimilation of channel 16. At 0000 UTC within 100° E– 105° E, there was an area with a negative temperature increment (marked by the dashed rectangle) at an altitude of about 4000 m. The high-altitude topography made the assimilation of CO₂ channel 16 of the AHI susceptible to the lower troposphere atmosphere under the influence of westerly winds, meaning a negative temperature anomaly appeared to the west of the Haihe River basin, mainly located between the ground and 500 hPa. The negative-anomaly area at 0000 UTC gradually moved downstream and reached 110° E, i.e., near the Haihe River basin, at 1800 UTC. The decrease in temperature caused a corresponding decrease in the height field, while the increase in temperature upstream led to a more pronounced deepening of the low-pressure trough near 110° E.

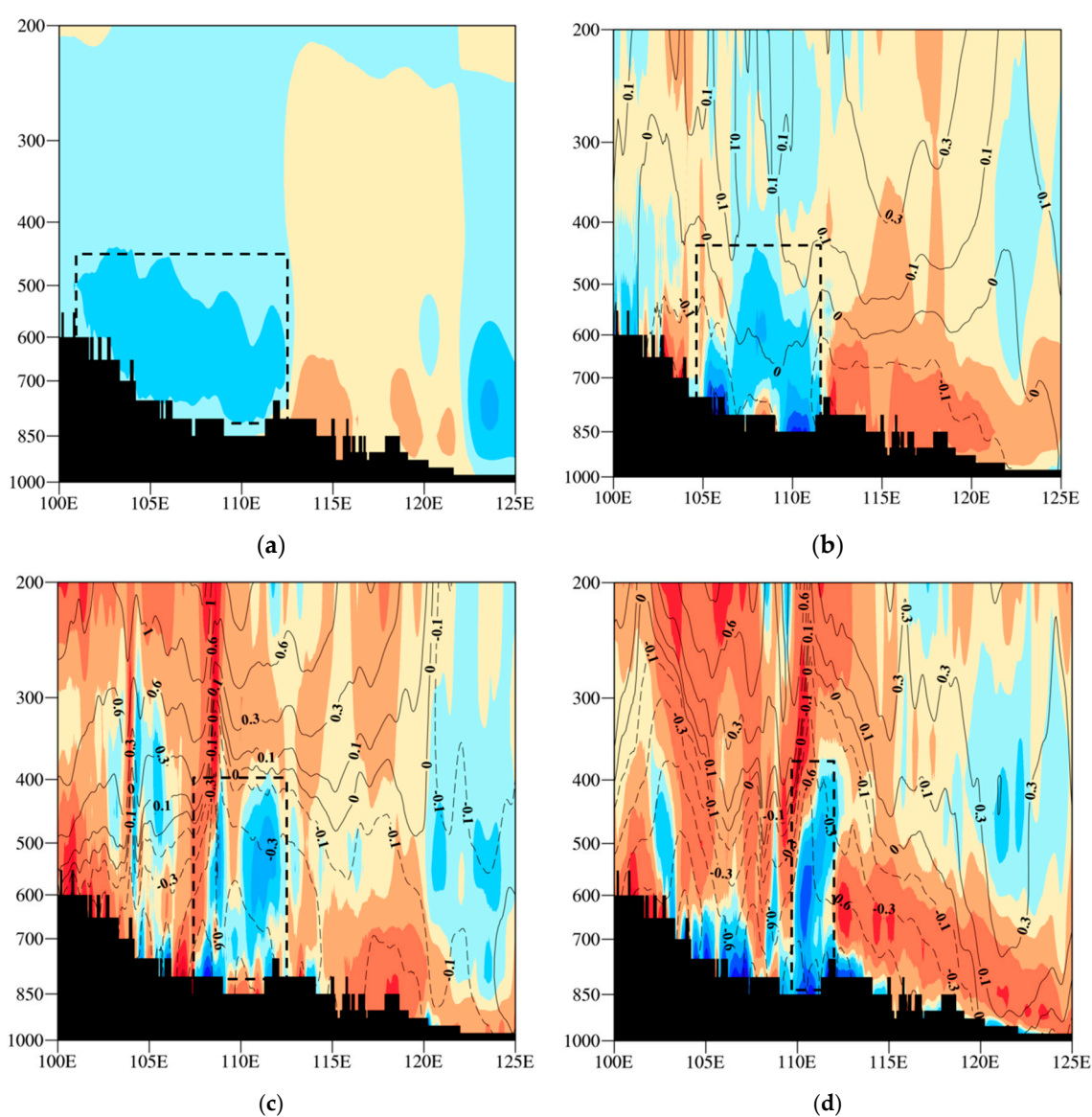


Figure 8. Cont.

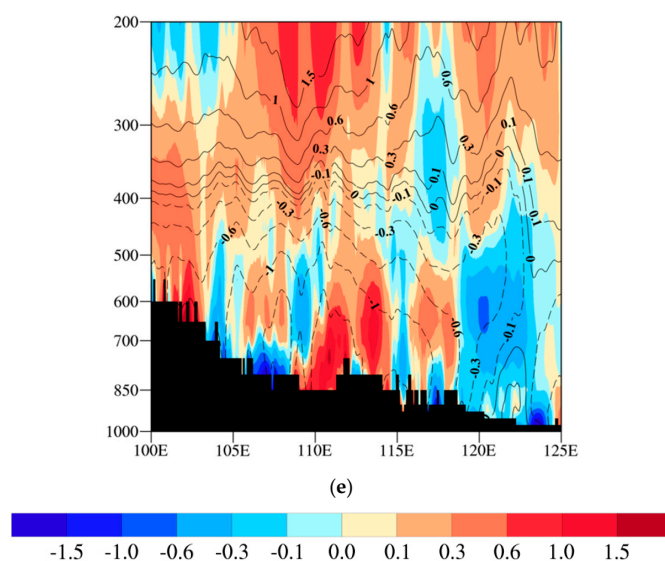


Figure 8. The (100° E, 33° N)–(125° E, 45° N) profiles in which the color shading is the temperature difference and the contours denote the height field differences after assimilating channel 16 on July 10 at (a) 0000 UTC, (b) 0600 UTC, (c) 1200 UTC, (d) 1800 UTC, and (e) 2400 UTC. The dashed rectangle indicates the key areas of assimilation impact.

The effects of the analytical differences between the VAPOR and SURF tests on short-term quantitative precipitation forecasts are shown in Figures 9–12. Figure 9 shows the 3-hourly cumulative rainfall observations for 0000–0300 UTC, 0600–0900 UTC, and 1800–2100 UTC on July 11 2016, and the precipitation difference between forecasts and observations for the corresponding periods are also shown. The observed precipitation showed a band shape associated with a low-pressure trough, with the maximum precipitation occurring in the western periphery of the Haihe River basin and the precipitation mainly affecting most areas of North China. From the rainfall differences, it can be seen that the SURF experiment had too much precipitation at the periphery of the Haihe River basin at the initial moment of the forecast, but the precipitation range within the Haihe River basin was smaller and closer to the actual precipitation in the later stage of the forecast. After assimilation of channel 16, the low-pressure trough deepened by lowering the temperature in the western part of the Haihe River basin, and then the water vapor increased in the western part of the Haihe River basin and decreased in the basin. Finally, the precipitation fell mainly over the western part of the Haihe River basin, and then it moved into the Haihe River basin and decreases and the forecast effect in the basin improved.

