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The application of radar-gauge comparison for bias adjustment of radar observations in an alpine environment

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Abstract. This research investigates the adjustment and validation of radar rainfall estimates in a mountainous region (Swiss Alps) by comparison with raingauge data. Operational radar rainfall estimates from the Monte Lema radar, corrected for visibility and vertical profile effects, and raingauge measurements are used as an input to the Weighted Multiple Regression technique (Gabella et al., 2000) to adjust for biases still affecting the radar rainfall estimates after correction. The adjustment is carried out at the monthly time scale in order to analyse the improvement obtained by applying the radar-gauge adjustment with varying weather situations and rain types during different seasons. The analysis is carried out over two years. Validation is performed with use of a jack-knifing technique in which, for every station, the corresponding radar value is corrected on the basis of all other radar-gauge pairs. Results show that the application of the technique is capable to reduce the biases and also the fractional standard error: the Mean Relative Error reduces (in absolute values) from 86% to 5%, while the Fractional Standard Error reduces from 0.9 to 0.7. This last finding is remarkable, since the application of the WMR technique increases the radar values by a factor of six.

1 Introduction

Mountainous areas pose particular challenges and difficulties for radar rainfall estimation. On one hand, severe ground clutter and radar beam shielding complicates radar measurements; on the other hand, orography plays a key role on the precipitation mechanisms themselves, thus enhancing the space-time variability of the precipitation fields. Development of appropriate algorithms for radar data processing represent, therefore, a major step for radar rainfall estimation in rugged terrain. Research studies by Joss and Lee (1995), Andrieu et al. (1997) and Borga et al. (2000, 2002) – among others – have reported approaches for addressing this issue. Most of the studies agree on a three-stage radar rainfall correction approach (provided that the radar calibration problem can be considered reasonably solved): (1) the preliminary identification of the radar detection environment, (2) radar data-based adjustment of range-related errors associated with the vertical profile of reflectivity (VPR), and (3) long-term adjustment with use of data from rain gauges to achieve the required accuracy for quantitative precipitation estimation.

Gabella et al. (2000, 2001) proposed the use of a Weighted Multiple Regression (WMR, hereafter) for radar-gauge adjustment in mountainous regions. The WMR technique allows the correction of each radar pixel as a function of three explanatory variables: the distance from the radar, the height a meteorological target must reach to be visible from the radar site, and the ground height. The WMR technique is here applied to radar data from the Monte Lema radar, in Switzerland. Radar observations, corrected for the effects of ground clutter and vertical profile of reflectivity (VPR, hereafter), are adjusted using a network of raingauges operating at the monthly time scales over a two-year time period. This analysis allows to assess (i) the residual biases in radar rainfall estimates (after application of all the radar processing procedures not involving radar-gauge comparison) and their seasonal variability, and (ii) the improvement obtained by applying a radar-gauge adjustment with varying weather situations and rain types during different seasons. The paper is organised as follows. Section 2 describes the WMR procedure. Section 3 describes the study area and the radar rainfall estimation algorithm. Assessment of the radar-gauge differences before and after WMR technique application is reported in Sect. 4. Section 5 completes the paper with discussion and conclusions.

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2 Description of the WMR technique

For each radar-gauge data pair and for an assigned time step, the Assessment Factor (AF, hereafter) is defined as the ratio of the radar rainfall estimate to the corresponding gauge measurement (both accumulated over the assigned time step). In the WMR technique, the spatial variability of the AF is related to the following variables: (1) D, the distance between the radar site and the gauge (significant because it reflects effects caused by beam broadening and, to some extent, by attenuation); (2) HV, the minimum height a target must reach to be visible from the radar site (it reflects the degree of beam shielding at the specific gauge location); (3) HG, height of the gauge (it reflects the effects caused by precipitation growth related to orography). Earlier experiences with this technique (Gabella et al., 2001) showed better results using HV and HG separately, rather than as a difference between the two.

The WMR technique is applied here in the following way:

(1) Data are integrated over the monthly period. For each radar-gauge data pair, $AF = R/G$ has been computed, where R is the radar rainfall estimate and G is the corresponding total amount measured by the gauge.

