

QUANTITATIVE RAINFALL ESTIMATION USING WEATHER RADAR BASED ON THE IMPROVED KALMAN FILTER METHOD

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(Received 24th Aug 2018; accepted 11th Oct 2018)

Abstract. To reduce the error of radar rainfall evaluations, an improved Kalman filter (KF) method is used to calibrate the radar quantitative rainfall estimation (QRE). First, the rain gauge rain rate/radar rain rate (G/R) calibration factor model is created in this approach. The prediction and measurement system of the G/R are then established based on the KF. The calibration process of the system parameters and the adaptive estimation process of the system error are introduced to dynamically adjust the KF parameters. Subsequently, the G/R calibration ratio is used to correct the quantitative radar rainfall estimation. The radar and rain gauge hourly rain data of two rain cases in Changchun, China on August 19–20, 2015, and August 6–7, 2016, are used to test the efficiency of the proposed method. The results show that the QRE result based on the KF calibration is better than that without calibration. The average relative errors of the two rain cases decreased from 0.6047 to 0.3557 and 0.2645 and from 0.8052 to 0.3096 and 0.1715 due to the ordinary and improved KFs, respectively. The improved KF is even better than the ordinary KF.

Keywords: *G/R ratio; calibration factors; parameters estimate; state system; adaptive estimation*

Introduction

Radar-based quantitative rainfall estimation with high temporal resolution plays an important role in the monitoring and early warning of meteorological disasters caused by strong convective weather such as storms and floods. Radar-based rainfall estimation commonly uses the empirical relationship model $Z = aI^b$ (where a and b are parameters of the model, Z is the radar reflectivity factor, and I is the rainfall intensity) to estimate the rainfall intensity. However, the radar quantification is affected by factors such as clutter from terrestrial objects, raindrops, and super refraction. In addition, systematic errors of the radar reflectivity values cannot be completely eliminated. The a and b parameters also greatly vary in different areas at the same time or in different rainfall process models, resulting in a relatively large deviation of the radar-based rainfall estimated value and actual rainfall volume (Zheng et al., 2004).

To obtain more accurate radar-based rainfall estimates, the rain gauge rain rate/radar rain rate (G/R; i.e., automatic weather station measurements/weather radar estimates) ratio is generally used to correct the radar estimates. Current methods to obtain G/R mainly include the average calibration method, variational method, and Kalman filter method. The Kalman filter is a linear, unbiased, minimum-variance, recursive filter that is widely applied during the process when precipitation stations and radar are used for the joint rainfall estimation. Ahnert et al. (1986) first proposed to use the Kalman filter as a real-time prediction method of G/R calibration factors and pointed out that this method has advantages such as being able to correct measurement noise, demonstrating estimation errors, and avoiding G/R instability. Subsequently, researchers applied the Kalman filter for the calibration of different types of rainfall or different areas. The studies focused mainly on two areas: (1) Modification of the G/R calibration factor model to be suitable for different types of rainfall and improve the rainfall estimation results using Kalman filter optimization. For example, Chumchean et al. (2006) proposed a $\log_{10}(G/R)$ calibration model that has better filtering effects in areas with fewer precipitation stations. Yahya et al. (2012) comprehensively considered and analyzed the effects of meteorological elements, such as temperature and humidity, on Kalman filter effects and proposed a multi-factor calibration model; and (2) Modification of parameter values used during Kalman filter-based prediction and quantification and improvement of the stability and convergence speed of the Kalman filter algorithm. For example, Yin and Zhang (2005) analyzed the effects of various model parameters on the results and provided suggestions to improve various parameters. Monteiro and Costa (2015) carried out statistical analysis of transfer matrix parameters in the state equation of the prediction formula using rainfall data and obtained better parameters. Xu (2008) and Kim and Yoo (2014) proposed the usage of a self-adaptive filter as a method to estimate model parameters and improve the accuracy of the filter estimation. Zhao et al. (2001) employed a combination of the Kalman filter and variational method to optimize the model parameters and improve the accuracy of radar-based rainfall estimation. In studies in which the Kalman filter was used to calibrate radar-based rainfall estimations, the calibration factor is more associated with fixed rainfall types or the density of precipitation stations; this model is comparatively mature. On the other hand, because the filter algorithm parameters were set as empirical constants, problems occur, such as poor adaptability to different rainfall events or shorter rainfall, decreasing the accuracy of the filter algorithm during calibration. This affects the accuracy of radar-based rainfall estimates, which is one factor that this paper seeks to improve.

