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Use of dual-polarization weather radar quantitative precipitation estimation for climatology

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Abstract. Accurate, timely and reliable precipitation observations are mandatory for hydrological forecast and early warning systems. In the case of convective precipitations, traditional rain gauges networks often miss precipitation maxima, due to density limitations and high spatial variability of rainfall field. Despite several limitations like attenuation or partial beam-blockings, the use of C-band weather radar has become operational in most of European weather services. Traditionally, weather radar-based quantitative precipitation estimation (QPE) are derived by horizontal reflectivity data. Nevertheless, dual-polarization weather radar can overcome a number of shortcomings of the legacy horizontal reflectivity based estimation. For the first time, the present study analyses one of the longest datasets from fully operational polarimetric C-band weather radars; those ones are located in Estonia and in Italy, in very different climate conditions and environments. The study focuses on long-term observations of summertime precipitation and their quantitative estimations by polarimetric observations. From such derived QPEs accumulations for 1 hour, 24 hours and one month durations are calculated and compared with reference rain gauges to quantify uncertainties and evaluate performances.

1. Introduction

Detailed surface rainfall information is of great importance in many fields not only for agricultural or hydrological applications but also for assimilation purposes within numerical weather models. For decades gauge networks have provided the best reference datasets. E-OBS 50-years daily European gridded interpolated dataset has been widely used in climatological studies (Cornes et al., 2018). Gauge based datasets have well known shortcomings in their low spatial and to a lesser degree temporal resolution. Precipitation data from satellites provides good spatial coverage, but still not in very high temporal resolution, especially in higher latitudes (Sun et al., 2018). Polar orbiting satellites provide better spatial resolution data in higher latitudes, but they are very limited in temporal resolution (Tapiador et al., 2018). In the last decade various studies have used multi-year single polarization weather radar data to a good effect in deriving rainfall climatology with high spatiotemporal resolution (Overeem et al., 2009; Goudenhoofdt et al., 2016). However, quantitative precipitation estimation (QPE) with single polarization C-band radar is strongly affected by attenuation of the electromagnetic wave in heavy precipitation or a wet radome, hail contamination, partial beam blockage and absolute radar calibration (Krajewski et al., 2010; Cifelli et al., 2011). All prior shortcomings can be mitigated by the use of dual polarization weather radar data. A number of studies have shown that rainfall retrieved from dual polarimetric radar differential phase measurements outperforms rainfall estimated from horizontal reflectivity, especially in heavy precipitation (Wang and Chandrasekar, 2009; Vulpiani et al., 2012; Wang et al., 2013; Crisologo et al., 2014). Because differential phase measurements tend to be noisy and less reliable in low intensity precipitation Crisologo et al. (2014) and Vulpiani and Baldini (2013) improved the robustness of their rainfall retrieval technique by employing a combination of horizontal radar reflectivity $R(Z_H)$ and specific differential phase $R(K_{DP})$ where a threshold was set below which $R(Z_H)$ was used and over which $R(K_{DP})$ was used. Bringi et al. (2011) also compared performances of $R(Z_H)$, $R(K_{DP})$ and the combination product of the two on a relatively long set of data of four years.

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The main aim of this study is to evaluate the potential of using polarimetric weather radar QPE for climatological evaluation of precipitation regimes. The uniqueness of this paper is ensured by various features. First of all, we have a long multi-year dataset, starting already from 2011, derived by operational dual polarimetric C-band weather radar made by different manufacturers. The dataset is gathered from the archive of weather radar scans set up for operational surveillance in the meteorological services. Secondly, the study areas are from heterogeneous climatologies being the weather radar located in Estonia and Italy. What is more, we will assess the effect of radar scan interval as the radar data scan frequency is 5 and 15 minutes from Italy and Estonia respectively. The study analyses results at three accumulation intervals of 1 hour, 24 hours and one month. This is also the first ever study evaluating weather radar QPE in Estonia. Automatic rain gauge data are used as reference of radar based products. Based on this dataset we investigate the performance of different rainfall retrieval methods. Horizontal reflectivity data are re-calibrated using a combined set of polarimetric self-consistency techniques (Gorgucci et al., 1992; Gorgucci et al., 1999; Gourley et al., 2009). Rainfall estimations based on K_{DP} are derived from the unwrapped differential phase profile. As a third radar QPE product, an $R(Z_H)$ and $R(K_{DP})$ combination is also generated. All these weather radar-based QPE products are then compared with gauge accumulations.

The paper is organized as follows. Section 2 describes the rainfall estimation datasets from radar and rain gauges and methods used for comparisons. The results are discussed in Sect. 3. In Sect. 4 conclusions are provided.

