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ARTICLE

A Quality Control Scheme for Weather Radar Radial Speed toward Data Assimilation

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ABSTRACT

In order to further enhance the numerical application of weather radar radial velocity, this paper proposes a quality control scheme for weather radar radial velocity from the perspective of data assimilation. The proposed scheme is based on the WRFDA (Weather Research and Forecasting Data Assimilation) system and utilizes the biweight algorithm to perform quality control on weather radar radial velocity data. A series of quality control tests conducted over the course of one month demonstrate that the scheme can be seamlessly integrated into the data assimilation process. The scheme is characterized by its simplicity, fast implementation, and ease of maintenance. By determining an appropriate threshold for quality control, the percentage of outliers identified by the scheme remains highly stable over time. Moreover, the mean errors and standard deviations of the O-B (observation-minus-background) values are significantly reduced, improving the overall data quality. The main information and spatial distribution features of the data are preserved effectively. After quality control, the distribution of the O-B Probability Density Function is adjusted in a manner that brings it closer to a Gaussian distribution. This adjustment is beneficial for the subsequent data assimilation process, contributing to more accurate numerical weather predictions. Thus, the proposed quality control scheme provides a valuable tool for improving weather radar data quality and enhancing numerical forecasting performance.

Keywords: Weather Radar Radial Velocity; Quality Control; Data Assimilation

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1. Introduction

The Doppler weather radar has high sensitivity, stable and reliable hardware and software, and is capable of automatic unattended observation in all weather conditions [1]. It is an important tool for monitoring small- and medium-scale hazardous weather systems. Doppler weather radar can provide three basic data types with high temporal and spatial resolution: radial velocity, reflectivity factor, and spectral width [2]. Among them, radial velocity can accurately provide detailed wind field information of weather systems and has played an important role in disaster weather early warning for many years, making it an indispensable data source for nowcasting [3]. At the same time, with the continuous improvement of China's next-generation weather radar network and the rapid development of numerical weather prediction technology, the assimilation of Doppler weather radar radial velocity data has received increasing attention, and its role in improving the initial field of numerical models has become more significant [4]. However, whether for direct diagnostic analysis of weather radar radial velocity, the production of subsequent analysis products, or the assimilation of weather radar radial velocity data, quality control of raw radial velocity observations is necessary [5]. Currently, domestic and international scholars have focused on the quality control of weather radar radial velocity, mainly concentrating on velocity de-aliasing [6].

Ray et al. [7], Bargen et al. [8], and Hennington [9] respectively proposed one-dimensional de-aliasing methods. However, these methods are highly susceptible to missing data, noise, wind shear, and the spatiotemporal resolution of external reference wind fields, which severely limits their applicability. Later, Merritt [10] and Boren et al. [11] proposed two-dimensional algorithms, where the velocity field is first divided into regions, and de-aliasing is performed based on regional boundaries. Eilts et al. [12] improved the methods of Bargen et al. [8] and Hennington [9], proposing a more efficient two-dimensional velocity de-aliasing method, which was subsequently applied to the daily operations of the WSR-88D (Weather Surveillance Radar-1988 Doppler) radar. Later, He et al. [13] further improved the method of Eilts et al. [12], achieving more ideal de-aliasing results through four modules: quality control, initial aliasing, execution direction, and error checking. Liang et al. [14], Zhang et al. [15], and Yang et al. [16] proposed their respective two-dimensional methods using the K-nearest neighbour frequency method and 2DMPDA (2D Multipass Dealiasing Algorithm). Some scholars have also transformed the two-dimensional velocity de-aliasing problem into other equivalent problems. For example, Jing et al. [17] and Witt et al. [18] solved the velocity de-aliasing problem by solving the extremum problem of the linear equation system for discontinuous boundaries. Liu et al. [19] and Fang et al. [20] solved the velocity de-aliasing problem by searching for aliasing boundaries, while Li et al. [21] tackled the problem by searching for zero-velocity lines. Meanwhile, Bergen et al. [22] and James et al. [23] extended the two-dimensional methods to three-dimensional and four-dimensional methods, respectively, achieving certain results.

