Responses to comments from Anonymus Referee #1

On revised version of „Applicability of dual-polarization weather radar quantitative precipitation estimation for climatological purposes“ by Tanel Voormansik et al.(HESS-2019-624)

GENERAL COMMENTS

Referee's comment

The paper has been revised by the authors and some additional explanations and clarifications concerning the data and the processing methods have been brought. Some references have been added. This is highly appreciated. I would like to thank the authors for the careful attention given to most specific comments.
However, some majour concerns I expressed in my review remain in the revised version and, unfortunately, some suggestions for improving the paper have not been considered by the authors. The following issues remain :

- the focus of the paper is still unclear. The title has been changed but the focus is still on the use for climatological purpose while the scope of the paper is on the evaluation of the performance of the QPE methods.

Authors' response

Authors would like to sincerely thank the referee for the time and effort spent in reading the improved manuscript and for making many clear and constructive suggestions for further improvement. These suggestions were taken into account and the manuscript was edited accordingly. The title has been rephrased to fit more with the scope of the paper. The new proposed title is "Evaluation of the dual-polarization weather radar quantitative precipitation estimation using long-term datasets".

Referee's comment

- the tuning that was applied to optimize the processing is still unclear. The settings have been selected in order to produce the optimal results but very little is said on how the evaluation of the quality of the results has been performed in order to find the best parameters.

Authors' response

We agree that the manuscript would benefit from providing more details about the evaluation of the quality of the results in the section where the derivation of KDP is discussed. Following the referee comment, the manuscript was improved by adding details about the evaluation process. The detailed answer regarding the processing and evaluation of these results is provided under the specific comments section below.

Referee's comment

- the impact of re-calibrating the horizontal reflectivity has not been analyzed as suggested in the review.

Authors' response

Following the referee comment the manuscript was improved further by adding the description of the impact of re-calibration as the referee suggested:

"The impact of the re-calibration was evaluated on one month of 1-hour accumulation data from August 2018 using the verification measures introduced in Sect. 2.1 (Eq. 1-5). The verification results are presented in Table 1. QPE product based on re-calibrated reflectivity ($R(Z_{H\ cal})$) shows clearly superior results compared to the non-calibrated reflectivity based product ($R(Z_{H\ def})$), most notably by decreasing the negative bias."

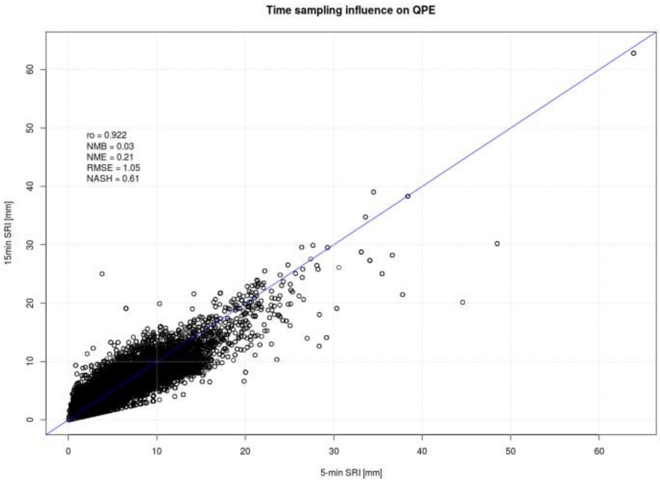
Table 1. Verification results of the test dataset of one month (August 2018) of the radar-based rainfall 1-hour accumulation products of Estonia.

	$R(Z_{H\ cal})$	$R(Z_{H\ def})$	$R(K_{DP\ tuned})$	$R(K_{DP\ def})$	$R(Z_{H15}, K_{DP})$	$R(Z_{H20}, K_{DP})$	$R(Z_{H25}, K_{DP})$	$R(Z_{H30}, K_{DP})$	$R(Z_{H35}, K_{DP})$
CC	0.699	0.699	0.659	0.428	0.687	0.721	0.726	0.713	0.705
NMAE	0.572	0.634	1.074	1.491	0.855	0.69	0.605	0.596	0.595
NMB	-0.212	-0.421	2.652	4.958	1.441	0.655	0.067	-0.118	-0.184
RMSE (mm)	1.611	1.709	2.329	2.656	2.071	1.832	1.714	1.718	1.704
NASH	0.247	0.202	-0.088	-0.241	0.032	0.144	0.199	0.197	0.204

Referee's comment

- using the Italian data, it was possible to analyse the impact of the temporal sampling, 5-min versus 15-min. A simple method was proposed that would have allowed to evaluate errors resulting from temporal sampling.

Authors' response



The Figure shows the effect of time sampling on QPEs. The scatterplot shows 1-hour precipitation accumulation reflectivity-based QPE, derived by 5-minutes sampling versus 15-minutes sampling. QPEs have derived from the second elevation PPI of Bric della Croce weather radar. The comparison is derived from hourly accumulation rainfall observed on October 10th, 2020 and the sample size is 253,514. As expected, the normalized mean bias is close to zero, while the **cross-correlation** is **0.922** and **the normalized mean absolute error is 0.21**.

If we compare different skill scores for 1-hour QPEs in Estonia and Italy, part of differences in cross-correlation and normalized mean absolute error can be explained as due to different time sampling. Table 2 below summarizes cross-correlation and normalized mean absolute error in Estonia and Italy.