(2) In order to reduce problems related to non-linearity and heteroscedasticity (i.e. non-constant variance), a logarithmic transformation is applied to AF and D. This is because reflectivity-to-rainrate (Z-R) relationship and range dependence of the radar signal follow power laws. Log (AF) also has the advantage of being symmetric with respect to R and G. If the vertical profile of reflectivity decreases logarithmically with height, Log(AF) is linearly related to HV and HG. The multiple linear regression is written as:

$$AF(dB)_{est} = 10\log(AF) = a_0 + a_D Log(D) + a_{HV} HV + a_{HG} HG \qquad (1)$$

(3) The regression coefficients are obtained by minimizing the square of the residuals. Gabella et al. (2000) has shown that better results are obtained by weighting the residuals by using radar rainfall estimates as weights, so heuristically keeping track of the radar observation quality.

(4) The final multiple regression model is used to compute *Log(AF)*$_{est}$ for each pixel in the radar surveyed area. These values are then (logarithmically) antitransformed to calculate the ratio R/AF$_{\mathrm{est}}$ in order to obtain the adjusted radar rainfall estimates. It is worth noting that as long as a HG map and a HV map are available, every pixel of the radar map can be corrected using the estimated value of Log$(AF)_{est}$.

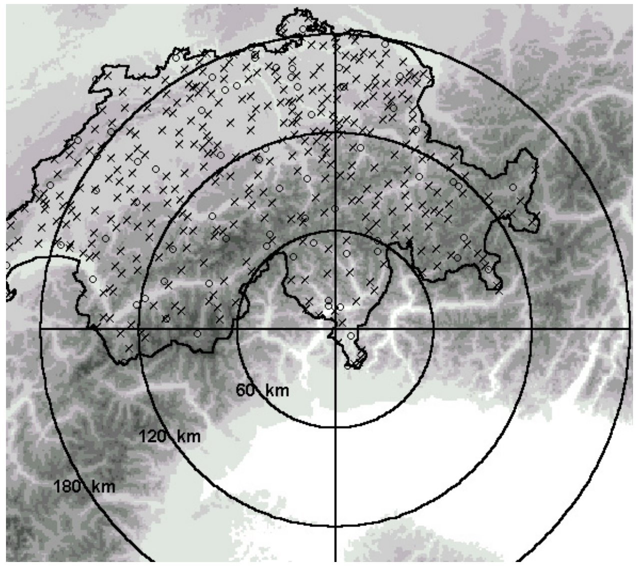

Fig. 1. Presentation of the study area. Relief map, location of Monte Lema weather radar and location of the rain gauge network: circles = ANETZ stations; crosses = NIME stations.

3 The study area and the radar rainfall estimation algorithm

Data used in this study are from the operational C-band Doppler radar Monte Lema of MeteoSwiss, located on the top of Monte Lema at 1625 m a.s.l.

The radar characteristics can be found in Table 1. The Digital Elevation map in Fig. 1 shows the study area, covering most of the Swiss Alps.

3.1 Description of the radar rainfall algorithm

The radar rainfall estimates used in this investigation are from the Swiss radar product named RAIN. With this product the precipitation at the ground is estimated taking into account all valid reflectivity measurements in the vertical column over each terrain pixels. Both reflectivity and Doppler data are used to detect clutter in each element of 1° in azimuth and 1 km in radial range, by applying various tests to each data sample of the element. The tests are based on the intensity value of the reflectivity, on the Doppler frequency

Table 1. Characteristics of Monte Lema radar

Parameter	
Wave length	5.5 cm
Peak power	251 kW
3 dB beam width	1 deg
Number of elevations	20 in 5 min
Max range	230 km