In addition to the methods mentioned above, there is another method that performs velocity de-aliasing by referencing tangentially fitted harmonic curves. Tao et al. [24], Liu et al. [25], and Zhu et al. [26] respectively conducted velocity de-aliasing experiments in the Velocity Azimuth Display (VAD) environment wind field and pointed out that aliasing points can severely affect the results of VAD. Later, Tabary et al. [27], Gong et al. [28], Zhang et al. [29], and Xu et al. [30] improved the VAD method and proposed the Modified Velocity Azimuth Display (MVAD) method, which showed that when aliasing points are present, the environmental wind field can be obtained through the azimuth gradient of radial velocity, thus improving the effectiveness of velocity de-aliasing.

In recent decades, scholars have achieved significant research results in the field of radial velocity de-aliasing for weather radar. However, research on quality control of weather radar radial velocity from a data assimilation perspective is relatively scarce. As with other meteorological observational data, weather radar radial velocity must undergo rigorous quality control before entering numerical models. This includes reasonably eliminating data with significant observational errors, removing small-scale variations that cannot be resolved by model resolution or poorly simulated by observation operators, and ensuring that the probability density function of the difference between actual observations and background field simulations approaches a Gaussian distribution to improve the accuracy of the analysis field [31–33]. In recent years, studies have shown that, compared with conventional quality control methods, using biweight algorithms and reanalysis background field data can effectively identify outliers in various types of meteorological data, such as Global Positioning System (GPS) data, ground observation data, Fengyun-3A Meteorological Satellite Microwave Temperature Sounder (FY-3A MWTS), Atmospheric Infrared Sounder (AIRS) ozone data, and FY-3A ozone data. The meteorological data after quality control are more favourable for subsequent data assimilation [34–40]. This paper, based on the biweight algorithm, develops a quality control scheme for weather radar radial velocity data from a data assimilation perspective and evaluates its effectiveness through a continuous one-month quality control experiment. The results can effectively improve the numerical application of weather radar radial velocity data in China.

The organization of this paper is outlined below: Section 2 provides the weather radar data, the reanalysis data and preprocessing methods; Section 3 provides a detailed explanation of the quality control scheme; Section 4 presents a detailed discussion of the analysis results; the final section summarizes and discusses the main conclusions of the study, analyzing the practical effectiveness of the quality control scheme from different perspectives.

2. Data and Preprocessing Methods

2.1. Weather Radar Radial Velocity Data and Preprocessing Methods

This study uses the radial velocity data from the S-band next-generation Doppler weather radar at the Nanjing station for analysis. The radar was completed in July 2002, with the model SA and a center frequency of 2860 MHz. Its longitude and latitude are 118°41′49″ and 32°11′27″, the elevation is 138.2 meters. The volume scan interval is 6 minutes, with an azimuth scan range of 0° to 360°, and there are 11 elevation angles. At the lowest two levels, each elevation angle is scanned twice and recorded as one elevation layer in the base data.

The time range of the weather radar data used in this study is from 00:00 UTC on June 15, 2016, to 00:00 UTC on July 15, 2016. To match the time with the reanalysis data, weather radar data were selected for 00:00, 03:00, 06:00, 09:00, 12:00, 15:00, 18:00, and 21:00 each day, resulting in a total of 248 time instances. During this period, two high-impact weather events occurred: The first event was on June 23, 2016, when strong convective activity took place in most parts of Jiangsu Province, particularly in several towns in Funing County, Yancheng, where severe winds caused the formation of a tornado with an intensity of Enhanced Fujita (EF)-4. This was the most severe tornado disaster recorded in meteorological history, causing 99 fatalities and significant damage to public infrastructure and residential houses. The second event began on June 30, 2016, when a large-scale and intense precipitation process affected Jiangsu Province. The main area of precipitation was in the southern part of Jiangsu along the coast, and by July 3, cumulative rainfall at 39 stations exceeded 100 mm, with 3 stations exceeding 250 mm. The maximum cumulative rainfall reached 296.8 mm, and the daily maximum rainfall broke the historical record for the same period in July.