Table 2. Verification of the 1-hour accumulation QPE products of Estonia and Italy and differences without (“Difference”) and with (“Comp. Diff”) compensating the impact of the temporal sampling. CC and NMAE values are obtained from Table 3 and Table 4.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$		$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC (Estonia)	0.679	0.674	0.697	NMAE (Estonia)	0.537	0.868	0.594
CC (Italy)	0.843	0.808	0.870	NMAE (Italy)	0.531	0.514	0.423
Difference	-0.164	-0.134	-0.173	Difference	0.006	0.354	0.171
Comp. Diff.	-0.086	-0.056	-0.095	Comp. Diff.	-0.204	0.144	-0.039

Compensating the values obtained in Estonia for loss of correlation (0.078) and increased NMAE (0.21) due to 15-minutes time sampling with values estimated in Italy, it is visible that CC and NMAE are comparable in Estonia and Italy (last row in Table 2). It is worth noting that after the compensation is applied, QPE estimated by $R(Z_H)$ shows lower NMAE in Estonia. The difference in NMAE of $R(K_{DP})$ and $R(Z_H)$ QPEs might stem from different precipitation regimes (more intense precipitation in Italy).

Referee’s comment

- the original aspect of the present study does not clearly appear

The paper has been improved but, in my view, only minor modifications have been brought by the authors.

Authors' response

Following the referee's comment, the manuscript was improved further to make the original aspects of the study stand out more clearly.

SPECIFIC COMMENTS

Abstract

Referee's comment

The length of the dataset is now mentioned. It is 5 years for both radars. It remains very short for climatological applications.

Authors' response

We agree that in a traditional meaning 5 years is very short to use the term "climatology". Therefore we changed the title of the paper and used the term "long-term" instead. Nevertheless, it has to be pointed out that in a number of studies with similar dataset lengths the term "climatology" has been used before. For example Kaltenboeck and Steinheimer (2015) used a 5 years of convective seasons in their paper titled "Radar-based severe storm climatology for Austrian complex orography related to vertical wind shear and atmospheric instability"

Chen et al (2012) in their study "Diurnal variations in convective storm activity over contiguous North China during the warm season based on radar mosaic climatology" (https://doi.org/10.1029/2012JD018158) used 4 years of warm season data.

"In radar climatology, the large spatial coverage and resolution of radar observations might allow us to partly make up for short time series by "trading space for time," that is, by retrieving larger samples of relevant events under the—admittedly strong—assumption that these can be considered as independent." Saltikoff et al (2019), An Overview of Using Weather Radar for Climatological Studies: Successes, Challenges, and Potential https://doi.org/10.1175/BAMS-D-18-0166.1

Referee's comment

1. Introduction

The aim of the study is described like this in the introduction :
"The main aim of this study is to evaluate the potential of using polarimetric weather radar QPE for climatological evaluation of precipitation regimes."
What do the authors mean with "precipitation regimes" ?

Authors' response

We agree that this sentence would benefit from better formulation and we rephrased it as follows: "The main aim of this study is to evaluate the potential of using polarimetric weather radar QPE on long-term warm-season datasets in various climatological environments."

Referee's comment

2. Data and methods

2.1 Rain gauge measurements

A short description has been added. Can the authors explain which kind of "weather sensor data" they use in the manual quality control ?

Authors' response

Weather sensor data used for manual quality control are obtained from Vaisala Present Weather Detectors PWD52 and PWD22 (precipitation type, intensity and accumulation) located on the same stations.

Referee's comment

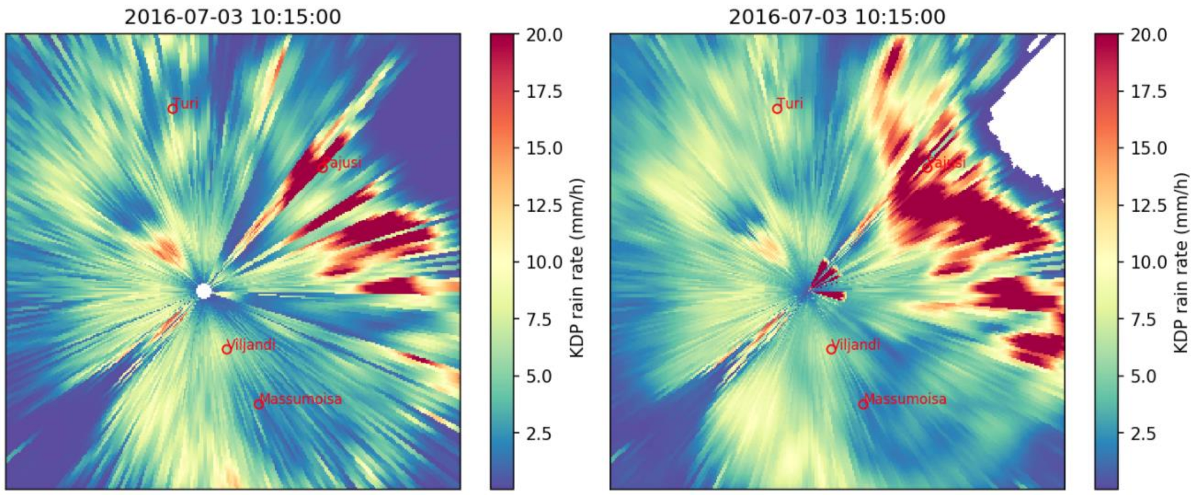
2.2 Weather radar precipitation estimates

Some additional information is provided in the revised version concerning the processing of the raw PHIDP data to derive KDP. However, some questions remain. For example, what is the resolution in range of the derived KDP ? Based on which criteria are the results considered as optimal ?

