An Integrated Approach to Error Correction for Real-Time Radar-Rainfall Estimation

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ABSTRACT

A procedure for estimating radar rainfall in real time consists of three main steps: 1) the measurement of reflectivity and removal of known sources of errors, 2) the conversion of the reflectivity to a rainfall rate ($Z$–$R$ conversion), and 3) the adjustment of the mean field bias as assessed using a rain gauge network. Error correction is associated with the first two steps and incorporates removing erroneous measurements and correcting biases in the $Z$–$R$ conversion. This paper investigates the relative importance of error correction and the mean field bias–adjustment processes. In addition to the correction for ground clutter, the bright band, and hail, the two error correction strategies considered here are 1) a scale transformation function to remove range-dependent bias in measured reflectivity resulting from an increase in observation volume with range, and 2) the classification of storm types to account for the variation in $Z$–$R$ relationships for convective and stratiform rainfall. The mean field bias is removed using two alternatives: 1) estimation of the bias at each time step based on the sample of observations available, and 2) use of a Kalman filter to estimate the bias under assumptions of a Markovian dependence structure. A 7-month record of radar and rain gauge rainfall for Sydney, Australia, were used in this study. The results show a stepwise decrease in the root-mean-square error (rmse) of radar rainfall with added levels of error correction using either of the two mean field bias–adjustment methods considered in our study. It was found that although the effects of the two error correction strategies were small compared to bias adjustment, they do form an important step of radar-rainfall estimation.

1. Introduction

Radar-rainfall estimation is based on a series of assumptions that introduce inaccuracies in the resulting estimates. Past studies have classified the associated errors into two categories (Joss and Waldvogel 1970; Austin 1987; Jordan et al. 2000): (a) sampling or measurement errors that lead to reflectivity measurements that are not representative of the ground rainfall, and (b) errors resulting from the procedure used to convert the reflectivity ($Z$) to a rainfall rate ($R$). Careful calibration and validation of radar rainfall cannot by itself eliminate the problems introduced through errors in the reflectivity measurement process (i.e., ground clutter, beam blocking, anomalous propagation, hail, bright band, attenuation, range-dependent bias resulting from increases in observation volume with range). Similarly, using a single $Z$–$R$ relationship that does not account for the variations due the effect of different storm types (e.g., stratiform and convective) leads to errors in the process of converting measured reflectivity to a rainfall rate ($Z$–$R$ conversion error). A comprehensive strategy to estimate radar rainfall must take into account strategies for correcting the measurement as well as the $Z$–$R$ conversion error.

Because accuracy in the estimated radar rainfall is measured with reference to the ground rain gauge mea-
measurements, differences in these measuring techniques can be expected to produce a “residual error” even if the other error sources are properly accounted for. This is because a rain gauge measures point rainfall continuously at the ground while radar measures rainfall averaged over a pixel for a specified temporal resolution at some height above the ground. Additionally, changes in raindrop size distribution in both space and time have a different effect on the corresponding rainfall. These residual errors often produce a uniform multiplicative bias in radar-rainfall estimation when compared to rain gauge data (Anagnostou et al. 1998; Krajewski and Smith 2002), necessitating the use of a technique to remove an average difference between the radar and rain gauge rainfall.

This paper aims to investigate the stepwise improvements in radar-rainfall estimation through a series of steps. Two strategies that aim to address errors in the measurement and the conversion of reflectivity to a rainfall rate are considered in this study. These are 1) the use of a scale transformation function to remove range-dependent bias in measured reflectivity resulting from an increase in the observation volume with range, and 2) classification of storm types to account for the variation in \(Z-R\) relationships for convective and stratiform rainfall. The issue of whether to integrate the error correction process in a procedure for real-time radar-rainfall estimation or to use a mean field bias-adjustment technique to adjust the differences between rain gauge and radar rainfall is also addressed in this paper. Twenty-eight rainfall events are recorded from November 2000 to May 2001 from the C-band Kurnell radar in Sydney, Australia, and hourly rainfall data from a network of 260 rain gauges (as illustrated in Fig. 1) are used in this study.

