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Zero-covariance hypothesis in the error variance separation method of radar rainfall verification

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Abstract

Empirical test of the zero-covariance assumption in the error variance separation (EVS) method is presented. The EVS method is a way to filter out ground reference (GR) errors in radar rainfall verifications. It is based on a hypothesis that the errors of radar and gauge area-rainfall estimates are not significantly correlated. The test area within the Little Washita watershed in Oklahoma is covered by a relatively dense network of raingauges providing good approximations of the true area-rainfall used for this test. The investigation uses a large data sample of two 6-month periods and regards accumulation intervals from 15 min to 7 days. The test results are provided with bootstrap error bounds that confirm their statistical significance. The results show that, for this testing setup, the zero-covariance assumption in its previously postulated rigorous formulation is not fulfilled. However, despite the drawbacks, the EVS method can often provide better estimates of the radar error variances than the radar–raingauge comparisons that ignore the GR uncertainties.

1. Introduction

Using uncertain ground reference (GR) data for verification of radar rainfall products and validation of the rainfall estimation algorithms is an important albeit still unresolved problem. The raingauge data are subject to instrumental errors and suffer from the inherent representativeness errors (or area-point sampling differences). The former have been fairly well recognized and can be effectively dealt with [12,20]. The later are usually large and can be reduced only by increasing the density of the raingauge networks [14,16,19,21]. Since most of the developments on estimating and forecasting of precipitation has to be based on the existing raingauge systems, it is necessary to recognize their errors and to quantify their effect on the results of the analyses. In the weather forecasting area, such research has been recently presented by Sigrest and Krzysztofowicz [23]. In radar rainfall estimation area, several researchers discussed the poor representativeness of point measurements among the factors responsible for the inconclusive results of radar–raingauge comparisons [7,15,27]. However, systematic analytical tools to deal with this problem are still underdeveloped. In our opinion, the inevitable uncertainties of the GR should be accounted for in a quantitative manner during any evaluation and/or intercomparison of the radar rainfall products. Below we describe a study in that direction.

Ciach and Krajewski [5] proposed an error variance separation (EVS) method that can be applied to verification of remote sensing rainfall estimates based on uncertain raingauge reference. To illustrate its potential usefulness, they implemented the method on radar rainfall estimates over a broad range of spatiotemporal scales [6]. Later, Anagnostou et al. [1] applied the EVS method to logarithms of radar and raingauge rainfall, and Krajewski et al. [17] used it to validate satellite products using the USA operational raingauge networks. Recently, also Young et al. [26] and Habib and Krajewski [13] applied the method to verification of the NEXRAD rainfall products. The EVS method originates from the variance partitioning principles used in statistics [2]. It enables decomposition of the variance of the GR and radar rainfall differences into its two components: the GR error variance and the radar error

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variance. A central assumption of the EVS is that the covariance of these two individual errors is small compared to the radar error variance. Here, we call this assumption the "zero-covariance hypothesis" of the EVS method. Ciach and Krajewski [6] discussed several conceptual and theoretical arguments that make this hypothesis plausible. However, due to the lack of appropriate data, they could not properly validate it at that time. Here, we revisit the question. Using a fairly accurate approximation of the true area-averaged rainfall based on a dense network of raingauges, we offer an empirical investigation of the zero-covariance assumption.

We investigate the zero-covariance hypothesis using data from WSR-88D radars and a raingauge network covering the Little Washita watershed in Oklahoma. The gauges are part of the Micronet system operated by the Agricultural Research Service of the United States Department of Agriculture (USDA ARS). In our investigation we use an extensive sample of two 6-month warm periods that enables us to analyze rainfall accumulation intervals ranging from 15 min to 7 days. The selected test area of about 800 km^2 is covered by 30 raingauges. One of them was rejected due to data quality problems, and 29 were applied to this analysis. As we verify below, this raingauge density proves to be sufficient to obtain quite accurate approximations of the area-averaged rainfall values in the considered time scales. To make sure that our results are statistically significant, we used the bootstrap technique to obtain the error bounds of the tested quantities.