This study is based on previous research. The Kalman state parameter model and maximum likelihood estimation are introduced into the ordinary Kalman filter. The state model parameters, state equation, and noise value of the quantitative equation in each step of the Kalman filtering process were corrected to decrease the effects of unreasonable model parameters on the whole filtering process and enhance the stability of the filter algorithm to effectively increase the accuracy of radar-based rainfall estimations.

Study methods

Ordinary Kalman filter algorithm

The Kalman filter algorithm is a process in which two independent estimation equations are established based on a random variable to obtain estimates and appropriate weighting factors are then selected to obtain the weighted average of the two estimates as filter output variables. The G/R calibration factor is used in this paper as the random variable x for the

Kalman filter algorithm.

The Kalman filter algorithm is mainly divided into the prediction and quantification processes. The former uses the estimate of the variable at a previous time to obtain the current a priori estimate. On the other hand, the latter uses the current measurement value to correct the a priori estimate of the previous process and obtain the current posteriori estimate (Liu et al., 2015; Liu et al., 2016; Noh et al., 2014). The specific recursive calculation process was:

Prediction process:

$$\hat{x}_k = A_{k-1}x_{k-1} \quad (\text{Eq.1})$$

$$\hat{P}_k = A_{k-1}P_{k-1}A_{k-1}^T + Q_{k-1} \quad (\text{Eq.2})$$

Quantification process:

$$K_k = \hat{P}_k(\hat{P}_k + R_k + Q_{k-1})^{-1} \quad (\text{Eq.3})$$

$$x_k = \hat{x}_k + K_k(z_k - H\hat{x}_k) \quad (\text{Eq.4})$$

$$P_k = (1 - K_k H)\hat{P}_k \quad (\text{Eq.5})$$

Equation 1 is the state equation. In the equations, $\hat{x}_k$ is the a priori estimate at the time k ; x_{k-1} is the posteriori estimate at time $k-1$; P is the estimated covariance and is one of the results of the filter; and A is the state transition matrix but is in fact a conjectural model of the target state transition, that is, the connection between x_k and x_{k-1} . If *Equation 2* is regarded as first-order linear autoregressive model AT, then A is the coefficient of this model and constant values are normally used.

Equation 3 is the measurement equation, where z_k is the x measured value at time k , that is, the actual G/R ratio; H is the gain of the state variable x_k to the measurement variable z_k ; K is the filter gain matrix, which is an intermediate calculation result of the filter; Q and R are the variances of the state equation and measurement equation, respectively, the mean of which is zero. In the actual calculation process, the Q and R values are usually obtained by analyzing samples from the previous rainfall process, which provides constant Q and R values (Kim and Yoo, 2014; Eldardiry et al., 2015).

Equations 1 to 5 are part of the specific calculation process of the ordinary Kalman filter algorithm. However, in the ordinary Kalman filter algorithm, the transition matrix A in the state equation and the errors of Q and R are assumed to be a priori constant values. This is unreasonable for complex rainfall systems.

Modification of the Kalman filter algorithm

To adapt to the variation characteristics of complex rainfall systems, two improvements were made to the parameters in the Kalman filter algorithm:

(1) The transition matrix A in *Equation 1* was assumed to be a temporal variable and the state and measurement equations for the ordinary Kalman filter were established for variable A . The value of A after filtering was substituted into the filter process of the G/R calibration factor to improve the accuracy of the state equation.

(2) Based on the maximum likelihood criterion, real-time estimation and adjustment of Q and R errors was carried out to reflect real-time changes of the system model and enable the Kalman filter to track the system model changes. The derivation process was:

$$R_k = \hat{C}_{vk} + H_k \hat{P}_k H_k^T \quad (\text{Eq.6})$$

$$Q_k = \frac{1}{N} \sum \Delta x_i \Delta x_i^T + P_k - A P_{k-1} A^T \quad (\text{Eq.7})$$

$$\Delta x_k = \hat{x}_k - \hat{x}_{k,k-1} = K_k v_k \quad (\text{Eq.8})$$

$$\hat{C}_{vk} = \frac{1}{N} \sum_{i=k-N+1}^k v_i v_i^T \quad (\text{Eq.9})$$

In the equations, $v_k = z_k - H \hat{x}_k$, N is the width of the smoothing window, $\hat{C}_{vk}$ is expressed as a covariance matrix for the v_k sequence in a smooth window, and R_k and Q_k are the systematic errors of the prediction and measurement, respectively (Maxwell et al., 2018; Monteiro and Costa, 2015).

