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A Novel Space-Time Adaptive Method for Rainfall Estimation by means of Weather Radar and Rain Gauges

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Abstract

In this paper, we show the application of a new method for merging weather radar data with point rainfall measurements from a network of rain gauges. The method, applied to a catastrophic rainfall event occurred in the Marche region in Italy, is based on the space-time adaptive computation of the coefficients of the power-law relationship with which radar reflectivity is converted into rainfall rate. Results are compared with those obtained by a standard method used for quantitative estimation of rainfall based on rain gauges and radar data.

1 Introduction

Quantitative precipitation estimation (QPE) is fundamental to forecast and prevent extreme precipitation events. Weather radars are excellent instruments to define rainfall patterns and their evolution in time with a remarkable temporal and spatial resolution, but they are not considered reliable from a quantitative point of view [1], [2]. As a matter of fact, radar estimates of rainfall are based on the power backscattered from a resolution volume aloft: the conversion of the radar reflectivity Z to rainfall rate R is demanded to *Z–R* relationships which may cause high errors if their coefficients are not chosen after proper comparison of radar and rain gauge data or at least by taking into account the type of rainfall phenomenon. For this reason, QPE relies mostly on networks of rain gauges, as they measure (cumulated) rainfall directly at ground, in a given position. Nevertheless, such networks alone may not result adequate to detect and monitor critical rainfall events, which often combine a very intense rainfall with a limited extension of the rainfall cells. Over the years several methods of merging radar and rain gauges data have been proposed with the aim of improving the QPE [3]. An example is kriging with external drift (KED), which is a solution based on the classical weighted interpolation of raingauge data (kriging) combined with further information provided by radar data [4]. As shown in [5], even KED may reveal inadequate to provide precise information in the aforementioned cases of critical events. An alternative to KED is the algorithm presented in [5] - referred to as STACC (Space-Time Adaptive Conversion Coefficients) in the following - which relies mostly on the radar reflectivity Z for what concerns the spatial pattern of the rainfall phenomenon, while uses the information provided by the rain gauge network to calibrate, on a cell-by-cell basis, the coefficients of the *Z–R* relationship providing the quantitative estimates of rainfall. In this paper, we show the results of the application of the STACC and KED methods to the case of a severe storm occurred on September 15, 2022 in the Marche region (Italy), which caused extensive damage and death to 12 people.

2 The STACC algorithm

The STACC algorithm is briefly summarized here, while the details can be found in [5]. At a given position expressed in longitude (ln) and latitude (lt), the average rainfall rate over a time interval T is given by $R_T(ln,lt)$. In the following, the model

$$log_{10}(R_T(ln,lt)) = A_T(ln,lt) + B_T(ln,lt) \cdot Z_T(ln,lt) \quad (1)$$

is used, where $Z_T(ln,lt)$ is the radar reflectivity (in dBZ) averaged in space (over N_z neighbor resolution cells) and in time (over T), while $A_T(ln,lt)$ and $B_T(ln,lt)$ are two space-varying parameters that rule the dependence between radar and rain gauges data. Let T_w be an interval such that $T_w \leq T$. For a generic kth rain gauge of the network, located in (ln_k,lt_k), let $ZW^{(k)}$ be the space-time average over T_w of the reflectivity measured by the radar in a neighbor of (ln_k,lt_k) and $RW^{(k)}$ be the time average over T_w of the rainfall rate measured by the rain gauge. The quantities $A_T(ln_k,lt_k)$ and $B_T(ln_k,lt_k)$, relative to the position to the specific position (ln_k,lt_k), are obtained by means of a weighted linear regression method, as proposed in [6], applied to the set of couples $(log_{10}(RW^{(k)}), ZW^{(k)})$. The values of $A_T(ln,lt)$ and $B_T(ln,lt)$, in a generic position (ln,lt), are calculated by spatial interpolation of the values $A_T(ln_k,lt_k)$ and $B_T(ln_k,lt_k)$, achieved with the previous procedure for the rain gauges positions. After all, the cumulated rainfall over the period T, at the generic position, is given by

$$CR_T(ln,lt) = T \cdot R_T(ln,lt). \quad (2)$$

In summary, this procedure generates a space-varying *Z–R* relationship over the specific observation time T; more specifically, at each rain gauge position the coefficients of the relations are calibrated by using the observed rain gauges data, while, at any other position, they are obtained by spatial interpolation.