2. Problem statement and methodology

2.1. The EVS method and zero-covariance assumption

Detailed formulation of the EVS method and its illustrative implementation was presented in Ciach and Krajewski [6], thus here we only outline its merits. Suppose that point raingauge measurements are to be applied as GR to verify a given sample of radar rainfall products. If R_r is a random variable representing the radar rainfall estimates at some grid pixel and R_g stands for the concurrent and collocated (i.e. within the same grid area) raingauge accumulations, then the variance of the radar–gauge difference can be decomposed in the following way:

$$\mathbf{V}\{D_{rg}\} = \mathbf{V}\{E_r\} - 2\mathbf{Cov}\{E_r, E_g\} + \mathbf{V}\{E_g\}, \tag{1a}$$

$$D_{rg} = R_r - R_g, \tag{1b}$$

$$E_r = R_r - R_t, \tag{1c}$$

$$E_g = R_g - R_t, \tag{1d}$$

where R_t is the true rainfall accumulation averaged over the area covered by the grid of the radar product, D_{rg} is the difference of the radar and raingauge rainfall, E_r is the error of the radar rainfall, E_g is the gauge representativeness error, and $\mathbf{V}\{\cdot\}$ and $\mathbf{Cov}\{\cdot,\cdot\}$ are the variance and covariance operators, respectively. We assume a specified and fixed accumulation (or time averaging) interval for all the variables stated above. The left-hand term in Eq. (1a) can be estimated directly from a sample of radar and raingauge data. If the rain-field spatial correlation structure is known, the variance of the gauge error can be estimated using basic spatial statistics:

$$\mathbf{V}\{E_g\} = \sigma_g\left(1 - \frac{2}{A}\int_A \rho(\boldsymbol{x}_g, \boldsymbol{x})\,\mathrm{d}\boldsymbol{x}^2 + \frac{1}{A^2}\int_A\int_A \rho(\boldsymbol{x}, \boldsymbol{y})\,\mathrm{d}\boldsymbol{x}^2\,\mathrm{d}\boldsymbol{y}^2\right), \tag{2}$$

where $\rho(\cdot,\cdot)$ is the spatial correlation function of the rainfall field, σ_g is the sample variance of the raingauge accumulations, A is the analyzed area (radar grid, in our case), $\boldsymbol{x}_g$ is the coordinate of the gauge located in this area, and $\boldsymbol{x}$ and $\boldsymbol{y}$ are spatial coordinates. A derivation of this formula can be found in Ciach and Krajewski [6], for example. If the inter-gauge sample correlations at given accumulation time provide enough information to retrieve the $\rho(\cdot,\cdot)$ function, the variance of the raingauge errors E_g can be estimated using Eq. (2). The zero-covariance hypothesis states that the covariance term in Eq. (1a) is small so that the error variance of the radar rainfall can be estimated using the following formula:

$$\mathbf{V}\{E_r\} \overset{?}{=} \mathbf{V}\{D_{rg}\} - \mathbf{V}\{E_g\}, \tag{3}$$

with accuracy sufficient for its practical applications to verification and quality assessment of radar products. For this to be true, it is enough that the absolute value of the covariance term in Eq. (1a) is much smaller than the radar error variance:

$$|2\mathbf{Cov}\{E_r, E_g\}| \ll \mathbf{V}\{E_r\}. \tag{4}$$

The proportion of the two sides of this inequality determines how much the possible non-zero values of the covariance distort the retrieval of the radar errors based on Eq. (3). Below, we investigate empirically the magnitude of the covariance term and the significance of the resulting departures of the EVS estimates from the actual variances of the radar rainfall errors.

2.2. Description of the data sample

The analyses in this study are based on an extensive data sample covering two 6-month periods (April–September) of the years 1998 and 1999. The raingauge data come from a dense network covering the Little Washita River watershed located in Oklahoma about 70 km

South–West from the Oklahoma City KTLX radar. The Little Washita is an average size experimental basin (about 1200 km^2) equipped with 43 Micronet multi-sensor stations deployed and operated by the USDA ARS [24]. The average distance between the neighboring stations is about 5 km, thus their coverage density is much better than that of the typical networks. For comparison, it has about 60 times smaller area/station ratio than the relatively dense Oklahoma Mesonet [4]. Among several atmospheric and soil parameters, precipitation data with 5-min temporal resolution are collected from each station. The ARS Micronet has been in operation since 1995 and, initially, the stations were equipped with weighing-bucket gauges [10]. During May–June 1997, these instruments were replaced with exactly the same raingauges as those used over the Oklahoma Mesonet [4]. They undergo the same modifications that increase their reliability and accuracy, and pass through the same calibration procedures performed by the Mesonet Laboratory of the Oklahoma Climatological Survey [22]. An outline of the network configuration on the background of the Little Washita River watershed is shown in Fig. 1. Also in the figure we indicate the Micronet station identification numbers (we refer to them later) and the rectangular test area of about 800 km^2 that we selected for this study.

