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RESEARCH ARTICLE

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Quality-based compositing of weather radar derived precipitation

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Abstract

The paper is focused on the problem of weather radar precipitation compositing and aims to produce the data for the whole measurement domain in a way that ensures the quality of the composite is as high as possible. This is achieved by employing information about the data quality in the form of a quality index (QI) map. Different techniques that take the QI values as the compositing criterion are investigated; they apply the maximum or the weighted mean from particular radars. The proposed method employs a combination of the QI value and the distance from the radar site as a criterion in a weighted mean approach. Different versions of the quality-based techniques are compared with standard techniques that are based on the maximum of estimated precipitation and distance from the nearest radar site. Verification of the techniques was performed employing statistical metrics by comparison against rain gauge observations. Moreover qualitative verification with assessment of seamlessness and the presence of contamination was carried out on long-term accumulations of the composites generated by means of different methods. The proposed method based on QI value and distance from the radar site was found to be the most suitable for radar precipitation compositing.

KEYWORDS

hydro-meteorology, weather radar products, radar data compositing, precipitation, precipitation estimation by weather radar, remote sensing, quality, verification

1 | INTRODUCTION

1.1 | The compositing problem

Weather radar has become a more and more common tool to provide precipitation data for many applications such as rainfall-runoff modelling, assimilation in numerical weather prediction models etc. Radar measurements are available with very high resolution in time and space over a large area which makes them highly valuable. However, the data are burdened with a wide spectrum of errors from different sources which cannot be neglected, comprehensively discussed by many authors (e.g. Meischner, 2004; Michelson *et al.,* 2005; Villarini and Krajewski, 2010). Hardware sources of errors are related to the instability of electronics, antenna accuracy and signal processing quality (Gekat *et al.,* 2004). Other errors result from electromagnetic interference with the Sun or external microwave emitters, ground clutter (Germann and Joss, 2004) or nearby objects such as trees and buildings, anomalous propagation of the radar beam due to vertical air temperature or humidity gradient (Bebbington *et al.,* 2007), shielding due to topography (Bech *et al.,* 2007), attenuation in rain, and echoes from birds and insects. The next group of errors is associated with scan strategy, radar beam geometry and the broadening of the beam width

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with distance from the radar site (Ośródka *et al.,* 2014). Thus, data quality control aimed at the removal of detected errors and quantitative characterization of the data uncertainty has become a subject of interest. However, it is a challenging task due to the complexity of radar measurements and, despite the recent progress in radar data correction, the dedicated algorithms are still not quite effective as it is practically impossible to eliminate all errors completely.

Weather radars are networked to cover a larger domain than a single radar does, and also to improve data quality in overlapping measurement areas. However, the above-mentioned errors, even if corrected, decrease the radar data quality and limit the advantages offered by radar networking. Therefore, one of the important purposes of compositing is to obtain an optimal final precipitation field through skilled merging of radar information characterized by spatially distributed uncertainties coming from particular radars. Commonly, the compositing problem is understood as a question, i.e. how to merge the data from individual radars exploring the same area in order to preserve all reliable measurement information but remove or at least minimize the influence of lower quality information.

1.2 | Compositing methods

A straightforward solution, which is commonly used in operational systems, is to attribute a maximum value to the pixel in the overlapping area. This compositing algorithm is willingly applied not only because of its simple form but mostly because it does not miss any potentially important information and because of its ability to mitigate typical radar errors such as attenuation in heavy rain and beam blockage on terrain. However, the approach does not guarantee a quality proof composite product and is obviously biased towards overestimation (Fornasiero *et al.,* 2006); it also propagates false (non-meteorological) echoes from individual radars. Moreover, the composite can be characterized by discontinuities at the maximum range of individual radars (see Section 4.2.2).

In the other approach the mean value from all radars covering a given pixel is calculated for overlapping areas. Even if non-meteorological echoes can be mitigated in this way, hydrometeors in most cases are also weakened resulting in an underestimated composite. An obvious weak point of the method is that it gives the same reliability to data at ranges far from and close to the radar.

More advanced compositing approaches take account of information about the data quality. Different quality factors can be applied for this purpose but most often distance from the radar site or height of the radar beam over the ground is employed as the main quality factor. In this regard, common approaches consist in attributing the data value from the closest radar (Fornasiero *et al*., 2006) or the data value from the lowest beam (Michelson *et al*., 2000) to the common pixel. This approach handles range-related problems, such as beam broadening and increasing measurement height above the ground along with distance from the radar site. However, these are only a part of the errors that affect the radar data and, for example, in areas close to the radar site non-meteorological echoes and artefacts are not eliminated and blockage areas are not completed with data from further data bins.

In a similar approach a distance-weighted mean is assigned to common pixels (Zhang *et al.,* 2005). This approach can be expressed by the following formula:

$$Z = \frac{\sum_{i=1}^{N} w_i^d Z_i}{\sum_{i=1}^{N} w_i^d} \tag{1}$$

where Z_i is the single-radar reflectivity, w_i^d is the weight of the ith radar located at a distance d, i is the radar number and N is the number of radars covering a given pixel. Applying this method, the discontinuities at the range edges of the individual radars in the composite are partially reduced; however, its weak point is assigning the same reliability to pixels located at the same distance from the radar site. Einfalt and Lobbrecht (2012) proposed employing a weight in the form of a simple reverse relationship with the distance from the radar site. The weights can be related to a (quantitatively preset) maximum range of measurement $d_{\max}$ within which the data are considered to be reliable:

$$w_i^d = 1 - \left(\frac{d_i}{d_{\max}}\right)^k \tag{2}$$

where k is the decrease rate parameter (for bigger k, the weight w_i^d decreases more slowly for small d_i and faster for big d_i). Holleman (2006, 2007) proposed a quadratic function to make the weights decrease rapidly with distance. Bousquet and Tabary (2014) applied the Cressman weighting function in the compositing procedure (with $d_{\max}$ arbitrarily fixed at 300 km):

$$w_i^d = \frac{d_{\max}^2 - d_i^2}{d_{\max}^2 + d_i^2} \tag{3}$$

Zhang *et al*. (2005), Langston *et al*. (2007) and Lakshmanan and Humphrey (2014) assumed an exponential shape of the function to achieve a more rapid decrease of weights with distance from the radar site:

$$w_i^d = \exp\left(-\frac{d_i^2}{D^2}\right) \tag{4}$$

where D is an adaptable length scale (set to about 25–50 km).