Model of the improved Kalman filter estimation

This paper set the unfiltered calibration factors as:

$$z_k = \frac{1}{n} \sum_{i=1}^n G_i / R_i \quad (\text{Eq.10})$$

In the equation, n is the total number of automatic weather stations that participated in the calibration, G_i is the rainfall value measured at the weather station at time k , R_i is the radar-based rainfall estimation value at the same location as the weather station obtained from the constructed radar-based rainfall estimation in Subsection: Ordinary Kalman filter algorithm. In *Equation 1*, the model parameters are: $a = 300$ and $b = 1.4$ (Yang et al., 2015; Marra et al., 2017).

During the Kalman filter algorithm, the parameters at time 0 are: $x_0 = 0$, $P_0 = 0.01$, $Q_0 = 0.25$, and $A_0 = 1$.

Improvement of the Kalman filter algorithm

The Kalman filter algorithm was improved through filter processing of calibration factors, which indirectly adjusted the initial field of the radar-based rainfall estimation and achieved the calibration of radar-based rainfall estimation. The main calculation process was:

(1) Assignment of initial values, $k = 0$ and $k = [0, n]$, where n is the number of hours during which data from radar and automatic weather stations were effectively recorded during rainfall; x is the calibration factor, that is, the G/R prediction value, and x_0 was set as 0; and Q_k and P_k are the systematic errors of the state system and measurement, respectively. At time 0, P_0 and Q_0 were set to 0 and the state transition matrix A was assumed to be 1.

(2) During the prediction process, the right hand side was the prediction process of the state transition matrix A and the left hand side was the prediction process for the calibration factor. In the state equation on the left hand side, the A_{k-1} value was the posteriori estimate of the output from the filtering process based on A at time $k-1$. The a priori estimate of variable x at time k was then obtained based on the left state system. It was assumed that the state transition matrix in the right state equation is always 1, then, the priori estimate of A at time k was obtained.

(3) The radar data at time k were processed based on *Equation 10* and the initial field of the radar-based rainfall estimation at time k was established.

(4) The rainfall data measured by automatic weather stations were inserted and the value of the G/R calibration factor at time k (i.e., Z_k) was calculated based on *Equation 10*. If no valid value exists for the unfiltered calibration factor, the next time was recalculated using a prediction process. If a valid value exists, measurement corrections of the state transition matrix A and calibration factor (variable x) were carried out to solve the Kalman filter equations. During the measurement of these two variables, Q and P have the same value. Finally, the posteriori estimates of the state transition matrix A and calibration factor x at time k were obtained, that is, the best calibration factor x_k at time k . The best calibration factor can be used to correct the initial field of the radar-based rainfall estimation at time k (Thorndahl et al., 2014; Fleming et al., 2017).

(5) If $k < n$, then steps 2–4 are repeated and the best calibration factor can be obtained at every time point.

Figure 1 shows the improved Kalman filter process.

Experiment and analysis

Data and processing

Two rainfall events in the Changchun Area, Jilin Province, China from 1 a.m. on August 19, 2015, to 10 p.m. on August 20 and 5 p.m. on August 6 to 6 a.m. on August 7, were used as study subjects. We used rainfall data from the Changchun weather radar station and encrypted hourly rainfall data from automatic stations. The Changchun weather radar station uses the CINRAD/CC radar series; the weather radar has a spatial resolution of 300 m, temporal resolution of 6 min, detection range of 150 km, and antenna height of 290 m. *Figure 2* shows the distribution of the radar and automatic weather stations; 80% of these stations were used in this experiment, while the remaining weather stations were used for the examination of experimental results.