The paper is organized as follows. Section 2 presents details on the integrated strategy for error correction as the basis for real-time radar-rainfall estimation. Section 3 presents the stepwise improvements in the accuracy of radar rainfall with an increased number of correction strategies being used. Finally, the conclusions from this study are drawn in section 4.

2. Error correction strategies in radar-rainfall estimation

The underlying philosophy for the estimation of radar rainfall in real time used in this study is that the estimated radar rainfall must first be corrected for the reflectivity measurement errors and the \(Z-R\) conversion errors using our understanding of the causes behind the errors as the basis for devising the correction strategies, and then a bias-adjustment method is used to remove the average differences (mean field bias) between radar estimates at the rain gauge locations and for the corresponding gauge rainfall amounts. A procedure for the estimation of radar rainfall in real time can thus be divided into the following three components: 1) reflectivity measurement, 2) conversion of reflectivity to a rainfall rate, and 3) bias adjustment using rain gauge data. Details of the three components of real-time radar-rainfall estimation are discussed next.

a. Reflectivity measurement errors

The reflectivity measurements represent the average reflectivity across the illuminated portion of the radar beam. Radar-reflectivity data are typically obtained in the form of a volume scan. A volume scan is available every 5–10 min and consists of data in the polar coordinates, with a resolution of radar beamwidth and bin length, which are transformed to a Cartesian grid for ease of use. Reflectivity measurement errors include temporal and spatial sampling errors (Harrold et al. 1974; Fabry et al. 1994; Jordan et al. 2000), height sampling errors that result in a range-dependent bias (Fabry et al. 1994; Kitchen et al. 1994; Andrieu and Creutin 1995; Fabry and Zawadzki 1995; Fulton et al. 1998; Vignal and Andrieu 1999; Vignal and Krajewski 2001), ground and sea clutter (Collier 1996), anomalous propagation (Battan 1973), beam blocking (Gabella and Perona 1998), beam attenuation (Hitzfeld and Bordan 1954; Hildebrand 1978), range-dependent bias resulting from increases in observation volume with range (Chumchean et al. 2004), electrical calibration error, and quantification of reflectivity error (Cluckie et al. 1991).

Rainfall map-viewing software (MapView) developed by Seed and Jordan (2002) was used in this study. The effects of ground and sea clutter have been removed from the data used in this analysis by using a map of known ground and sea clutter locations and radar measurement discarded in these areas. To avoid the effect of noise and high reflectivities caused by hail, echoes less than 15 and greater than 53 dBZ (Fulton et al. 1998) were excluded from the analysis. The climatological freezing level of the Sydney area is approximately 2.5 km. Hence, the 1.5-km constant altitude plan precipitation indicator (CAPPI) reflectivity data were used to avoid the effect of the bright band and different observation altitudes. It is to be noted that the CAPPI algorithm that was used in MapView (Seed and Jordan 2002) is based on a 3D kriging algorithm to interpolate the spherical coordinates onto a Cartesian grid. This algorithm accounts for the mean vertical profile of reflectivity and the convolution of the nonuniform distribution of power within the radar beam and this profile.
Orographic rainfall in Sydney during the summer (the period under investigation) is more commonly triggered convection rather than the seeder–feeder or autoconversion types. This is because of the modest height of the Blue Mountains to the west of Sydney. It is true that orographic enhancement is likely to be significant during major stratiform storms, but this will occur in very specific areas depending on the meteorology of the day and is not considered to be part of a range correction algorithm in this study. Attenuation for the C-band radar is considered to be a severe problem for measurement of high-intensity rainfall (reflectivity > 50 dBZ) (Hildebrand 1978; Austin 1987). The conditional mean rainfall rate of the data used in this study is about 4.2 mm h\(^{-1}\) and the conditional mean of measured reflectivity (reflectivity > 15 dBZ) is only 26 dBZ, hence the effect of attenuation is considered to be insignificant on average. In this paper, we evaluate the effectiveness-correcting range-dependent bias as a result of an increase in the observation volume with range, details on which are presented next.

