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Evaluation of radar-gauge merging methods for quantitative precipitation estimates

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Abstract

Accurate quantitative precipitation estimates are of crucial importance for hydrological studies and applications. When spatial precipitation fields are required, rain gauge measurements are often combined with weather radar observations. In this paper, we evaluate several radar-gauge merging methods with various degrees of complexity: from mean field bias correction to geostatical merging techniques. The study area is the Walloon region of Belgium, which is mostly located in the Meuse catchment. Observations from a C-band Doppler radar and a dense rain gauge network are used to retrieve daily rainfall accumulations over this area. The relative performance of the different merging methods are assessed through a comparison against daily measurements from an independent gauge network. A 3-year verification is performed using several statistical quality parameters. It appears that the geostatistical merging methods perform best with the mean absolute error decreasing by 40% with respect to the original data. A mean field bias correction still achieves a reduction of 25%. A seasonal analysis shows that the benefit of using radar observations is particularly significant during summer. The effect of the network density on the performance of the methods is also investigated. For this purpose, a simple approach to remove gauges from a network is proposed. The analysis reveals that the sensitivity is relatively high for the geostatistical methods but rather small for the simple methods. The geostatistical methods give the best results for all network densities except for a very low density of 1 gauge per 500 km^2 where a range-dependent adjustment complemented with a static local bias correction performs best.

1 Introduction

The interest for quantitative estimation of rainfall based on weather radar has increased during the last years. Indeed new applications have risen in the field of distributed hydrological modelling or numerical weather prediction which require accurate precipitation estimates at high spatial resolution.

Radar is a remote sensing instrument that measures the reflectivity of precipitation along the radar beam at a given altitude. Those measurements can be used to estimate precipitation at ground level. Several sources of errors affect the accuracy of this estimation (e.g., Wilson and Brandes, 1979; Joss and Waldvogel, 1990). The measure of reflectivity itself can suffer from electronic miscalibration, contamination by non-meteorological echoes or range effect (attenuation, increase of the sample volume due to beam broadening). When retrieving the rainfall estimation at ground level, additional uncertainties arise. Those are due to the non-uniform vertical profile of reflectivity (VPR) and the conversion of radar reflectivity into rain rates. Nevertheless, a weather radar provides precipitation estimation at high spatial and temporal resolution over a large area. A network of rain gauges can provide more accurate point-wise measurements but the spatial representativity is limited. The two observation systems are generally seen as complementary and it is interesting to combine them.

Merging radar and gauge observations has been an intense topic of research since the beginning of the operational use of weather radars in the 70's. A review of gauge adjustment methods and operational use in Europe can be found in a COST 717 report (Gjertsen et al., 2003). More complex methods have been proposed such as co-kriging (Krajewski, 1987), statistical objective analysis (Pereira et al., 1998) or Kalman filtering approach (e.g., Todini, 2001; Seo and Breidenbach, 2002; Chumchean et al., 2006). Some of those methods are very time consuming and are not well suited in an operational context. Note that those merging methods must be seen as a final step in the processing of radar data. All kind of corrections should be applied first to improve the radar-based precipitation estimates like ground echo elimination, VPR correction or attenuation correction (e.g., Germann et al., 2006; Tabary, 2007; Uijlenhoet and Berne, 2008).

The aim of this study is to perform a long-term verification of different existing merging methods. Several methods of various degrees of complexity have been implemented and tested. All selected methods are appropriate for operational use. Verification of the merging methods faces the problem that the real precipitation field is unknown. A traditional approach is to compare precipitation estimates with rain gauges. Cross-correlation (i.e. removing a gauge from the adjustment network to use it for verification) is a possible method but the drawback is that the network used for adjustment varies. In this study an independent verification network is used, more suitable to analyse the performance of the methods. Since the time sampling of this network is 24 h, the merging is made on daily accumulation. Several statistics are then computed to evaluate and compare the different methods. Similar long-term verification has been performed in recent studies but limited to one (e.g., Borga , 2002; Holleman, 2007) or a few methods (e.g., Heistermann et al., 2008; Salek and Novak, 2008). In Schuurmans et al. (2007), three different geostatistical methods have been compared based on 74 selected rainfall events.

The impact of the gauge network density on the merging methods performance has been little assessed in past studies (see however Sokol, 2003 or Chumchean et al., 2006). It allows to determine the best method for a given network density.