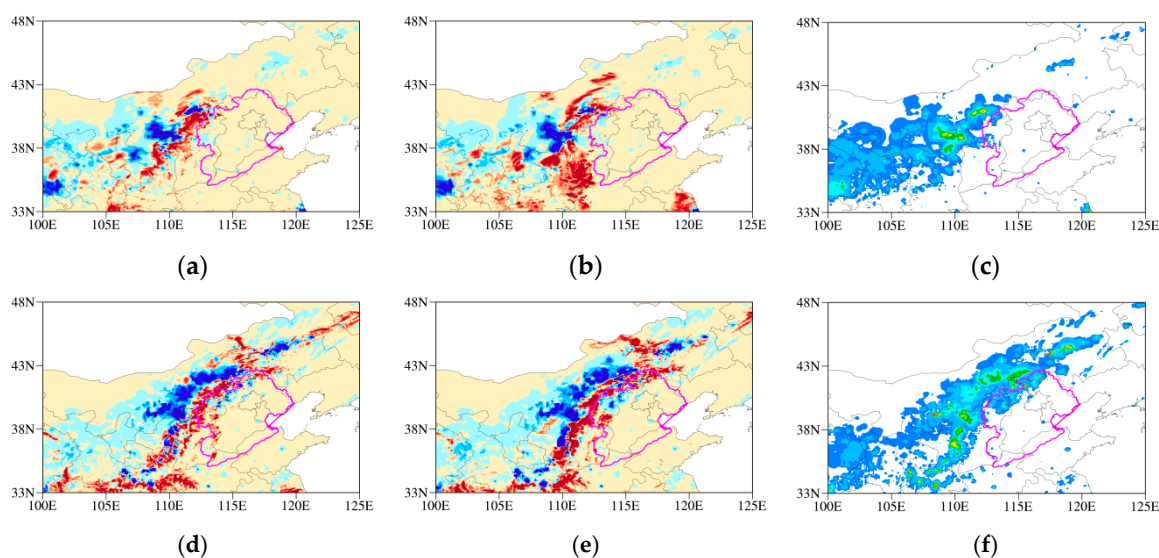


Figure 9. Cont.

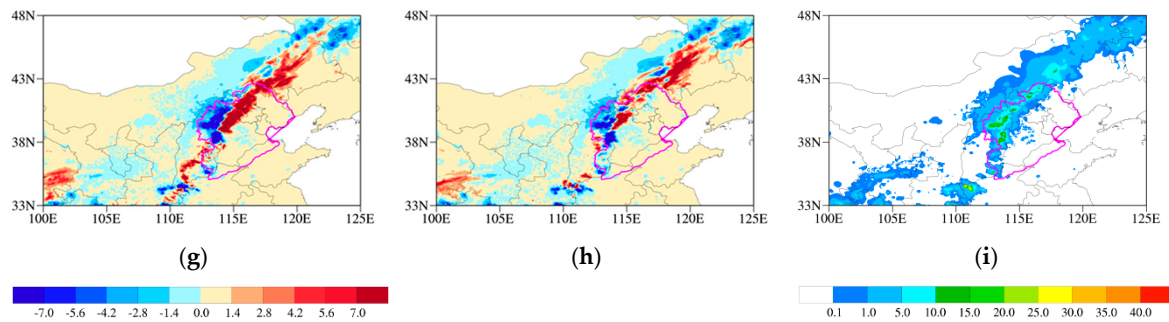


Figure 9. Spatial distribution of 3 h accumulated precipitation and rainfall difference between forecasts and observations (a,b,d,e,g,h) at 0000UTC–0300UTC (a–c), 0600UTC–0900UTC (d–f), and 1800UTC–2100UTC (g–i) on 11 July 2016. The first column is for (VAPOR–OBS), the second column is for (SURF–OBS), and the third column is the observation.