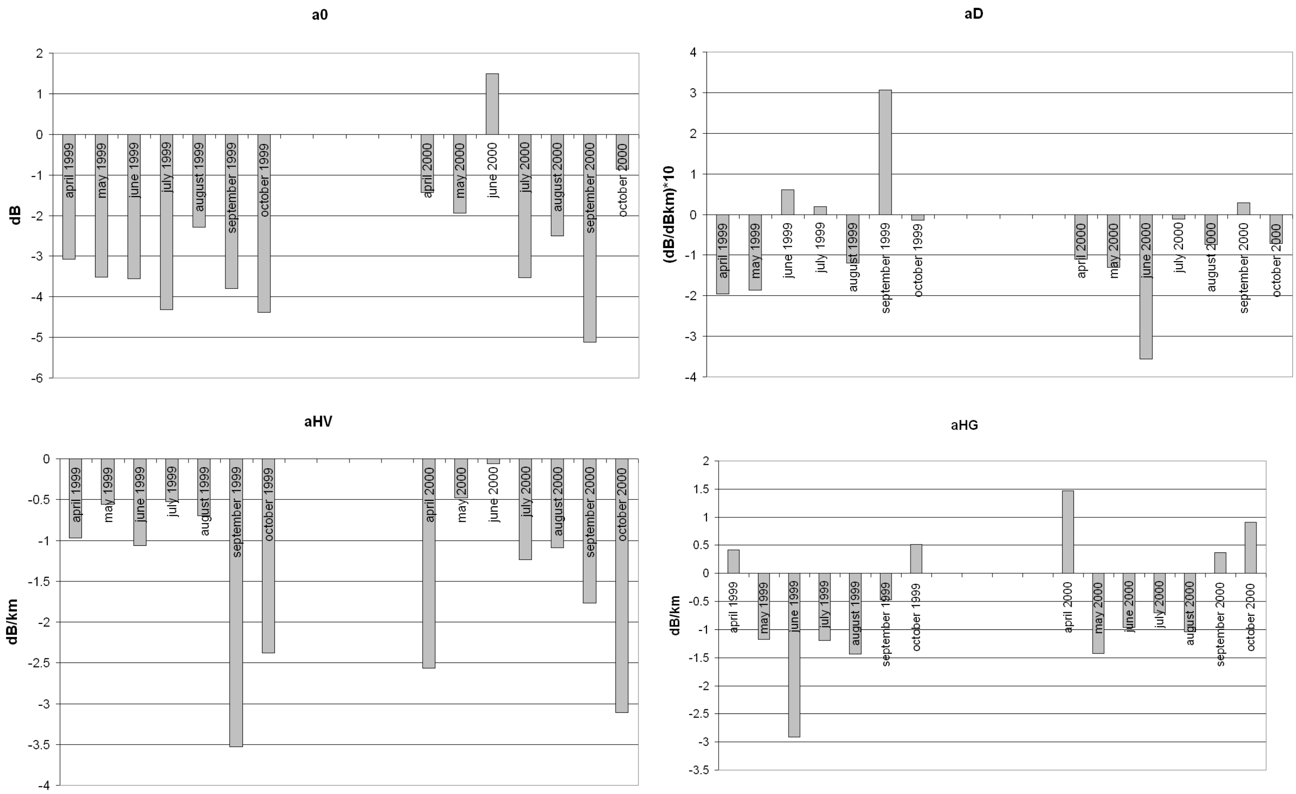

Fig. 2. Regression coefficients resulting from the application of the WMR for the various months.

spectrum, on velocity of the target and on the spatial distribution. Only clutter-free range bins are averaged and resampled over a 1 km Cartesian grid, generating the volume data in 12 horizontal planes of 1 km thickness extending from 0.5 to 12.5 km in altitude. Reflectivity values are quantized on 15 levels ranging from 13 dBZ to 55 dBZ with 3 dBZ resolution. Reflectivity is converted to rainrate using a pre-defined $Z = a R^b$ relationship, with “a” equal to 316 and “b” equal to 1.5, as derived by Doelling et al. (1998). The average of non-clutter samples in a given element is retained, and then polar data are converted to 3-dimensional Cartesian coordinates.

The long-term averaged radar visibility and the terrain height is considered together with a vertical reflectivity profile estimated from the currently measured data. The overall visibility of each element of the volume of interest represents an estimate of the average percentage of the precipitation seen in a pixel. The vertical profile is calculated in real-time based on the mean precipitation amount calculated over the last 30 min from each of the 12 CAPPI images corresponding to 12 height levels. This operation is performed within a range of 70 km side length, centered over the radar station.

The product, characterized by a pixel size of 1 km, is available every 5 min, and is computed as a running average over the last 6 samples (reflectivities of 6 successive volume scans, i.e. 30 min) to improve the representativity of the estimate and make the system less vulnerable to short losses of data communication channels.

4 Application of the WMR technique and analysis of results

The application of the WMR technique is based on the availability of measurements from 449 raingauge stations (Fig. 1), 72 from the ANETZ network (automatic 10 min raingauges) and 377 from the NIME network (manual daily raingauges). The analysis is extended over 14 months: from April 1999 to October 1999 and from April 2000 to October 2000.