Range-dependent bias in measured reflectivity resulting from an increase in observation volume with range can be corrected using a scale transformation function (Chumchean et al. 2004). The scaling correction of measured reflectivity should be performed on the volume scan reflectivity data while these data are still in the form of instantaneous measurement in plan position indicator (PPI) polar coordinates. The climatological reflectivity data are required for estimating a scaling exponent. Because the climatological volume scan data corresponding to the studied period were not

**Fig. 1.** Map of the Sydney area, showing rain gauges (small circles), the Kurnell radar (radar symbol), and range rings at 20, 40, 60, 80, and 100 km from the radar.
available, the 7-month 10-min 1.5-km CAPPI reflectivity data were used to estimate the scaling exponent, and the scaling correction was performed on the instantaneous CAPPI reflectivity data instead. The scaling exponent of the instantaneous 1.5-km CAPPI reflectivity data was found to be equal to 0.033. The climatological scale transformation function of an instantaneous 1.5-km CAPPI reflectivity in a Cartesian grid obtained from the 1° radar beamwidth can then be written as (see Chumchean et al. 2004 for more detail)

$$Z_{\text{transformed}} = \left( \frac{20}{D} \right)^{-0.033} Z_D$$

(1)

where $D$ (km) is the observation range of the measured reflectivity beyond 20 km and $Z_D$ (dBZ) is the instantaneous 1.5-km CAPPI Cartesian reflectivity at that range. The reflectivity’s cumulative distribution function (CDF) at the 20-km range interval is selected as the reference CDF because the scaling behavior is most noticeable from the 20-km range onward (see Fig. 2a) and the accuracy of the reflectivity CDF that is closest to the radar is the highest because of a smaller observation volume. The scaling exponent for use with the data where the attenuation has been removed is expected to be less than 0.033. Attenuation by rain can be corrected as a function of the range from a radar (Burrows and Attwood 1949); therefore, for the case of the Kurnell radar, we consider that the attenuation effect has also been implicitly reduced via the use of the proposed scale transformation function. Future research will attempt to develop a means of altering the scaling relationship to explicitly account for attenuation. The scale transformation function [Eq. (1)] was used to transform the measured reflectivity at different range intervals to have the same CDF as that of the measured reflectivity at the 20-km range interval (hereafter “scale-transformed reflectivity”), as illustrated in Fig. 2b. It is to be noted that the conditional mean of rain gauge rainfall at the 0–20-, 20–40-, 40–60-, 60–80-, and 80–100-km range intervals were 4.41, 4.19, 4.32, 4.02, and 4.27 mm h$^{-1}$, respectively. The average measured reflectivities at those range intervals were 24, 23.8, 23.5, 23.4, and 23.2 dBZ, and the average scale-transformed reflectivities were 24, 24.3, 24.3, 24.4, and 24.5 dBZ, respectively. This illustrates that the scaling correction helps remove the range-dependent bias in the hourly Cartesian reflectivity at range within 100 km from the radar.

b. Errors in conversion of measured reflectivity to rainfall rate

Differences between raindrop size distributions of convective and stratiform rainfall lead to a different $Z$–$R$ parameters of these two rainfall types (Battan 1973; Tokay and Short 1996; Atlas et al. 1999). Using a single $Z$–$R$ relation applied universally to all rain fields irrespective of inherent differences in raindrop size distributions can result in erroneous estimates of radar rainfall (Atlas et al. 1999). The studies of Joss and Waldvogel (1970), Rogers (1971), Battan (1973), Kla- zura (1981), Austin (1987), Rosenfeld et al. (1992), Rosenfeld et al. (1993), Tokay and Short (1996), and Amitai (2000) reported that the $Z$–$R$ conversion error can be substantially reduced if the parameters of the $Z$–$R$ relationship are estimated using data that represent the type of events for which the developed relationship will be used. Anagnostou and Krajewski (1999) show that radar–rain gauge root-mean-square error (rmse) can be reduced by about 10% when rainfall classification is included in the radar-rainfall estimation procedure. In the results of the study of Anagnostou and Morales (2002) it is also evident that differentiating between the convective and stratiform $Z$–$R$
multiplier is essential for improving the performance of the radar-rainfall estimation algorithm. It is recommended that separate Z–R relations be developed for different types of rain fields and available information be used to classify the current rain field into the appropriate type. In this study, we assume that the Z–R relations for convective and stratiform rainfall are stationary, both within events and across the entire record. Radar rainfall of each pixel should be estimated based on the predefined Z–R relation of convective or stratiform rainfall that corresponds to the identified rainfall type for each radar grid. Hence, a storm classification needs to be integrated into a Z–R process and it is considered as the second step of error correction strategies in radar-rainfall estimation in this study.