The radar rainfall data that we use here are based on radar reflectivity maps obtained from the NASA Global Hydrology Research Center. We describe our conversion of the reflectivities into rain-rates in the next section. The reflectivity maps are based on the NEXRAD Level III data from the WSR-88D radars and they are nation-wide mosaic composites. These products are created by the Weather Service International (WSI) after some quality control of the NEXRAD data. The products have spatial resolution of about 2 km by 2 km and temporal resolution of 15 min. The reflectivities are delivered in 16 levels every 5 dBZ starting from 0 dBZ [25]. This crude quantisation is a source of additional errors in the estimated rainfall. However, since radar rainfall estimates that we investigate are averaged over the test area, which is about 200 times larger than the elementary 2×2 km radar grid, the reflectivity quantisation errors average out to some degree.

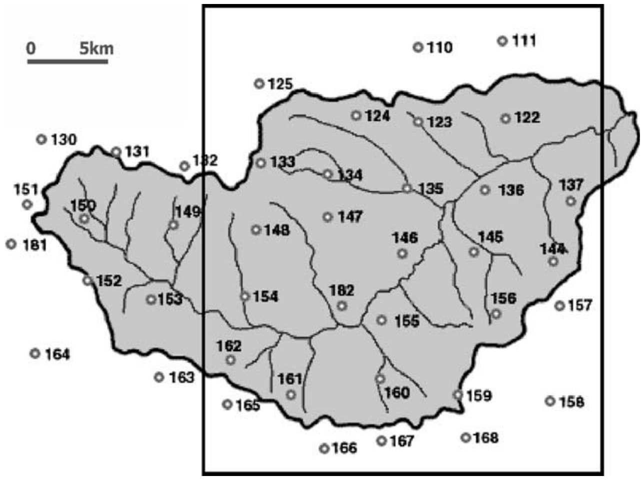

Fig. 1. The Little Washita River watershed with the USDA ARS Micronet stations. The superimposed rectangle indicates the test area of about 24 km by 34 km that is selected for this investigation.

2.3. Analysis method

We approach the questions formulated in Section 2.1 in a straightforward way, through estimation of all the terms in Eq. (1a) based on the data sample described above. Next, we compare the estimates for different accumulation intervals and selected gauge locations, with regard to the zero-covariance hypothesis and practical consequences of its possible violations. Since both the radar and point rainfall values (R_r and R_g) come directly from the measurements, the only missing element in Eq. (1a) is the true area-averaged rainfall R_t. Accurate measurements of this quantity are still beyond our technological capabilities, however, fairly good approximations of R_t can be obtained from dense networks of raingauges. The gauges used in such setups have to be of good quality, thoroughly calibrated and carefully maintained, therefore such networks are expensive and rare. We use data from experimental raingauge network over the Little Washita River watershed described above. We selected a rectangular area outlined in Fig. 1 as a test area for this analysis. It has the size of about 34 km by 24 km and is covered fairly uniformly with 29 raingauges. The accuracy of this particular ground truth approximation is assessed in the next section.

Our verification of the zero-covariance hypothesis starts with specification of the rainfall accumulation (averaging) time that ranges from 15 min to 7 days. For each interval, we computed the following quantities in a stepwise manner:

1. time averaged rain-rates R_g for each raingauge,
2. R_t approximated as gauge-averages of the R_g values,
3. area-time averaged radar rain-rates R_r over the test area,
4. variances and covariances of E_g and E_r for each gauge,
5. variances of the radar–gauge differences for each gauge,
6. EVS approximations of the radar error variances,
7. confidence intervals of the sample statistics.