The basic philosophy of this method is using radar as the primary instrument to estimate the spatial pattern of the rainfall – thanks to its excellent resolution – and using rain gauges as auxiliary instruments to improve the poor quantitative accuracy, typical when a non-adaptive, neither in time nor in space, *a priori* Z–R relationship is used.

3 Experimental results

In this Section we show some sample results of the application of the STACC algorithm to the severe rainfall phenomenon occurred over the Marche region in Italy on September 15, 2022. The results obained with the STACC algorithm are compared with those obtained with the KED method [4]. A leave-one-out cross-validation is presented in order to quantitatively assess the performance of both methods.

3.1 Cumulated rainfall estimation

The parameters of the STACC algorithm were set as follows: $N_z = 9$, $T_w = T = 60$ min. Fig. 1 shows $Z_T(ln, lt)$ over T jointly with position and number of the rain gauges available over the Marche region.

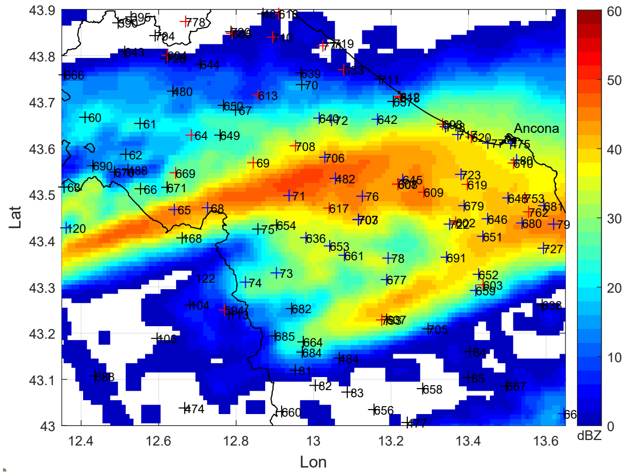

Figure 1. Radar reflectivity $Z_T(ln, lt)$ from 16:30 to 17:30 (local time), September 15, 2022.

The regression yielding $A_T(ln_k, lt_k)$ and $B_T(ln_k, lt_k)$ (i.e., for rain gauges positions) is assumed valid if the output parameters fall within (suitably defined) ranges that identify reasonable model coefficients (typically found in the literature); in the other cases, invalid data are assumed. In Figure 1, valid rain gauges, which are also those utilized in the interpolation procedure to find $A_T(ln, lt)$ and $B_T(ln, lt)$ everywhere, are marked with blue crosses, whereas those marked with black crosses represent the invalid rain gauges; red crosses indicate rain gauges with missing data. As can be noted, the majority of the black crosses are found in areas where reflectivity (and presumably rainfall) is very low.

The cumulated rainfall, obtained from (2), is shown in Figure 2-(a). For comparison, the cumulated rainfall map estimated through the KED method – performed by the open-source library `GSTools` [7] – is shown in Figure 2-(b): in this case, all available rain gauges data are used for interpolation (also the ones indicated with black cross). Note that the area in Figure 2-(a) is limited by the convex hull delimited by the blue-crossed rain gauges, as these are the ones available for spatial interpolation.

The difference between the two approaches is shown in Figure 2-(c). It is evident that STACC identifies a larger area where high cumulated rainfall occurs with respect to KED. In general, KED tends to smooth quite heavily the information brought by the spatial reflectivity pattern, unless point information rain gauges confirm such information. A typical example can be seen in the case under exam by observing the four circled high reflectivity areas in Figure 2-(c). The area marked with ’B’ includes rain gauges #65 and #68, which have recorded the highest cumulated rainfall: therefore, the KED estimation has placed there a peak in the interpolated map (see Figure 2-(b)) and the difference with respect to the STACC estimate is very small. On the contrary, since no rain gauges are located within areas marked with ’A’, ’C’ and ’D’ in Figure 2-(c), KED assumes that rainfall is not so heavy there. Evidently, the STACC estimate is not affected by this issue, while in general there is a risk that KED fails to detect high rainfall areas.