Zhang *et al*. (2005) compared three methods, based on maximum value, distance to the radar site and the distance-weighted mean in Equation 1 using the different weighting functions in Equations 2–4. They analysed some case studies to evaluate the efficiencies of the methods. Finally, a weighting method defined by equations in the form of Equation 1 with a steep exponential weighting function (Equation 4) was found to be the best to produce the most smooth and spatially consistent fields.

Other quality factors apart from the distance d can be applied as well, such as height above sea level. A weighted average of all contributing radars with weights having an exponential dependence on the beam altitude is employed, e.g. in the ODYSSEY database (OPERA Radar Data Centre) (Matthews *et al.,* 2012), in analogy with the exponential distance-related formula (Equation 4).

An example of the combination of the above two quality factors, distance d and altitude h, is the National Mosaic and Multi-Sensor Quantitative Precipitation Estimation System employed in the United States (Zhang *et al.,* 2011):

$$Z = \frac{\sum_{i=1}^{N} w_i^d w_i^h Z_i}{\sum_{i=1}^{N} w_i^d w_i^h} \tag{5}$$

where

$$w_i^d = \exp\left(-\frac{d_i^2}{D^2}\right) \qquad w_i^h = \exp\left(-\frac{h_i^2}{H^2}\right) \tag{6}$$

and H is a constant value.

Roca-Sancho *et al*. (2014) proposed a hybrid approach which simultaneously allows the composites to be generated and the radar data to be corrected implicitly, by analysing attenuation and reflectivity fields. The methodology follows the concept of an inverse method wherein a cost function defined by discrepancies between actual and simulated measurements for each radar is minimized. However, the high computational cost of the method is a limitation for operational implementation.

It is expected that taking more quality factors into account should be more effective; however, the compositing formula will be more complicated. Thus, employing a single but more general quality metric seems more convenient. Such a comprehensive quality metric calculated for each radar pixel is the quality index (QI), which is a dimensionless quantity ranging from 0 (bad data) to 1 (perfect data) (Einfalt *et al.,* 2010). A determined quality field should be attached to each radar product, e.g. in a manner defined by the EUMETNET OPERA programme (Operational Programme for the Exchange of Weather Radar Information) (see Huuskonen *et al.,* 2014; Michelson *et al.,* 2014). It should be borne in mind that the QI is not explicitly related to radar errors but ingests *a priori* factors affecting data quality; it is not clear how to synchronize the particular quality factors.

A natural approach, in the context of radar data merging, is to attribute to the common pixel the best quality data, so the maximum of QI is treated as a quality criterion (Fornasiero *et al.,* 2006; Sandford and Gaussiat, 2012). In this manner only data of the best quality are composited, while some measurements with relatively high but not the best qualities are rejected even though they can provide valuable information.

Another quality-based composition method is a weighted QI approach, whereby the weights in Equation 1 are directly replaced with the quality indices for the individual radars: $w_i = \mathrm{QI}_i$ (Fornasiero *et al.,* 2006; Peura *et al.,* 2006; Peura and Koistinen, 2007). Thus, it is assumed that the higher the quality of the data, the larger its contribution to the final value of the composite pixel. In this way, incorrect spurious echoes are minimized. On the other hand, the influence of measurements with high quality can be partially weakened, in most cases due to the contribution of data with a low quality connected with range-related problems, chiefly caused by increasing altitude of the lowest radar beam and beam broadening and subsequent decrease in spatial resolution. As a result, the merged data may be biased.

Quality-based compositing is increasingly appreciated because it is considered to produce more reliable composite products. Processing software implemented in modern national radar networks often provides the possibility of selecting an optimal method according to specific needs (Rathmann and Mott, 2012).

The crucial points for quality-based methods are the design of algorithms for radar data correction and the reliable determination of the quality. The problem is that the methodology of QI estimation is not unambiguous. A scheme of QI determination should be as comprehensive and objective as possible. However, in practice, both expectations are hard to achieve. It is difficult to define and detect all radar errors and to determine their significance quantitatively, so the scheme of integration of all quality factors into a single dimensionless QI value is arbitrary to a large extent. Despite the difficulties, QI values make a very convenient and effective metric and thanks to normalization in the range [0, 1] can be directly used as weights for the compositing.

The compositing methods described above are mostly designed for radar reflectivity Z. For hydrological applications, especially due to operational needs, the most important weather radar derived product is a precipitation estimation R. Thus, in this paper the investigated compositing methods have been adapted to precipitation as the approaches remain the same.

The aim of the present work was to define an efficient methodology of 2D compositing of data from individual radars in order to generate a radar-based precipitation field covering a specific domain. The approach based on a combination of quality descriptors expressed by the QI and the distance from the radar site as a mosaicking criterion was developed and verified. The proposed technique was compared with other methods, such as maximum value, minimum distance from the radar site, maximum quality and quality-weighted mean, using rain gauge observations as reference.

The paper is organized as follows. After a general introduction in Section 1, the proposal in this work is introduced in Section 2. Data used in the paper are described in Section 3, and Section 4 contains an evaluation of the proposed technique and comparison to other methods. Conclusions are presented in Section 5.

2 | PRECIPITATION RATE COMPOSITE USING A TWO-FACTOR (QUALITY INDEX AND DISTANCE TO RADAR) WEIGHT

Within this framework, the focus is on the challenges in creating a radar composite product identified with quantitative precipitation estimates on the ground, so that all effects that influence radar data quality are taken into consideration. It was decided to put a special stress on range-related errors as a key factor in the underestimation of rainfall estimates at far ranges (Villarini and Krajewski, 2010). Bearing this in mind, the proposed merging scheme employs, apart from the QI value, the distance d from the radar site as the quality factor related to this effect. Generally, a quality characterization scheme depends on the further application of quality information, among other things (Einfalt *et al.,* 2010). Beam broadening is already accounted for in the QI generated by the RADVOL-QC system (Ośródka *et al*., 2014); however, it is mostly dedicated to quantitative precipitation estimation, i.e. for hydrological uses (Ośródka *et al.,* 2012), and so an additional factor d is incorporated as another weight.

The proposed quality-based compositing scheme, hereafter called WQD, extends Equation 1 using Equation 4, so that the weights include both the QI_i values and the distances d_i:

$$R = \frac{\sum_{i=1}^{N} \mathrm{QI}_i \exp\left(-d_i^2/D^2\right) R_i}{\sum_{i=1}^{N} \mathrm{QI}_i \exp\left(-d_i^2/D^2\right)} \tag{7}$$

where D is preset to 120 km. Since QI_i is determined dynamically, i.e. based on the errors degrading data from a single term of observation, this compositing algorithm is dynamic as well. Although the number of radars covering the same area can reach a maximum of five (in a small part of the domain), the algorithm considers only the two radars with the highest weights for the composite.