Rainfall drop size distribution varies in time and space, causing temporal and spatial variation of storm type within an hour. To account for the effect of storm types and the movement of rainfall in hourly radar-rainfall estimation, a storm classification must first be performed using instantaneous reflectivity data, which should be followed by conversion into instantaneous radar rainfall using appropriate Z–R relations for each rainfall type separately; thereafter, an accumulation process that accounts for the movement of rainfall within an hour is used to accumulate the instantaneous rainfall into hourly radar rainfall. The Kurnell radar scans every 10 min. The storms in Sydney can move very quickly indeed, frequently at 60 km h$^{-1}$ so this is a significant effect even for 5-min data. Fabry et al. (1994) showed that the effect is significant even at 5 min and should be a standard procedure for any accumulation algorithm. The accumulation method proposed by Fabry et al. (1994) was used in this study. This method assumes that the rain field moves at a constant velocity (single-radar wide vector) and varies linearly in intensity. The storm velocity was first computed for each time interval.

The accumulation was then computed by assuming that rainfall rate of each shower pixel varied linearly with time between each time interval. The advantage of this accumulation method is that the movement and evolution of the rainfall field between the instantaneous rainfall intensity field produced by the radar has been taken into account. A procedure that integrates storm classification and consequent estimation of initial hourly radar rainfall in real time proposed by Chumchean (2004) (as shown in Fig. 3) were used in this study.

According to the steps outlined in Fig. 3, the first step in converting reflectivity into rainfall rate is to formulate appropriate Z–R relations for the two rainfall types. The hourly pixel classification method, which is a minor modification of a texturing algorithm presented by Steiner et al. (1995) and the hourly pixel classification parameters proposed by Chumchean (2004), were used to classify the hourly scale-transformed reflectivity of the ensemble of 28 events into convective and stratiform components, and the climatological Z–R relations of the two rainfall types were estimated by calibration with the corresponding hourly rain gauge rainfall. The result from the study of Seed et al. (2002) shows that the rmse between radar-rainfall estimates and the corresponding rain gauge rainfall is quite insensitive to the value of $b$ over a wide range ($b = 1.6, 1.5, \text{and} 1.4$). Therefore, in this study the $b$ parameter of the Z–R relationship was fixed equal to 1.5 while the $A$ parameter was estimated by minimizing the mean square error (mse) between rain gauge and radar-rainfall estimates. The climatological $A$ parameters of the Z–R relation of the scale-transformed reflectivity for convective and stratiform rainfall and the no-scaling correction reflectivity are presented in Table 1. It is to be noted that the convective Z–R multiplier obtained from this study is 1.72 times larger than the stratiform multiplier, which is close to the ratio of 2 and 2.1 determined by Tokay and Short (1996) and Anagnostou and Morales (2002), respectively.

The classification parameters of the instantaneous pixel classification method proposed by Chumchean (2004) were then used to classify the instantaneous scale-transformed reflectivity into convective and stratiform components. Thereafter, the climatological Z–R relations of convective and stratiform rainfall were used to convert the instantaneous reflectivity into rainfall rate depending on the classified rainfall types. Figure 4 shows an example of the classification result of the scale-transformed reflectivity (at 0355:01 UTC 31 January 2001). It can be seen that the classified results correspond well with a subjective classification based on two-dimensional CAPPI reflectivity data.