3.2 Cross-validation

In order to evaluate the STACC and KED algorithms from a quantitative point of view, a leave-one-out cross-validation has been carried out [8]. The procedure consists in excluding in turn one of the available rain gauges from the application of both rainfall estimation methods. The measurement recorded by such rain gauge is assumed as ground truth and compared to the estimates obtained in that position by each of the two methods.

The errors ΔCR between the estimates, obtained by using either STACC or KED, and the ground truth measured by each valid rain gauge of the network, are shown in Figure 3-(a). Table 1 shows the cross-validation results for some of the rain gauges characterized by large errors. KED underestimates the real amount of rainfall in rain gauges placed where radar reflectivity is highest (see rain gauges #65, #68, #71 and #482 in Figure 3-(b) and Table 1). The error increases if neighbouring rain gauges have recorded very different values: for instance, remarkable underestimates are obtained for rain gauges #65 and #68 due to the proximity of rain gauges #168 and #671; for the same reasons, we get a remarkable overestimates for rain gauges #168 and #671. Also in the STACC method the errors depend on the neighbours rain gauges, but STACC is less sensitive to this issue

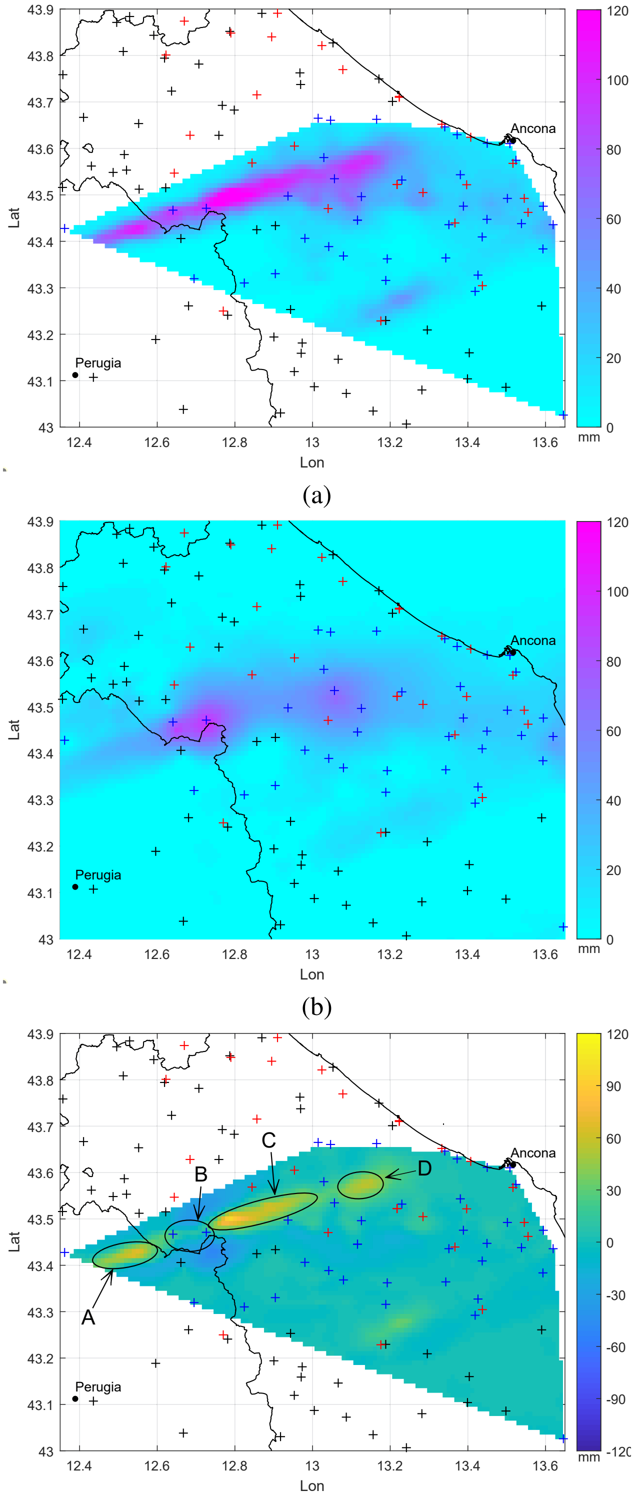

Figure 2. Cumulated rainfall $CR_T(ln, lt)$ from 16:30 to 17:30 (local time), September 15, 2022, estimated by the STACC algorithm (a) and by the KED method (b). The difference between the two maps is shown in (c).