2. Data and methods

2.1 Rain gauge measurements

In Estonia major renewal and automation of the rain gauge network run by the Estonian Environment Agency (EstEA) started in 2003. Since 2003 to 2006 the network was updated to automatic tipping-bucket gauges. Starting from 2006 the tipping-bucket gauges were progressively replaced by weighted gauges. This process was finished by the end of the year 2011. By that time there were 33 automatic weighted gauge stations and 27 stations with tipping-bucket gauges. According to the comparison study of parallel measurements of the tipping-bucket gauges and weighted gauges the latter exhibited much higher quality (Alber et al., 2015). From the end of 2010 the data has been recorded with 10 minute interval. Until 2010 the temporal resolution was one hour. Both 10-minutes and 1-hour data are being saved by EstEA since then, but only one hour data have been quality controlled by EstEA staff. Because the 10-minutes data are not quality controlled one hour gauge data was used in this study as a more reliable ground truth. Only weighted gauge data was used because of the higher quality of these measurements and to ensure uniformness of the dataset. In this work 8 rain gauges close to Sürgavere, Estonia are included (Fig. 1). Data is with 0.1 mm resolution.

Since 1987, Arpa Piemonte, the regional agency for environment protection in Piemonte, Italy, operates the regional automatic gauges network made by about 380 tipping-bucket gauges. Most of the gauges are heated to avoid solid precipitation accumulation during the cold season. The temporal resolution of the gauges network is 1-minute with 0.2 mm resolution data. Automatic data quality check is run on real time data, followed by off-line manned data validation. In this study a network subset made of 42 rain gauges close to Torino, Italy, have been considered (Fig. 1). Precipitation measurements range from 2012 to 2016.

2.2 Weather radar precipitation estimation

Data from C-band dual polarization Doppler weather radars in Estonia and Italy were used in this study. The weather radars considered in this study are from different manufacturers, in Estonia Vaisala WRM200 and in Italy Leonardo Germany Gmbh METEOR 700C radar. Figure 1 illustrates the location of Estonian radar (Sürgavere) and Italian radar (Bric della Croce) together with the locations of available rain gauges.

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Sürgavere radar, located in central Estonia at altitude 128 m a.s.l., has been operational since May 2008 but for this study data starting from 2011 was used because the gauge network was updated by that time. The radar performs a surveillance volume scan at 8 elevation angles (0.5°, 1.5°, 3.0°, 5.0°, 7.0°, 9.0°, 11.0° and 15.0°) every 15 min starting each scan from the lowest elevation angle. Only the lowest elevation angle data were used. The resolution of the raw radar data is 300 m in range and 1° in azimuth. Data up to 10 km from radar were discarded because of the ground clutter and unreliable K_{DP} estimation. Doppler filter was used to eliminate residual non-meteorological fixed clutter. After careful analysis some of the data from Sürgavere radar had to be omitted completely. Years 2014 and 2015 were excluded because of gradually decreasing polarimetric data quality caused by a broken limiter which was replaced in March 2016. Data from 2017 was discarded because the quality was inconsistent as a result of a broken stable local oscillator (STALO) which was replaced in May 2018. From Estonia the investigated period ranges then from 2011-2018 and includes 5 years of data.

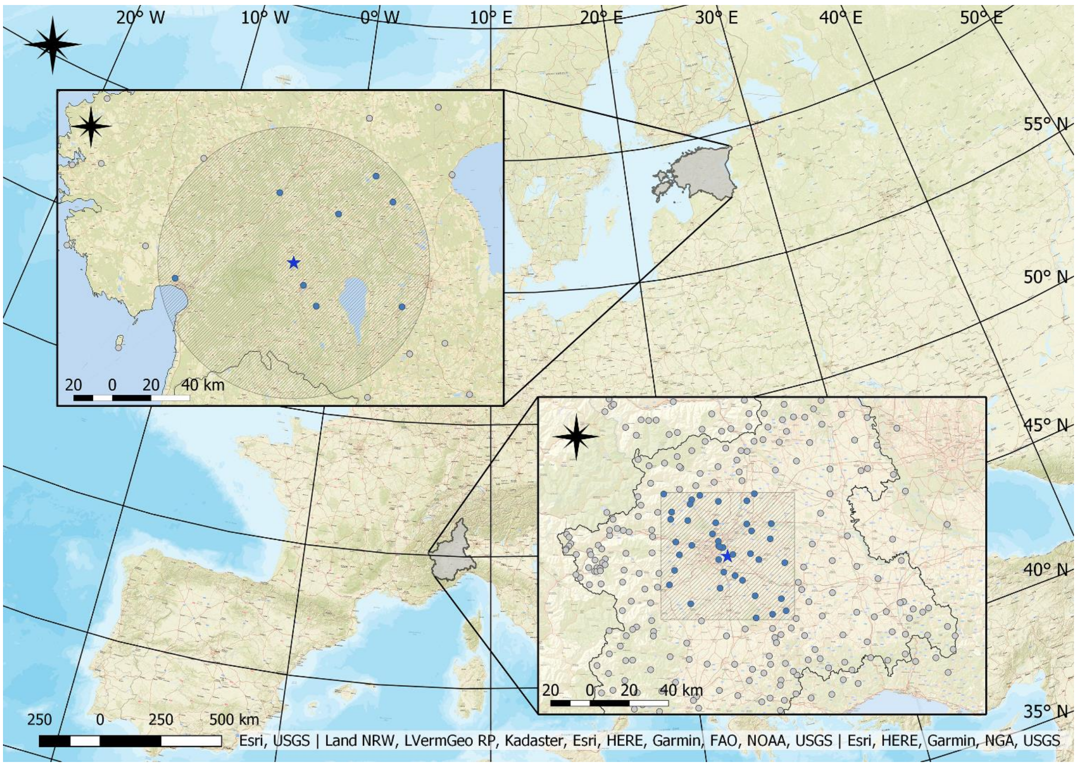

Figure 1. Study areas (shaded) located in Estonia (upper left zoomed area) and in Piemonte, Italy (lower right zoomed area). Grey dots denote gauge locations of Estonian and Piemonte region respectively and blue dots gauges inside the study area. Blue stars reveal radar locations.