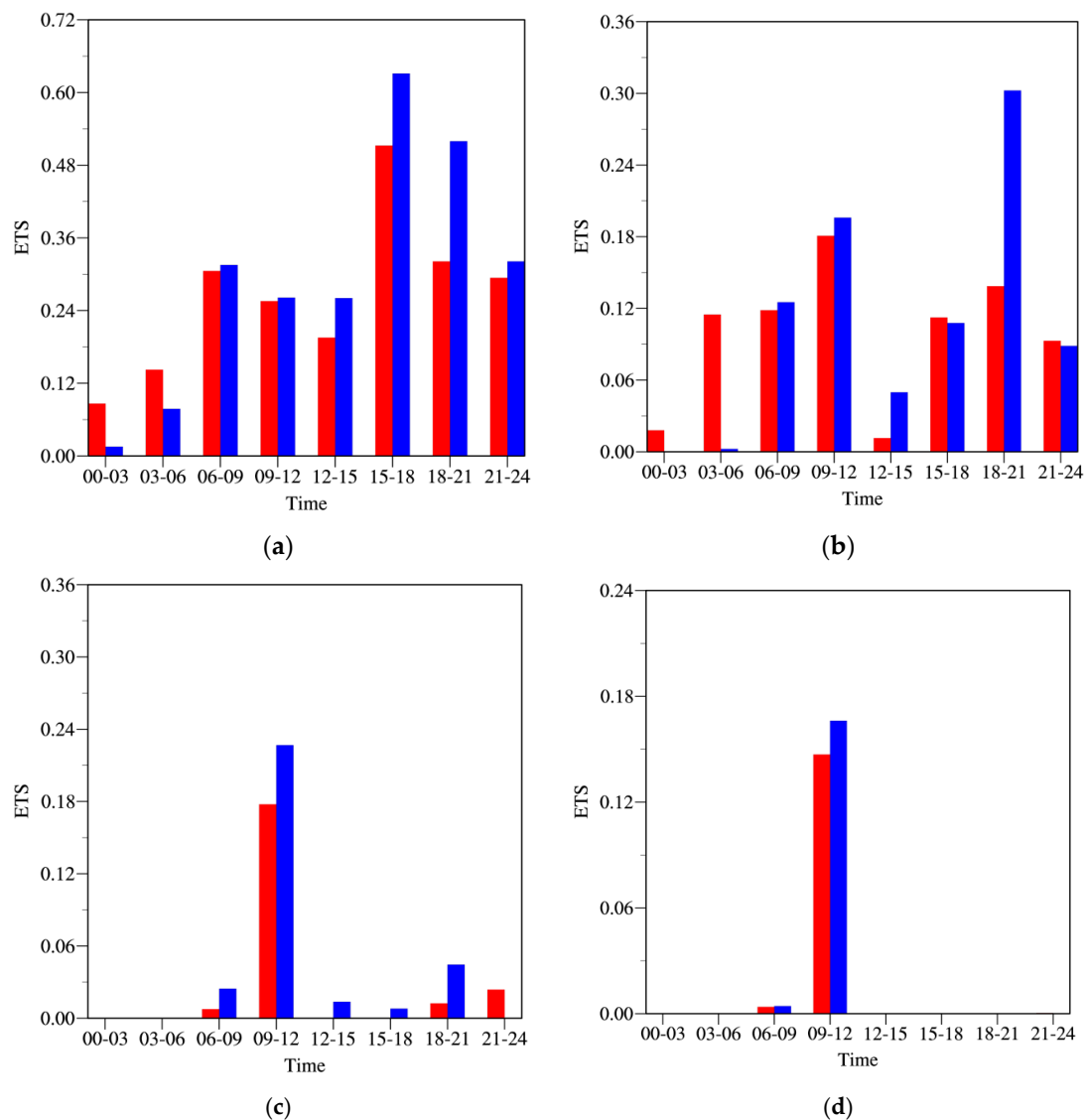


Figure 10. The 3 h accumulated precipitation ETS variation on July 11 2016, in which the blue bars denote the SURF experiment and the red bars the VAPOR experiment, for a threshold of (a) 1 mm, (b) 5 mm, (c) 10 mm, and (d) 15 mm.