Simultaneously with the composited radar precipitation R the relevant quality field QI for the composited data is determined analogously from QI_i from all radars covering the same area.

3 | WEATHER RADAR DATA

3.1 | Radar network

The investigation was carried out on data from the Polish weather radar network POLRAD operated by the Institute of Meteorology and Water Management – National Research Institute (IMGW-PIB). The POLRAD consists of eight weather radars manufactured by Selex ES; all are C-band Doppler radars with about 0.9°–1.0° radar beam width. Three of them have dual polarization of the radar beam available: Ramża, Pastewnik and Rzeszów.

The computation domain encompasses the whole territory of Poland (900 km × 800 km) with a spatial resolution of 1 km × 1 km Cartesian grid (see Figure 1).

3.2 | Radar data corrections and quality characterization

The 3D raw data (so-called volumes) generated by POLRAD are quality controlled by the RADVOL-QC system. The RADVOL-QC quality control system includes data correction and QI determination due to each recognized error source and multiplication of the particular QIs into a total QI as a quantitative quality metric. In the case of dual-polarization measurements the quality control algorithms constitute a separate category, as such data offer more possibilities for efficient actions (Bringi *et al.,* 2011) but require different techniques.

The different kinds of errors taken into consideration by the RADVOL-QC system can be divided into several groups. Apart from hardware parameters, the first is connected with radar beam geometry and includes effects related to increasing distance from the radar site along the beam, such as beam broadening, increasing distance between neighbouring bins and increasing height of the radar beam above ground level. As a result, extrapolation to the Earth's surface is burdened with higher and higher errors along with distance from the radar site. Thus, in order to compensate the rainfall underestimation due to these range-related problems, a correction is performed considering two factors: the altitude of the radar beam above ground level and a scaling function that modifies the correction

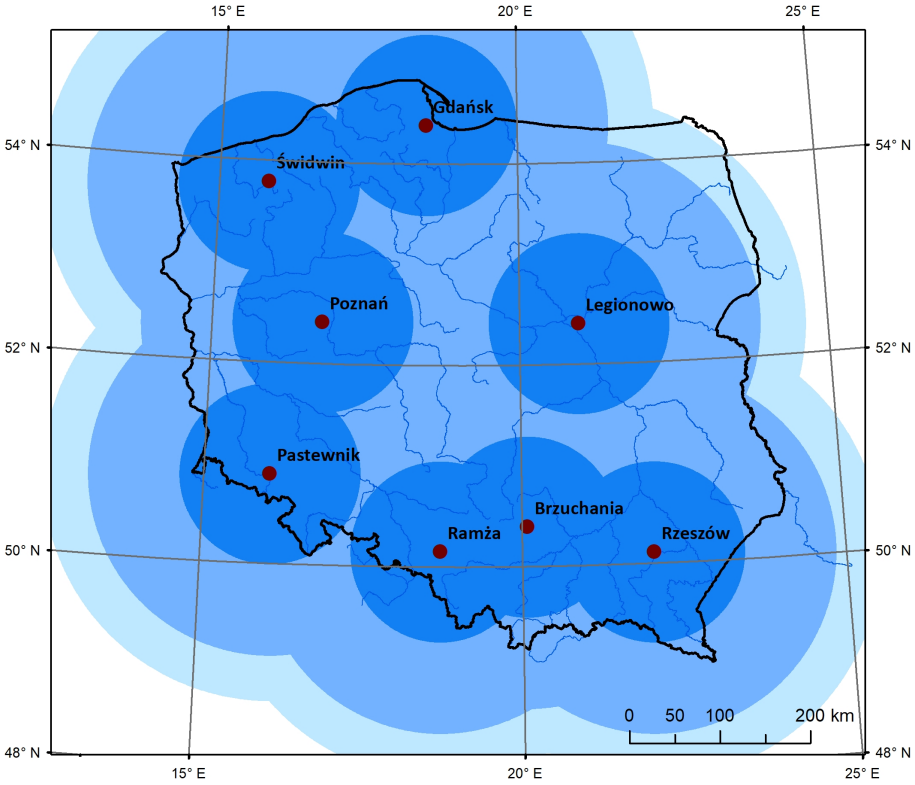


FIGURE 1 Domain of Poland locations of weather radars with 100, 200 and 250 km ranges (from dark to light)

magnitude depending on the precipitation type, i.e. limits its value for convective precipitation.

The next group is contamination by non-meteorological echoes. The echoes may be caused mainly by (a) ground clutter (mountains or high structures close to the radar site), (b) external signals from radio local area network emitters or the Sun interfering with radar signals, which are usually visible in the radar image in the form of spikes pointing from the radar site towards the emitter (they can be removed using a geometrical algorithm that analyses the variability of the echo along and across the radar beam), (c) measurement noise, so called speckles, and (d) biological targets such as birds or insects. Moreover, a fuzzy logic scheme (Szturc *et al.,* 2012) is designed to detect and remove different classes of non-meteorological echoes for dual-polarization radars based on polarimetric parameters.

Other groups of errors result from (a) beam blockage on terrain (mountains) resulting in a decrease of radar signals, which is corrected using a digital terrain map as reference, (b) attenuation in rain, especially in heavy rain, corrected by iterative estimation of signal loss along the beam path in cases of single-polarization radars and by an algorithm based on polarimetric information in cases of dual-polarization radars, and (c) anomalous propagation of the radar beam which causes, for example, echoes received from non-meteorological (terrain) and meteorological (hydrometeors) objects located outside the radar range.

Each category of errors burdening radar data is characterized by specific properties, spatial and temporal structure, and the possibility of diagnosis and correction, so it requires dedicated quality control techniques.

The quality control is performed on 3D raw reflectivity data in polar co-ordinates and is applied individually to each bin, so QI values are determined for the polar bins. In this way a 3D volume of QI data is generated. Based on the transformation from polar to Cartesian representations through an interpolation method, which takes the four nearest bins into account, the 3D data are processed to obtain 2D fields in the same way for both precipitation and the QI. Consequently, each pixel of 2D product is assigned a specific QI value taking account of various sources of radar errors and the efficiency of the applied corrections.

From the corrected 3D data 2D surface precipitation products are generated, such as surface rainfall intensity (PseudoSRI), i.e. a cut-off at constant height above ground that fills in non-sampled far ranges with projected data from the lowest elevation; 10 min precipitation accumulation products are then accumulated employing spatio-temporal interpolation to avoid data sampling discontinuities.

The task of radar data correction and quality characterization is difficult and still does not reach a satisfactory level. For that reason networking and quality-based compositing of radar products is an effective way to improve data reliability under the condition, however, that the quality is quantitatively and correctly estimated.