Authors' response

The results were considered optimal after comparisons of the resulting KDP rainfall fields and verification statistics of a test period. The values were first chosen after preliminary tests with single scans from multiple years between 2011-2018 and then confirmed after a final test with one month of 1-hour accumulation data from August 2018. The quality of the results was evaluated by using the verification measures introduced in Sect. 2.1 (Eq. 3-7).

The KDP retrieval process involves filtering that reduces the range resolution of KDP to approximately 1 km.



KDP rainfall fields. On the left based on default parameters of the Py-ART phase_proc_lp function and on the right based on the optimal parameter values that were chosen for final calculations (parameters self_const (self-consistency factor) and low_z (low limit for reflectivity – reflectivity below this value is set to this limit) values were changed from 60000.0 and 10.0 to 12000.0 and 0.0 respectively. It is visible that with the default parameter values (left) the rays where differential propagation phase folding occurred did not unfold correctly and thus the function did not produce correct specific differential phase values. Finding the optimal parameters fixed that issue (right).

Following the referee comment the following was added to the manuscript:
"The values were first chosen after preliminary tests with single scans from multiple years between 2011-2018 and then confirmed after a final test with one month of 1-hour accumulation data from August 2018. The quality of the results was evaluated by using the verification measures introduced in Sect. 2.1 (Eq. 1-5). The final test results are shown in Table 1. The product with optimal values for the KDP processing algorithm ($R(K_{\mathrm{DP\ tuned}})$) improves all verification measures when compared to the product based on the KDP processing with default parameters values ($R(K_{\mathrm{DP\ def}})$). The KDP retrieval process involves filtering that reduces the range resolution of KDP to approximately 1 km."

Referee's comment

The selection criteria based on PHIDP and Delta PHIDP are not perfectly clear (L 142 to 148). It is indicated that bins with PHIDP larger than 12 deg. are removed and that ΔPHIDPobs should be larger than 8 deg. Is this not too restrictive ?
How is the 25 dBZ threshold selected ? The authors explain that this threshold is chosen because it is the one which performs best without explaining in the revised version how this performance is evaluated. Which time period is used to make this evaluation ?

Authors' response

The reason to use the upper PHIDP limit of 12 degrees is that Zh and ZDR can be reduced due to attenuation in heavy precipitation. The reason why to use the lower PHIDP limit of 8 degrees is that PHIDPobs is noisy in light rain.

We agree that the selection of the 25 dBZ threshold would benefit from additional details. To improve the manuscript, the following was added to the paper:
"The reflectivity threshold was selected after verifying QPE performances at different reflectivity levels from 15 dBZ to 35 dBZ by 5 dBZ steps. The evaluation is based on 1-hour accumulation rainfall for August 2018 in Estonia and the verification statistics introduced in Sect. 2.1 (Eq. 1-5) are applied using the same gauges employed in the latter parts of the study as reference. From Table 1 it can be seen that best scores are reached using 25 dBZ (QPE product $R(Z_{H25},K_{DP})$)."

The same evaluation for the $R(Z_{H},K_{DP})$ algorithm was carried out for Bric della Croce in Italy. The Table below shows skill scores for hourly rainfall accumulation for convective precipitation on June 9th, 2020 derived comparing QPEs based on traditional Z_H and $R(Z_{H},K_{DP})$ with 72 automatic rain gauges, located within 50 km from the radar site. One-hour accumulations QPEs verification for different reflectivity thresholds for $R(Z_{H},K_{DP})$ demonstrates that 25 dBZ threshold gives best performances.

	$R(Z_{H15},K_{DP})$	$R(Z_{H20},K_{DP})$	$R(Z_{H25},K_{DP})$	$R(Z_{H30},K_{DP})$	$R(Z_H)$
CC	0.864	0.862	0.865	0.869	0.778
NMAE	0.39	0.39	**0.38**	0.38	0.42
NMB	0.08	0.07	**0.01**	-0.09	-0.26
RMSE (mm)	4.5	4.65	4.66	4.68	4.14
NASH	0.29	0.29	0.29	0.29	0.25

Referee's comment

2.3 Comparison framework

Concerning hail, the following sentence was added by the authors : "Possible occurrence of hail was not removed from the data because of the intention to keep additional data processing minimal and allow level comparison of the various QPE methods.".
I don't catch what "level comparison" means.

Authors' response

By "level comparison" we mean equality among the QPE methods. We intend to keep processing minimal to be able to compare the baseline performance of each method. The word "level" was replaced by "equal" in the manuscript to be more easily understandable.

Referee's comment

3. Results and discussion

The discussion of the results has been improved but the interpretation remains sometimes unclear.

Authors' response

Following the referee's comment, the Results and discussion section was improved by updating Figure 9 and Figure 10 to be more clearly understandable.

Referee's comment

TYPOS AND FORMULATIONS
Some strange formulations and spelling errors remain present throughout the text. I would recommend having the text proofread by a native English speaker.

Authors' response

Following the referee's comment, the whole manuscript was checked for formulation, spelling and grammar errors and improved accordingly.

Responses to comments from Anonymus Referee #2

On revised version of „Applicability of dual-polarization weather radar quantitative precipitation estimation for climatological purposes“ by Tanel Voormansik et al.(HESS-2019-624)

GENERAL COMMENTS

Referee's comment

The Manuscript deal with a relatively long period of 5 summer seasons of two weather radar observations in Italy and Estonia. The motivation of the work is convincing to me although 5-seasons cannot be properly defined as climatological dataset. This must be stressed through the manuscript. The results are not really new as implicitly recognised by the Authors. However, the relatively long time period and sites analysed are worth to be considered for a possibile publications.