On the Torino hill, at altitude 770 m a.s.l., the operational dual-polarization Doppler C-band weather radar Bric della Croce is located. The radar site is central respect Piemonte extent: toward west and north at about 20 km Alps start with peaks 2,500 - 3,000 meters above sea level. The radar performs a fully polarimetric volume scans, made by eleven elevations up to 170 km range, with 340 meters range bin resolution. Bric della Croce observations range from 2012 to 2013 with ten-minutes interval and from 2013 to 2016 with five minutes interval time resolution later.

QPEs, based on horizontal reflectivity, are extensively described by Cremonini and Bechini (2010) and by Cremonini and Tiranti (2018), meanwhile K_{DP} precipitation estimates are derived according to Wang et al. (2009). When K_{DP} was equal to or

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less than zero, then $R(K_{DP})$ was set to zero. The area close to the weather radar up to eight kilometers has been left out due to heavy ground clutter contamination and unreliable estimations of K_{DP}.

Sürgavere radar specific differential phase (K_{DP}) and differential propagation phase (ϕ_{DP}) were recalculated from raw ϕ_{DP} data using Py-ART function phase_proc_lp (Giangrande et al., 2013) with carefully tuned parameter values according to data specifics. Horizontal reflectivity (Z_H) was re-calibrated using a method that utilizes the knowledge that Z_H, Z_{DR} (differential reflectivity) and K_{DP} are self-consistent with one another and one can be computed from two of the others. The calibration was carried out using the self-consistency theory set down in Gorgucci et al. (1992) and Gourley et al. (2009) where the methodology is described in detail. As a result Z_H bias values from the range of -2.0 to -5.0 dB were obtained depending on date. The bias values were used to correct the corresponding observed Z_H prior to rain rate estimation.

In order to convert reflectivity Z_H to rainfall rate R (mm/h) the following relation was used:

$$Z_H = 300R^{1.5}. \quad (1)$$

Specific differential phase K_{DP} was converted to rainfall rate using the expression suggested by Leinonen et al. (2012):

$$R = 21.0K_{DP}^{0.720}. \quad (2)$$

A number of studies have shown that $R(K_{DP})$ provides much more reliable intensity estimates in heavy rainfall (Vulpiani et al., 2012; Wang et al., 2013; Chen and Chandrasekar, 2015). On the other hand it has been indicated that K_{DP} retrieval itself is less reliable in light precipitation conditions (Giangrande and Ryzhkov, 2008; Ryzhkov et al., 2014). Thus combining the two methods has the potential to be superior to using each method separately. For example Vulpiani et al. (2013) used a weighted combination of $R(Z_H)$ and $R(K_{DP})$ where only reflectivity data was used for bins with K_{DP} less than or equal to 0.5 °/km and K_{DP} was used additionally with increasing weight over that value up to 1 °/km over which it was solely used. Cifelli et al. (2011) used simple threshold method where $R(K_{DP})$ was used when $R(Z_H)$ was exceeding 50 mm/h intensity. Several authors have successfully added $R(Z_{DR})$ based intensity estimation to the combination on S-band weather radars (e.g. Ryzhkov and Zrnic, 1995; Ryzhkov et al., 2005; Chandrasekar and Cifelli, 2012). Due to residual effects such as resonance, noise and attenuation $R(Z_{DR})$ should not be used at C-band (Ryzhkov and Zrnic, 2019).

In our study rainfall from a combined threshold approach was used for both weather radars as a third product $R(Z_H,K_{DP})$. In the combined product $R(Z_H)$ was used in areas with Z_H less than or equal to 25 dBZ and $R(K_{DP})$ otherwise if available.

2.3 Comparison framework

In order to estimate the performance of the radar rainfall products they were compared with gauge accumulations. The study period was limited to the warm season (May - September for Estonia and April - October for Italy). In Estonia, the mean annual precipitation is 649 mm. Precipitation climatology has distinct seasonality with maxima in summer (215 mm) followed by autumn (198 mm), winter (128 mm) and spring (108 mm). The summer maxima of seasonal mean precipitation is especially pronounced in the continental part of Estonia (246 mm in Mauri, South-East Estonia), Tammets et al. (2013).

In Piemonte, close to the radar, the mean annual precipitation is 870 mm having bimodal distribution with peaks in spring (266 mm) and in autumn (255 mm), Devoli et al. (2018).