The characteristics of the radar and the rain gauges networks can be found in Sect. 2. The different methods used for merging are described in Sect. 3 and the results of a 3-year verification against rain gauges are presented in Sect. 4. In Sect. 5, a sensitivity analysis of the performance to the density of the network used for merging is carried out.

2 Radar and gauge observations

The Royal Meteorological Institute of Belgium (RMI) operates a single-polarisation C-band weather radar located in Wideumont. The radar observations are routinely used at RMI for operational short-term precipitation forecast, detection of severe thunderstorms (Delobbe and Holleman, 2006) and a-posteriori analysis in case of severe weather events. The use of the Wideumont radar observations for hydrological studies and applications is also an important field of research and development (e.g., Berne et al., 2005; Delobbe et al., 2006; Leclercq et al., 2008).

The radar performs a 5-elevation watchdog scan every 5 min with reflectivity measurements up to 240 km. A time-domain Doppler filtering is applied for ground clutter removal. An additional treatment, based on a static clutter map, is applied to the volume reflectivity file to eliminate residual permanent ground clutter caused by some surrounding hills. A Pseudo CAPPI (Constant Altitude Plan Position Indicator) at 1500 m is extracted from the volume data and reflectivity factors are converted into precipitation rates using the Marshall-Palmer relation $Z = aR^b$ with $a=200$ and $b=1.6$. The available reflectivity images are integrated in time to produce a 24 h rainfall accumulation starting at 08:00 LT.

The hydrological service of the Walloon region (MET/DGVH) operates a dense (1 gauge per 135 km^2) and integrated network of 90 telemetric rain gauges. Most of them are tipping bucket systems providing hourly rainfall accumulations. The collected data are used for hydrological modelling and directly sent to RMI. The rain gauges are controlled on site every three months and in a specialised workshop every year. Every day, a quality control of the data is performed by RMI using a comparison with neighbouring stations. Radar data are also used in this quality control for the elimination of outliers.

RMI maintains also a climatological network including 270 stations with daily measurements of precipitation accumulation between 8 and 8 local time (LT). Most of these stations are manual and the data are generally available with a significant delay. The data undergo a drastic quality control. This network is used for the long-term verification of radar precipitation estimates. It will be used here to evaluate the radar-gauge merging methods.

Since the estimation of precipitation can be very inaccurate at large distance from the radar, a maximum range of 120 km is used. The MET network, used for adjustment, is then reduced to 74 gauges. Several stations of the RMI network are not always available during the 3-year verification period. Those stations are removed to ensure that the same network is used for the whole period. The remaining verification network includes 110 gauges. The positions of the radar and the two rain gauge networks can

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be seen in Fig. 1.

3 Description of the methods

Various methods combining radar and rain gauge data have been implemented to obtain the best estimation of precipitation. The radar data are given on a Cartesian grid with a pixel size of 600 × 600 m. Rainfall accumulation of 24 h is computed to match the time step of the RMI network used for verification. For validity, the minimum number of available radar scans is fixed at 280 (for a maximum of 288). Several methods require the comparison between a rain gauge measurement G and a corresponding radar value R. This value is computed as the mean value on a square of 9 pixels centred at the gauge location. Only the pairs where both R and G exceed 1 mm are considered as valid. A day is valid if there are at least 10 valid pairs. The methods are applied on a square domain containing the Walloon region. It means that some areas fall outside the network convex hull (i.e. the boundary of the minimal convex set containing all the gauges). On those areas, adjusted values must be seen as extrapolation. The uncertainties associated with those values are then higher.

3.1 Mean field bias correction (MFB)

The assumption here is that the radar estimates are affected by a constant multiplicative error (this error being mainly due to a bad electronic calibration or a wrong Z-R relationship). The adjustment factor is estimated as a mean field bias:

$$C_{\mathrm{MFB}} = \frac{\sum_{i=1}^{N} G_i}{\sum_{i=1}^{N} R_i} \tag{1}$$

where N is the number of valid radar-gauge pairs, G_i and R_i are the gauge and radar value associated with gauge i.

3.2 Range-dependent adjustment (RDA)

This method assumes that the R/G ratio is a function of the distance from the radar due to the increasing height of the measurements. The range dependent adjustment is mainly based on the BALTEX adjustment method (Michelson et al., 2000). The relation between R/G expressed in log-scale and range is approximated by a second order polynomial whose coefficients are determined using a least squares fit.

$$\log C_{\mathrm{RDA}} = ar^2 + br + c \tag{2}$$

where r is the distance from the radar. The range dependent multiplicative factor C_{RDA} is derived from the polynomial fit.