I am in doubt about the appropriateness of the journal with respect the novelty of the work presented.

Authors' response

Authors would like to sincerely thank the referee for the time and effort spent in reading the improved manuscript and for making a number of constructive suggestions for improvement. This helped a lot to improve the manuscript. We agree that in a traditional meaning 5 years is short to use the term „climatology“. Therefore we changed the title of the paper and used the term "long-term" instead. The originality of the study is ensured mostly by the length of the dataset that was used. There have been several studies using selected short cases or datasets consisting of a number of days. To our knowledge, this is the first time multi-year dual-polarization radar QPE methods are studied as is stressed also in the manuscript.

SPECIFIC COMMENTS

Referee's comment

- Since the manuscript focuses on summer seasons I guess that convective events mainly populate the analysed dataset. The representativeness of the dataset considered is then biased toward more severe events. So, maybe the manuscript's title is not fully appropriate. Please consider this option "Applicability of dual-polarization weather radar quantitative rainfall estimation for climatological extremes"

Authors' response

We agree with the comment as the convective events are quite frequent in the warm season. To make it more clear for the reader we improved the introduction to put more emphasis on the use of warm-season data and also changed the title to be more appropriate: "Evaluation of the dual-polarization weather radar quantitative precipitation estimation using long-term datasets". Because we used all the data from the period which includes also stratiform precipitation and to show that we are not picking only severe cases we would not use the term "extremes".

Referee's comment

- Path attenuation in convection can be severe at C band but is not corrected by the authors to avoid introducing further errors. On the other hand, Pdp (Kdp actually) is used for QPE. So If you trust in Kdp for QPE you should do the same for path attenuation compensation too. Isn't it?

Authors' response

Adding path attenuation correction carries along risks that were also elaborated more in the last version of the manuscript. Its performance is dependent on multiple external parameters (temperature, drop shape and size distribution) which makes it difficult to quantify the error in various situations and on both locations, Estonia and Italy. Path attenuation might also fail in hail. What is more, we intended to keep the comparison simple.

Referee's comment

- Conclusions of the work are not really new. See for example (https://doi.org/10.1175/JAMC-D-10-05024.1 and https://doi.org/10.3390/atmos8020034)

Authors' response

We would like to thank the referee for pointing at the examples, references for both papers have been now added to the manuscript as we find them highly relevant to our study as well. We agree that the conclusions are similar, but as we have stated in the manuscript, one of the main strengths compared to earlier studies on the same topic is the length of our used datasets. The first referred example (https://doi.org/10.1175/JAMC-D-10-05024.1) is based on 10 selected days and is already cited in the manuscript. The second example (https://doi.org/10.3390/atmos8020034) is based on 3 days of data.

Minor comments:

Referee's comment

- Introduction L 30 "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 and climatologies."
I do not think rain is directly assimilated into NWP. About Climatological models verify their output with large scale (100km at best) satellite retrievals . Thus the required rain fields for climatology do not need to be too much "detailed ". By reading next It is clear what do you mean but I suggest to rephrase the beginning of the manuscript.

Authors' response

We agree with the comments and to make the beginning of the manuscript more clear the following was added to the manuscript:
"Detailed surface rainfall information is of great importance in many fields not only for agricultural or hydrological applications. In the recent past the COST 717 Action entitled "Use of Radar Observations in Hydrological and NWP models" investigated the assimilation of weather radar based precipitation in NWP (Macpherson, 2004). Weather radar data have been assimilated in a variety of assimilation systems and models of increasing resolution. At the beginning the latent heat nudging was the most popular technique (Gregorč et al., 2000), while researchers recently moved towards volume reflectivity assimilation techniques: for example, Schraff et al. (2016) proposed the KENDA (ensemble

Kalman filter for convective-scale data assimilation) operator to assimilate reflectivity volume data in the COSMO (COnsortium for Small-scale MOdelling) model.”

References

MacPherson, B., Lindskog, M., Ducrocq, V., Nuret, M., Gregoric, G., Rossa, A., Haase, G., Holleman, I., and Alberoni, PP.: Assimilation of Radar Data in Numerical Weather Prediction (NWP) Models, Weather Radar – Principles and Advanced Applications. Springer, Berlin, Germany, https://doi.org/10.1007/978-3-662-05202-0_9, 2004.

Gregorč, G., Macpherson, B., Rossa, A., and Haase, G.: Assimilation of radar precipitation data in NWP Models—a review, Phys. Chem. Earth, Part B; Hydrol. Oceans Atmos., 25, 1233-1235, https://doi.org/10.1016/S1464-1909(00)00185-4, 2000.

Schraff, C., Reich, H., Rhodin, A., Schomburg, A., Stephan, K., Periáñez, A., and Potthast, R.: Kilometre-scale ensemble data assimilation for the COSMO model (KENDA), Quart. J. Roy. Meteor. Soc., 142, 1453–1472, https://doi.org/10.1002/qj.2748, 2016.

Referee’s comment

- Could you please give more explicit detail on the automatic gauge quality control?

Authors’ response

Automatic checks are performed at real-time rain gauges data collection. First of all, range controls verify that the instrumental range is correct. Then, time series checks - e.g. constant values for several hours suggest instrumental anomaly - and cross-checks with other sensors (i.e. temperature and relative humidity) are performed. Finally, proximity checks (i.e. between close rain gauges) are performed to avoid zero rainfall accumulation recorded when all neighbouring rain gauges are recording precipitation.

Referee’s comment

- Page 5, “self_const (self-consistency factor) “ is not explained.