Maximum distance of the gauges to be included in the comparison was limited to 70 km radius from radar location in case of Estonia and up to 30 km distance in Italy. Thus, in Estonia and in Italy rainfall data were from 8 and 42 gauges respectively. By limiting data analysis to warm season and constraining the maximum radar range, we were able to ensure that radar data were originating only from liquid precipitation which is required for more reliable rainfall intensity estimation.

In the case of Italy, the applied range limit is also aimed at eliminating uncertainties due to complex orography, like shielding by the mountains, overshooting, bright band contamination. Up to 30 km from Bric della Croce, terrain is relatively flat, while beyond mountains block most of the radar signal for lowest elevations. Radar-based QPEs have been accumulated to 1-hour

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duration and longer durations have been calculated by these accumulations. No missing data for radar or gauges was tolerated to prevent underestimation.

The quality of the rainfall estimates was estimated by the following verification measures (where r_i is the i-th out of n radar precipitation estimates, g_i the i-th out of n gauge observations, r_m the mean of all n radar precipitation estimates, and g_m the mean of all n gauge observations):

Pearson's correlation coefficient: $CC = \frac{\sum_{i=1}^{n}(r_i - r_m)\cdot\sum_{i=1}^{n}(g_i - g_m)}{\sqrt{\sum_{i=1}^{n}(r_i - r_m)^2}\cdot\sqrt{\sum_{i=1}^{n}(g_i - g_m)^2}}$, (3)

Normalized Mean Error: $NME = \frac{\sum_{i=1}^{n}|r_i - g_i|}{\sum_{i=1}^{n} g_i} \cdot 100\%$, (4)

Normalized Mean Bias: $NMB = \frac{\sum_{i=1}^{n}(r_i - g_i)}{\sum_{i=1}^{n} g_i}$, (5)

Root Mean Squared Error: $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - g_i)^2}$, (6)

Nash-Sutcliffe Efficiency: $NASH = 1 - \frac{\sum_{i=1}^{n}(r_i - g_i)^2}{\sum_{i=1}^{n}(g_i - g_m)^2}$. (7)

The Nash coefficient is typically used to assess accuracy of hydrological predictions, but it has also been used for weather radar-based rain rates and gauges comparisons (Nash and Sutcliffe, 1970).

3. Results and discussion

3.1 Case comparisons

In this section radar rainfall estimation products are compared with gauge measurements of short period and on a specific gauge location basis. This allows to evaluate how well radar products capture single events and how they follow gauge values on location basis.

Figure 2 shows one month of precipitation on Jõgeva station location (60 km away from the radar site) in Estonia with one hour temporal resolution. Overall radar products follow the gauge measurements well but there are considerable differences among them. Reflectivity based product $R(Z_H)$ is not affected by noise and clutter in clear weather or in light rain cases but on the other hand it is underestimating rainfall amounts particularly in medium to heavy precipitation cases. By the end of the month its sum of 40.5 mm was 19.6 mm less than gauge measured accumulation (70.1 mm). $R(K_{DP})$ then again is heavily overestimating precipitation amounts especially during light rain cases. By the end of the month the accumulated amount of 150.2 mm was more than double of the gauge sum. Third product, $R(Z_H,K_{DP})$, was showing the best performance of all the three compared and it was correlating well with gauge accumulation time series and one month accumulation of 69.5 mm was just 0.6 mm lower than rain gauge sum.

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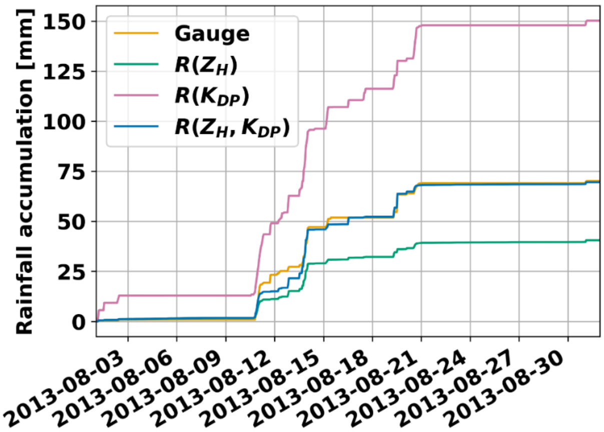

Figure 2. One month 1-hour rainfall cumulative accumulations, Sürgavere radar data, Jõgeva station gauge data.

Figure 3 illustrates a case from Italy, comparison of a gauge located within 30 km distance from radar to Bric della Croce radar precipitation estimation products. In the end of the 34-hour period the specific differential phase based product $R(K_{DP})$ has the smallest error compared to gauge as it overestimates the gauge measurement of 40.6 mm by 2.0 mm. On the other hand in light rain $R(K_{DP})$ is overestimating significantly - in the first 13 hours when gauge measured 3.4 mm of accumulated rainfall it already estimated 12.2 mm. $R(Z_H)$ was underestimating even in light rain and in heavy rain the difference compared to gauge measurement increased further. In the end of the period the underestimation was nearly threefold (15.6 mm compared to gauge accumulation of 40.6 mm). $R(Z_H,K_{DP})$ product showed good correlation with gauge in light precipitation as it was mostly based on reflectivity data, but in more intense precipitation it was still underestimating compared to gauge data. In the end of the period the accumulated value for $R(Z_H,K_{DP})$ was 26.7 mm.