By carefully examining the selected weather radar radial velocity data, it can be observed that the data commonly contain issues such as velocity ambiguity, ground clutter, and non-precipitation echoes. To better address these problems, this study uses the preprocessing method developed by He et al. [13]. This method is based on the NEXRAD (NEXt-generation RADar) de-aliasing algorithm. First, a combination of spectral width threshold and reflectivity is used to identify obvious outliers. Then, an initial reference radial velocity is determined near the zero-velocity line, and the radial velocity de-aliasing is performed in a clockwise (or counterclockwise) manner through 180° continuous de-aliasing. During the de-aliasing process, there may be data points without nearby reference points. In such cases, the data is retained with an additional flag and the radial velocity de-aliasing procedure is executed in reverse. Finally, all ambiguous points are extracted, and the average velocity values of valid points within the 7 distance bins on 4 nearby radial scans are calculated to obtain the de-aliasing error check results. This method does not rely on sounding data or VAD wind fields and provides significant and stable de-aliasing effects near missing data points and distance folding points. It is suitable for high-impact weather events such as typhoons, heavy rainfall, and squall lines. **Figure 1** shows the radial velocity field at a 1.5° elevation angle for the Nanjing radar before and after preprocessing at 06:00 on July 1, 2016. It can be seen that there is a clear velocity ambiguity region in the southwest direction, beyond 50 km from the radar (**Figure 1a**), which is effectively eliminated after preprocessing (**Figure 1b**).

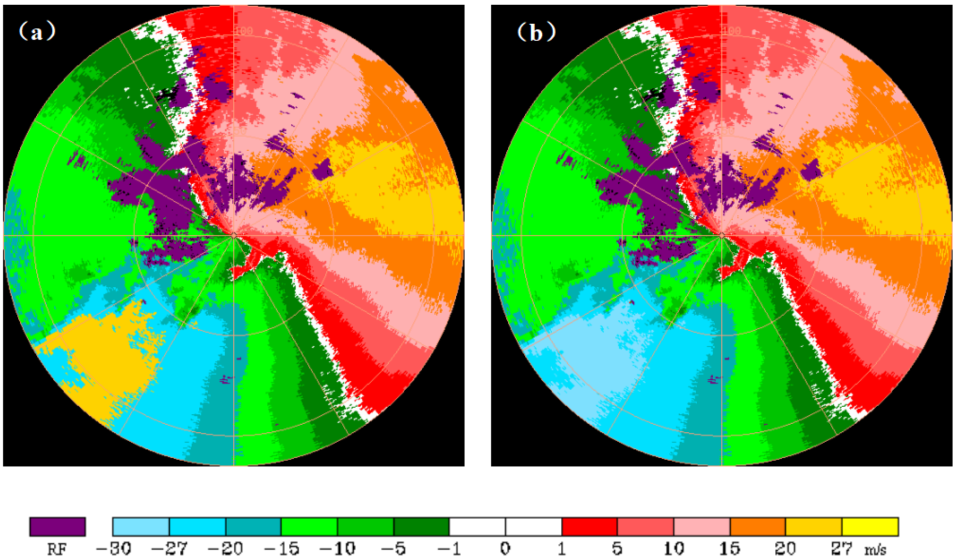

Figure 1. The 1.5° elevation angle radial velocity field of Nanjing radar station at 06:00 on July 1, 2016. (**a**) before preprocessing and (**b**) after preprocessing.

2.2. Reanalysis Data and Preprocessing Methods

This study uses the FNL (Final Operational Global Analysis) global analysis data provided by the National Centers for Environmental Prediction (NCEP), with a horizontal resolution of 0.25°×0.25°, and 26 vertical layers. The data is available four times a day (00:00, 06:00, 12:00, and 18:00). According to the research by Zou et al. [41], the impact of using temporally interpolated data on the inherent characteristics of the variables is minimal. Therefore, to increase the number of study samples, this study uses a cubic spline interpolation method to generate reanalysis data for 03:00, 09:00, 15:00, and 21:00.