Radar data were obtained from CAPPI data at a 3 km height. Scanning data of different elevation angles at a certain time were interpolated to the same height as field data of reflectivity factors. At the same time, to eliminate the effects of clutter, data with reflectivities < 15 or > 78 were removed because a reflectivity < 15 is thought to not be able to induce rain, while a reflectivity > 78 might reflect ice–water mixtures and will not induce rainfall (Gou et al., 2014). Spatial and temporal differences exist because the measured values from automatic weather stations represent 1-hour rainfall at a certain

time point and the radar detection values are reflectivity factors. For the uniform comparison, the radar data were processed using the following methods and the weather station as a benchmark.

(1) The polar coordinate data of the radar were converted into a Cartesian coordinate system on a grid plane. The grid and minimum resolution of the polar coordinates of the raw radar data were the same ($0.3 \text{ km} \times 0.3 \text{ km}$).

(2) Every 6 minutes, radar-based data were collected and the constant altitude plan position indicator (short for CAPPI) was generated, which was used to estimate the rainfall intensity at that moment based on Equation 1. The calculated rainfall intensities during 1 hour were weighted and summed to generate the radar-based rainfall estimate for 1 hour and establish the initial field of the radar-based rainfall estimation value (Kim et al., 2018).

$$Z = aI^b \quad (\text{Eq.11})$$

In this equation, Z is the reflectivity factor, I is the rainfall intensity, and a and b are model parameters.

(3) Based on the coordinates of the automatic weather stations, the radar-based rainfall estimation field and 12 valid points adjacent to the automatic weather stations were selected. The weighted average of the valid data was used to calculate the radar-based rainfall estimate at the same location of the weather station.