Authors’ response

Agreed. Short description of the factor added to the manuscript:
”Self-consistency factor takes into account the spatial variability of reflectivity and differential reflectivity within a given path. It is used to improve KDP field behaviours to more closely follow the cell patterns found in Zh.”

Referee’s comment

- please increase the readability of figure 9 and 10

Authors’ response

We agree that the readability of Figures 9 and 10 was not sufficient. The figures were updated to increase readability. Updated figures:

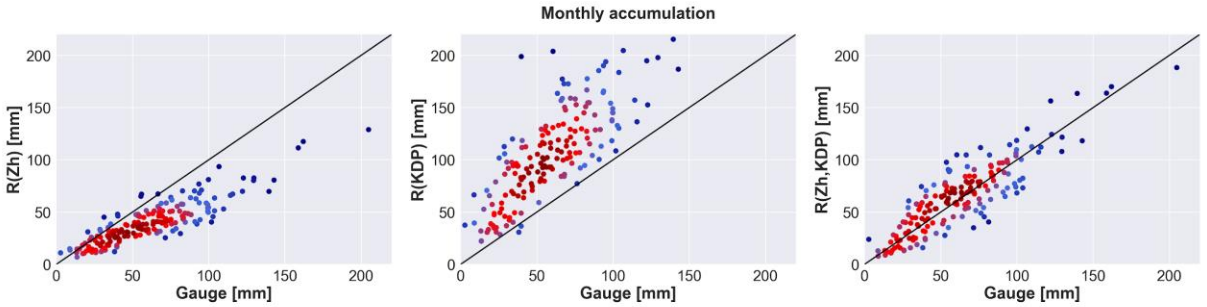


Figure 9. Estonia monthly accumulations 2011-2018. The corresponding verification measures are presented in Table 5. The number of radar-gauge data pairs with 8 gauges is 179.

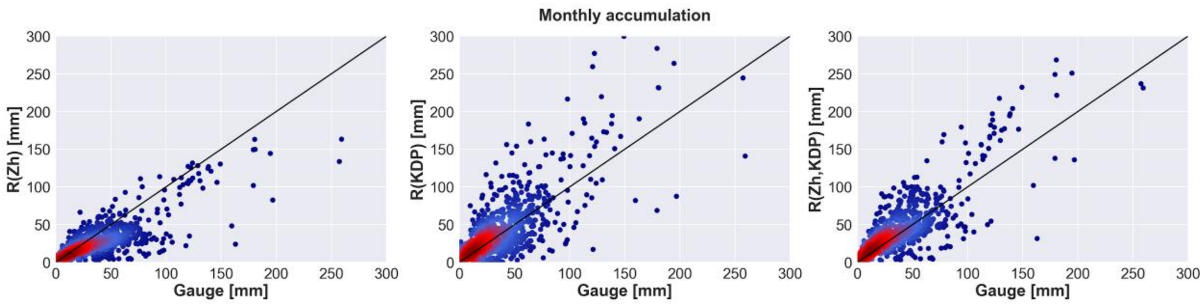


Figure 10. Italy monthly accumulations 2012-2016. The corresponding verification measures are presented in Table 6. The number of radar-gauge data pairs with 42 gauges is 675.

~~Applicability of dual-polarization weather radar quantitative rainfall estimation for climatological purposes~~Evaluation of the dual-polarization weather radar quantitative precipitation estimation using long-term datasets

Tanel Voormansik[1,2], Roberto Cremonini[3,4], Piia Post[1], Dmitri Moisseev[4,5]

[1] Institute of Physics, University of Tartu, Estonia

[2] Estonian Environment Agency, Estonia

[3] Regional Agency for Environmental Protection of Piemonte, Department for Natural and Environmental Risks, Torino, Italy

[4]Institute for Atmospheric and Earth System Research / Physics, University of Helsinki, Finland

[5]Finnish Meteorological Institute, Helsinki, Finland

Correspondence: Tanel Voormansik (tanel.voormansik@ut.ee)

Abstract. Accurate, timely and reliable precipitation observations are mandatory for hydrological forecast and early warning systems. In the case of convective precipitation, traditional rain gauge~~s~~ 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) is~~are~~ derived from~~by~~ horizontal reflectivity data. Nevertheless, dual-polarization weather radar can overcome several~~a number of~~ shortcomings of the conventional horizontal reflectivity based estimation. As weather radar archives are growing they are becoming increasingly important for climatological purposes in addition to operational use. 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 length of the datasets used in the study is 5 years for both Estonia and Italy. 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. Overall, the radar products showed similar results in Estonia and Italy when compared to each other. The product where radar reflectivity and specific differential phase were combined based on a threshold exhibited the best agreement with gauge values on all accumulation periods. In both countries reflectivity based rainfall ~~quantitative precipitation estimation~~QPE underestimated and specific differential phase based product overestimated gauge measurements.

1. Introduction

Detailed surface rainfall information is of great importance in many fields not only for agricultural or hydrological applications. In the recent past the COST 717 Action entitled "Use of Radar Observations in Hydrological and NWP models" investigated the assimilation of weather radar based precipitation in NWP (Macpherson, 2004). Weather radar data have been assimilated in a variety of assimilation systems and models of increasing resolution. At the beginning the latent heat nudging was the most popular technique (Gregorč et al., 2000), while researchers recently moved towards volume reflectivity assimilation techniques: for example, Schraff et al. (2016) proposed the KENDA (ensemble Kalman filter for convective-scale data assimilation) operator to assimilate reflectivity volume data in the COSMO (COnsortium for Small-scale MOdelling) model. ~~but also for assimilation purposes within numerical weather models and climatologies.~~ 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). What is more, satellite-based precipitation estimates are limited by the accuracy of the estimates. The accuracy of the estimates has a regional dependency and therefore can vary due to the physiography of the study areas (e.g. precipitation climate, land use, and geomorphology) (Petropoulos and Islam, 2017). Now that weather radars have been used already for decades in many countries their archives are getting long enough to use the data in climate studies (Saltikoff et al., 2019). In the last decade, various studies have used multi-year single-polarization weather radar data successfully 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. Several~~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.