In the above sequence, steps 1–3 prepare the sample of raingauge, radar, and area-averaged rainfall. Steps 4–6 produce sample estimates of the investigated statistics, and the last step delivers the estimation errors of these results using a bootstrap technique.

Since there are a number of missing data points in the large sample that we use, we had to reject from the analysis those intervals that are affected strongly by the gaps. However, in order not to deplete the sample too much, we tolerated intervals missing only 2% or less of the data and filled the gaps using the average of the remaining values. This was especially important for long accumulation times. For example, for the 7-day case more than a half of the intervals contain some gaps. Since each of the raingauges has different missing points, the variance of E_g as well as the covariance of the radar and gauge errors pertain each time to a slightly different sample. Thus, although the radar error variance is a field average quantity, it is also computed 29 times for each gauge-related sample. This way the statistical consistency is assured in a sense that the statistics that we directly compare are always based on exactly the same time series of the R_g, R_r and R_t values.

Regarding the radar rainfall estimates (step 3), we used a typical power-law *Z–R* relationship to convert the radar reflectivities described in the previous section to the radar rain-rates. We assumed the *Z–R* exponent value of 1.4, which is used operationally in the NEXRAD radar rainfall estimation algorithm [11]. We adjusted the multipliers of the power-law functions each time so that the sample averages of R_r and R_t are equal. Ciach et al. [8] discussed the advantages of this removal of the sample overall bias in verification of radar rainfall products. It enables focusing the analysis specifically on the second order statistics.

In addition to the statistics enumerated above, we also computed the bootstrap distributions of their sample estimates to assess the statistical significance of the results [9]. We obtained them by random drawing with replacement from a sample created in the steps 1–3 above and repeating steps 4–6 for each of these bootstrap pseudo-samples that had the same size as the original data sample. We repeated this resampling procedure 1000 times for each case to deliver stable uncertainty bounds for the discussed results. For each of the considered statistics, about 95% out of its 1000 resample estimates were within the $\pm 2\sigma$ limits. This confirms that, in each case, the sampling error distributions are quite similar to Gaussian.

2.4. Accuracy of the area-rainfall approximation

An essential prerequisite for testing the zero-covariance hypothesis is a relatively accurate approximation of true area-averaged rainfall over the specified test area. It allows estimating all the components in Eq. (1), checking if the inequality (4) is fulfilled and evaluating the possible inaccuracies of the EVS method. In our case, this "ground truth" is an average of rainfall measurements from the 29 carefully maintained gauges of the Micronet that we described above. The error variance of the average of the point measurements can be computed for any raingauge configuration using the well established statistical methods [3,19]. We applied them to obtain the error variances of the area-rainfall approximations for the accumulation times considered in this study.

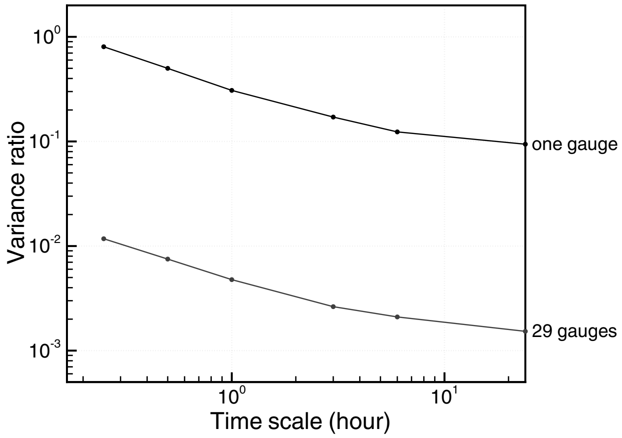

Fig. 2. Relative error variances of the area-averaged rainfall estimated from a single raingauge (upper curve) and the 29 Micronet raingauges (lower curve). The true rainfall is averaged over the test area shown in Fig. 1. The error variances are normalized by the true area-rainfall variances.

We used a popular isotropic exponential model of spatial correlations in function of distance and fitted it to the inter-gauge correlations based on our data sample. For each accumulation interval, we computed the error variances of the rainfall averages of the 29 gauges covering the test area. We also obtained the area–point difference variances (single gauge error) for the gauge 146 that is the closest to the center of the test area. The two error variances, normalized by the estimated variance of the underlying process (true area-averaged rainfall), are presented in Fig. 2 in function of the accumulation time. These results prove that the error variances of the 29-gauge average rainfall are very small for all intervals and are less than 1.5% of single gauge errors. The rest of these analyses showed that the radar errors are comparable or larger than the single gauge errors. Thus, we can conclude that the accuracy of the area-rainfall approximation used here is sufficient for the purposes of this investigation.