4 | VALIDATION

4.1 | Methods of validation

The area covered by the Polish weather radar network POLRAD constitutes the testbed for the investigation. As a case study, the dataset from 2017 was employed, after the quality control described in Section 3.2.

The benefits of introducing distance from the radar site as additional information in the developed algorithm named WQD (see Section 2) was tested against two other quality-based composition methods: QI, which chooses the measurement with the highest quality, and WQ, which computes a quality-weighted average to include all available measurements. Additionally, in comparative analysis the two simple but commonly used methods were employed: MAX, consisting in the selection of the maximum value from all measurements, and DIST, taking the measurement value from the nearest radar (see Section 1). The performance of the methods was compared with data from rain gauge observations as reference. In total, data from 491 gauges of the IMGW-PIB network were employed after quality control. The control includes the following algorithms: range control based on climatological data, spatial consistency control and temporal consistency control (Szturc *et al.,* 2018).

The effectiveness of the proposed quality-based compositing scheme was evaluated employing both daily and long-term accumulations. The 10 min precipitation products were aggregated into daily accumulations running from 0600 to 0600 UTC and into long-term accumulations for particular months and the whole year, considering only those records where both radar (R) and gauge (G) data were available. Each rain gauge record was compared with the radar data in the pixel containing this gauge. The results were examined by an analysis of two statistical criteria, Pearson's correlation co-efficient (r) and the root mean square error (RMSE), which are defined as follows:

$$r = \frac{\mathrm{cov}(R,G)}{\sigma_R \sigma_G} \tag{8}$$

where cov(R, G) is the covariance between R and G data and σ_R and σ_G are the standard deviations of R and G, respectively;

$$\mathrm{RMSE} = \frac{1}{n}\sqrt{\sum_{j=1}^{n}\left(R_j - G_j\right)^2} \tag{9}$$

where j is the number of the rain gauge and n is number of rain gauges. The correlation co-efficient is a metric of strength of the linear relationship between radar and rain gauge data, and RMSE indicates the general fit of these variables.

4.2 | Results of validation

4.2.1 | Evaluation of short-term accumulations

In order to compare the outcomes of the five compositing methods (MAX, DIST, QI, WQ and WQD) with rain gauge observations, they were aggregated into daily accumulations. Verification results, by means of the correlation co-efficient and RMSE, for particular months of 2017 are listed in Table 1 and for the whole of 2017 are depicted in Figure 2a,c.

With regard to the correlation co-efficient, it can be observed that all the methods seem to work comparably. Its values are quite good and change within a very small range, for the whole year between 0.73 and 0.75 (Figure 2a). For most months, the best values were obtained using the WQD algorithm as a compositing rule (Table 1a).

In terms of the RMSE, it is noticeable that the performance of the MAX method is somewhat better than the other compositing methods (Table 1b). The RMSE value, calculated on daily accumulations, is equal to 4.16 mm, whereas for the other methods the values are between 4.34 and 4.50 mm (Figure 2c). Mean daily radar accumulations for different compositing methods range from 2.51 to 3.47 mm while for rain gauge data the result is 4.23, which indicates that radars underestimate the precipitation values.

The MAX method generally causes overestimation of data if they are unbiased, which results from the algorithm itself. Since POLRAD data are negatively biased, i.e. underestimated, the composites obtained with the MAX method provide the highest precipitation values and the closest ones to the rain gauge observations (i.e. the RMSE is the smallest). However, the correlation co-efficient for the MAX method is the lowest for most months in comparison to the results obtained with the other methods (Table 1a). This observation leads to the conclusion that bias of radar data distorts the findings of the above analysis, so a mean field bias correction was applied to eliminate the underestimation in the radar-based precipitation estimates.

The bias adjustment factor (c) is calculated individually for each radar and for each 10 min accumulation period. The factor is derived from a comparison of total amounts of collocated radar and rain gauge precipitation values so it is constant for the whole range of each radar:

$$c = \frac{\sum_{j=1}^{n} G_j}{\sum_{j=1}^{n} R_j} \tag{10}$$

where j is the number of the rain gauge and R_j is the radar precipitation in the pixel within which the j gauge is located, so the unbiased radar observation in the pixel is cR. The factor c is determined by considering only the gauges located

TABLE 1 Comparison of daily accumulations of radar composites (POLRAD network) against rain gauge data for particular months of 2017 considering (a) the correlation co-efficient and (b) the root mean square index (RMSE)

Method	January	February	March	April	May	June	July	August	September	October	November	December
(a) Correlation co-efficient												
MAX	0.536	0.656	0.656	0.697	0.785	0.772	0.734	0.790	0.745	0.686	0.586	0.492
DIST	0.555	0.659	0.658	0.702	0.799	0.767	0.754	0.799	0.773	**0.687**	0.596	0.511
QI	0.552	0.664	0.663	0.694	0.797	0.768	0.753	0.805	0.774	0.678	0.599	0.509
WQ	**0.574**	0.660	0.661	0.698	0.798	0.771	0.760	0.805	0.766	0.683	**0.616**	**0.518**
WQD	0.573	**0.669**	**0.667**	**0.706**	**0.805**	**0.777**	**0.762**	**0.811**	**0.776**	0.685	0.606	0.512
(b) RMSE (mm)												
MAX	1.82	**2.86**	**2.69**	**3.73**	3.53	4.60	**4.64**	**5.59**	**6.22**	**4.68**	**2.58**	**3.14**
DIST	**1.80**	2.92	2.79	3.88	3.23	4.63	4.83	6.22	6.62	4.88	2.63	3.18
QI	1.82	2.95	2.84	3.95	3.23	4.61	4.78	6.04	6.58	5.00	2.66	3.22
WQ	1.90	3.16	3.04	4.20	3.28	4.64	4.80	6.00	6.91	5.35	2.78	3.34
WQD	**1.80**	2.97	2.85	3.96	**3.19**	**4.56**	4.77	6.04	6.64	5.02	2.67	3.23

The best values are marked in bold.