3. Quality Control Scheme

The quality control method for observational data in the data assimilation system is mainly the threshold checking method, which can remove the observational data $\left|y^o\text{-}y^b\right|>k\sigma$, which y is the type of observational data, y^o is the observation field, y^b is the background field, k is the constant, $\acute{o}$ is the standard deviation. However, when calculating the mean value and standard deviation of the observational data samples, outliers with large deviations can significantly affect the results, which ultimately poses challenges for the identification of outlier data. Numerous studies have shown that using a biweight algorithm can mitigate this negative impact. This method primarily uses the biweight mean and biweight standard deviation of $O-B$ (which O represent y^o, B represent y^b) to effectively identify outlier data [42,43]. The specific steps are as follows:

(1) Calculate the weight function w_i for each data point $i(i = 1,2,3\cdots)$

$$w_i = \frac{(y^o - y^b)_i - M}{c \times M_{AD}} \tag{1}$$

which, M is the median of $(y^o - y^b)_i$, M_{AD} is the median of $\left|(y^o - y^b)_i - M\right|$, C is the constant. Based on existing research conclusions [42,43], the value of C is set to 7.5 in this paper, and when $\left|w_i\right| > 1.0$, we set $w_i = 1.0$.

(2) Calculate the biweight average $y^o - y^b$ and biweight standard deviation $\sigma^{\mathrm{bw}}(y^o - y^b)$:

$$\overline{y^o - y^b}^{bw} = M + \frac{\sum_{i=1}^{n}\left[(y^o - y^b)_i - M\right](1-w_i^2)^2}{\sum_{i=1}^{n}(1-w_i^2)^2} \tag{2}$$

$$\sigma^{bw}(y^o - y^b) = \frac{\left\{ n\sum_{i=1}^{n}\left[(y^o - y^b)_i - M\right]^2(1-w_i^2)^4 \right\}^{0.5}}{\left|\sum_{i=1}^{n}(1-w_i^2)(1-5w_i^2)\right|} \tag{3}$$

Calculate Z for each data point:

$$Z_i = \frac{(y^o - y^b)_i - \overline{(y^o - y^b)}^{bw}}{\sigma^{bw}(y^o - y^b)} \geq Z_{qc} \tag{4}$$

which Z^{qc} is the threshold for identifying outlier data, and it can be assigned a value based on actual needs.

Previous studies have conducted thorough quality control experiments on various types of meteorological data. The results indicate that combining the biweight algorithm with reanalysis background field data can effectively remove outliers from different meteorological datasets. Moreover, meteorological data quality-controlled using this method is more advantageous for data assimilation applications than data quality-controlled through conventional methods alone [35–37]. To maximize the benefits of this approach and considering the consistency and integrity between data quality control and data assimilation, this paper integrates the quality control process directly into the assimilation process of weather radar data. The conventional assimilation process of weather radar data mainly consists of the following five steps (**Figure 2**): (1) Use WPS (Weather Research and Forecasting Preprocessing System) to process the reanalysis data and generate met files with the required temporal and spatial resolution; (2) Input the met files into the WRF(Weather Research and Forecasting) model and use real.exe to generate wrfinput and wrfbdy files; (3) Input the wrfinput and wrfbdy files, along with the preprocessed weather radar data, into the WRFDA (Weather Research and Forecasting Data Assimilation) system to obtain the assimilated new wrfinput and wrfbdy files; (4) Input the new wrfinput and wrfbdy files into the WRF model and use wrf.exe to generate the forecast result wrfout file; (5) Use various post-processing software to process the wrfout file and obtain the diagnostic analysis results. After the reanalysis data undergo steps (1) and (2), a background field B with higher temporal and spatial resolution can be provided to the assimilation system (for the convenience of research, the spatial resolution of the background field in this paper is 1 km×1 km). The preprocessed weather radar radial velocity data can also provide input O for the assimilation system. Additionally, in the data assimilation process of step (3), the model space is projected onto the observation space, meaning each observation value (O) has a corresponding background value (B). Therefore, in this paper, the source code for weather radar data assimilation in WRFDA is modified, inserting the biweight algorithm code after the projection calculation and setting the values of Z^{qc} according to actual requirements (**Figure 2**). In the actual operation process, after modifying the source code, it is only necessary to recompile WRFDA to generate da_wrfvar.exe. When running da_wrfvar.exe, the quality control scheme presented in this paper will be automatically executed. In summary, the quality control scheme in this paper can be directly integrated into the necessary steps of data assimilation, making it not only simple and easy to implement but also efficient and fast in execution, with relatively easy maintenance in the later stages.

