

Postprint: Precipitation Retrieval in Xinjiang Region Based on Radar and Remote Sensing Satellite

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Abstract

To obtain more accurate precipitation distribution information in remote regions, this study combines the high-resolution capability of radar with the large-scale detection advantage of satellite to obtain high-precision Quantitative Precipitation Estimation (QPE) analysis products through fusing radar-retrieved and satellite-retrieved precipitation. Taking the two-day severe convective events on August 12–13, 2023 in Xinjiang as an example, radar precipitation retrieval is performed using radar reflectivity through cloud classification and Z-R relationship methods; Himawari-9 satellite brightness temperature and IMERG precipitation are input into a BP neural network model to establish the relationship between average brightness temperature and average rainfall intensity, and subsequently Himawari-9 satellite instantaneous brightness temperature is input into the BP neural network model to retrieve instantaneous precipitation; simultaneously, Scheme 1 is proposed to fuse radar-retrieved and satellite-retrieved precipitation using a uniform correction value, and based on this, Scheme 2 considering rainfall intensity levels for fusion is further developed for comparison, finally obtaining high-precision precipitation retrieval products for Xinjiang. The results show that: (1) Precipitation within radar coverage can be estimated in detail by classifying cloud types through brightness temperature, and utilizing brightness temperature differences can reduce the influence of non-precipitating clouds to a certain extent. (2) The root mean square error of satellite-retrieved precipitation is $1.793 \text{ mm} \cdot \text{h}^{-1}$, the coefficient of determination is 0.572, the model accuracy is relatively reasonable, and the binary classification scoring results indicate that the model can accurately retrieve over 70% of precipitation areas. (3) The fusion precipitation from both schemes has limited improvement in accuracy for short-duration light rain, Scheme 2 outperforms Scheme 1 for short-duration moderate rain, and Scheme 2 shows a slight decrease compared to Scheme 1 for short-duration heavy rain. This

indicates that the asynchrony between high-altitude satellite observations and near-surface precipitation has certain impacts. (4) Under the 95% confidence interval, the P-values from significance tests for differences in root mean square error and coefficient of determination between both schemes and satellite retrieval are less than 0.005, while the P-value of Scheme 2 compared to Scheme 1 is greater than 0.05. Both precipitation fusion schemes significantly improved satellite precipitation accuracy, but Scheme 2 considering rainfall intensity levels provided only minor accuracy improvement over Scheme 1 using uniform correction values.

Full Text

Precipitation Retrieval for Xinjiang Region Based on Radar and Remote Sensing Satellites

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Abstract

To obtain more accurate precipitation distributions in remote areas, this study combines the high-resolution advantages of radar with the large-scale detection capabilities of satellites. By integrating radar-derived and satellite-derived precipitation, we generated high-precision quantitative precipitation estimation analysis products. Using the strong convective weather process in Xinjiang on August 12-13, 2023 as a case study, we employed cloud classification and Z-R relationships to perform radar precipitation retrieval using radar reflectivity. We fed Himawari-9 satellite brightness temperature and IMERG precipitation data into a BP neural network model to establish the relationship between average brightness temperature and average rainfall intensity, then used instantaneous Himawari-9 brightness temperature as input to the BP neural network model to retrieve precipitation at specific moments. We proposed Scheme I, which uses a uniform correction value to fuse radar and satellite precipitation retrievals, and Scheme II, which further considers precipitation intensity levels for comparison. The final product provides high-precision precipitation retrieval for Xinjiang. The results show that: (1) Cloud classification based on brightness temperature can finely estimate precipitation within the radar coverage area, and brightness temperature differences can reduce the influence of non-precipitating clouds to some extent. (2) The satellite retrieval achieved a root mean square error (RMSE) of $1.793 \text{ mm} \cdot \text{h}^{-1}$ and a coefficient of determination (R^2) of 0.572, indicating reasonable model accuracy. The binary classification score shows the model can accurately retrieve precipitation in over 70% of the area. (3) Both fusion schemes showed limited improvement for short-duration light rain accu-

racy. Scheme II outperformed Scheme I for short-duration moderate rain, but performed slightly worse for short-duration heavy rain, suggesting that asynchrony between satellite observations and near-surface precipitation has some impact. (4) Under a 95% confidence interval, the P-values for RMSE and R^2 differences between both schemes and satellite retrieval were all less than 0.005, while the P-value between Scheme II and Scheme I was greater than 0.05. Both fusion schemes significantly improved satellite precipitation accuracy, but the improvement of Scheme II over Scheme I was minimal.