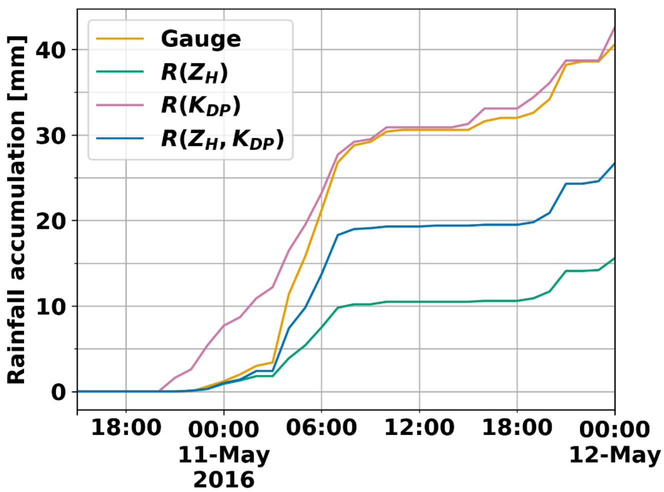

Figure 3. 1-hour rainfall cumulative accumulations from Verolengo gauge, located at 29 km from the radar, and co-located Bric della Croce radar QPE.

In both cases the general behaviour of QPEs is similar. Weather radar estimations, even when sampled by 15-minutes interval observations, follows gauge measurements with good agreement. It has to be mentioned though that this was just one case and there were numerous shorter time period based cases where the 15-minute Estonian radar products did not capture precipitation

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as well as gauge and missed some events. Longer scan interval increases the randomness and particularly with small scale convective precipitation for which minimal sampling interval is the most beneficial. From Italy the example case was much shorter, but the precipitation intensity was higher. On both cases $R(K_{DP})$ generally overestimates precipitation amounts, especially in light rain cases. In Italy the $R(K_{DP})$ overestimation is smaller. One of the causes of this behaviour might be more intense precipitation in Italy where K_{DP} measurement became more accurate. More intense rainfall on the other hand caused greater underestimation of $R(Z_H)$ based precipitation accumulation from gauge values compared to Estonia. These example cases demonstrated that radar can be used for 1-hour accumulations, but systematic errors cannot be excluded. In order to find out errors and uncertainties and to see how QPEs compare to gauge measurements on longer scale will be looked at in the next sections.

3.2 Comparison of one hour accumulations

The quality of the rainfall estimates is compared at various accumulation intervals. Comparing different intervals can also be useful to point out representativeness issues caused by low radar scan rates. Investigated period covers the years 2011-2018 in Estonia and 2012-2016 in Italy.

First, in this section hourly accumulations are analysed. Hourly accumulations are especially important for small basins and in extreme precipitation climatology analysis. Hourly rainfall maxima can provide valuable data for flash flood nowcasting and other hydrological applications.

Table 1. Verification of the radar-based rainfall 1-hour accumulation products of Estonia.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC	0.679	0.674	0.697
NME	0.537	0.868	0.594
NMB	-0.143	1.861	0.298
RMSE(mm)	1.615	2.131	1.677
NASH	0.214	-0.037	0.184

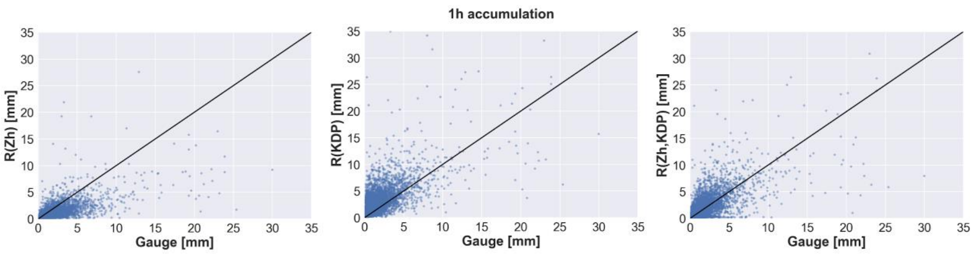

Figure 4. Scatter plots of radar-based rainfall estimates against rain gauge observations for 1-hour accumulation intervals in Estonia 2011-2018. The corresponding verification measures are presented in Table 1. Number of radar-gauge data pairs with 8 gauges and accumulations > 0.1 mm is 7,019.

Table 1 presents the verification results for the hourly accumulation interval in Estonia. Figure 4 shows the corresponding scatter plots. As can be seen, the $R(Z_H)$ estimation generally underestimates rainfall, especially heavy events while it has the best error verification values (Nash-Sutcliffe Efficiency 0.214, NME 0.537, NMB -0.143 and RMSE 1.615 mm). $R(K_{DP})$ on the other hand overestimates accumulations for low intensity events as could be presumed. $R(Z_H,K_{DP})$ shows considerable

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improvement in both other product's weak points as it captures heavy rainfall events better and does not underestimate weak precipitation. It has the highest correlation coefficient (0.697) of all the products.