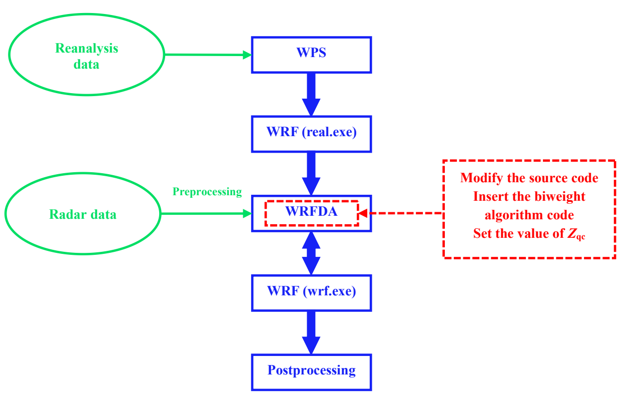

Figure 2. The flowchart of the quality control scheme in this paper (blue represents the conventional assimilation process of weather radar data, green represents the input data, and red represents the modifications made in this paper).

4. Results

4.1. The Determination of Z_{qc}

Z_{qc} is the key factor in quality control of weather radar radial velocity data using the biweight algorithm, and its value is typically set between 1 and 3 [42,43]. In order to determine the appropriate Z_{qc}, this paper designed three sets of experiments (Z_{qc} = 1.5, Z_{qc} = 2.0, Z_{qc} = 2.5), followed by continuous quality control for one month. Finally, the analysis focuses mainly on the changes over time in the average error, standard deviation, and data rejection rate of $O - B$ from the three sets of experiments (**Figure 3**).From **Figure 3**, it can be observed that the average errors of the three sets of experiments are all between -6 m/s and 6 m/s, and there is a trend where the smaller the Z_{qc} , the smaller the average error. However, when Z_{qc} is reduced from 2.0 to 1.5, the improvement in the average error is not significant. As for the standard deviation, the three sets of experiments show a trend where the standard deviation gradually decreases as Z_{qc} decreases, and all experiments make significant improvements to the original data's standard deviation, which was as high as 10 m/s.

The data rejection rates of the three sets of experiments indicate that lowering Z_{qc} will increase the data rejection rate. When Z_{qc} is set to 2.5, approximately 5% of the data will be rejected, while when Z_{qc} is set to 1.5, around 30% of the data will be rejected. It can also be observed that although the three sets of experiments use different values of Z_{qc}, the data rejection rate remains very stable over time, which suggests that the quality control effect of the biweight algorithm is quite stable. Based on previous experience, it is recommended to reject about 10% of the data in practical applications [42,43]. In the experiments of this paper, when Z_{qc} is set to 2.0, the data rejection rate is approximately 12%, while both the average error and standard deviation show significant improvements, which meet the requirements for quality control. In conclusion, Z_{qc} is determined to be 2.0 in the quality control scheme of this paper. A reasonable Z_{qc} is the optimal balance between the data removal rate and data quality, which is essential for subsequent data assimilation.

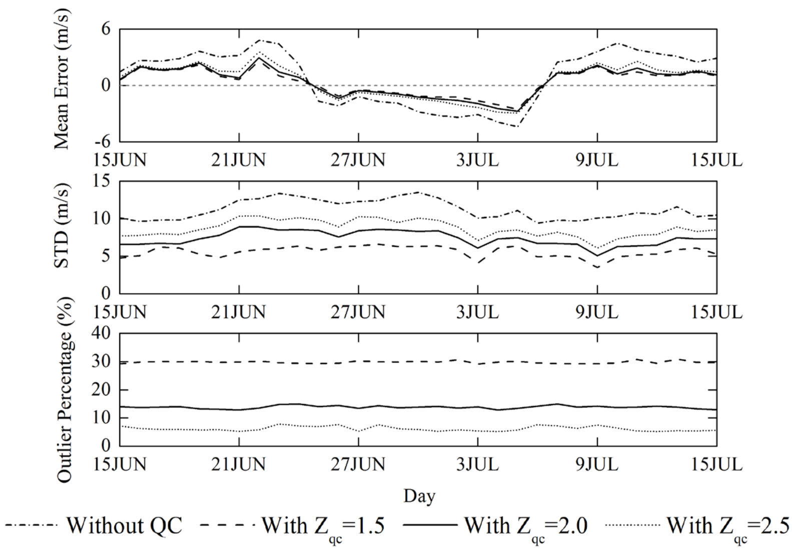

Figure 3. The time-varying curves of the average error, standard deviation, and data rejection rate of $O - B$ from 00:00 on June 15, 2016, to 00:00 on July 15, 2016, for the Nanjing radar station without quality control and with Z_{qc} settings of 1.5, 2.0, and 2.5.