Even if the scaling correction and the storm classification have been integrated into the radar-rainfall estimation procedure, there remain biases in the radar-rainfall estimates when compared to rain gauge measurements. These residual biases can be removed by using a bias-adjustment method based on rain gauge rainfall data. Details on how this is accomplished in real time are presented next.

c. Bias adjustment using rain gauge data

“Bias adjustment is the key factor in achieving high-quality radar rainfall estimates” (Steiner et al. 1999). Krajewski and Smith (2002) defined “bias” as the systematic departure from the true, unknown rainfall. A
systematic difference between radar rainfall and rain

gauge rainfall can be progressively removed using in-
formation provided by rain gauges (Brandes 1975; Cain
and Smith 1976; Wilson and Brandes 1979; Collier et al.
1983; Steiner et al. 1999; Krajewski and Smith 2002).
This is performed through the estimation of an adjust-
ment factor that is estimated as the ratio of the accu-
mulated rain gauge rainfall and the accumulated radar
rainfall \( \frac{G_i}{R_i} \). This is the simplest way to remove the
average difference (bias) between radar estimates at
the rain gauge locations and the corresponding gauge
rainfall amounts. This bias-adjustment factor is esti-
mated as

\[
B_t = \frac{\sum_{i=1}^{n} G_{i,t}}{\sum_{i=1}^{n} R_{i,t}},
\]

where \( G_{i,t} \) is hourly rain gauge rainfall (mm) at gauge \( i \)
for hour \( t \), \( R_{i,t} \) is the initial radar-rainfall estimates (mm)
at gauge \( i \) for hour \( t \), and \( n \) is total number of rain
gauges that measure nonzero rainfall at that hour.

However, considerable uncertainty remains in the es-
timated mean field bias \( \frac{G}{R} \) ratios. Much of this un-
certainty is a result of a systematic bias in the initially

<table>
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TABLE 1. Climatological Z–R parameters of convective and stratiform rainfall \( Z = AR^{1.5} \).
estimated radar rainfall, which can be attributed to the many sources of errors that have not been considered in formulating the estimation procedure. Some of these factors include nonstationarity in the reliability of radar-rainfall estimates as a function of range (Chumchean et al. 2003), electrical calibration, quantification error (Cluckie et al. 1991), and temporal and spatial sampling errors (Harrold et al. 1974; Fabry et al. 1994; Jordan et al. 2000), in addition to the error resulting from a rather simple characterization of the rainfall drop size distribution as a conforming to either convective or stratiform rainfall alone. To reduce the uncertainty in the estimated mean field bias, many studies such as Ahnert (1986), Smith and Krajewski (1991), Anagnostou et al. (1998), Seo et al. (1999), Dinku et al. (2002), Anagnostou and Morales (2002), and Chumchean (2004) have presented Kalman filtering techniques for the automated correction of mean field bias in real time. These techniques account for both temporal fluctuations of the mean field bias and observation error resulting from the limited sampling of the rain gauge network.

A Kalman filter (Kalman 1960) is an iterative procedure to smoothly update bias and error variances that gives initial weight to the expected value. The equations to estimate time-varying mean field bias using Kalman filtering consist of two sequential stages. The first stage is referred to as the “time update” and the second as the “measurement update.” The time update involves projecting forward (in time) the current state of the variable being modeled, and its associated error variance to obtain an a priori estimate. The measurement update involves correcting the a priori estimate for the effect of the new (noisy) measurement recorded at the current time step. This corrected estimate is then referred to as the a posteriori estimate (Welch and Bishop 2002). The advantages of the Kalman filter over simply computing G/R ratios are that the technique 1) accounts for the “noise” in the measurements when updating the mean field bias, 2) provides an estimate of the error in the computed bias, and 3) combines an estimate of the bias and its error variance made an hour earlier with the current measurements and its estimated measurement error variance to compute an updated bias estimate and new forecast for the next hour (Ahnert 1986).