3.3 Static local bias correction (SLB)

The static local bias correction aims at correcting for visibility effects. The correction is calculated from a one-year data set using the climatological gauge network. The 24 h radar accumulations are first adjusted by a mean field bias correction. Then, for each gauge location, the averaged residual bias over 1 year is estimated. Finally a spatial interpolation based on kriging is performed to obtain the correction field. To simulate an operational context, the correction calculated over a given year is used for the next year. The fields obtained for 2004, 2005 (see Fig. 2), 2006 and 2007 are very similar. This correction is applied before a range dependent adjustment (SLB + RDA = SRD).

3.4 Brandes spatial adjustment (BRA)

This spatial method was proposed by Brandes (1975). An assessment factor is calculated at each rain gauge site. All the factors are then interpolated on the whole radar field. This method follows the Barnes objective analysis scheme based on a negative exponential weighting to produce the calibration field:

$$C_{\mathrm{BRA}} = \frac{\sum_{i=1}^{N} w_i\,(G_i/R_i)}{\sum_{i=1}^{N} w_i} \quad w_i = \exp\frac{-d_i^2}{k} \tag{3}$$

where d_i is the distance between the grid point and the gauge i. The smoothing is controlled by the parameter k which can be linked to the density δ of the network. An empiric inverse relation is chosen here :

$$k = (2\delta)^{-1} \tag{4}$$

The performance of this method is also strongly influenced by the structure of the network.

3.5 Ordinary kriging (KRI)

A geostatistical method like ordinary kriging deals with the spatial interpolation of a random field from observations at several locations (see Goovaerts (1997) for a general description). It requires the definition of a variogram describing the spatial variability of the field. Then the method allows one to take into account the spatial correlation between stations to predict values at any position. The estimation U_0 at a specific location is a linear combination of the gauge values G_i:

$$U_0 = \sum_{i=1}^{N} \lambda_i G_i \tag{5}$$

The weights λ_i are computed to obtain the best linear unbiased estimator assuming a constant unknown mean across the field. This involves solving a linear equation system whose size is equal to the number of gauges.

In this study, only the 20 nearest gauges are used to reduce the computational cost. The model variogram, assumed isotropic, is a first order linear function of the distance. More complex climatological variograms (i.e. Gaussian, exponential and spherical) were tested but no significant improvements of the performance were observed.

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Those results are consistent with the study of Haberlandt (2007). The KRI method, based only on rain gauges, is used to evaluate the added value of radar in the other methods.

3.6 Kriging with radar-based error correction (KRE)

This method referenced as "conditional merging" in Sinclair and Pegram (2005) uses the radar field to estimate the error associated with the ordinary kriging method based on rain gauges and to correct it. First, radar values at each gauge site are used to produce a radar-based kriging field. This field is then subtracted from the original radar field to obtain an error field. Finally, the error field is added to the gauge-kriged field. This method based on kriging is relatively simple and computationally efficient.

3.7 Kriging with external drift (KED)

This method is a non-stationary geostatistical method (see Wackernagel (2003) for a general description) that uses the radar as auxiliary information. It follows the same scheme as the ordinary kriging except that the mean of the estimated precipitation field is now considered as a linear function of the radar field. Additional constraints are then added to this scheme:

$$\sum_{i=1}^{N} \lambda_i R_i = R_0 \tag{6}$$

where R_i is the radar value at gauge location i, λ_i the corresponding weight and R_0 the radar value at the estimation location. The weights are given by solving the augmented system of linear equations. The variogram is also assumed linear in this study. This is the most complex and time consuming method. Note that an automatic method to compute a variogram model has been proposed recently by Velasco-Forero et al. (2008).

4 Long-term verification

4.1 Methodology

The performance of the merging has been evaluated by comparing the adjusted 24h precipitation accumulations to the measurements of the climatological gauge network (RMI). The testing period is 3 years, from 2005 to 2007. The days not allowing adjustment for all methods (i.e. with less than 10 valid pairs) are removed. The gauge data used for the adjustment and for the verification are independent. Unfortunately the two networks have several locations in common or very close. The gauges of the RMI network situated at a distance less than 2 km from a gauge of the MET network are then removed. The remaining verification network includes 75 gauges.