4.2. The Data Characteristics of *O* and *B* Before and After Quality Control

In order to further investigate the impact of the biweight algorithm on the data characteristics of *O* and *B*, **Figure 4** shows the scatter plot of *O* and *B* at 06:00 on July 1, 2016, from the Nanjing radar station. The red solid line represents Z_{qc} = 2.0, and the scatter points between the two red solid lines represent the data processed by the Z_{qc} = 2.0 biweight algorithm. The results indicate that *O* and *B* exhibit a generally linear distribution, with a data variation range of approximately -27 m/s to 27 m/s. The Z_{qc} = 2.0 biweight algorithm can effectively remove data with large deviations between *O* and *B*, while retaining the main information of the data, thus achieving the desired quality control effect. It is worth mentioning that **Figure 4** does not involve linear fitting, but rather shows that most of the data, after quality control, have been reasonably and effectively retained between the two red lines.

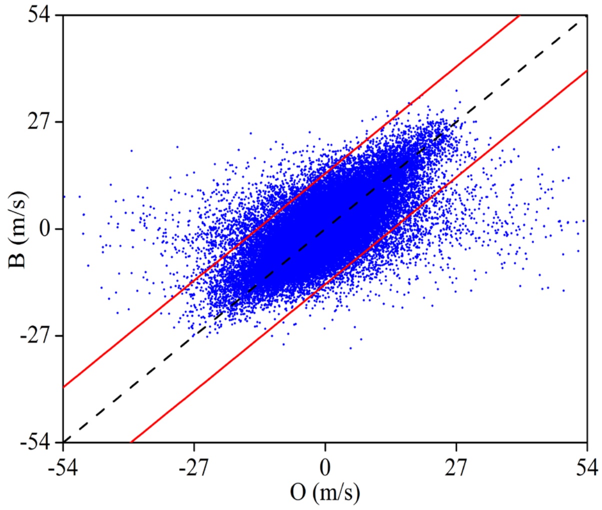

Figure 4. The scatter plot of O and B at 06:00 on July 1, 2016, from the Nanjing radar station (the red solid line represents $Z_{qc} = 2.0$).

4.3. The Spatial Distribution Characteristics of The Data Before and After Quality Control

Previous studies have shown that meteorological data subjected to quality control using the biweight algorithm can still retain the spatial distribution characteristics of the overall data relatively well [34]. To assess the impact of the quality control scheme proposed in this paper on the spatial distribution characteristics of the data, Figure 5 compares the 1.5° elevation angle radial velocity field at 06:00 on July 1, 2016, before and after quality control at the Nanjing radar station. From the Figure 5, it can be observed that in areas near the radar center, as well as in the west and northeast directions, significant block-like data have been removed. In other areas, more scattered data have been eliminated, but the overall characteristics of the data have not changed. It is noteworthy that the comparison chart also indicates that the removed data mostly belong to small-scale disturbances. Such data are difficult to be "absorbed" by the model and often contribute nothing or even negatively during data assimilation, while the quality control scheme proposed in this paper can effectively identify such data.