The studies of Ahnert (1986), Smith and Krajewski (1991), Anagnostou et al. (1998), and Seo et al. (1999) used the Kalman filtering equations for prediction and updating the mean field bias, but used different procedures to estimate the optimal parameters of the process and observation error variance models. In their studies, the observation errors of mean field bias were empirically estimated without considering variations in the reliability of the measured bias. In reality, the reliability of radar rainfall decreases as one moves away from the radar because of the effect of radar beam geometry as illustrated in Fig. 5 (Chumchean et al. 2003). It should be noted that we consider that the reliability of radar-rainfall estimates is inversely proportional to the variance of radar-rainfall error. Hence, the variance of the
observed mean field bias should affect the magnitude of the Kalman filtering observation error model.

In this study, a procedure for automated correction of the mean field bias based on Kalman filtering approach proposed by Chumchean (2004) was used as the bias-adjustment process. According to this method, the mean field bias being characterized as an autoregressive order-one (AR1) model, with parameters being updated using a Kalman filter and the time-varying error variance of the observed logarithmic mean field bias, was followed by the variance of the measured log_{10}(G/R) model proposed by Chumchean et al. (2003). The observation error variance was estimated based on (a) the number of rain gauges that measure nonzero rainfall at that hour, (b) the location of the observation rain gauges, (c) the conditional mean of rain gauge rainfall, and (d) the number of pulses used for reflectivity measurements. This allows the Kalman filtering measurement update to account for changes in the reliability of the initial radar-rainfall estimates as a function of range from the radar. The optimal parameters of the Kalman filtering model proposed by Chumchean (2004) were used for the filter to operate. [See more details in Chumchean (2004).] Details of the proposed steps and layout of the general procedure for real-time radar-rainfall estimates for the Kurnell radar are summarized in Fig. 6.

3. Effect of radar error correction strategies and bias adjustment in real-time radar-rainfall estimates

The stepwise improvements attained through the use of the error correction strategies presented in the previous section were evaluated using the ensemble of 28 events. The evaluation was conducted in the following three stages: (a) correction for ground clutter, hail, noise, bright band, and different observation altitude;
(b) correction for the range-dependent bias resulting from an increase in observation volume with range (scaling correction) in addition to the correction in (a); and (c) use of $Z-R$ relations for convective and stratiform rainfall based on results of storm classification algorithm and the strategies in (a) and (b). The mean field bias adjustment was then used to remove the residual differences between radar rainfall obtained from the above three datasets and rain gauge data. Three mean field bias–adjustment methods were considered. These were 1) no bias correction, 2) sample $G/R$ method, and 3) Kalman filtering techniques based on the approach proposed by Chumchean (2004). The analysis was performed in an hourly time step. Reflectivity data of 28 events from November 2000 to May 2001 from the Kurnell radar at Sydney and the network of 260 hourly rain gauges were used to evaluate the stepwise improvements obtained through each stage.

It is to be noted that rain gauge data used in this study were obtained from the dense network of 260 hourly tipping-bucket gauge stations. Eighty-nine of these stations are owned and operated by the Australian Bureau of Meteorology (BoM). Most of these stations have a tipping-bucket size of 1.0 mm. The other 171 stations are owned and operated by the Sydney Water Corporation (SCA). All of these stations have a tipping-bucket size of 0.5 mm. All of the BoM gauges are available in real time, while those of the SCA are not available in real time. The locations of the gauges are shown in the map of the Sydney area in Fig. 1. All of the gauges are located within 109 km from the radar. The vast majority of the gauges are located within 50 km of the Kurnell radar site. The tipping-bucket type of rain gauge records the time of bucket tips, hence they are subject to significant quantification error at low rainfall intensity. Therefore, only the rainfall amounts that are greater than the volume of that gauge’s tipping bucket were used in this study.