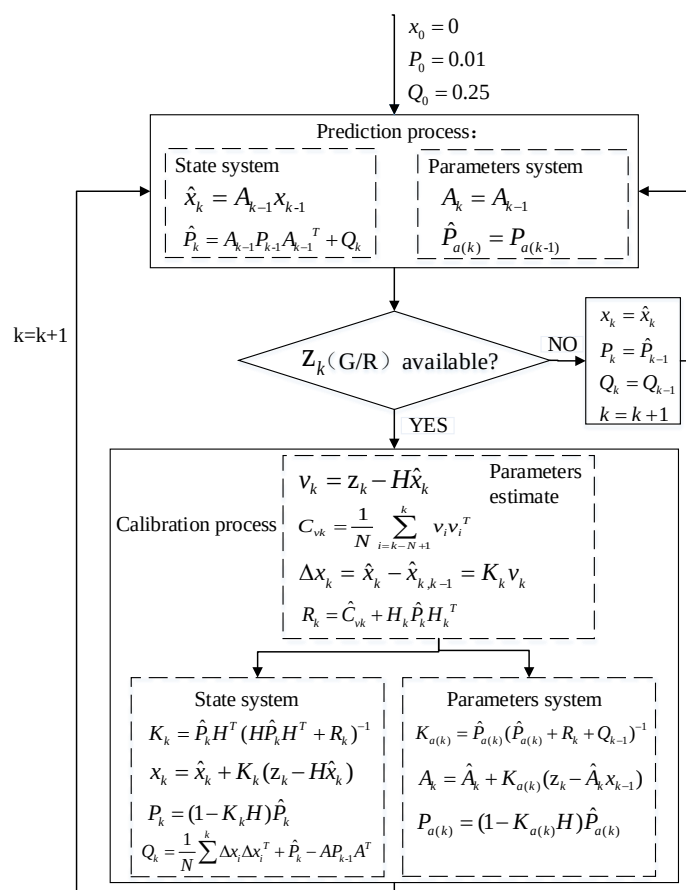


Figure 1. Flow chart of the improved Kalman filter method

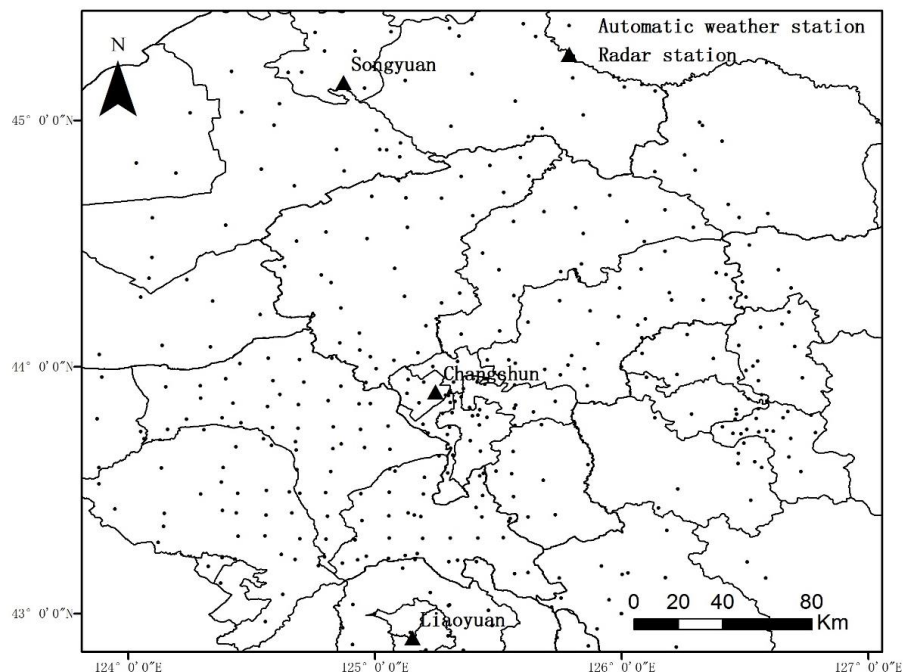


Figure 2. Radar and automatic weather stations

Results of the improved Kalman filter algorithm

G/R ratio

The study area is the effective detection range of the Changchun Radar Base Station. The study area is divided into test area and evaluation areas. In the test area, radar data and data from the automatic weather stations were used to obtain the posteriori estimate of G/R through the Kalman filter method. In the evaluation area, the estimated G/R calibration factor was used for the correction of radar estimates, which were compared with values measured at weather stations in the evaluation area (Cheng and Li, 2013; You et al., 2014; You et al., 2018).

Figure 3 shows that the G/R ratio of the two rainfall events, estimated with the improved Kalman filter, is more consistent with the actual value.

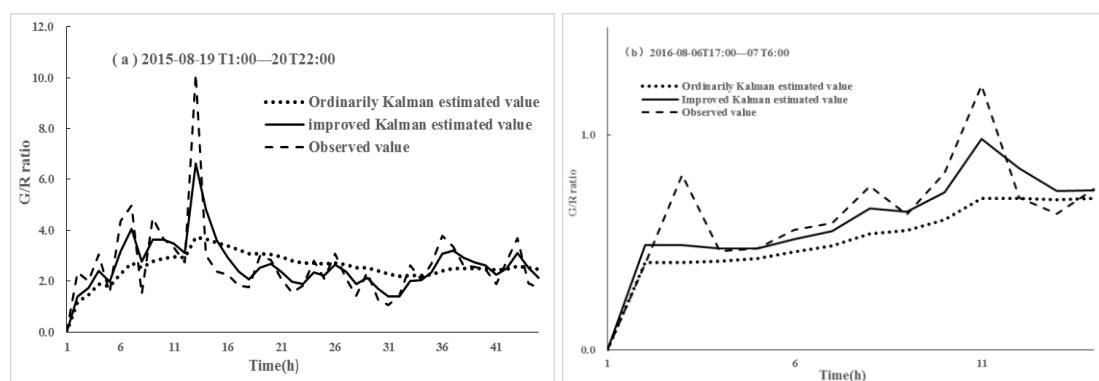


Figure 3. Comparison of the observed G/R ratio and that predicted using the ordinary and improved Kalman filters for the two rainfall events

The improved Kalman filter has a faster convergence speed and strong adaptive ability and the deviation between the estimated value and the actual value of the deviation is small. On the other hand, the G/R ratio estimated with the ordinary Kalman filter shows a greater deviation from the actual value. The convergence speed is slower and the effects of the test sample are larger. The deviation between the estimated and actual values is larger when the time series includes a relatively large value.

Figure 3 also shows that the sample quantity has a greater effect on the Kalman filter. For the ordinary Kalman filter, a rainfall process with a larger sample quantity (Figure 3a) will result in the convergence and gradual stabilization of the filter value; the convergence is very slow in rainfall events with a small sample quantity (Figure 3b). On the other hand, the improved Kalman filter is less affected by the sample quantity, showing a relatively fast convergence speed during both rainfall events. Therefore, the improved Kalman filter has better convergence effects on short rainfall events. Based on the comparison of the estimated and measured values of the two rainfall events (Figure 4), the points of the improved Kalman filter are more clustered, while the points of the ordinary Kalman filter method are more dispersed. The G/R estimate from the improved Kalman filter calibration shows a better correlation with the actual value. The correlation coefficient of the two rainfall events increased from 0.1245 and 0.3721 to 0.7295 and 0.6222, respectively.