Keywords: multi-radar; Himawari-9 satellite; brightness temperature; precipitation retrieval; BP neural network; precipitation data fusion; Xinjiang

1. Materials and Methods

1.1 Study Area Overview

The research event is a strong convective weather process in Xinjiang. The study area ($34^{\circ}5'-49^{\circ}5'N$, $80^{\circ}0'-96^{\circ}7'E$) includes most regions detectable by satellites in Xinjiang (Figure 1). To ensure temporal consistency among radar, remote sensing satellite, and station observations, the study period was unified from 00:00 on August 12 to 23:30 on August 13, 2023. The base map uses the standard map from the Ministry of Natural Resources (approval number GS(2019)1822), with no modifications to boundary lines.

1.2 Data Sources

Himawari-9 Satellite Data: Obtained from the Japan Aerospace Exploration Agency (JAXA) website, with a temporal resolution of 10 minutes and spatial resolution of 2 km. Compared with other remote sensing data, its short time interval and high resolution better meet research needs. Himawari-9 has 16 band channels: visible light (B1-B3), near-infrared (B4-B6), infrared (B7-B16), with the last two channels representing solar elevation and azimuth angles. Existing studies often use visible, water vapor, and infrared channels for precipitation retrieval. Himawari-9's infrared channels provide rich precipitation information and substantial data support. This study excluded shortwave infrared (B4-B6), ozone (B7), and CO_2 channels (B8-B11) that have low correlation with precipitation, and avoided the limitation of nighttime unobservable visible light. Finally, three water vapor channels (B8-B10) and four infrared channels (B13-B15) brightness temperature data were selected for precipitation retrieval, with wavelengths of 6.2 m, 6.9 m, 7.3 m, 10.4 m, 11.2 m, and 12.4 m, respectively. The data have been projected and radiometrically calibrated.

IMERG Precipitation Data: Downloaded from the NASA website as the "Final Run" version. With a temporal resolution of 30 minutes and spatial resolution of 10 km, IMERG precipitation products reference gauge data during production, making them relatively consistent with ground radar observations. Therefore, using IMERG data as ground truth for satellite precipitation retrieval is reliable and ensures good compatibility for subsequent data fusion.

CINRAD/CC Weather Radar Base Data and Rain Gauge Observations: Provided by the Urumqi Meteorological Satellite Ground Station. Radar stations include Kuitun, Wujiaqu, Jinghe, Urumqi, and Shihezi, with temporal resolution of 6 minutes and spatial resolution of 500 m. Every 30-minute frame corresponding to satellite data was selected for study. Rain gauge data are cumulative rainfall observations from national automatic weather stations in Xinjiang during the 10 minutes before each hour, with 67 stations in the study area.

1.3 Radar Data Processing

Using the PyCINRAD library to parse radar base data yields information on station coordinates, elevation angles, scan times, and data dimensions. Original radar echoes contain significant ground clutter, non-precipitation weak echoes, super-refraction echoes, and singular points. Based on echo characteristics, the following quality control methods were applied, with changes in radar composite reflectivity mosaics shown in Figure 2.

The composite reflectivity mosaic combines five single-station radar echoes at the same time using the maximum value method. To reduce boundary data discontinuities and preserve high-resolution radar echo features, a Cressman weighting scheme was applied:

$$V_x = \frac{\sum_{i=1}^N W_i V_i}{\sum_{i=1}^N W_i}$$

where V_x is the interpolated value at pixel x , V_i is the value at pixel i , W_i is the influence weight of pixel i on pixel x , and N is the total number of pixels affecting pixel x . Quality control included: (1) removing echoes < 5 dBZ using a $3\text{S} \times 3\text{S}$ grid convolution kernel filter to eliminate ground clutter, false echoes, and singular points; (2) applying median and bilateral filters to process super-refraction and fluctuation echoes.