### a. Calibration results

Hourly radar rainfall of the three data settings of the ensemble of 28 events were estimated using the three bias-adjustment methods. The rmse of the radar-rainfall estimates at the rain gauge locations were used to evaluate the quality of radar rainfall. The rmse of the calibration case can be estimated as

$$\text{rmse} = \sqrt{\frac{1}{N} \sum_{t=1}^{N_t} \sum_{i=1}^{N_G} (R_{i,t} - G_{i,t})^2},$$

where $R_{i,t}$ is the radar-rainfall accumulations at the pixel corresponding to the $i$th rain gauge for hour $t$, $G_{i,t}$ is the corresponding rainfall for hour $t$, $N_G$ is the number of rain gauges that measure nonzero rainfall, $N_t$ is the number of time periods (hours), and $N$ is the number radar–gauge pairs used in the computation.

Figure 7 illustrates the calibration rmse results for the ensemble of 28 events using all of the available rain gauges to evaluate the calibration performance of the three alternatives investigated. The results show that there is a stepwise decrease in the rmse of radar rainfall with added levels of error correction with either of the mean field bias–adjustment procedures used. The improvement in the accuracy of radar rainfall resulting from applying the scaling correction was found to be smaller than the storm classification. This is possibly because about 75% of the total gauges used in this study are located within 50 km of the Kurnell radar, which causes difficulty in investigating the performance of the scenarios when applying the scaling correction because the volume (or diameter) of the range bin at the range less than 50 km is not significantly different.

The sample $G/R$ bias-adjustment method gives the smallest rmse compared to that of the other two methods. This corresponds to the fact that we measure the accuracy of radar rainfall by comparing with rain gauge data; therefore, for the calibration case, the sample $G/R$ method will always give the lowest rmse compared to the other methods. However, the same cannot be said for cross-validation case.

### b. Cross-validation results

Cross validation was performed so as to confirm whether the calibration results presented earlier hold
true in a generic situation. The three rain gauge–based adjustment techniques were used to adjust the final radar rainfall obtained using the various error correction strategies considered. We also evaluated the sensitivity to the density of the rain gauge network on the quality of the results obtained. The assessment is performed based on the rain gauges that were not used for estimating the bias, and hence provides a good indication of how either approach performs at ungauged locations. The analysis was conducted as follows.

(a) Specify \( N_G \), the number of rain gauges to be used to estimate the mean field bias.

(b) Randomly select \( N_G \) rain gauge locations from the entire network.

(c) Calculate the hourly \( G/R \) ratio based on the rain gauges selected. Use this as the basis for estimating the radar rainfall for the current past hour.

(d) Estimate the mean field bias for the current time step using the Kalman filter. Use this to estimate the radar rainfall, and compare with the estimates in (c). Note that the comparisons are based on the rainfall across the rain gauges not included in the subsample in steps (a) and (b).

Steps (a)–(d) were repeated 100 times for different random selections of the rain gauge subnetwork, and performance assessed based on the remaining gauges using the rmse estimated as

\[
\text{rmse} = \sqrt{\frac{1}{NV} \sum_{i=1}^{N} \sum_{t=1}^{N-G} (R_{it} - G_{it})^2},
\]

where \( R_{it} \) is the radar-rainfall accumulations at the pixel corresponding to the \( i \)th validation rain gauge for hour \( t \), \( G_{it} \) is the corresponding rainfall for hour \( t \), \( N - N_G \) is the number of rain gauges not included in the subset used to estimate the bias at each time step, \( N_s \) is the number of time periods (hours), and \( NV \) is the number of validation radar–gauge pairs used in the computation.

The calibrated rain gauge network sizes \( (N_G) \) were changed to 1/2, 1/4, 1/8, 1/16, 1/32, and 1/64 of the available observation gauges. Results from this exercise for the ensemble of 28 events are illustrated in Figs. 8a–8c. The box plots reflect the variations in the rmse across the 100 subsamples that were used in the analysis. The results expectedly show that the approach of correcting the sample \( G/R \) bias results in the lowest rmse when a large number of rain gauges have been used in the calibration (i.e., greater than 130 gauges). The sample bias-adjustment method performs better than the Kalman filtering only when a large number of rain gauges have been used in the calibration (greater than 130 gauges).