3. Results and discussion

In the upper panels in Fig. 3, we present examples of the relative covariance terms in Eq. (1) for two different accumulation times (1 h and 1 day). The schematic maps show sample-estimated values of the following expression:

$$\frac{2\mathbf{Cov}\{E_r, E_g\}}{\mathbf{V}\{E_r\}}, \tag{5}$$

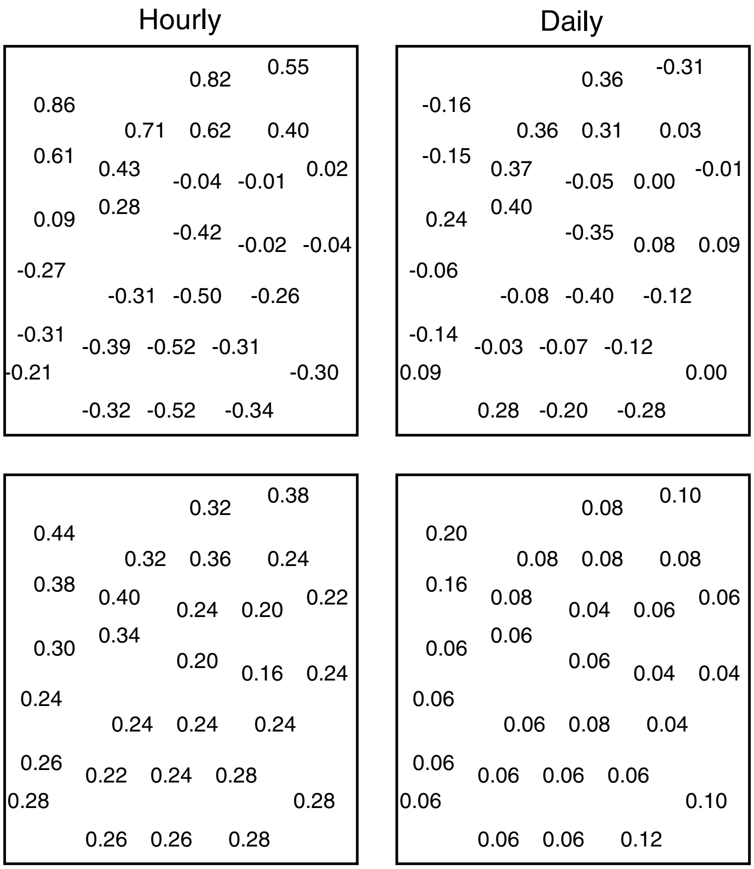

Fig. 3. Upper panels: sample estimates of the expression (5), covariance factors in Eq. (1) normalized by error variances of the radar rainfall. Lower panels: $\pm 2\sigma$ error bounds of the above results obtained using the bootstrap technique. The two examples are for the hourly and daily accumulation intervals (left and right panels, respectively).

for each of the Micronet raingauges in the analyzed rectangular area of the Little Washita watershed (see Fig. 1). Expression (5) is a proportion of two terms in Eq. (1) that we are directly concerned with, the covariance term and the radar error variance. The lower panels contain the $\pm 2\sigma$ bootstrap confidence bounds of these sample-estimated ratios. Although we show only results for two intervals, we have to conclude that the zero-covariance hypothesis as stated formally by Eq. (4) is *not* fulfilled. We can see that, for a few gauge locations, the magnitude of the covariance term is almost comparable with the radar error variance. The proportions in Fig. 3 exhibit a fairly regular spatial behavior. They change from the prevailing positive values in the North and Northwest part of the test area to negative values over the center and in its South part. Specifically, for raingauge 146, which is close to the area center, the covariance term in Eq. (1) is negative. Its value is −42% (±20%) of the radar error variance for the hourly accumulations, and −35% (±6%) for the daily intervals (the numbers in the parentheses are the $\pm 2\sigma$ error bounds). This leads to an overestimation of the radar errors, if the EVS is applied to these cases, and the magnitude of the biases is discussed below. On the other hand, for gauge 124, the covariance term is positive and constitutes 71% (±32%) and 36% (±8%) of the radar error variance for hourly and daily intervals, respectively. For this raingauge location, the EVS results are underestimated. We can also see that, for all the cases where the covariance departure from zero is larger than 30% of the radar error variance, zero value is outside of the $\pm 2\sigma$ bootstrap error bounds. This indicates that our estimates of the larger departures of the covariance terms from zero are statistically significant. However, this only means that the data sample used here is of sufficient size to formally reject the zero-covariance hypothesis stated by Eq. (4). The next, and more important, question concerns the practical significance of the resulting biases in the EVS estimates of the radar errors.