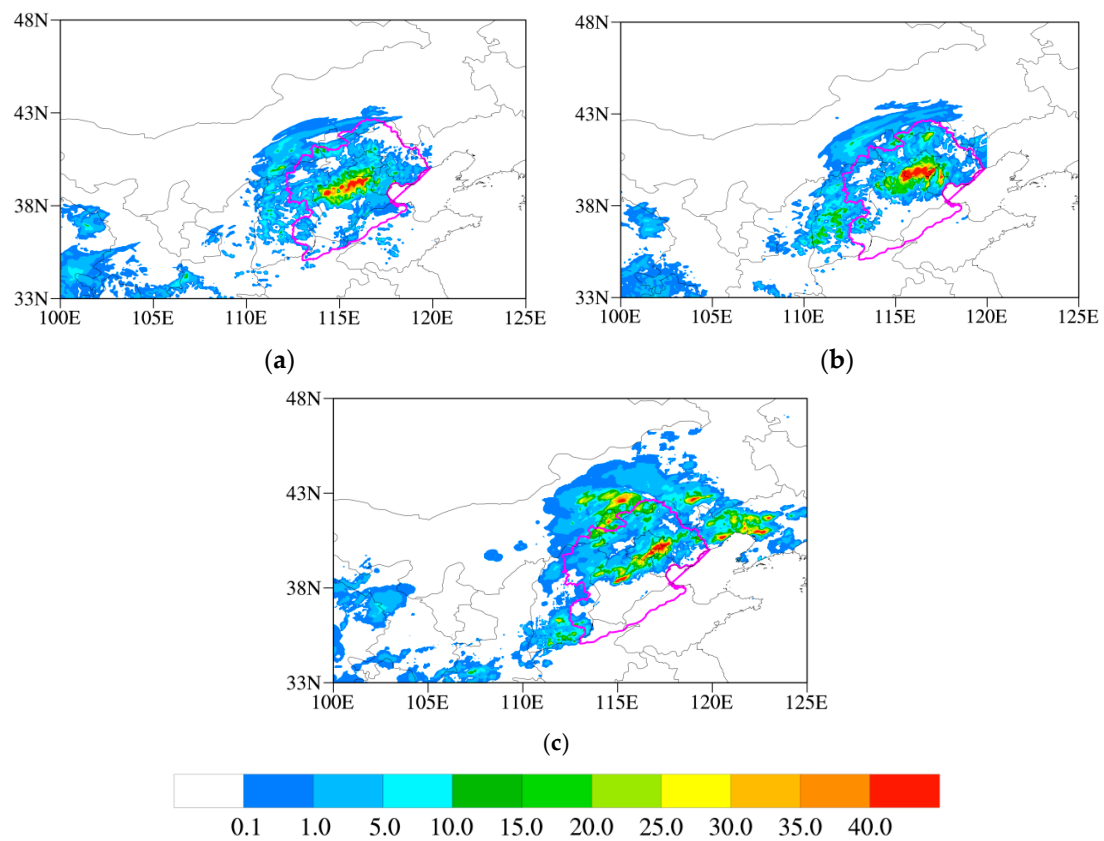


Figure 11. The 3 h accumulated precipitation distribution from 1800 to 2100 UTC on 24 July 2016: (a) forecast field of the VAPOR experiment, (b) forecast field of the SURF experiment, and (c) observed field.