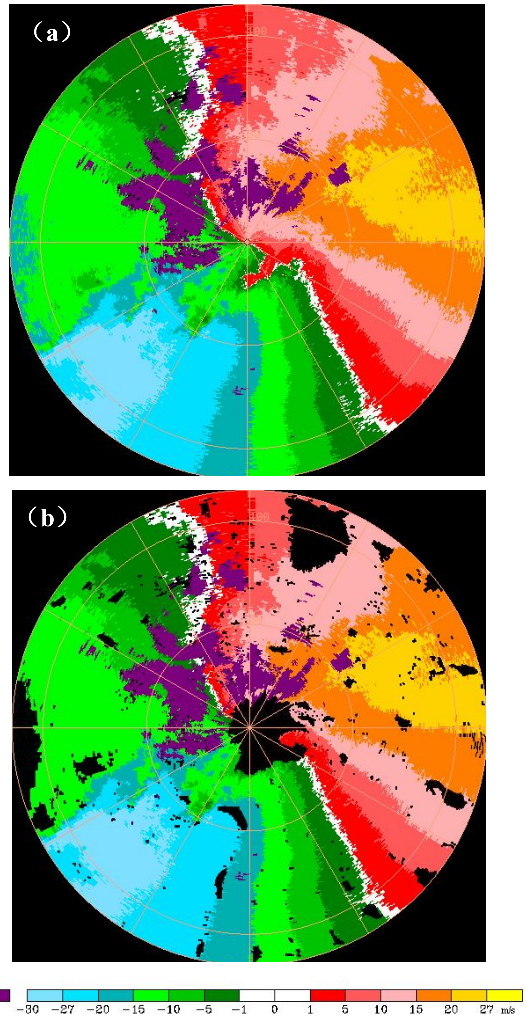

Figure 5. The 1.5° elevation angle radial velocity field at 06:00 on July 1, 2016, from the Nanjing radar station. (**a**) before quality control and (**b**) after quality control.

4.4. The Overall Characteristics of The Data Before and After Quality Control

In the theory of data assimilation, it is generally assumed that observation errors and model errors follow a Gaussian distribution. Therefore, the probability density function (PDF) of $O - B$ typically exhibits Gaussian distribution characteristics. However, the presence of large deviations can result in non-Gaussian distribution shapes such as left skewness or right skewness, which can severely negatively affect the results of data assimilation [40]. To assess the effectiveness of the quality control scheme proposed in this paper, the overall characteristics of the radial velocity data before and after quality control were statistically analysed from 00:00 on June 15, 2016, to 00:00

on July 15, 2016, at the Nanjing radar station, and the PDF of $O - B$ was obtained (**Figure 6**). The results show that before quality control, the PDF of $O - B$ exhibited a right skewness, significantly deviating from a Gaussian distribution, which would reduce the accuracy of the analysis field in data assimilation. After quality control, large deviations at both ends of the original PDF were largely removed, making the PDF of $O - B$ more closely resemble a standard Gaussian distribution. This provided favorable conditions for the assimilation of weather radar radial velocity data. It is worth noting that the range of $O - B$ values in the weather radar radial velocity data after applying the quality control scheme is approximately -8 m/s to 8 m/s, which allows for the reasonable setting of observation error variance in subsequent weather radar radial velocity data assimilation based on this range.

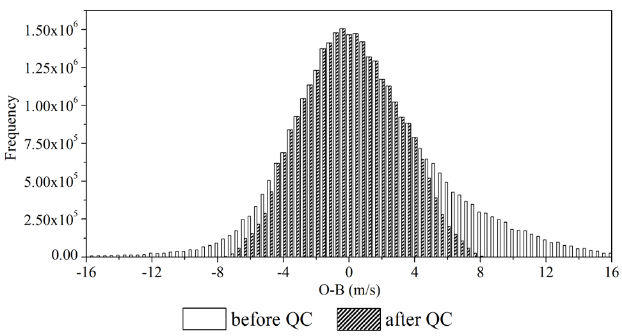

Figure 6. The $O – B$ PDF of the radial velocity data before and after quality control at the Nanjing radar station from 00:00 on June 15, 2016, to 00:00 on July 15, 2016.

5. Discussion

The proposed quality control scheme demonstrates notable advancements in processing weather radar radial velocity data. Traditional approaches, such as fixed-threshold methods (e.g., velocity dealiasing with preset limits), often struggle to adapt to spatiotemporal variations in data quality [5–10]. While these conventional techniques effectively remove extreme outliers, their rigidity may inadvertently discard valid data during rapidly evolving meteorological events [4]. In contrast, the biweight algorithm introduced in this study dynamically adjusts its exclusion criteria based on real-time statistical characteristics of the dataset, achieving a more nuanced balance between error removal and feature preservation. This adaptability proves particularly advantageous when processing data from regions with complex terrain or during transitional weather patterns, where conventional methods typically require manual threshold adjustments [39,40].