Several quality parameters are found in the literature. The Root Mean Square Error (RMSE):

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(R_i-G_i)^2}{N}} \tag{7}$$

is the most common parameter used in verification studies. However, the Mean Absolute Error (MAE):

$$\mathrm{MAE}=\frac{\sum_{i=1}^{N}|R_i-G_i|}{N} \tag{8}$$

is less sensitive to large errors and it will be used here as first quality parameter. All pairs of gauge radar values are taken into account for this parameter.

A standard for objective judgement of radar performance is proposed in Germann et al. (2006). The mean bias, the error distribution and the scatter as defined in that paper are also used in the present study. The mean bias (MB) is the total precipitation as seen by the radar divided by the total precipitation measured by the gauges. The error distribution is the cumulative contribution to total rainfall as a function of the radar-gauge ratio expressed in dB. The scatter is half the distance between the 16% and

84% percentiles of the error distribution. It is a robust measure of the spread of the multiplicative error, insensitive to outliers. The standard deviation (STD) and the root mean square of the multiplicative error (RMSF) have also been calculated. Only pairs with both adjusted and gauge values larger than 1 mm for all the methods are taken into account. This ensures that the same data set is used for comparison between the different methods.

4.2 Results

The verification methodology has been first applied for the three years separately. The goal is to verify the consistency between the three datasets. In Fig. 3, the relative performance of the different methods looks similar for the three years. Nevertheless, the ordinary kriging method (KRI), using only rain gauges, exhibits some variability between the years. The 3 years taken as a whole will now be considered for the rest of the evaluation.

As shown in Fig. 4, the Mean Absolute Error (MAE) is significantly reduced for all methods compared to the original data (ORI). A simple mean field bias (MFB) correction reduces the error by more than 25%. Using the range dependent adjustment (RDA) allows a small additional improvement. A further improvement is obtained when a static local bias (SRD) correction is applied. The performance of the latter method is close to the Brandes one (BRA), which is also a spatial method. The ordinary kriging method (KRI), only based on rain gauge data, shows a result close to the RDA method. This good result is due to the high density of the rain gauge network (see Sect. 5). The two geostatistical methods using both radar and rain gauges observations (KRE, KED) perform best for this quality parameter. When the KED method is used, the error decreases by almost 40% with respect to the original data.

Figure 5 shows the error distribution for the original data and for four methods of increasing complexity. The vertical line divides the R/G ratios (in dB) in underestimation (left) and overestimation (right). A perfect match should give a step function, with a mean bias and a scatter equal to zero. The original radar data (ORI) reveal a significant

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underestimation with a mean bias of −1.2 dB. The mean field bias correction (MFB) succeeds in balancing the error distribution. The method combining a range-dependent adjustment and a static local bias correction (SRD) slightly reduces the spread of the error while the most sophisticated geostatistical method (KED) further tightens the error distribution. The ordinary kriging (KRI) shows a small underestimation.

The results for the scatter (Fig. 6) are similar. It is worth pointing out that the relative performance of Brandes compared to the other methods is slightly better. Actually this method can sometimes lead to large errors that are taken into account for the MAE but not for the scatter. This figure also shows that methods with a daily spatial correction feature based on radar and gauges (BRA, KRE, KED) perform significantly better.

The results of the different statistics for all the methods can be found in table 1.

4.3 Seasonal variation

The spatial pattern of 24 h rainfall accumulation varies significantly along a year, from widespread precipitation during stratiform events in winter to very local precipitation cells during convective events in summer. Therefore the accuracy of radar precipitation estimates and the spatial representativity of gauge measurements depend on the season.

Figure 7 shows the value of the MAE (normalised by the MAE of the radar) with the dataset sorted by month. The ranking of the methods slightly varies along the year. As expected, the estimation from the gauges only (KRI) is relatively inaccurate in the summer. The performance is worse than the mean field bias correction in this period and even worse than the original radar data in July. In the winter, the ordinary kriging (KRI) is better and very close to the kriging with external drift (KED). KED is the best method for nearly all months, being sometimes slightly outperformed by KRE or SRD method. This analysis points out that the additional information given by the radar is especially valuable during summer.

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4.4 Range-dependence

The performance of the different algorithms as a function of range is analysed up to 120 km from the radar. The verification network is divided into 6 range intervals of 20 km as shown in Fig. 8. The gap between the performance of the radar and that of the gauges is significant at short distance (<20 km) due to the bright band effect. This is also the case at long distance (>100 km) due to the decreasing accuracy of radar estimates. The small difference between KRI and KRE or KED at those ranges shows that the radar added values is very limited. The positive effect of the range dependent adjustment when compared to the mean field bias appears at distances further than 80 km (RDA vs MFB). KED is the best method for all distances.