The main aim of this study is to evaluate the potential of using polarimetric weather radar QPE on~~for~~ long-term warm-season datasets in various climatological environments ~~climatological evaluation of precipitation regimes~~. Previous studies where the benefits of dual polarimetric radar QPE have been shown are mostly based on selected short ~~time~~ periods or only single events (Wang and Chandrasekar, 2010; Chang et al., 2016; Montopoli et al., 2017; Cao et al., 2018). While the performance of the QPE methods can be compared based on short periods as well, only a study based on long-term data can prove the robustness of a method and suitability for long-term operational use. The uniqueness of this paper is ensured by various features. First of all, we have a long 5-~~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. This is also the first-ever study evaluating weather radar QPE in Estonia. 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 first in~~at~~ a few selected cases. The whole dataset is analysed at three accumulation intervals of 1 hour, 24 hours, and one month. Three radar QPE products are generated for comparison. First the horizontal reflectivity based product $R(Z_H)$, then the specific differential phase based product $R(K_{DP})$ and ~~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. A~~as a third radar QPE product, an $R(Z_H)$ and $R(K_{DP})$ combination ~~is also generated~~. To investigate the performance of ~~A~~all these weather radar-based QPE products they 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 Statistical methods for comparison

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 maximum in summer (215 mm) followed by autumn (198 mm), winter (128 mm), and spring (108 mm). The summer maximum 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 a bimodal distribution with peaks in spring (266 mm) and autumn (255 mm), Devoli et al. (2018).

Radar-based QPEs have been accumulated to the 1-hour duration and longer durations have been calculated based on these accumulations. Accumulations were calculated by adding subsequent instantaneous radar QPE values without any space-time interpolation. No missing data for radar or gauges was tolerated to prevent underestimation. A threshold of 0.1 mm was set and applied such that both gauge and radar QPE values must exceed this value to make the pair valid.

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: $$CC = \frac{\sum_{i=1}^{n}(r_i - r_m)\cdot(g_i - g_m)}{\sqrt{\sum_{i=1}^{n}(r_i - r_m)^2}\cdot\sqrt{\sum_{i=1}^{n}(g_i - g_m)^2}}, \quad (1)$$

Normalized Mean Absolute Error: $$NMAE = \frac{\sum_{i=1}^{n}|r_i - g_i|}{\sum_{i=1}^{n} g_i}, \quad (2)$$

Normalized Mean Bias: $$NMB = \frac{\sum_{i=1}^{n}(r_i - g_i)}{\sum_{i=1}^{n} g_i}, \quad (3)$$

Root Mean Squared Error: $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - g_i)^2}, \quad (4)$$

Nash-Sutcliffe Efficiency: $$NASH = 1 - \frac{\sum_{i=1}^{n}(r_i - g_i)^2}{\sum_{i=1}^{n}(g_i - g_m)^2}. \quad (5)$$

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

2.2~~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. From~~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 comparative~~ison~~ 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 a 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 1-~~one~~ hour data have been quality controlled by EstEA staff. Because the 10-minutes data are not quality controlled ~~one~~ 1-hour gauge data was used in this study as a more reliable ground truth. The off-line manned data quality control includes using mainly weather sensor data as an additional source for comparisons but also neighbouring stations and weather radar data on some

occasions. 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 a~~the~~ regional automatic gauges network made of~~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. The Arpa Piemonte weather stations are equipped with CAE PMB2 tipping-bucket rain gauges. Their resolution (0.2 mm) is the amount of precipitation for one tip of the bucket. The working range of measures is from zero mm to 300 mm/h with underestimation for high precipitation intensities. Such errors are corrected according to results of WMO Field Intercomparison of Rainfall Intensity Gauges (Vuerich et al., 2009). 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, has~~ve~~ been considered (Fig. 1). Precipitation measurements range from 2012 to 2016.

2.3~~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.
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. Close to the radar stable and reliable differential phase observations are not available due to both the antenna itself and the TR-limiters response time or the dual-pol switch in case of alternate transmission. Doppler filter was used to eliminate residual non-meteorological fixed clutter. In addition to speckle and clutter to signal ratio filtering at the signal processor level, polarimetric hydrometeor classification was used to filter non-meteorological targets from the display (Chandrasekar et al., 2013). 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.