Even if the zero-covariance assumption in its rigorous form of Eq. (4) is not valid, one can still find it beneficial to apply the EVS method to verify radar rainfall using point measurements as the reference. Now, instead of the formal inequality in Eq. (4), we consider a question of the actual effects of non-zero covariances on the EVS results. Next, we compare them with biases caused by the traditional approach neglecting the GR errors. The upper panels in Fig. 4 show two examples of the sample

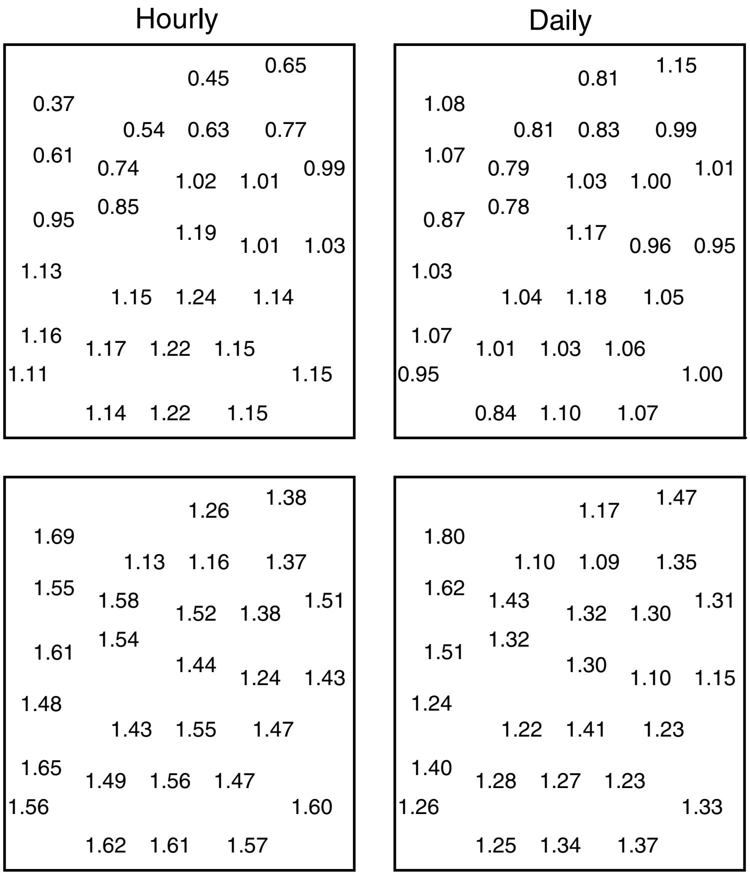

Fig. 4. Upper panels: sample estimates of the expression (6), EVS estimated standard errors normalized by true standard errors of the radar rainfall products. Lower panels: sample estimates of the expression (7), RMS radar–gauge differences normalized by true standard errors of the radar rainfall products. The two examples are for the hourly and daily accumulation intervals (left and right panels, respectively).