5 Effect of the network density

The effect of gauge density on the performance of the different merging methods has been analysed. This is useful to select the most appropriate method for a given network density or to determine the minimum network density needed to achieve a given level of performance. None of the methods takes directly into account the density of the network except the Brandes method through the smoothing factor.

5.1 Removing gauges

As the region seen by the radar is characterised by low climatological variations, the assumption that the probability of precipitation is the same everywhere is valid. Consequently, a perfect network should be made of a regular grid of points considering a rectangular area. Actually the position of the gauges depends on practical constraints and specific interest on catchment. The spatial distribution of gauges in a real network is then less uniform. It is obvious that gauges cannot be randomly removed from the network. Indeed, when the furthest gauge is removed, the coverage area decreases.

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Furthermore, a gauge that belongs to the convex hull (see Sect. 3) cannot be removed without decreasing the study area.

Eventually a rain gauge is removed from the network in such a way that the spatial distribution of the remaining gauges is as uniform as possible. A simple approach is proposed here, based on the distance between gauges. For each gauge, the sum of the inverse of the distance to the four nearest gauges is computed. Then the gauge with the maximum value (that is too close to its neighbours) is removed. The effect of the algorithm can be seen in Fig. 9 which shows the reduced network with 50 and 20 gauges. Note that the convex hull is relatively well preserved while the number of gauges decreases.

5.2 Global statistics

A long term verification is performed with decreasing network densities. For the sake of consistency, the valid days for adjustment (see Sect. 3) at the lower density are taken as the common verification dataset for all densities.

Figure 10 shows that a mean field bias correction is not very sensitive to the gauge density and the performance remains acceptable even for a low density network. The performance of the range dependent adjustment, involving a second order polynomial fit, slightly increases with density but only for low densities. As expected, the ordinary kriging (KRI) is the most sensitive method to this parameter. Indeed, the error significantly grows when the density decreases. The MAEs of the Brandes (BRA) and the two other kriging methods (KED, KRE) follow the same tendency but the improvement is smaller when the density increases. KED is the best method for all networks densities except for the lowest density (1 gauge per 500 km^2) for which the SRD method performs slightly better. Similar results have been obtained with the other quality parameters.

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6 Conclusions

Various methods combining rainfall estimations from a C-band weather radar and an automatic gauge network have been implemented. A 3-year verification up to 120 km range was carried out against an independent gauge network of daily measurements. Several statistics have been computed to evaluate the performance of the radar-gauge merging methods. The effect of the network density has also been tested.

The results point out that simple methods like mean field bias correction can significantly reduce the error of the radar estimation. Nevertheless, there is a clear benefit of using a spatial correction factor. Based upon our verification study, the best method is the kriging with external drift which makes use of the radar as secondary information to improve the spatial interpolation of gauges values. The kriging with radar-based error correction shows very similar performance while the computational cost is reduced. A seasonal verification shows interesting results. In the winter, when stratiform widespread precipitation prevails, the ordinary kriging based on gauges only performs as well as the best radar-gauge methods. In the summer, when convective events occur, the benefit of the radar on radar-gauge methods is clear. The sensitivity analysis to the gauge density shows that the geostatistical merging methods perform best for all network densities except a very small network density (1 gauge per 500 km^2) for which a method combining a static local bias correction and a range dependent adjustment gives the best result.

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Table 1. Several statistics (see Subsect. 4.1) for the 3-years verification of merging methods.

	MB (dB)	RMSE (mm)	RMSF (mm)	MAE (mm)	Scatter (dB)	STD (dB)
ORI	−1.186	5.342	1.866	2.422	2.230	2.477
MFB	0.033	3.940	1.521	1.788	1.509	1.806
RDA	0.006	3.932	1.501	1.736	1.468	1.753
SRD	−0.073	3.692	1.472	1.621	1.362	1.677
BRA	0.068	3.820	1.467	1.583	1.245	1.654
KRI	−0.167	4.011	1.529	1.708	1.404	1.844
KRE	−0.068	3.479	1.459	1.511	1.212	1.639
KED	−0.075	3.458	1.450	1.489	1.196	1.612