1.4 Radar Data Precipitation Retrieval

Considering that radar and Himawari-9 data are instantaneous observations while IMERG data represent 30-minute average rainfall intensity, we performed 30-minute averaging. Table 1 shows the cloud classification method and corresponding parameters. Different cloud types were classified using brightness temperature differences from the B13 channel at corresponding times, and radar quantitative precipitation retrieval was performed using the Z-R relationship with coefficients a and b according to cloud type. This method effectively distinguishes different cloud types, enabling detailed precipitation estimation for various reflectivity values and improving retrieval accuracy.

The Z-R relationship is expressed as:

$$Z = aR^b$$

where Z is radar reflectivity ($\text{mm}^6 \cdot \text{m}^{-3}$) and R is rainfall intensity ($\text{mm} \cdot \text{h}^{-1}$). Due to limited observational data in remote Xinjiang regions, empirical a and b coefficients were used. The B13 channel (10.4 μm) is less absorbed and scattered by the atmosphere, directly reflecting cloud top temperature characteristics.

1.5 Remote Sensing Satellite Data Precipitation Retrieval

Non-precipitating clouds such as stratiform and cirrus clouds can cause low brightness temperatures in some channels without actual precipitation, leading to large errors when using single-channel brightness temperature and rainfall intensity to establish empirical exponential functions. This study used brightness temperature differences from three water vapor channels (B8-B10) and four infrared channels (B13-B15) from Himawari-9. Following a pixel-to-pixel approach and based on IMERG precipitation data, we trained a BP neural network model for retrieval.

The main steps were: (1) Within each 30-minute period starting at time t , calculate the overall average brightness temperature at times t , $t+10$ min, $t+20$ min, and $t+30$ min to match IMERG average precipitation; (2) Resample the 10-minute average brightness temperature images to 10 km resolution to match IMERG precipitation images, yielding 2,160 pairs of average brightness temperature and IMERG precipitation images from 00:00 on August 12 to 05:30 on August 13 and from 14:00 on August 13 to 23:30 on August 13 as the training set, and 1,080 groups from 06:00 to 13:30 on August 13 as the test set; (3) Use the 7-channel average brightness temperature images as input and average precipitation images as targets; (4) Apply bilinear interpolation to resample 10-minute brightness temperature data to 500 m resolution, then input into the model for pixel-by-pixel retrieval.

Due to scattered low brightness temperature areas and different satellite data resolutions, retrieval results may contain singular points and isolated regions with large differences. After returning data to the corresponding grid positions, singular points were identified using mode statistics with a gradient threshold of $1.5 \text{ mm} \cdot \text{h}^{-1}$. For each pixel, the average of 8 surrounding pixels in a 3×3 grid was calculated; if the difference exceeded the threshold, the point was replaced by the average. Points with fewer than 4 surrounding pixels were considered isolated and removed.

1.6 BP Neural Network Model Design

Following precipitation retrieval methods using BP neural networks, we designed a three-layer network. The number of hidden layer nodes was calculated using:

$$s = \sqrt{n + l} + a$$

where s is the total hidden layer nodes, n is input layer nodes, l is output layer nodes, and a is a constant between 1-10. The transfer functions were: hidden layers using Tansig, output layer using Purelin:

$$\text{Purelin} = x$$

The algorithm includes forward and backward propagation. In forward propagation, hidden and output layer activation values are calculated. Gradient descent computes minimum errors backward through layers. In backward propagation, output layer error terms calculate hidden layer errors, then update weights and thresholds iteratively until convergence.