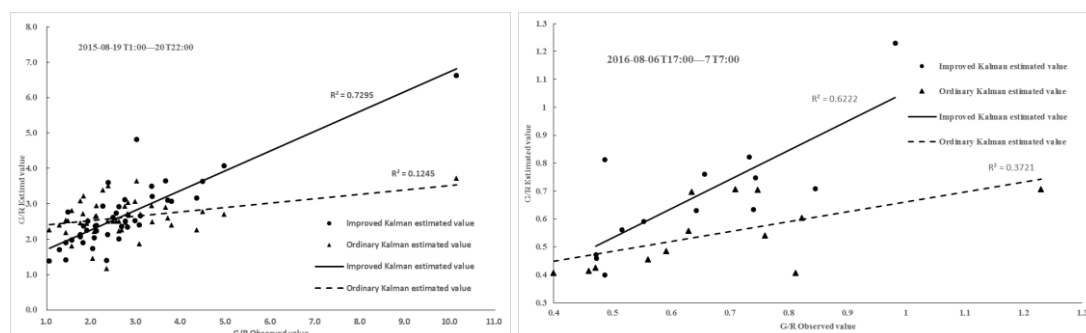


Figure 4. Scatter plots of the observed G/R ratio and that predicted with the ordinary and improved Kalman filters for the two rainfall events

Error analysis

The G/R calibration factor of the two rainfall events was used for the correction of the radar-based rainfall estimates in the evaluation zone. The corrected radar-based rainfall estimate was used for the comparison of the data from the precipitation stations inside the evaluation area (Costa et al., 2016).

Figure 5 shows that, compared with the uncorrected radar-based rainfall estimates, the absolute error of the improved Kalman filter-corrected estimate of hourly radar-based rainfall of the two rainfall events is relatively small, generally in the 0–1 mm range. On the other hand, the absolute error of the ordinary Kalman filter-corrected estimates of hourly radar-based rainfall is ~0–2 mm. Table 1 shows that both Kalman filter methods can solve the poor adaptability of Z–R relationship model parameters and lower radar-based estimates due to errors in the radar estimation system itself. The average relative error of the hourly rainfall during August 19–20, 2015, decreased from 0.6047 to 0.3557 and 0.2645, respectively, with decreases of 41% and 53%. The root-mean-square error decreased from 1.5246 to 0.9794 and 0.6928, respectively. During

the August 6–7, 2016, rainfall event, the average relative error decreased from 0.8052 to 0.3906 and 0.1715, respectively, with decreases of 51% and 85%. The root-mean-square error decreased from 1.3596 to 0.3131 and 0.2163, respectively. This shows that the Kalman filter algorithm could effectively increase the radar-based rainfall estimation accuracy. At the same time, the improved Kalman filter significantly improved the accuracy and stability of the estimates compared with ordinary Kalman filter.

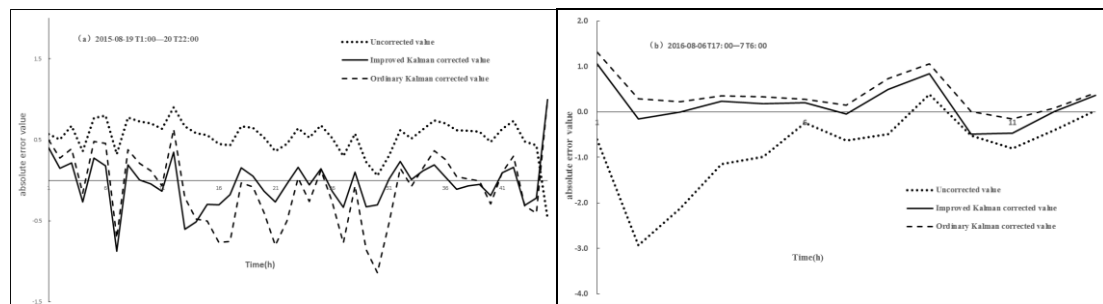


Figure 5. Comparison of the absolute error of different methods for the two rain events