standard deviations of the EVS-estimated radar errors normalized by standard deviations of the true radar errors:

$$\frac{\sqrt{\mathbf{V}\{D_{\mathrm{rg}}\} - \mathbf{V}\{E_{\mathrm{g}}\}}}{\sigma\{E_{\mathrm{r}}\}}, \tag{6a}$$

$$\sigma\{E_{\mathrm{r}}\} = \sqrt{\mathbf{V}\{E_{\mathrm{r}}\}}, \tag{6b}$$

for the same two accumulation times as before. We can see that, due to the assumed zero covariance, the EVS results differ from the estimated truth for most locations of the point rainfall measurements. The overestimation of the radar errors ranges up to about 25% and could be perhaps tolerated in most practical applications. More dangerous are cases of underestimation for which the EVS estimates can be more than 50% below the actual standard error of the radar rainfalls. In practice, such assessments might result in wrong decisions based on unjustified confidence in the overall performance of the radar rainfall products. However, for the data sample and spatial scale analyzed here, such strong underestimation occurs only for a few peripheral locations of the point rainfall in the North and Northwest area of the test area. Although we cannot yet generalize and expect the same pattern in different rainfall regimes and spatial scales, it seems that the EVS gives useful results, if one can avoid the gauges that are too far from the grid-center of the verified area-rainfall.

We can further strengthen these conclusions by comparing the above EVS estimates with the biases of the root-mean-square (RMS) radar–raingauge differences. This statistic is the most popular outcome of the traditional radar–raingauge comparisons and is often used to evaluate the radar rainfall products. In this study, due to removal of the overall bias described in the previous section, it is equal to sample standard deviation of D_{rg}. In the lower panels of Fig. 4, we present these RMS differences normalized, as before, by the actual radar errors:

$$\frac{\sqrt{\mathbf{V}\{D_{\mathrm{rg}}\}}}{\sigma\{E_{\mathrm{r}}\}}, \tag{7}$$

for the same cases as in the upper panels. As expected, the raingauge representativeness errors cause large and systematic overestimation of the radar errors determined this way. Now, the biases can be almost as big as

80%. For smaller areas the impact of the GR errors can be lower. However, the EVS definitely performs better for the test area used here, if peripheral gauge locations are not used in this method.

As we mentioned before, we carried out these analyses over a broad range of accumulation times from 15 min to 7 days. Concerning the zero-covariance hypothesis, the results are essentially the same for all these time scales. Therefore, we limit the examples presented above to the hourly and daily intervals that are most commonly used in operational practice.

4. Conclusions and directions

We presented an empirical test of the zero-covariance hypothesis in the EVS method of estimation of the radar rainfall errors. We conclude that this assumption in its rigorous formulation is not fulfilled in our particular testing setup. For example, for the gauge close to the center of the test area and the hourly intervals, the covariance term in the separation formula constitutes about 42% of the true radar error variance. The $\pm 2\sigma$ bootstrap confidence interval for this result is equal to [22%, 62%], therefore the assumption violation is proven with high level of statistical significance. However, closer examination of the actual effects of the non-zero error covariances on the EVS outcomes shows that they can be tolerated in many practical applications. For example, for the same central raingauge, the EVS-estimated standard error of the radar rainfall is only about 20% higher than its true value. A necessary condition for this small effect of the assumption violation is that gauges that are closer to the grid borders than to its center are avoided in radar–raingauge comparisons. Despite its imperfections, careful application of the EVS method can provide better estimates of the standard errors of radar rainfall products than the traditional radar–raingauge analyses that neglect the gauge representativeness errors.

Filtering out the GR uncertainties in radar rainfall verification is a difficult question. However, solving it seems necessary, if we want to evaluate the products in a meaningful way. The EVS method is a simple way to reduce the impact of the GR errors, but violation of its zero-covariance assumption implies using it with caution. The physical and/or statistical origin of the non-zero covariances is unknown to us at present and requires further research. Future studies of the problem should also include the effects of the non-zero covariances in other spatial scales and rainfall regimes. The observed regularities could then be used to correct the covariance-induced biases. In addition, other methods of the error filtering are certainly possible and should be investigated. To address these issues, we need to collect large radar–raingauge samples based on dense and reliable networks that could provide sufficiently accurate approximations of the true area-averaged rainfall. An example of such high-precision network design, created in 1993 in Great Britain, is described by Moore et al. [18]. Another system has been deployed recently by the Oklahoma University and consists of 25 double gauge stations covering a field of about 3 × 3 km. A similar design to cover uniformly a larger area is currently planned at the University of Iowa. Hopefully, good quality data from such systems will become broadly available in the next few years and enable real progress in the verification methodologies of the remote sensing rainfall products.

Acknowledgements

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