1.7 Fusion of Radar and Satellite Precipitation Retrieval

Fusion methods reference existing research. In radar-covered areas, radar quantitative precipitation R_R is used directly. In radar-uncovered areas, two schemes were implemented:

Scheme I: Calculate normalized relative error W_N for each precipitation pixel in the co-covered area, then compute average W_N across all pixels. Apply W_N to correct satellite precipitation data in radar-uncovered areas: $R'_S = R_S \times (1 - W_N)$.

Scheme II: To explore how precipitation intensity levels affect fusion accuracy, Scheme II extends Scheme I by classifying radar-derived precipitation into short-duration light rain ($R \leq 2.0 \text{ mm} \cdot \text{h}^{-1}$), moderate rain ($2.0 < R \leq 4.0 \text{ mm} \cdot \text{h}^{-1}$), and heavy rain ($4.0 < R \leq 8.0 \text{ mm} \cdot \text{h}^{-1}$) according to short-term nowcasting standards. It calculates average normalized relative errors for each intensity level in radar-covered areas, then applies corresponding corrections to satellite data in uncovered areas.

To ensure boundary continuity, weight parameters were adjusted using 5 times the radar data resolution (2.5 km), setting fusion weights to 0.5 within this buffer zone.

1.8 Evaluation Methods

We used Probability of Detection (POD), False Alarm Rate (FAR), and Heidke Skill Score (HSS) for binary classification evaluation:

$$\text{POD} = \frac{H}{H + M}, \quad \text{FAR} = \frac{F}{H + F}, \quad \text{HSS} = \frac{2(H \times Y - F \times M)}{(H + M)(M + Y) + (H + F)(F + Y)}$$

where H is hits, M is misses, F is false alarms, and Y is correct negatives. $\text{POD} = 1$ and $\text{FAR} = 0$ indicate perfect overlap between simulated and actual precipitation areas.

We also used coefficient of determination (R^2) and root mean square error (RMSE) to evaluate retrieval accuracy:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - z_i)^2}{\sum_{i=1}^n (z_i - \bar{y})^2}, \quad \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - z_i)^2}$$

where z_i is observed value, y_i is simulated value, $\bar{y}$ is mean observed value, and n is total grid points.

2. Results and Analysis

2.1 Radar Retrieval Precipitation Results

Radar-derived precipitation images show that high rainfall intensity generally corresponds to low brightness temperature. The precipitation area calculated from radar clearly corresponds to lower brightness temperature in Figure 3. However, low brightness temperatures (240–280 K) exist in non-precipitating regions within radar coverage, consistent with cirrus clouds, indicating non-precipitating clouds with low brightness temperature during this event. The distribution contours of brightness temperature and precipitation are not completely consistent, suggesting a time lag between high-altitude satellite observations and near-surface precipitation, which affects this study.

2.2 Satellite Retrieval Precipitation Analysis

Low brightness temperature values in all channels correspond to high rainfall intensity, particularly evident in water vapor channels. In the four infrared channel images in Figure 4, a southwest-northeast oriented low brightness temperature band around 280 K exists in the east-southeast direction. In water vapor channel images, this brightness temperature is consistent with non-precipitating regions (260–280 K), allowing discrimination of non-precipitating clouds.

The 6.2 m channel shows sensitive relationships between brightness temperature and rainfall intensity. Figure 5 shows the scatter distribution between retrieved average precipitation from the test set and IMERG precipitation, with most data clustered around the 1:1 line. Statistical analysis of 1,080 test samples yielded $\text{RMSE} = 1.793 \text{ mm} \cdot \text{h}^{-1}$ and $R^2 = 0.572$, indicating reasonable model accuracy. The binary classification scores (Table 2) show the model can identify >70% of precipitation areas but performs relatively poorly for light rain and below.

Brightness temperature and rainfall intensity show good negative correlation, consistent with precipitation characteristics under low brightness temperature conditions. Smaller absolute brightness temperature differences between water vapor and infrared channels correspond to higher rainfall intensity, helping identify non-precipitating cloud interference.