Nevertheless, it can be seen from the scatterplots that there is a lot of randomness in the hourly radar accumulations with all products. Mostly, it can be linked to the low spatial representativeness of the point measurements of ra in gauges. This effect is more pronounced on a short time scale and they originates from scarce gauge network and low 15-minute radar scan rate. Small scale effects like wind drift might also be more influential on shorter accumulation period (Lauri et al., 2012). The reason why $R(Z_H)$ might have the best performances when NME and RMSE are considered because there are not very many heavy rainfall cases in Estonia and this tends to favour $R(Z_H)$ in the verification comparisons.

From Italian hourly accumulation scatterplots in Fig. 5, it can be seen that the overall behaviour of the radar products is similar to Estonia. Table 2 presents the corresponding verification results. $R(Z_H)$ underestimates particularly at intense precipitation events. $R(K_{DP})$ generally overestimates hourly accumulations especially at low intensity cases: as stated by Wang et al. (2013), $R(K_{DP})$ generates noisier estimations at low rain rates. $R(Z_H,K_{DP})$ outperforms both other products in Italy which is confirmed by verification metrics as it overcomes the shortcomings of the other estimations.

Less random scatter is visible in Italian hourly data due to frequent scan strategy. $R(Z_H)$ is underestimating more than in Estonia as expected because in Italy intense rainfall is more frequent - it has larger RMSE and even more negative NMB. Probably for the same reason $R(K_{DP})$ is more accurate in Italy than in Estonia as it has smaller NME and NMB while having larger RMSE due to higher rainfall intensities recorded in Italy.

Table 2. Verification of the radar-based rainfall 1-hour accumulation products of Italy.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC	0.843	0.808	0.870
NME	0.531	0.514	0.423
NMB	-0.296	0.678	0.120
RMSE(mm)	3.136	3.037	2.750
NASH	0.364	0.385	0.443

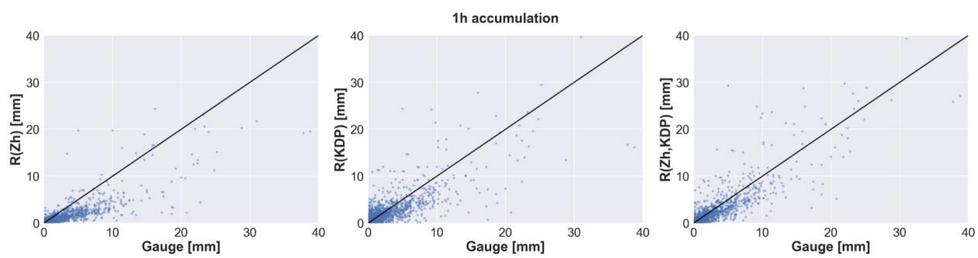

Figure 5. Italy 1-hour accumulations 2012-2016. The corresponding verification measures are presented in Table 2. Number of radar-gauge data pairs with 42 gauges and accumulations > 0.1 mm is 1,233.

3.3 Comparison of 24-hours accumulations

Table 3 shows the verification results for the daily accumulation interval in Estonia, while Fig. 6 presents the corresponding scatter plots. As expected, much less scatter can be seen than on the hourly level but overall the results are consistent with the hourly interval verification outcomes. Reflectivity based product, $R(Z_H)$, is still underestimating rain depths while the negative bias is considerably smaller than in hourly interval data. $R(K_{DP})$ is the least accurate of the three products also on daily

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accumulation level with the lowest correlation and highest error scores. The combined product, $R(Z_H,K_{DP})$, removes the negative bias of $R(Z_H)$ and shows better correlation and substantial improvement in terms of both the systematic error and the overall error compared to $R(K_{DP})$. $R(Z_H,K_{DP})$ has the smallest NME of 0.438, RMSE of 3.992 mm and highest Nash-Sutcliffe Efficiency equal to 0.392. Overall there is noticeably less randomness in the daily radar accumulations compared to 1-hour interval.

Table 3. Verification of the radar-based rainfall 24-hours accumulation products of Estonia.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC	0.831	0.792	0.827
NME	0.475	0.845	0.438
NMB	-0.050	2.290	0.343
RMSE(mm)	4.366	7.195	3.992
NASH	0.335	-0.097	0.392

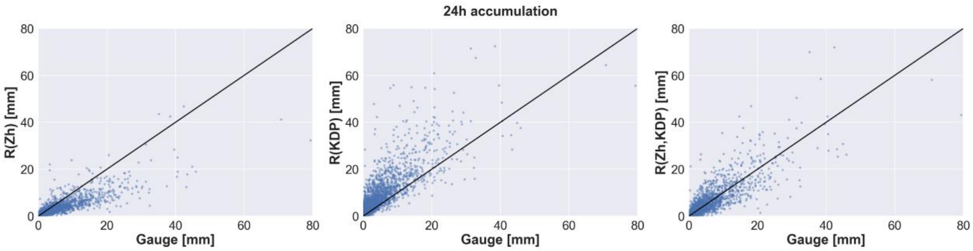

Figure 6. Estonia 24-hours accumulations 2011-2018. The corresponding verification measures are presented in Table 3. Number of radar-gauge data pairs with 8 gauges and accumulations > 0.1 mm is 2,148.