Table 1. Comparison of the error of different methods during two rain events

Method	8-19-2015 1 a.m. to 8-20-2015 10 p.m.		8-6-2016 5 p.m. to 8-7-2016 6 a.m.	
	Average relative error	Root-mean-square error	Average relative error	Root-mean-square error
Radar estimation	0.6047	0.605	0.8052	1.3596
Kalman	0.3557	0.356	0.3906	0.3131
Improved Kalman	0.2645	0.265	0.1715	0.2163

Rainfall distribution

The improved Kalman filter was used to correct the G/R factors for the calibration of the original radar-based rainfall estimate. The improved Kalman filter better calibrates the radar-based rainfall estimate during the two rainfall events than the ordinary Kalman filter. In addition, the comparison of the two rainfall events shows that the calibration effects are better when the rainfall duration in the experiment is longer.

To study the spatial distribution of the rainfall field, a calibration analysis of the rainfall estimate of a certain area at 1–2 a.m. on August 19, 2015 was carried out. Based on the statistical calculations, 52 valid rainfall data points were obtained at 1–2 a.m. on August 19, 2015. Geographical methods were used to interpolate the observed rain gauge values to obtain the surface rainfall distribution (*Figure 6a*). *Figures 6b and 6c* show the distribution of the radar-based estimate of rainfall before and after calibration. The radar and rain gauge both show the general range of the rainfall, the centers of the rainfall are relatively notable. However, the radar rain detection centers are smaller than the rainfall range measured by the rain gauges. After correction, the Kalman filter-calibrated radar echo images and the rainfall range obtained from the interpolation of the rain gauges were consistent and could better highlight the rainfall intensity centers. The accurate radar-based rainfall estimation is more conducive for the regional analysis of rainfall in actual applications.