To compute the monthly base Assessment Factor, radar and gauge derived monthly accumulations were computed. In order to avoid ground clutter contamination, when the daily gauge accumulation was zero, the day was considered dry and discarded from successive analysis (even if the radar value was different from zero). In the regression analysis only AF values corresponding to monthly-cumulated radar-gauge pairs with radar value greater than 0.5 mm and gauge measurement greater than 5 mm were used. These limits were set in order to include in the analysis significant AF values and to avoid sampling errors. Operating in this way, the number of radar-gauge pairs considered in the regression analysis potentially changes each month. As such, the statistical characteristics of the network changes with the month. For LogD (with D in km), the average value varies from 1.36 (Oct 99) to 2.02 (Jun 00) (with standard deviations respectively equal to 0.256 and 0.27). For HV (in km), the average value varies from 1.99 (Oct 99) to 5.6 (Jun 00) (with standard deviations respectively equal to 0.62 and 1.74). For HG (in km), the average value varies from 0.71 (Oct 99) to 1.1 (Sep 00) (with standard deviations respectively equal to 0.42 and 0.57). As expected, the explanatory variable HV (HG) is the one exhibiting most (least) variability across the various months.

4.1 Analysis of regression coefficients

Figure 2 shows the values of the regression coefficients (Eq. 1) for the various months. The a_0 coefficient is always negative (with the exception of Jun 00); this observation, together with analysis of the pattern of the other coefficients, shows that in general the RAIN product underestimates rainfall at the ground. In contrast, a_D values exhibit a more erratic behaviour, even though most of the values are negative even in this case, indicating an increase of underestimation with the distance from the radar. Analysis of precipitation and AF spatial patterns shows that this coefficient is greatly influenced by the spatial distribution of the precipitation: this is the case for Sep 99, for which an increase of AF with distance is computed, due to the presence of intense precipitation accumulations far from the radar site. Negative values are reported for a_{HV}, with larger values (in absolute value) for April, September and October, indicating a poorer correction for the VPR effects for these months. Interestingly enough, positive values are reported for the same months for the coefficient a_{HG} (with the exception of Sep 99), with negative values for all other months. This may suggest that a_{HG} and a_{HV} coefficients are counter-balancing each other in the equation, indicating the risk of multi-collinearity in the regressions. Results for specific months gives ground to this observation: this is the case for Jun 00, with a very high value for a_0 probably counter-balanced by a very low a_D value and by a small value for a_{HV}. Concern for multicollinearity, which is the condition where at least one explanatory variable is closely related to one or more other explanatory variables, is strongest when the purpose of the analysis is to make inferences about the coefficients, and somewhat less when only predictions are of interest. In any case, research is on-going to diagnose these issues in the context of the WMR technique.

4.2 Assessment of the WMR technique

Assessment of the WMR technique was carried out through analysis of the prediction residuals. These are computed as e(i)=y(i)$-$y$_{\mathrm{est}}$(i), where y$_{\mathrm{est}}$(i) is the regression estimate of y(i) based on the regression equation for the Assessment Factor computed leaving out the ith observation. The procedure is repeated for each observation. For a statistical evaluation of the WMR technique two criteria are selected:

1. The mean relative error (MRE),

$$MRE = \frac{\frac{1}{N_t}\sum_{i=1}^{N_t}\left(R_i^r - R_i^s\right)}{\frac{1}{N_t}\sum_{i=1}^{N_t} R_i^s} \tag{2}$$

   where N_t is the number of valid stations in the considered month, R_i^s is the raingauge measurement for station i, and R_i^r is the corresponding radar adjusted value, based on a regression equation computed leaving out the ith observation.

2. The fractional standard error (FSE):

$$FSE = \frac{\left[\frac{1}{N_t}\sum_{i=1}^{N_t}\left(R_i^r - R_i^s\right)^2\right]^{0.5}}{\frac{1}{N_t}\sum_{i=1}^{N_t} R_i^s} \tag{3}$$

The values of MRE and FSE statistics are reported in Figs. 3a, b. Several observations can be made from these figures. First, it is noted that the radar rainfall observations in the RAIN product suffer from systematic underestimation, with biases being between 80% and 90% of the precipitation accumulation. This is likely to be caused by beam occultation, beam broadening combined with vertical profile of reflectivity (systematic underestimation of precipitation with height), attenuation and radar hardware mis-calibration. Reasonable performances are obtained by applying the WMR technique. A minor residual underestimation (5%) still affects WMR-adjusted radar estimates, even though there are two cases with residual overestimation (Apr 99 and Sep 99). Residual overestimation for Apr 99 is relatively large, and is caused by the presence of outliers which severely limit the predictive capability of the regression model. For this month, the large positive bias resulting from the WMR application implies an increase of FSE with respect to the unadjusted estimates. For all other months, the FSE is almost always significantly reduced. Overall, FSE is reduced by 23% (from 0.9 to 0.7).