Table 4 shows the verification results for the daily accumulation interval in Italy, while Fig. 7 presents the corresponding scatter plots. $R(Z_H)$ is slightly underestimating compared to gauge results and surprisingly it outperforms other competing products in all metrics except Pearson's correlation coefficient. $R(K_{DP})$ is again overestimating the most and has the lowest correlation with gauge data. $R(Z_H,K_{DP})$ notably improves the $R(K_{DP})$ on all verification metrics but does not exceed $R(Z_H)$ except for correlation coefficient which is the highest of all three products with r of 0.708. In Italy the decrease in randomness of radar accumulations cannot be observed compared to 1-hour level.

Table 4. Verification of the radar-based rainfall 24-hours accumulation products of Italy.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC	0.692	0.661	0.708
NME	0.504	0.636	0.553
NMB	-0.01	0.789	0.459
RMSE(mm)	8.909	11.071	10.552
NASH	0.238	0.054	0.098

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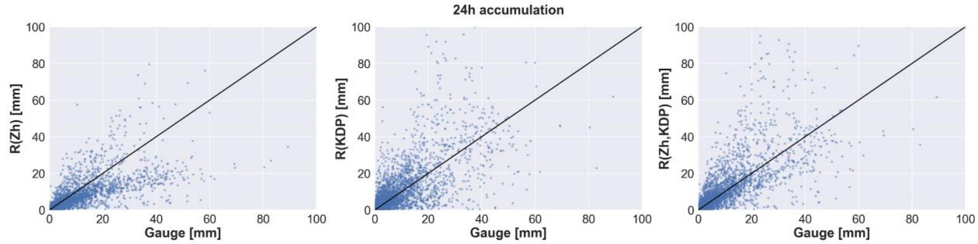

Figure 7. Italy 24-hours accumulations 2012-2016. The corresponding verification measures are presented in Table 4. Number of radar-gauge data pairs with 42 gauges and accumulations > 0.1 mm is 3,010.

3.4 Comparison of monthly accumulations

Table 5 shows the verification results for the monthly accumulation interval in Estonia, while Fig. 8 presents the corresponding scatter plots. Compared to shorter time scales overall on monthly scale the correlation of all the products with gauge accumulations is higher. $R(Z_H)$ is underestimating with larger mean bias (-0.284) than on daily level but with smaller normalized mean error (0.360). $R(K_{DP})$ is showing less scatter than on shorter time scales like other products while still heavily overestimating accumulations (NMB equal to 1.042 with RMSE equal to 62.466 mm). On monthly accumulation level $R(Z_H, K_{DP})$ outperforms the two other products to a great extent. It is well correlated to gauge values with small scatter as it is performing great both in low and high accumulation cases. The correlation coefficient is nearly identical to $R(Z_H)$, but it removes the systematic underestimation of $R(Z_H)$ and overestimation of $R(K_{DP})$ and exceeds them in all other verification metrics.

Table 5. Verification of the radar-based rainfall monthly accumulation products of Estonia.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC	0.877	0.789	0.875
NME	0.360	0.822	0.214
NMB	-0.284	1.042	0.109
RMSE(mm)	27.448	62.466	16.704
NASH	0.155	-0.924	0.486

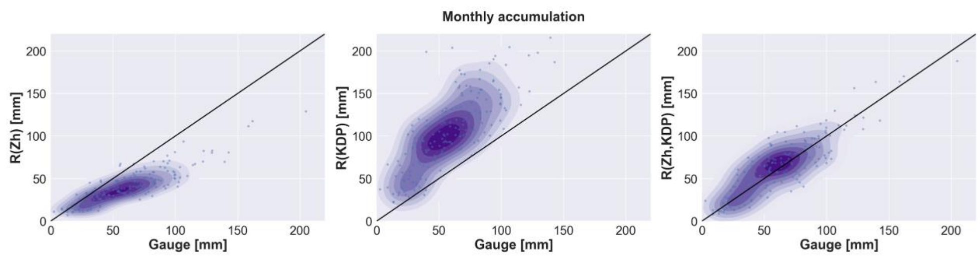

Figure 8. Estonia monthly accumulations 2011-2018. The corresponding verification measures are presented in Table 5. Number of radar-gauge data pairs with 8 gauges is 179.

Table 6 shows the verification results for the monthly accumulation interval in Italy, while Fig. 9 presents the corresponding scatter plots. Scatterplots reveal similar characteristics to the daily level accumulations of the products. $R(Z_H)$ is underestimating rainfall also on monthly scale and $R(K_{DP})$ overestimating. $R(Z_H, K_{DP})$ is still overestimating but with a

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decreased RMSE compared to $R(K_{DP})$ product. It also exhibits the highest correlation coefficient of the three. According to the verification results most of the metrics indicate better performance of the radar products on monthly scale compared to daily intervals. Correlation coefficient is higher and NME is lower on all the products when the two timescales are compared.