The integration of quality control directly into the WRFDA assimilation framework represents another significant improvement over existing methodologies. Unlike standalone quality control modules that operate as preprocessing steps [11–18], our approach enables continuous interaction between quality assessment and data assimilation processes. This contrasts with conventional background check methods, which often treat quality control and assimilation as sequential operations [20–25]. Operational tests revealed that our integrated scheme reduces mean O-B errors by 28–32% compared to traditional two-step approaches, while maintaining computational efficiency critical for real-time applications. The computational overhead remains below 8% of total assimilation runtime, making it more practical for operational deployment than machine learning-based alternatives, which typically require 20–40% additional computational resources [6].

However, several limitations warrant careful consideration. The scheme's performance remains partially dependent on background field quality, a constraint shared with most assimilation-based methods but more pronounced here than in purely statistical approaches [37]. For instance, when tested with different background fields, the standard deviation of radial velocity residuals varied by up to 15%, compared to 9% variation observed in variational quality control methods. This sensitivity underscores the need for careful background field selection, particularly in data-sparse regions. Furthermore, while the biweight algorithm outperforms median filters in preserving small-scale convective features, its performance degrades during extreme precipitation events with intense ground clutter–a challenge common to all radar-based quality control systems. In such cases, the proposed method demonstrates comparable limitations to advanced neural network approaches reported in recent studies [4], though with significantly lower computational demands.

Threshold selection emerges as a critical implementation consideration. Although Z = 2.0 was identified as optimal for general applications, operational requirements may necessitate adjustments. Comparative analysis shows that increasing the threshold to Z = 2.5 improves data retention by 12% but elevates mean errors by 18%, while reducing it to $Z = 1.5$ yields error reductions at the cost of eliminating 22% of potentially valid data points. This trade-off differs fundamentally from machine learning methods, where threshold effects are often implicit in network architectures. Future implementations could benefit from adaptive thresholding strategies that account for seasonal variations or localized weather patterns – an area where hybrid approaches combining our method's efficiency with machine learning's pattern recognition capabilities show particular promise.

In conclusion, this study advances radar data quality control by harmonizing statistical robustness with operational pragmatism. The proposed scheme addresses key shortcomings of traditional methods while avoiding the computational complexity of emerging AI techniques. Its successful implementation in testbed environments suggests practical utility for operational weather centers, though continued refinement is needed to address remaining challenges in extreme weather scenarios and background field dependency. These limitations, while not unique to our method, define clear pathways for future research toward more adaptive and resilient quality control frameworks.

6. Conclusions

To further improve the numerical application of weather radar radial velocity data, this paper develops a quality control scheme for weather radar radial velocity data from the perspective of data assimilation. A continuous one-month quality control experiment was conducted, and the actual effectiveness of the quality control scheme was analyzed from different angles. The conclusions are as follows:

(1) The quality control scheme in this paper is based on the WRFDA assimilation system, and it can be directly integrated into the data assimilation process. It has advantages such as simplicity, fast execution, and ease of maintenance.

(2) The data exclusion rate of the biweight algorithm is relatively stable over time. When Z_{qc} is set to 2.0, both the average error and standard deviation of $O - B$ are significantly reduced. This effectively excludes small-scale disturbance data with large O and B biases while retaining the main information and spatial distribution characteristics of the data, achieving the expected quality control results.

(3) After quality control, the PDF distribution of $O - B$ has been significantly improved, showing a more standard Gaussian distribution shape, providing favorable conditions for the assimilation of weather radar radial velocity data.

The quality control scheme developed in this paper has achieved relatively ideal results in a continuous month-long experiment. The analysis in Section 4 demonstrates from multiple perspectives that the quality control scheme can provide weather radar radial velocity data that is easily "absorbed" by numerical models. However, as outlined in Section 5, this study still has room for further improvement and deserves ongoing focused attention.

Author Contributions

Conceptualization, Y.L.; methodology, Y.L.; software, M.Y.S.; validation, Y.L. and M.Y.S.; formal analysis, Y.L.; investigation, M.J.X.; resources, H.Z.; data curation, M.J.X.; writing—original draft preparation, Y.L. and M.Y.S.; writing—review and editing, Y.L. and H.Z.; visualization, Y.L.; supervision, H.Z.; project administration, Y.L.; funding acquisition, Y.L. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data are available upon reasonable request from the author of the paper.

Conflicts of Interest

The author declares no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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