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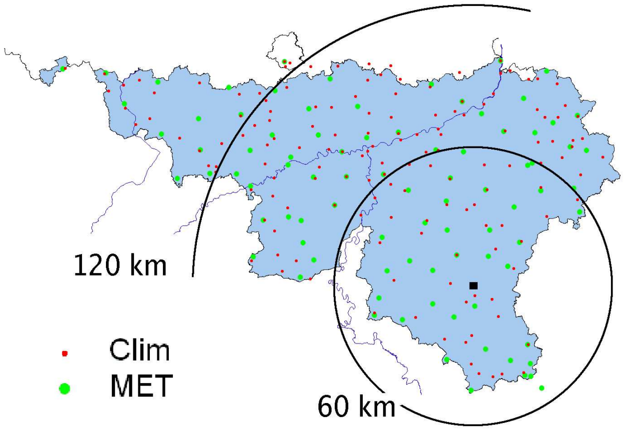

Fig. 1. Walloon Region with Wideumont radar (black square), MET telemetric gauge network and RMI climatological gauge network.

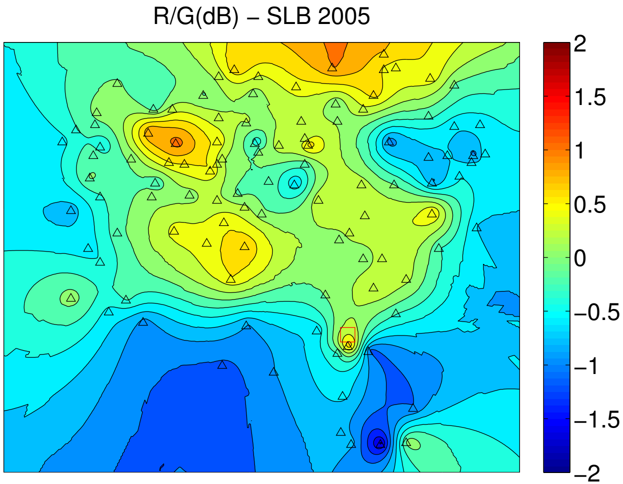

Fig. 2. Static local bias correction field (in dB) for the year 2005 with gauges (triangles) and radar (square) locations.

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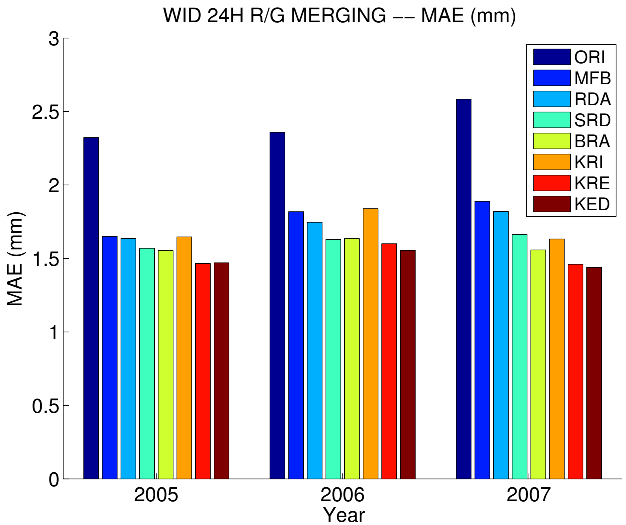

Fig. 3. Mean absolute error for all methods and 3 years of verification.

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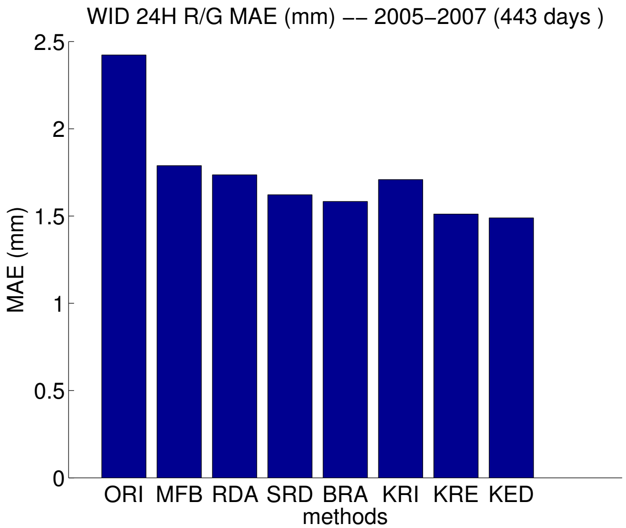

Fig. 4. Mean absolute error for all methods based on a 3-year verification.