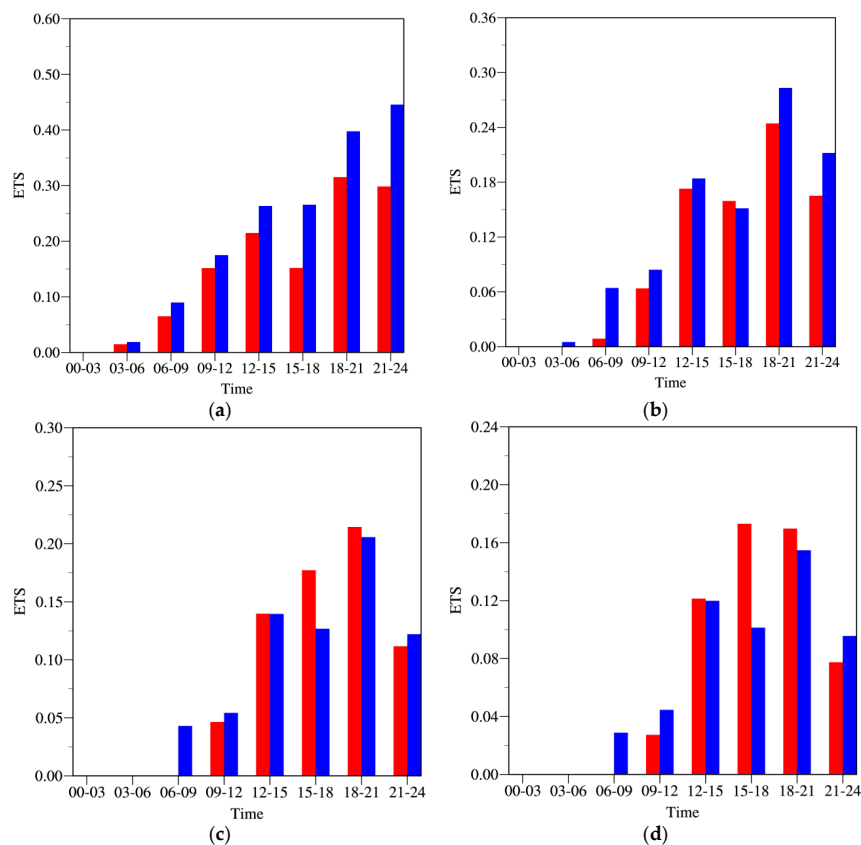


Figure 12. ETS for 3 h accumulated precipitation at thresholds of (a) 1 mm, (b) 5 mm, (c) 10 mm, and (d) 15 mm from VAPOR (red bars) and SURF (blue bars) on 24 July 2016.

To quantitatively evaluate the effect of the two experiments on precipitation forecasting in this case of the Haihe River basin, we presented equitable threat scores (ETSs) for the two experimental thresholds of 1, 5, 10, and 15 mm, as shown in Figure 10.

The ETS is calculated as follows [55]:

$$\text{ETS} = (H - R) / (O + F - H - R) \quad (2)$$

Here, $R = F \times (O/N)$ is the probability of correct stochastic forecasts, the observed rain area exceeding the criterion is O , and the model-predicted area is F . Their intersection (i.e., the hit area) is denoted by H , while the entire verification domain is N .

The ETSs of SURF were generally higher than those of VAPOR for 1 mm and 5 mm, indicating that the addition of channel 16 improves the prediction of the precipitation extent in the Haihe River basin, but the scores of VAPOR were higher than those of SURF at the two initial moments of the forecast, indicating that the effect of assimilating channel 16 is mainly concentrated in the later stages of the forecast. In the ETSs of 10 mm and 15 mm, SURF scores were higher than VAPOR scores except at 2100–2400 for 10 mm, indicating that the assimilation of channel 16 also improves the forecasting of heavy precipitation.