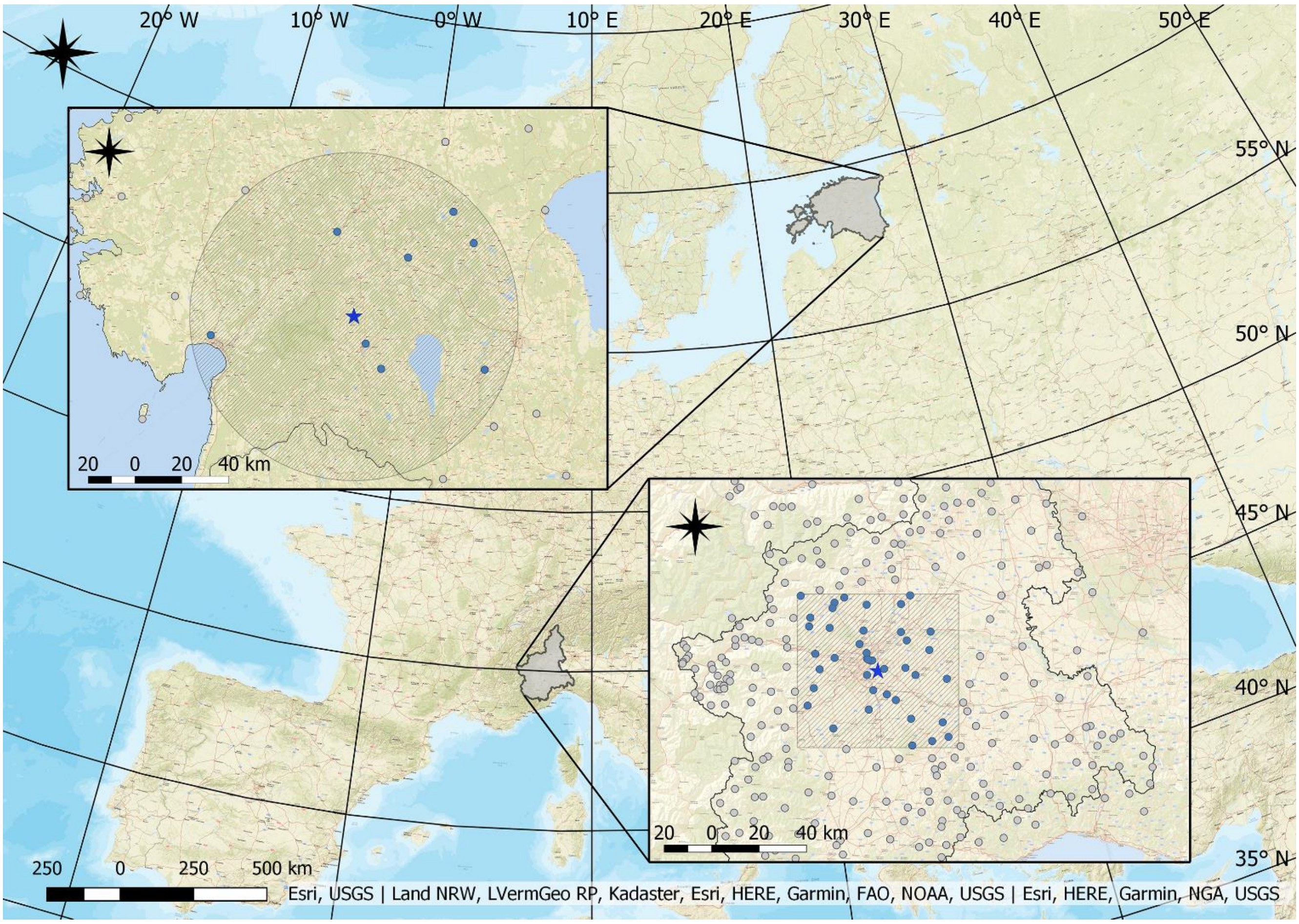


Figure 1. Study areas (shaded) located in Estonia (upper left zoomed area) and in Piemonte, Italy (lower right zoomed area). Grey dots denote gauge locations of Estonian and Piemonte region respectively and blue dots gauges inside the study area. Blue stars reveal radar locations.

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 in the central part of the Piemonte region: toward west and north at about 20 km the 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 used in the study ranged from 2012 to 2016 whereas observations from 2012 to 2013 are with ten-minutes interval and from 2013 to 2016 with five minutes interval ~~time resolution~~. As can be seen from Fig. 1 circular area around the radar is used in Estonia but in Italy rectangular area is used. The reason for this is that orography in Piemonte is very complex ranging from flat plains in the Po valley (about 100 m a.s.l.) to the Alps up to more than 4,000 m a.s.l. The Bric della Croce weather radar is located on Torino hill that is about 30 km from the Alps. Therefore, the elegant and simple limitation in range by some kilometres from the radar site does not work. To avoid mountainous areas, where partial and total beam-blocking, heavy ground contamination increases, a rectangle area, that extends towards flat grounds, has been preferred.

The ~~M~~maximum distance of the gauges to be included in the comparison was limited to a 70 km radius from the radar location in the 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 mainly from liquid precipitation (hail can also occur) which is required for more reliable rainfall intensity estimation. The ~~P~~possible occurrence of hail was not removed from the data because of the intention to keep additional data processing minimal and allow equal~~level~~ comparison of the various QPE methods. 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.

~~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 that mountains block most of the radar signal for lowest elevations.~~