5 Conclusions

In this research a gauge-based adjustment technique (the Weighted Multiple Regression, WMR, Gabella et al., 2000) has been applied and evaluated at the monthly time scale to mitigate large biases in radar rainfall products, still affecting the estimates even after correction for visibility and vertical profile effects due to the ostile orography in the Alpine environment. The application at the monthly time scale over two years provided some indications about the characteristics of the radar rainfall estimates before and after adjustment with varying weather situations and rain types during different seasons. It has been shown that the radar estimates before gauge-based adjustment are affected by large negative biases,

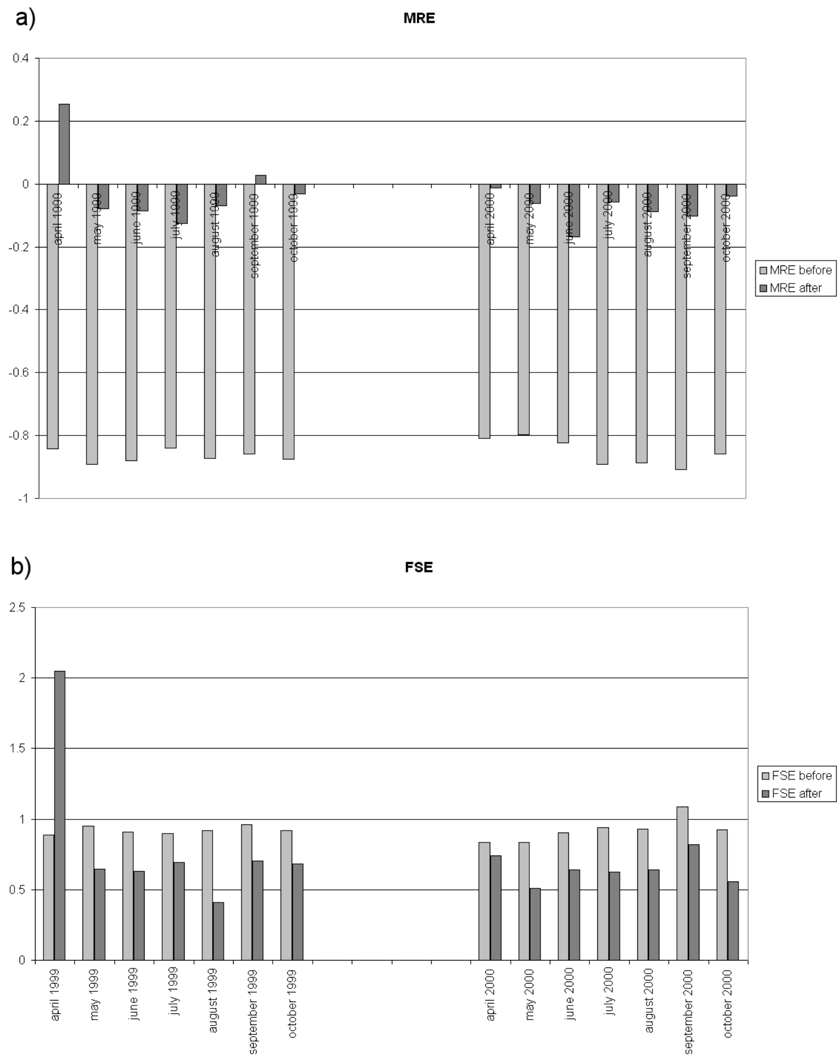

Fig. 3. Comparison between monthly raingauge accumulations and radar estimates before and after WMR-adjustment: **(a)** MRE, **(b)** FSE.

varying in the range 80%–90%. Both biases and variance of the error are significantly reduced with the application of the WMR technique. The assessment of the technique is carried out in terms of prediction residuals. The overall bias is reduced from 86% to 5%, while the overall fractional standard error decreases from 0.9 to 0.7. This is remarkable, since the application of the WMR technique increases the radar rainfall values by a factor of six. However, for one of the months (April 1999) the correction procedure had a detrimental influence on the radar estimates. Among the factors adversely affecting the correction performances for this case, sensitivity of regression results to outliers is probably the most important. Efforts are underway to diagnose the multiple regression models used for the WMR technique. This will help also to mitigate possible effects caused by multicollinearity.

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