The reason is because we evaluate the accuracy of radar rainfall by comparing with the rain gauge data. When a large number of \( G/R \) values are available, the sample bias adjustment can be represented by the average hourly \( G/R \) better than the value that was calculated from Kalman filtering. However, when fewer rain gauges are used, the estimated bias is a poorer representation of the true value, and the results over the validation sample are worse than the other approaches considered. Additionally, the spatial correlation between the errors becomes important when working with a dense rain gauge field. These errors are assumed to be independent in the Kalman filtering approach. Note that use of sample \( (G/R) \) bias correction is considerably worse because the rmse values are greater than 4 mm for the cases where the calibration rain gauges are less than 32 gauges, so box pots presented in Fig. 8b were not covered by those high rmse values. The consistency of each calibration method can be measured by comparing the variance or interquartile range (IQR) of rmse across the 100 subsamples. A smaller variance or a shorter length of the box plot indicates a higher consistency of a calibration method. The results of this study are evidence that the Kalman filtering technique is more consistent than the observed \( G/R \) method. These results correspond to the result obtained from the study of Dinku et al. (2002). In their study, the stochastic filtering bias adjustment outperforms the deterministic approach (observed \( G/R \)) and no bias correction by 24% and 28%, respectively, when 23 rain gauges have been used in the calibration.

The results presented in Figs. 8a–8c show the stepwise decrease in rmse values with added levels of radar error correction being used. This corresponds to studies of Borga et al. (2000) and Dinku et al. (2002). The results of their studies are evident for the mountain radar operation for which the mean field bias and vertical profile of reflectivity (VPR) adjustments are two correction approaches that need to be complementary. They also found a stepwise improvement in radar-rainfall estimates when levels of radar error correction in the radar-rainfall estimation procedure were added. The effect of radar error correction strategies was found to be small compared to the effect of mean field bias adjustment as presented in Table 2. This result agrees with the study of Steiner et al. (1999) who found that the differences resulting from radar data processing scenarios were small compared to the effect of bias adjustment and using high-quality rain gauge data.

Interestingly, the results presented in Table 2 show that the bias adjustment based on Kalman filtering may not always result in an increase in the accuracy of radar rainfall. Use of the Kalman filtering techniques with the
data that have not been corrected for the scaling and Z–R conversion error result in a higher rmse than that without the bias-adjustment method if the calibrated rainfall gauge network is small (less than 16 gauges). This is because of the high uncertainty in the estimated mean field bias if the initial radar-rainfall estimates contains some systematic biases. In contrast, using the Kalman filtering approach with all error correction strategies results in an improvement in accuracy of radar rainfall for all cases, irrespective of the number of calibrated rain gauge network. This result corresponds to the study of Borga et al. (2000) who found the danger of applying only mean field bias correction without correcting other sources of error in measured reflectivity before calculating real-time radar rainfall. One can thus conclude that although the effect of using the error correction strategies is small compared to mean field bias adjustment, it is still an important step of radar-rainfall estimation and needs to be integrated into procedure to estimate radar rainfall in real time.

4. Summary

This paper proposed a procedure for integrating radar error correction strategies into real-time radar-rainfall estimation. The error correction consists of correcting errors in the reflectivity measurements and the Z–R conversion processes. The error correction of re-
The results show that there is a stepwise decrease in the rmse of radar rainfall with added levels of error correction irrespective of the mean field bias–adjustment methods used.

2) Correcting for the mean field bias appears to be more important than correcting the other error sources of error.

3) Using the storm classification is relatively more important for radar-rainfall estimation than the scaling correction. This is possibly because about 75% of the total number of gauges used in this study are located within 50 km of the Kurnell radar, which causes difficulty in evaluating improvements scenarios when applying the scaling correction, which does not offer significant differences for ranges less than 50 km.

4) By using the bias-adjustment based on the Kalman filtering approach with other error sources accounted for, we achieved radar-rainfall estimates with the lowest rmse for all cases where the calibrated rain gauges network is less than 130 gauges.

5) While the effects of radar error correction resulting from range or storm classification were found to be small compared to the effect of removing the mean field bias, they do form an important step of radar-rainfall estimation.

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