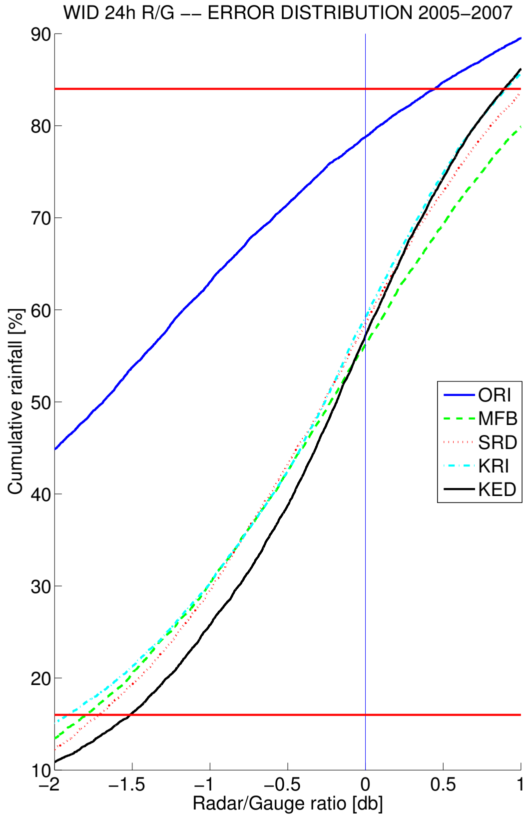

Fig. 5. Error distribution for the original data and 4 merging methods. The scatter is half the distance between the 2 intersections of the error curve with the red lines.

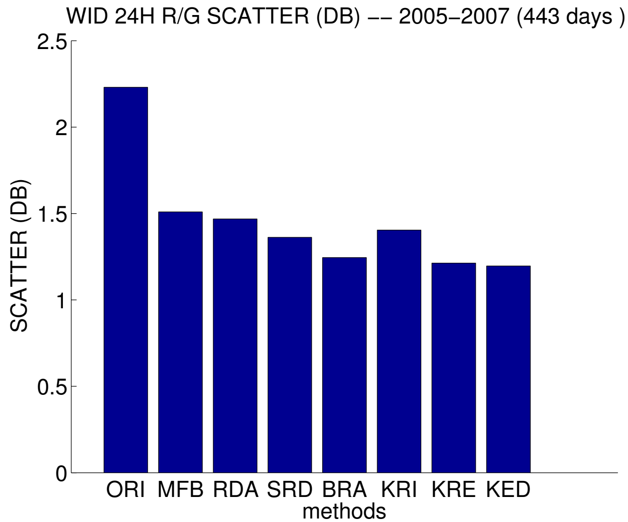

Fig. 6. Scatter score for all the methods based on a 3-year verification.

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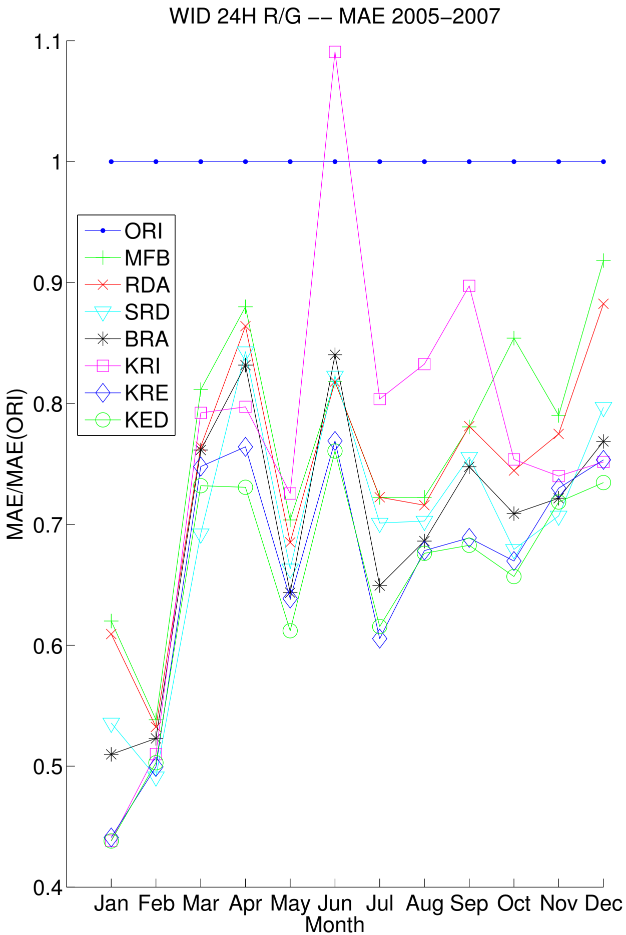

Fig. 7. Mean absolute error for all the methods computed for each month.