Table 6. Verification of the radar-based rainfall monthly accumulation products of Italy.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC	0.776	0.726	0.799
NME	0.375	0.488	0.408
NMB	-0.128	0.310	0.337
RMSE(mm)	23.737	30.802	24.914
NASH	0.288	0.076	0.253

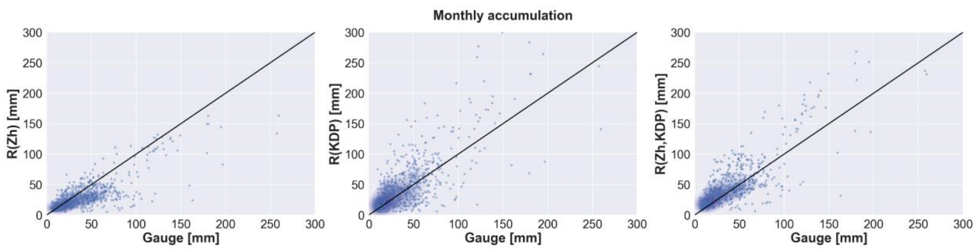

Figure 9. Italy monthly accumulations 2012-2016. The corresponding verification measures are presented in Table 6. Number of radar-gauge data pairs with 42 gauges is 675.

4. Conclusions

In the present study polarimetric rainfall retrieval methods for the fully operational C-Band radars in Sürgavere, Estonia and Bric della Croce, Italy have been analysed. The study focuses on the warm period of the year and long period of multi-year data is used. From Estonia five years data from 2011 to 2018 has been included, from Italy the data interval ranges from 2012 to 2016. Reflectivity data were calibrated following a self-consistency theory and measured horizontal reflectivity (Z_H) was corrected accordingly. In order to calculate rainfall from polarimetric variables, differential propagation phase (ϕ_{DP}) was reconstructed and based on that specific differential phase (K_{DP}) retrieved. To achieve this the transparently implemented algorithm phase_proc_lp (Giangrande et al., 2013) in the open source toolkit Py-ART was used for Estonian data. For Italian data, K_{DP} precipitation estimates were obtained following the theory set down in Wang et al. (2009).

Three radar rainfall estimation products were computed: horizontal reflectivity based product $R(Z_H)$, specific differential phase based product $R(K_{DP})$ and a combined product based on the previous two $R(Z_H,K_{DP})$. Rain gauge network data of Italy and Estonia were used as ground truth. 1-hour, 24-hours and monthly accumulations were derived from the radar products and gauge data.

Time series comparison revealed that even with 15-minute scan interval radar is suitable for QPE, at least with more widespread precipitation like stratiform rain. Still on the shortest accumulation period of 1-hour the more scarce radar data from Estonia had more random scatter than data from Italy where the scan interval was 10 minutes on older data and 5 minutes since 2013. As an overall trend, the longer the accumulation period the less random scatter was visible.

When the three products are compared to each other in case of Estonia the $R(Z_H,K_{DP})$ was clearly superior to $R(Z_H)$ and $R(K_{DP})$ on all accumulation periods. Especially on monthly accumulation scale it was performing distinctly better as it had RMSE

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39% lower than the nearest competitor, the $R(Z_H)$ product and even 73% lower than $R(K_{DP})$. In Italy the $R(Z_H,K_{DP})$ product was exceeding the two other clearly on hourly level. On 24-hours and monthly accumulation scale it had the highest correlation with gauge measurements but the error verification measures were slightly higher than those of the $R(Z_H)$. Nevertheless it outperformed $R(K_{DP})$ on all timescales.

The products were behaving similarly in Estonia and Italy also in the way that $R(Z_H)$ was underestimating and $R(K_{DP})$ overestimating precipitation. In case of Estonia the underestimation of $R(Z_H)$ was less than in Italy and the overestimation of $R(K_{DP})$ was higher than in Italy. We hypothesize that this is mostly due to different climatological regimes between Italy and Estonia as higher intensity rainfalls occur more frequently in Italy. Although one has to keep in mind that the radars were from different manufacturers and thus also the used K_{DP} retrieval algorithms were different which might be the cause of some discrepancy. Another source of error might originate from the implemented Z_H-R and K_{DP}-R relations which might not perform equally in different climates.

Synoptic patterns could be used as an additional source for filtering the radar accumulations. This would enable to verify the performance of each radar product on stratiform and convective events. Moreover, it could be used to see that frequent scans play the bigger role in convective events than stratiform as could be hypothesized and to quantify the effect.

For future studies, it would also be useful to calculate probabilities and return periods of extreme rainfall for weather radar-based rainfall climatology .

Code and data availability. The code used to conduct all analyses in this paper is available by contacting the authors. Gauge and radar data used in this study are available by contacting the authors.

Author contributions. TV, RC, PP and DM directly contributed to the conception and design of the work. TV and RC collected and processed the various datasets and wrote the original draft with input from PP and DM. All authors reviewed and edited the final draft.

Competing interests. The authors declare that they have no conflict of interest.

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