– compared to KED – because it gives more weight to radar reflectivity. In fact, as can be seen in Table 1, the errors related to the same four rain gauges are smaller. However, also the STACC approach can lead to errors, which typically occur when at least two close rain gauges with similar associated reflectivity have recorded different cumulated rainfall. For instance, it is possible to refer to rain gauges #65 (with #68) and #71 (with #68 and #482).

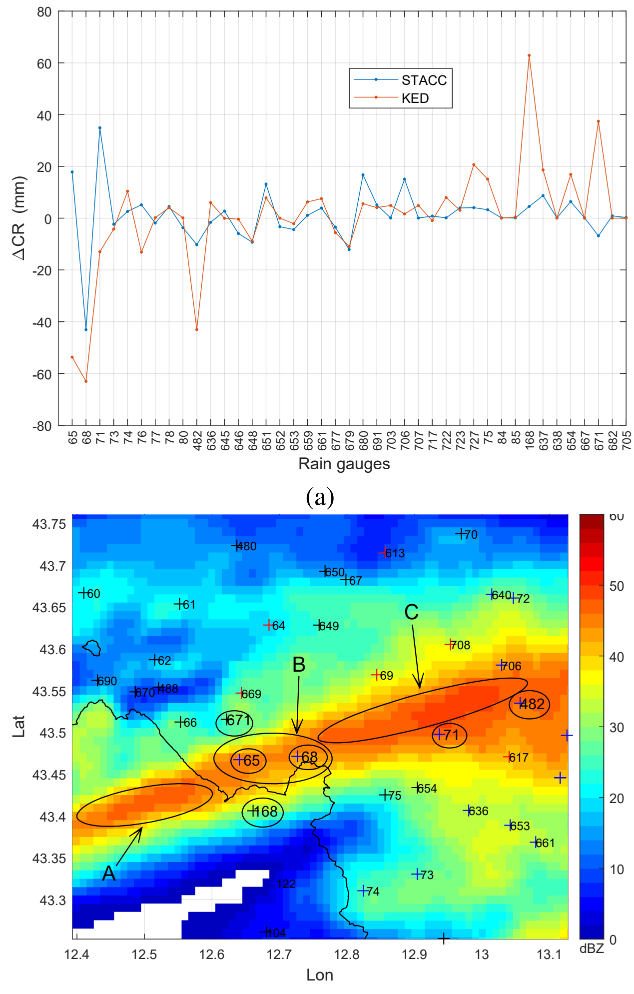

Figure 3. Cross-validation of data from 16:30 to 17:30 (local time), September 15, 2022: error between estimates and ground truth vs. rain gauges id (a); positions of the rain gauges with the highest estimation errors (b).

Table 1. Cross-validation results in selected rain gauges

Rain gauge	$Z_T(ln_k, lt_k)$ (dBZ)	Recorded rainfall (mm)	STACC estimate (mm)	KED estimate (mm)
#65	45.6	90	107.8	36.3
#68	43.6	98.4	55.3	35.4
#168	27.6	2	6.5	64.9
#71	45.3	44.6	79.5	31.6
#482	45.7	71.4	61.2	28.4
#671	26.5	11.4	4.6	48.8

4 Conclusion

The sample results shown in this paper demonstrate that merging rain gauge and radar data through the KED approach may not always be the most appropriate way to retrieve rainfall pattern and to quantitatively estimate cumulated rainfall, especially where the rain gauge network is not sufficiently dense with respect to the size of the local rainfall peaks. A solution comes from giving a greater weight than in KED to the spatial pattern of radar reflectivity. This is the approach used by STACC, which seems to perform much better particularly in those areas where radar reflectivity is high but rainfall information by rain gauges is not available.

5 Acknowledgements

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