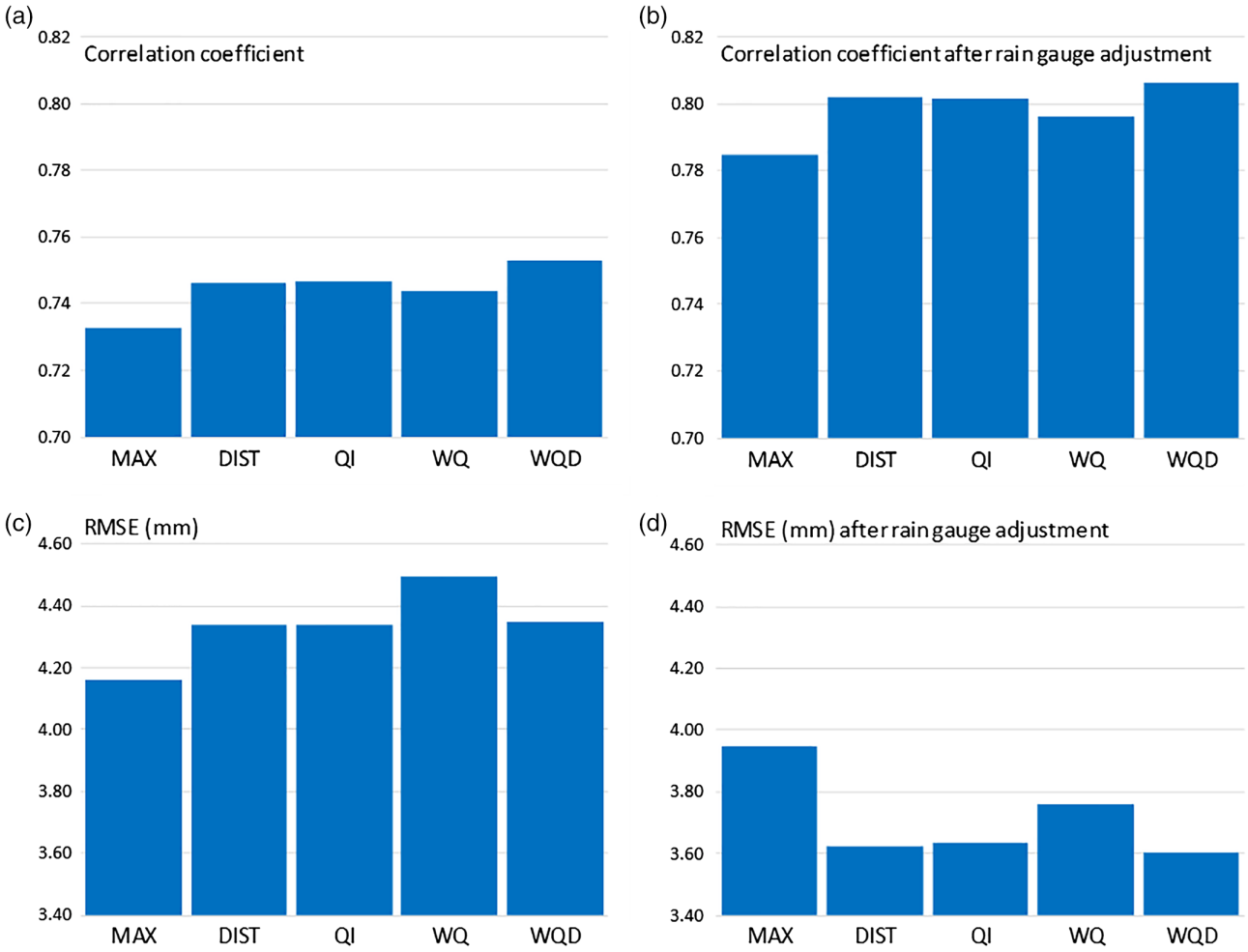


FIGURE 2 Comparison of daily accumulation of radar composites (POLRAD network) against rain gauge data for the whole of 2017 by means of (a) the correlation co-efficient, (b) the correlation co-efficient with radar data after rain gauge adjustment, (c) the root mean square error (RMSE) and (d) the RMSE with radar data after rain gauge adjustment

up to 120 km from the radar site and both gauge and related radar data with a high quality above 0.7.

The results of verification of all tested compositing methods after mean field bias adjustment are presented in Table 2. As expected, the RMSE is reduced significantly and its values range from 3.60 to 3.95 mm for the whole year (Figure 2d). This reduction in RMSE is relatively small in the case of MAX compositing and moreover the method presents the highest RMSE after bias removal. The correlation co-efficient slightly increases to values from 0.78 to 0.81 for the whole year (Figure 2b), because bias adjustment generally does not influence correlation apart from cases when a different radar is chosen (in the MAX method) or when the contribution of particular radars changes (in weighted methods). The proposed WQD compositing method after mean field bias correction outperforms the other methods for most months considering both RMSE and the correlation co-efficient (Table 2).

The scatter plots of hourly accumulation for the whole of 2017, derived by means of WQD before and after rain gauge adjustment, confirm the above finding, i.e. strong underestimation (Figure 3). The solid line represents linear regression fitted using the least squares approach. For WQD composites before bias removal, most scatter points lie below the identity line ($y = x$) and the regression gives a slope of 0.51 and a correlation of 0.73. In the scatter plot for WQD composites after bias removal, the points are distributed a little more evenly around the identity line. The correlation and slope increase to 0.8 and 0.74 respectively although a large amount of scatter points are still below the identity line.

4.2.2 | Evaluation of long-term accumulations

The compositing results were also verified on long-term accumulations derived from the 10 min data aggregated for the whole of 2017 (Figure 4). The differences between particular composites, which are related to specific properties of

TABLE 2 Comparison of daily accumulations of radar composites after rain gauge adjustment (POLRAD network) against rain gauge data for particular months of 2017 considering (a) the correlation co-efficient and (b) the root mean square index (RMSE)

Method	January	February	March	April	May	June	July	August	September	October	November	December
(a) Correlation co-efficient after rain gauge adjustment												
MAX	0.583	0.727	0.720	0.785	0.817	0.787	0.811	0.835	0.796	0.661	0.632	0.516
DIST	0.599	0.734	0.726	0.786	0.845	0.797	0.841	0.861	**0.827**	**0.663**	0.641	0.527
QI	0.589	0.735	0.731	0.780	0.840	0.794	0.840	0.859	0.824	0.657	0.644	0.531
WQ	**0.610**	0.732	0.730	0.778	0.833	0.789	0.834	0.851	0.813	0.659	**0.651**	**0.537**
WQD	0.609	**0.742**	**0.736**	**0.788**	**0.846**	**0.799**	**0.845**	**0.865**	0.825	0.662	0.647	0.532
(b) RMSE (mm) after rain gauge adjustment												
MAX	1.95	2.65	2.46	3.15	3.52	4.77	4.16	5.93	5.29	4.97	2.46	2.95
DIST	1.85	2.54	2.38	3.01	2.84	4.33	3.74	4.72	**4.93**	**4.95**	2.41	**2.94**
QI	1.85	2.53	2.33	3.03	2.89	4.37	3.73	4.71	4.95	4.99	2.39	2.95
WQ	**1.74**	2.61	2.41	3.15	2.94	4.41	3.86	4.82	5.27	5.17	2.43	3.03
WQD	1.78	**2.49**	**2.30**	**2.97**	**2.83**	**4.30**	**3.71**	**4.63**	4.97	4.97	**2.37**	2.95

The best values are marked in bold.