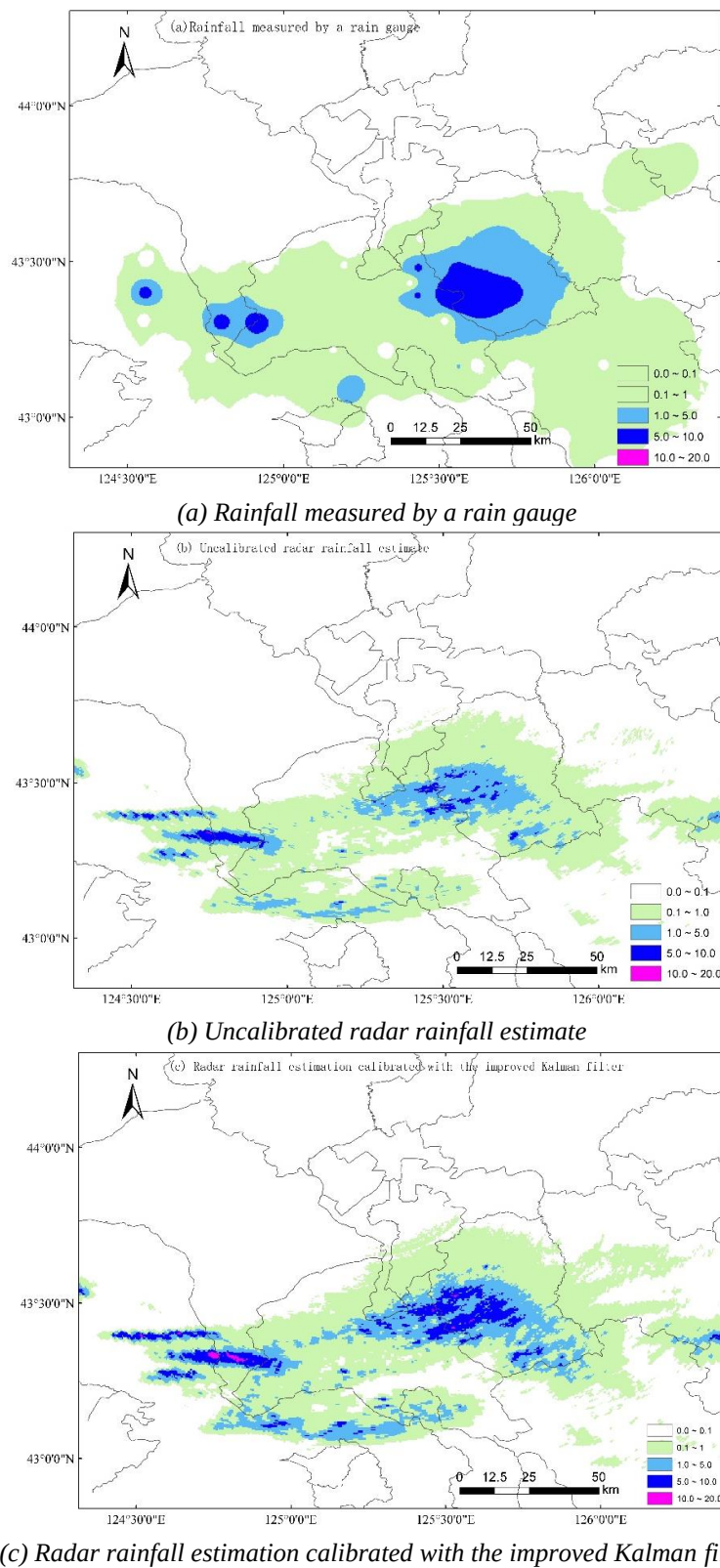


Figure 6. Rainfall distribution estimated by different methods from 1–2 a.m. on August 19, 2015 (unit: mm)

Discussion and conclusion

(1) The G/R calibration model is simultaneously affected by the radar-based rainfall estimation model and measurement factors of automatic rainfall stations. Differences exist in different stages of the rainfall event or different rainfall areas. Kalman filter calibration can result in a smaller variation range for longer rainfall events and tends to be stable, while the variation range of shorter rainfall events is larger and instable. Therefore, better radar-based rainfall estimation results could be obtained during longer rainfall events.

(2) The initial values and setting of model parameters greatly affect the estimation accuracy of the Kalman filter calibration. In contrast to previous studies, such as Zhao et al. (2001) who used empirical constants as model parameters for the Kalman filter, the improved Kalman filter carries out parameter corrections of the state and measurement equations at every step, which decreases the effects of unreasonable model parameters on the whole filtering process and increases the self-adaptive ability of the filter algorithm. During the experiment, the correlation coefficients of the two rainfall events increased from 0.1245 to 0.7295 and from 0.3721 to 0.6222, which increases the accuracy of the G/R calibration factor. This also results in the improvement of the corrected radar-based rainfall estimate.

(3) The G/R ratio from the filter output of the corrected radar-based rainfall estimate was used in this study. The results show that the ordinary Kalman filter could decrease the average relative error from 0.6047 to 0.3557 and from 0.8052 to 0.3096, respectively. On the other hand, the improved Kalman filter could decrease the average relative error from 0.6047 to 0.2645 and from 0.8052 to 0.1715, respectively. Compared with the ordinary Kalman filter method, the improved Kalman filter method can increase the accuracy of radar-based quantitative estimates of regional rainfall. At the same time, after improved Kalman filter calibration, the radar-based estimated field highlights regions with heavy rainfall and that with supplement rainfall that are not measured by automatic weather stations. Compared with other calibration methods for radar-based estimates, such as the dynamic grading method, the proposed Kalman filter does not require large amounts of experimental data for the calculation. At the same time, it is able to provide a filter variance output, which is more conducive for the evaluation and optimization of the calibration system (Hill et al., 2013; Yucel et al., 2015).

As above, the proposed algorithm improves the quality of rainfall estimate effectively, which has a special significance for disasters warning and assesment, such as storm events. However two rainfall events in the Changchun Area in different years were considered in this study. However, the average rainfall is relatively low and there is a lack of validation analysis of different types of rainfall events. To further improve the applicability of the Kalman filter to actual radar-based rainfall estimation, more researches on large amounts of rainfall events are required, and the calibration factors need to be considered into actual rainfall estimate model.

Acknowledgements. The research reported herein was sponsored by the National Key Research and Development Program of China (Grant No. 2017YFB0503605), the Hebei Province Natural Science Fund (Grant No. D2016210008), the National Natural Science Foundation of China (Grant No. 41771478) and the Beijing Natural Science Foundation (Grant No. 8172046).

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