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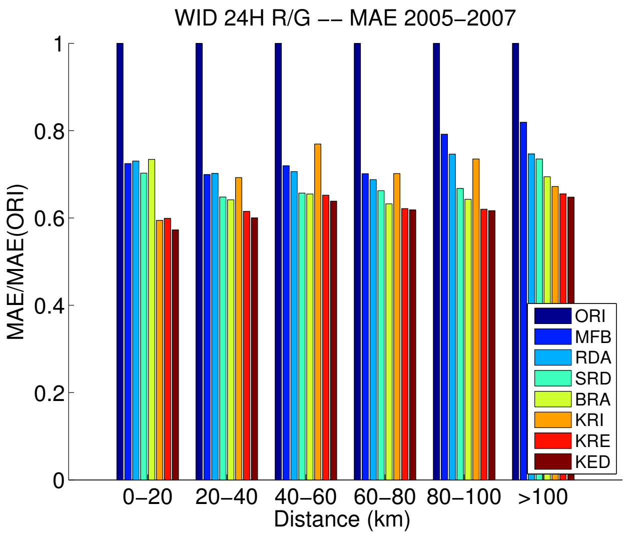

Fig. 8. Effect of the distance from the radar on the mean absolute error of the merging methods.

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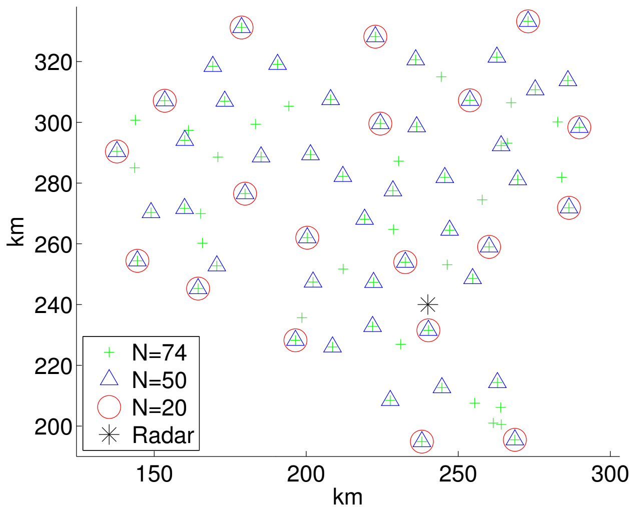

Fig. 9. Gauge network of decreasing densities obtained by an algorithm for removing gauges.

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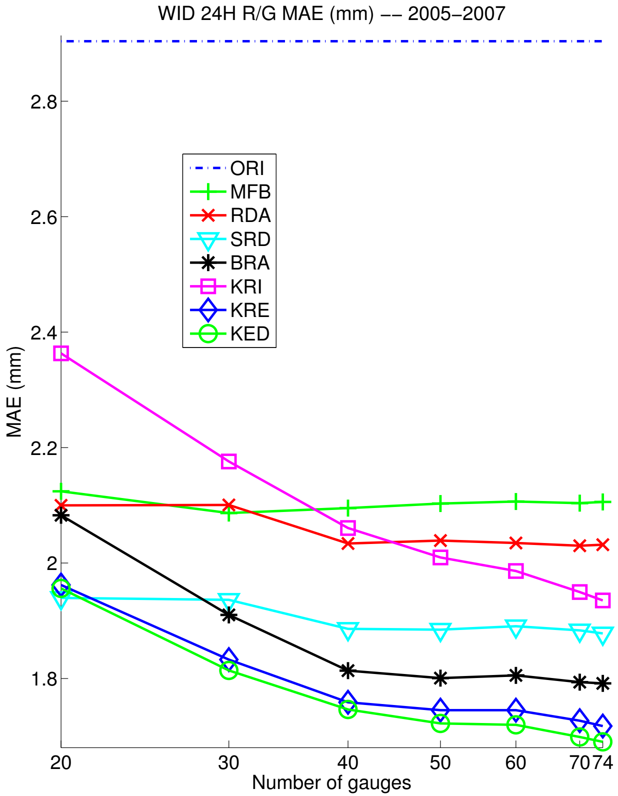

Fig. 10. Mean absolute error of the merging methods for different network densities from 1 gauge per 500 km^2(N=20) to 1 gauge per 135 km^2 (N=74).