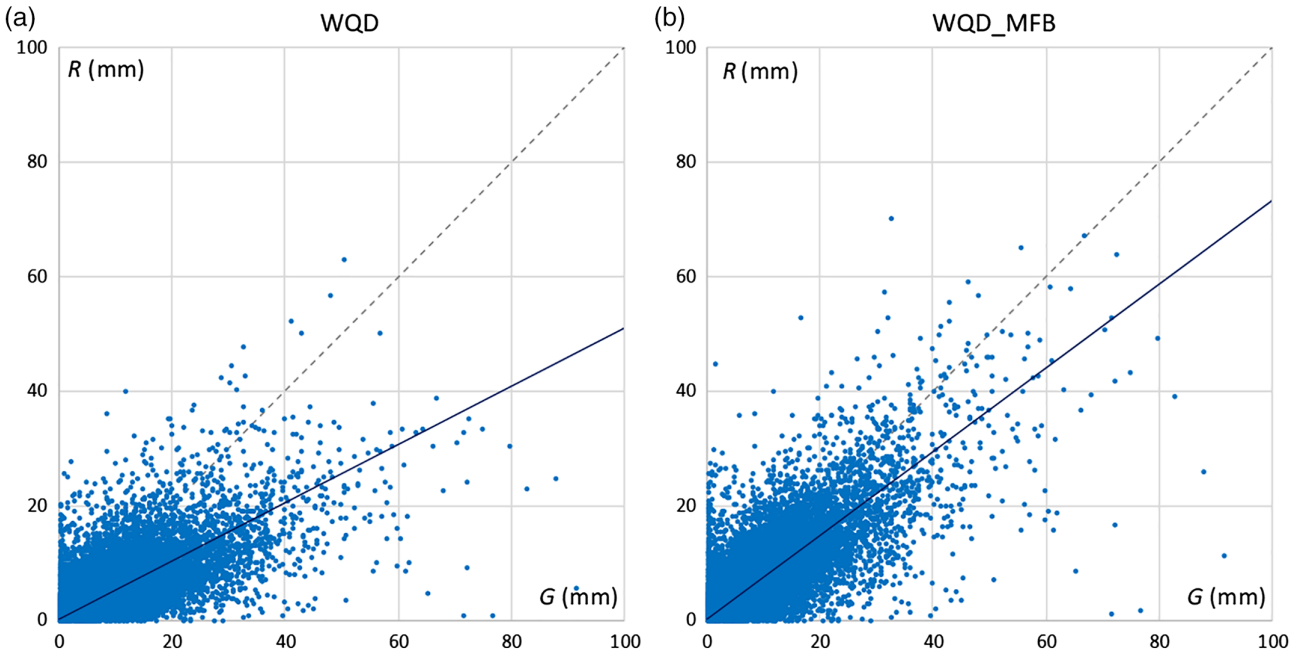


FIGURE 3 Comparison against rain gauge data of composited radar precipitation using (a) WQD and (b) WQD employing rain gauge adjustment. Radar data from the POLRAD network for the whole of 2017, hourly accumulations

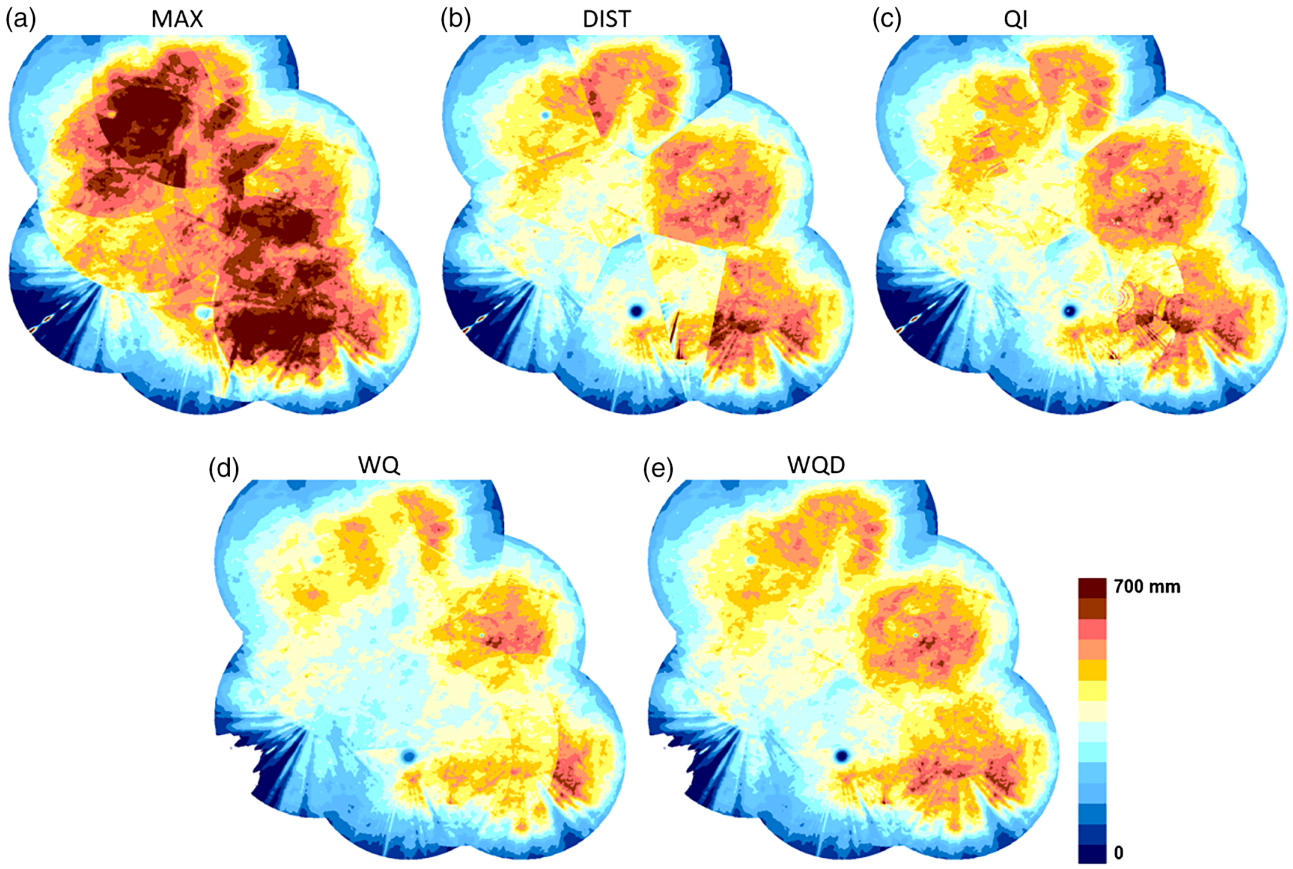


FIGURE 4 Result of employing different methods of weather radar data compositing. Ten minute precipitation accumulations aggregated for the whole of 2017: (a) MAX, (b) DIST, (c) the quality index QI, (d) WQ and (e) WQD. Data from the POLRAD radar network