Figure 11 shows the spatial distribution of the 3 h accumulated rainfall observations from 1800 to 2100 UTC on July 24 2016 (Figure 11c, case 2), and the 18–21 h model forecasts of rainfall in VAPOR and SURF (Figure 11a,b), which were forecast at the same time as Figure 11c. The observed precipitation was concentrated in the northern part of the Haihe River basin, with larger amounts occurring at the central and northern edges of the Haihe River basin. Both forecasts captured the general trend of precipitation, but VAPOR appeared to over-report the precipitation in the southern part of the Haihe River basin to a large extent and under-report the precipitation in the northern part. In contrast, SURF had better control of the precipitation extent in the southern part of the Haihe River basin and captured the precipitation in the north that was missed by VAPOR. From the precipitation observation map, the large-value center of this precipitation appeared in the northeast of the Haihe River basin, and the large-value center obtained from the VAPOR test forecast was in the middle of the Haihe River basin, while the SURF test forecast results moved to the northeast, which was closer to the observation. The above analyses can provide a more accurate forecast for this case after adding channel 16. We calculated the ETSs of the two experiments for this case for quantitative analysis, as shown in Figure 12. The red bars represent the ETS scores of the 3 h cumulative precipitation of the VAPOR experiment with assimilated AHI channels 8–10, while the blue bars are for the SURF experiment with AHI channel 16 added. After 6 h, the main precipitation area reached the Haihe River basin, and the magnitude of precipitation gradually increased. The ETS scores of the two forecasts also increased over time. From the comparison of scoring results, it can be seen that assimilating AHI channel 16 observations in the land area showed an obvious improvement in the precipitation prediction below 10 mm, the ETS score at all times significantly increased, and the improvement effect of channel 16 was more obvious with the increase in forecasting time. For areas with large rainfall, except for a slight decline in prediction skills in the time period between 15 and 21 h, the SURF experiment with data assimilated from channel 16 still had a good improvement effect on the precipitation prediction skills at other times.

To further assess the stability of the impact of channel 16 assimilation on the precipitation forecasts, we also conducted a 20-day cyclic assimilation forecast experiment starting on 10 July 2016. The experimental design was consistent with the two individual cases. The background field for every day was a 6 h forecast initialized at 1800 UTC of the previous day using the NCEP final analysis data, and then a 24 h prediction was made after five assimilation cycles at 6 h intervals. To make the results clearer, we provided the results of daily average ETS scores. According to the results of the 20-day forecast experiments, assimilating AHI channel 16 improved the rainfall forecast of Haihe River basin. It can be seen from Figure 13a that the ETS score decreased slightly in only 4 of the 20 days, and there was a steady improvement in ETS scores for the last 8 consecutive days. Similar to the two experiments analyzed above, there were relatively large uncertainties in the heavy rain

forecast. Among the results of the 5 mm and 10 mm threshold, 6 of 20 days had negative effects, but it was still characterized by improvement on the whole.