2.3 Radar and Satellite Precipitation Fusion Results

After processing singular points and isolated regions in the retrieved images and fusing radar precipitation data, the final precipitation distribution was obtained (Figure 7). Compared with satellite precipitation, both fusion schemes increased heavy rainfall intensity values, while light rain values changed little. Scheme II further improved moderate rain intensity compared with Scheme I, but heavy rain intensity changes were minimal.

To analyze specific intensity changes, rainfall from 67 meteorological stations was converted to hourly rainfall intensity values. Both schemes improved rainy-period retrieval accuracy, with Scheme II performing better (Table 3). For light rain, both schemes showed limited improvement but Scheme II was superior. For moderate rain, Scheme II's accuracy improvement was more significant (RMSE decreased by $0.306 \text{ mm} \cdot \text{h}^{-1}$, R^2 increased by 0.234). For heavy rain, both schemes improved accuracy, but Scheme II performed slightly worse than Scheme I, indicating limitations in optimizing heavy rain retrieval accuracy, possibly due to spatial offset of high-intensity areas caused by asynchrony between satellite and surface observations.

Significance tests on 1,620 sample points (Table 4) showed that under 95% confidence intervals, differences between both schemes and satellite retrieval were significant ($P < 0.005$), while differences between Scheme II and Scheme I were not significant ($P > 0.05$). Both fusion methods significantly improved satellite precipitation accuracy, but Scheme II's improvement over Scheme I was limited.

3. Discussion

The precipitation retrieval method proposed in this study has certain applicability in Xinjiang. Satellite cloud classification provides fine estimation of radar precipitation, offering high spatiotemporal resolution monitoring information, particularly for capturing small-scale, rapidly developing local convective precipitation. Using multi-channel brightness temperature differences from satellites reduces non-precipitating cloud effects, enabling accurate precipitation retrieval and large-scale distribution mapping. The correction fusion method for different rainfall intensity levels further improves retrieval accuracy.

However, Xinjiang's precipitation complexity, closely related to terrain and local convection, features strong suddenness, short duration, high intensity variability, intermittency, and discontinuity, increasing retrieval difficulty. Both fusion schemes showed limited improvement for short-duration light rain, possibly due to strong convective cloud effects and orographic lifting that alter precipitation intensity and distribution. The 500 m resolution of satellite brightness temperature data, even after resampling, struggles to capture these subtle effects.

Asynchrony between high-altitude satellite observations and near-surface precipitation causes spatial offsets in precipitation distribution, interfering with

retrieval results. Future research should: (1) Incorporate more microphysical processes and meteorological elements (temperature, humidity, wind fields) to broaden data types and optimize processing; (2) Apply CNN and RNN models for improved image processing, combined with real-time monitoring to better capture precipitation details and reduce spatial offsets; (3) Analyze long-term climate change impacts on precipitation patterns to optimize retrieval methods for different timescales; (4) Use super-resolution techniques or combine FY-4A data to solve Himawari-9's limited coverage over Xinjiang.

4. Conclusions

This study proposes a high-resolution, large-scale precipitation distribution retrieval method, yielding high-precision quantitative precipitation estimation products for Xinjiang. Main conclusions are:

- 1) Radar and satellites both detect precipitation through electromagnetic waves with similar product characteristics, and satellite brightness temperature correlates with precipitation. Cloud classification based on brightness temperature enables detailed radar reflectivity estimation, while brightness temperature differences from 3 water vapor and 4 infrared channels reduce non-precipitating cloud effects.
- 2) Both fusion schemes improved short-duration moderate rain and above, but showed limited correction for light rain. Compared with Scheme I's uniform normalized relative error correction, Scheme II's intensity-level-specific correction improved overall retrieval accuracy and light/moderate rain performance, but had limitations for heavy rain.
- 3) Asynchrony between high-altitude satellite observations and near-surface precipitation affects retrieval accuracy. The proposed method overcomes limitations of traditional satellite-only retrieval in data-scarce remote areas, providing efficient and accurate technical support for precipitation monitoring in Xinjiang. Future work should integrate more meteorological elements and optimize models for complex conditions.

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