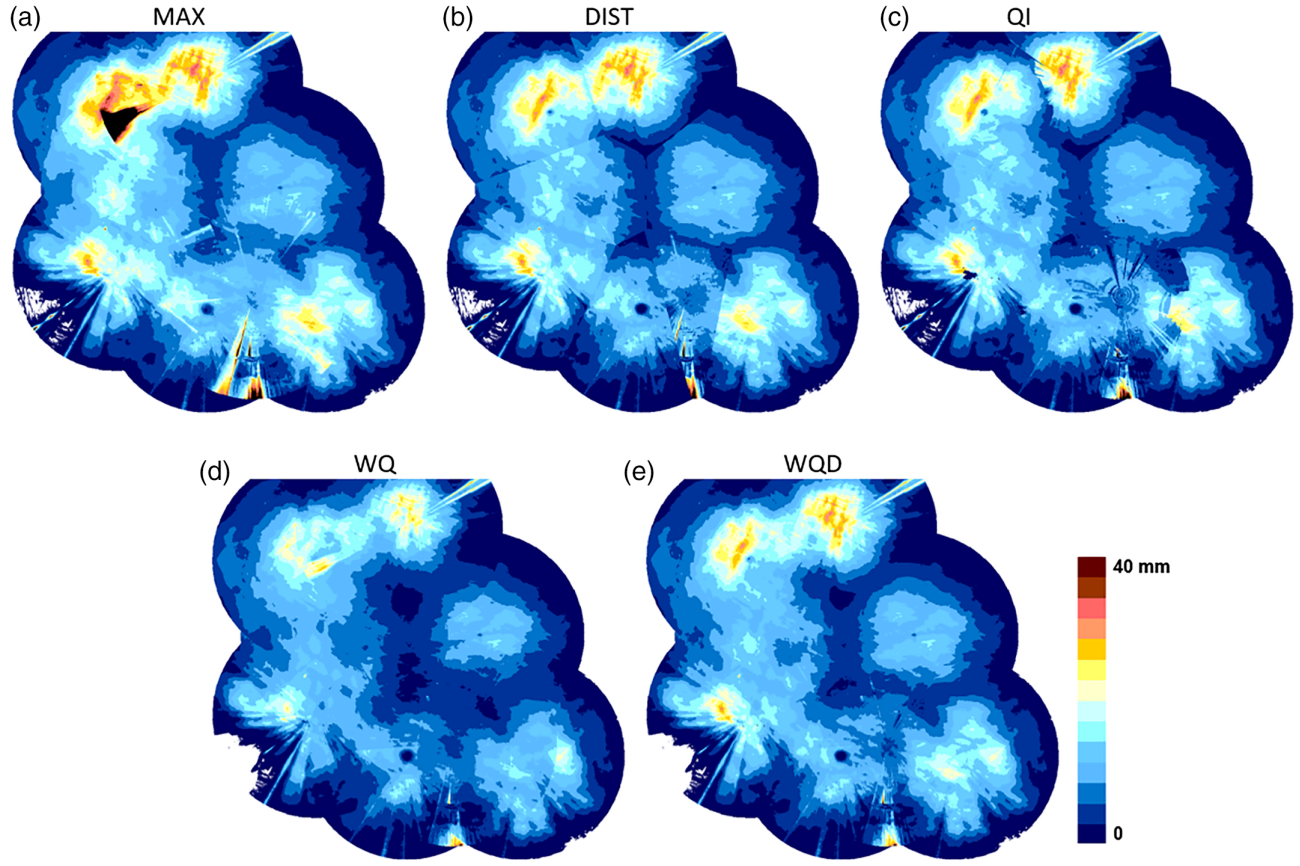


FIGURE 5 Result of employing different methods of weather radar data compositing. Ten minute precipitation accumulations aggregated for January 2017: (a) MAX, (b) DIST, (c) the quality index QI, (d) WQ and (e) WQD. Data from the POLRAD radar network

the algorithms employed, are clearly visible, so the qualitative assessment is also important and should be treated on a par with quantitative criteria.

It can be observed that the MAX method gives the highest precipitation values, as expected. This is due to employing the PseudoSRI product as the quantitative precipitation estimation and in consequence attributing the maximum value to the common cell even if it comes from a higher altitude for more distant measurements. Moreover, the MAX approach cumulates artefacts and errors originating from all radars, especially non-meteorological echoes such as those caused by radio local area network emitters, so called spikes. These echoes are readily seen in the composite, especially for the Brzuchania and Rzeszów radars in the south of Poland. Unfortunately, the echoes can be observed despite applied corrections because in the case of very numerous and overlapping spikes the RADVOL-QC algorithms are not efficient enough.

With the DIST method many fewer spurious echoes are visible, because only the echoes from the nearest radar remain. However, discontinuities at the edge of the radar coverage, resulting from different technical calibrations, are noticeable.

All the quality-based methods (QI, WQ and WQD) produce relatively similar composites. The above-mentioned discontinuities are less appreciable in the composite with the QI algorithm whereas for both QI-weighted methods (WQ and WQD) these discontinuities do not occur and smooth transitions between individual radar coverages are obtained. Thus, it can be concluded that employing all available radar data in overlapping areas leads to an improvement in the continuity at radar boundaries. Comparing the last two methods, the WQD method yields a somewhat more seamless precipitation field. For all the quality-based methods the number and shape of contaminations in the composites are visually comparable to those on the DIST composite.