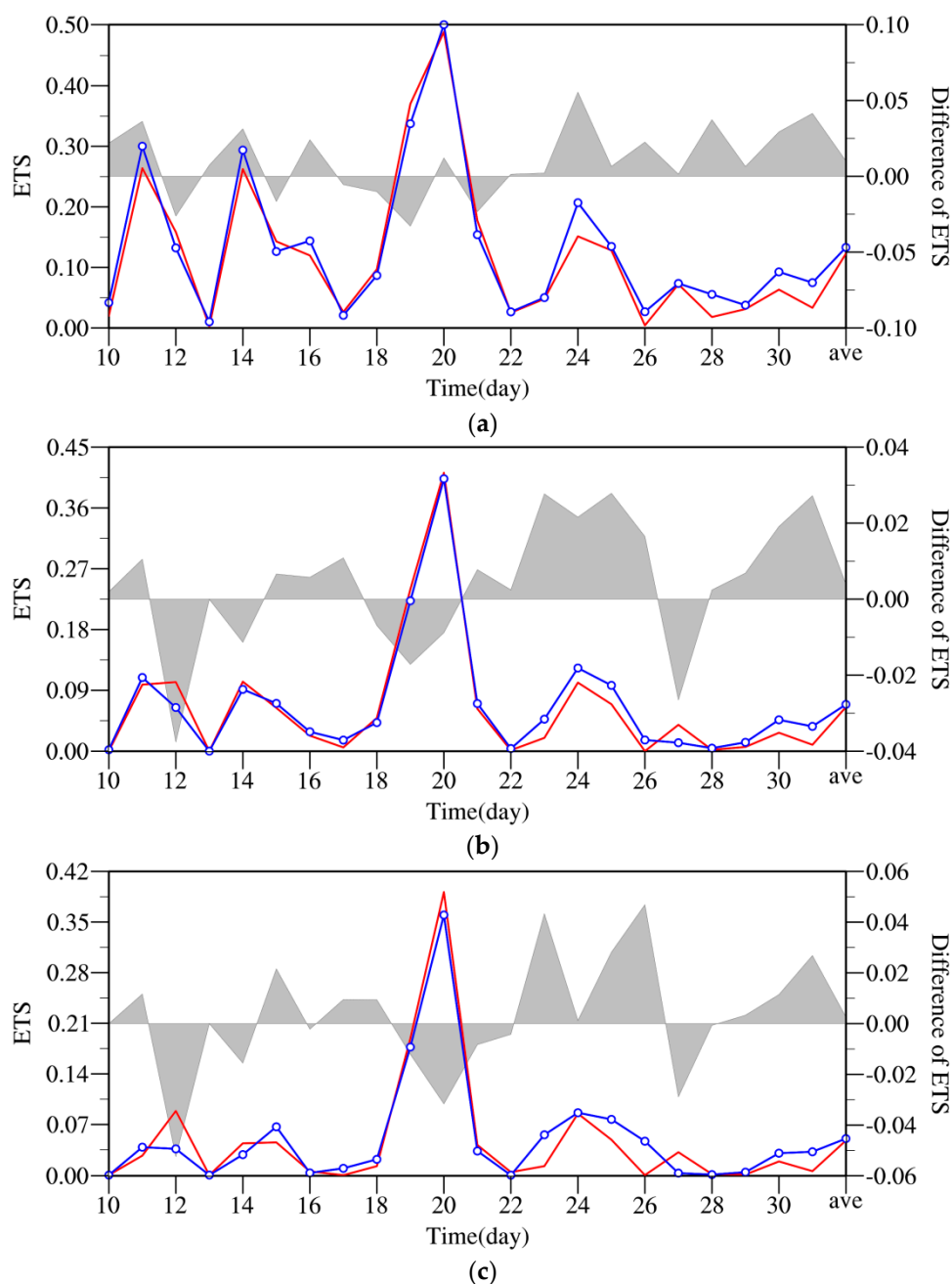


Figure 13. Daily average accumulated precipitation ETS variation for July 2016, in which the blue line denotes the SURF experiment, the red line denotes the VAPOR experiment, and shading indicates the difference (blue line minus red line) for thresholds of (a) 1 mm, (b) 5 mm, and (c) 10 mm.

4. Summary and Discussion

Accurate forecasting of basin precipitation is crucial for flood warnings and flow forecasting for hydroelectric power generation. In addition, most basin precipitation possesses small-scale characteristics, so we need to use high spatial- and temporal-resolution data to improve the accuracy of forecasting. Geostationary satellite imager observations meet these needs, and imagers, such as the AHI, include more water vapor and surface channels, which has improved the spectral resolution of their observations. The sensitivity of the brightness temperature of AHI channel 16 to the lower-tropospheric temperature is greater

than the sensitivity to the surface emissivity, as derived from concomitant model sensitivity tests. Therefore, we added channels to the assimilation of AHI data over land.

This study compared the precipitation forecast results of two sets of experiments—one that assimilated AHI channels 8–10 and the other that assimilated channels 8–10 and 16—for the Haihe River basin in China. The results showed that the addition of channel 16 data assimilation over land areas can improve the 24 h short-term precipitation forecasts by affecting the temperature field, thus leading to changes in other environmental fields. The 20-day cyclic assimilation experiments also demonstrated that assimilating channel 16 leads to a stable improvement in forecasts of the precipitation extent; however, assimilating channel 16 in basin precipitation forecasts can result in overestimation, which needs to be addressed in follow-up work.

Due to the limitation of computational resources, the paper only conducted a 20-day rolling test, although the results of the rolling test show that adding AHI channel 16 data can improve the precipitation prediction level of the Haihe River basin. However, the 20-day rolling test is not enough for statistical significance, so there is inevitable uncertainty in the current results. In future research, we will add more rolling tests in different time periods to better evaluate the impact of AHI channel 16 data assimilation on watershed precipitation forecasting.

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