The 10 min products were also aggregated into accumulations for particular months. As an example, accumulations for January (Figure 5) and August 2017 (Figure 6) are presented. The effects described above, such as the presence of spurious echoes and discontinuities at the edges of radar ranges, are also observed in the composites accumulated for particular months. In August (summer season), when convective precipitation prevails, the composites for particular compositing methods differ less between each other than for

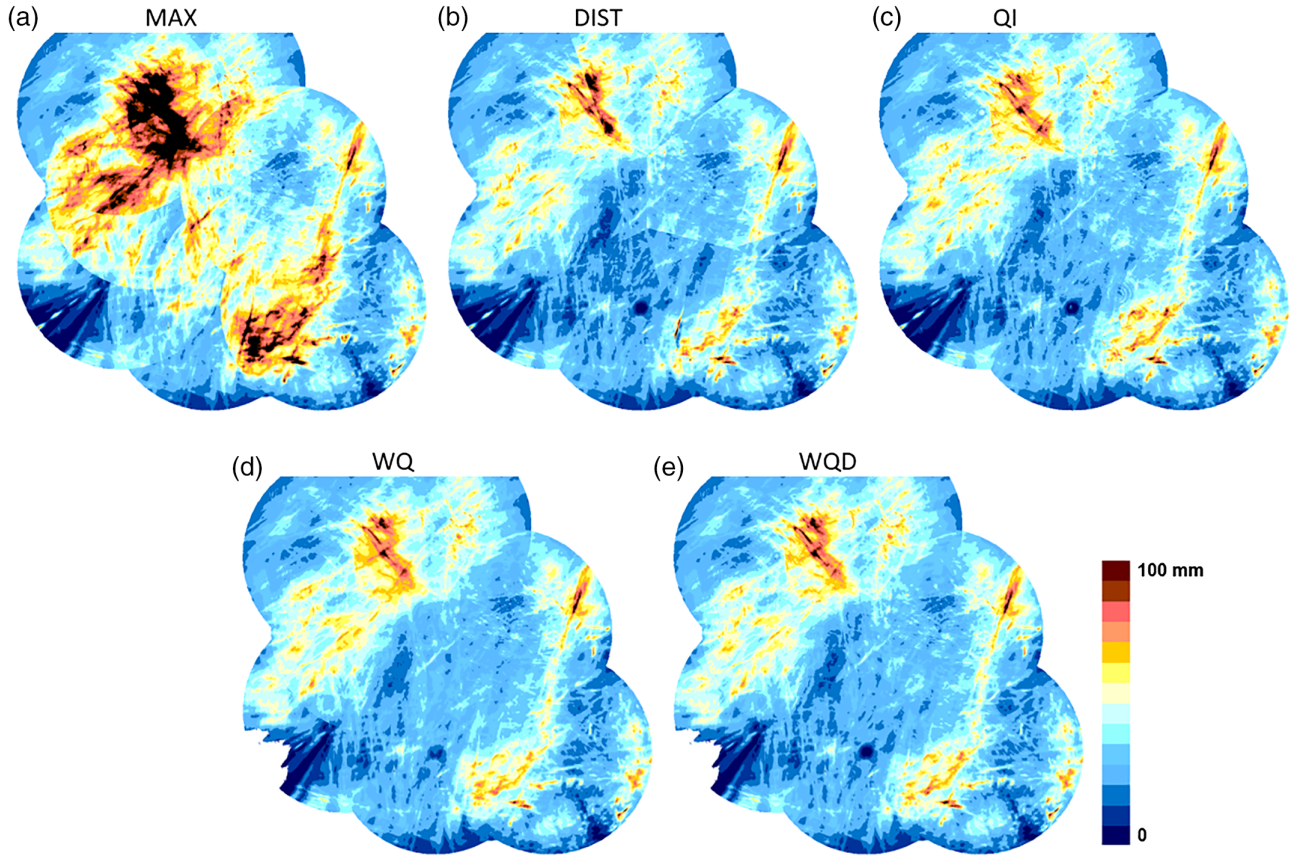


FIGURE 6 Result of employing different methods of weather radar compositing. Ten minute precipitation accumulations aggregated for August 2017: (a) MAX, (b) DIST, (c) the quality index QI, (d) WQ and (e) WQD. Data from the POLRAD radar network

the whole year, especially those from quality-based methods. It is clearly visible that the MAX composite differs significantly from the rest, which can be explained by the overlapping of higher values from higher altitudes during convective events as the PseudoSRI algorithm is used to generate radar data. Larger differences are noticeable in the accumulations for January (winter season), when stratiform precipitation, mainly snowfall, predominates. The WQD method seems to perform much better than the WQ method. This is because the WQD merging scheme employs, apart from the QI value, the distance from the radar site as the weight for compositing, which means that closer radar observations are favoured over far observations.

5 | CONCLUSIONS

The paper presents the benefits of including real-time quality information in combining data from areas of multiple radar coverage to obtain a radar precipitation composite. Compositing was performed on rainfall intensity data from the weather radar network POLRAD applying different quality-based methods: the quality index (QI) with maximum quality value as a criterion, WQ which combines all available radar information in a quality-weighted averaging scheme, and WQD which additionally takes the distance from the radar site as the weight for compositing and limits the number of considered radars to avoid measurements with low quality. For comparison, radar composites were also produced by employing simple algorithms such as MAX based on a selection of maximum values from all measurements and DIST which employs the distance to the radar site as a compositing criterion.

The results were evaluated both quantitatively by comparing against rain gauge data and qualitatively by means of visual analysis. The validation, described in Section 4.2, demonstrates that the quality-based weighting methods, i.e. WQ and WQD, have the potential to improve the composited data. WQD was found preferable in terms of correlation co-efficient compared against rain gauge data. These findings were confirmed by visual evaluation of long-term accumulation. With regard to the root mean square error, it was found that it is not a proper criterion to evaluate the performance of different compositing methods as the data of POLRAD radars are negatively biased. Therefore, the MAX method, which gives the highest precipitation

value resulting from the algorithm itself, produced the best results. After implementation of a mean field bias correction to eliminate the underestimation, the root mean square error was significantly reduced and the WQD compositing method outperformed the other methods for most months.

In conclusion, the proposed WQD approach seems to be a promising method in the context of radar rainfall intensity data compositing. However, it should be borne in mind that the performance of quality-based methods indirectly depends on the completeness and efficiency of the quality control of radar data and algorithms for determination of the QI. The radar data are burdened with a wide spectrum of errors and each error category is characterized by specific properties and different temporal and spatial structures. Therefore, quality control and determination of the QI, which should represent accurately and comprehensively uncertainty and reliability in each radar pixel in an objective way, are very difficult tasks (Ośródka and Szturc, 2015). Furthermore, these algorithms have to work automatically in real-time mode. Taking the complexity of the quality control problem into account, it is not certain that they work correctly in each case for each pixel, so quality-based weighting methods, which employ all available data according to their quality, seem to be a reasonable solution to improve the quality of the composites measurably, as confirmed by the obtained results.

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