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 less than zero, then $R(K_{\mathrm{DP}})$ was set to zero. The area close to the weather radar up to eight kilometres 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 the Python ARM Radar Toolkit (Py-ART) (Helmus and Collis, 2016) function phase_proc_lp (Giangrande et al., 2013) with carefully tuned parameter values according to data specifics. With default parameter values the rays where differential propagation phase folding occurred did not unfold correctly and thus the function did not produce correct specific differential phase values. ~~In order T~~To fix the folding issue function parameters *self_const* (self-consistency factor) and *low_z* (the low limit for reflectivity – reflectivity below this value is set to this limit) had to be tuned. The self-consistency factor takes into account the spatial variability of reflectivity and differential reflectivity within a given path. It is used to improve K_{DP} field behaviours to more closely follow the cell patterns found in Z_{H}. The default values for *self_const* and *low_z* were 60000.0 and 10.0 respectively and after testing with various combinations of various values the values 12000.0 and 0.0 were found to produce optimal results and therefore were chosen for final calculations. The values were first chosen after preliminary tests with single scans from multiple years between 2011-2018 and then confirmed after a final test with one month of 1-hour accumulation data from August 2018. The quality of the results was evaluated by using the verification measures introduced in Sect. 2.1 (Eq. 1-5). The final test results are shown in Table 1. The product with optimal values for the K_{DP} processing algorithm ($R(K_{\mathrm{DP\ tuned}})$) improves all verification measures when compared to the product based on the K_{DP} processing with default parameters values ($R(K_{\mathrm{DP\ def}})$). The K_{DP} retrieval process involves filtering that reduces the range resolution of K_{DP} to approximately 1 km. 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. Z_{DR} is not suitable for QPE on C-band radars, but it can be used in this calibration methodology after applying strict restrictions on the data used for this purpose. The calibration was carried out using the self-consistency theory set down in Gorgucci et al. (1992), Gorgucci et al. (1999) and Gourley et al. (2009) where the methodology is described in detail. The method essentially compares the observed differential propagation phase (ϕ_{DP}^{obs}) to a calculated theoretical differential propagation phase (ϕ_{DP}^{th}). The data used for calibration had to be filtered using ~~a number of~~several restrictions: only data from June to September was allowed; data from 0.5° elevation and 10-70 km range only used; only bins where horizontal and vertical polarization channel correlation coefficient was over 0.92 were used; any bins where ϕ_{DP} was greater than 12° were removed; whole ray where reflectivity was greater than 50 dBZ was removed; whole ray where Z_{DR} was greater than 3.5 dB was rejected; only rays where $\Delta\phi_{DP}^{obs}$ was greater than 8° and where the consecutive rain path was at least 10 km were used; any scans in which precipitation occurred on top of the radome were removed. As a result, Z_H bias values from the range of -2.0 to -5.0 dB were obtained depending on the date. The bias values were used to correct the corresponding observed Z_H ~~prior~~before to rain rate estimation. The impact of the re-calibration was evaluated on one month of 1-hour accumulation data from August 2018 using the verification measures introduced in Sect. 2.1 (Eq. 1-5). The verification results are presented in Table 1. QPE product based on re-calibrated reflectivity ($R(Z_{\mathrm{H\ cal}})$) shows clearly superior results compared to the non-calibrated reflectivity based product ($R(Z_{\mathrm{H\ def}})$), most notably by decreasing the negative bias.

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

$$Z_H = 300R^{1.5}. \qquad (6\cancel{1})$$

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

$$R = 21.0K_{DP}^{0.720}. \qquad (7\cancel{2})$$

The QPE of $R(Z_H)$ can be affected by attenuation on C-band radars especially in heavy precipitation and at long distances. While this can be corrected using ϕ_{DP} in our study it was not applied to the reflectivity data ~~in order~~ to not introduce another possible source of error between the results of Estonia and Italy that could not be easily quantified. The ~~E~~effectiveness of attenuation correction using ϕ_{DP} is hampered by its temperature, shape, and size distribution dependence which affect the accompanying error (Vulpiani et al., 2008). The QPE of $R(Z_H)$ can also be affected by the effect of the non-uniform vertical profile of reflectivity (VPR). In the current study, the effect of VPR will be limited because only data from the warm season was used and distance limits to the radar data were set (70 km for Estonia and 30 km for Italy, respectively).

~~A number of~~Several 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 a 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. The Z_H threshold value was selected after testing with various reflectivity levels. The reflectivity threshold was selected after verifying QPE performances at different reflectivity levels from 15 dBZ to 35 dBZ by 5 dBZ steps. The evaluation was based on 1-hour accumulation rainfall for August 2018 in Estonia and the verification statistics introduced in Sect. 2.1 (Eq. 1-5) were applied using the same gauges employed in the latter parts of the study as reference. From Table 1 it can be seen that the best scores are reached using 25 dBZ (QPE product $R(Z_{H25}, K_{DP})$). The same evaluation for the $R(Z_H,K_{DP})$ algorithm was carried out for Bric della Croce in Italy with a 1-hour accumulation period and it also confirmed the suitability of the 25 dBZ level. The threshold level is considerably lower than some of the thresholds used in the literature referred to above but on our datasets it performed the best.

Table 1. Verification results of the test dataset of one month (August 2018) of the radar-based rainfall 1-hour accumulation products of Estonia.

	$R(Z_{H\ cal})$	$R(Z_{H\ def})$	$R(K_{DP\ tuned})$	$R(K_{DP\ def})$	$R(Z_{H15}, K_{DP})$	$R(Z_{H20}, K_{DP})$	$R(Z_{H25}, K_{DP})$	$R(Z_{H30}, K_{DP})$	$R(Z_{H35}, K_{DP})$
CC	0.699	0.699	0.659	0.428	0.687	0.721	0.726	0.713	0.705
NMAE	0.572	0.634	1.074	1.491	0.855	0.69	0.605	0.596	0.595
NMB	-0.212	-0.421	2.652	4.958	1.441	0.655	0.067	-0.118	-0.184

RMSE (mm)	1.611	1.709	2.329	2.656	2.071	1.832	1.714	1.718	1.704
NASH	0.247	0.202	-0.088	-0.241	0.032	0.144	0.199	0.197	0.204

The impact of the temporal sampling was analysed using Italian Bric della Croce weather radar second elevation PPI data which produces a 5-minute interval dataset. A degraded dataset of a length of one day, October 10^{th} 2020, with a 15-minutes sampling rate was created by removing 2 out of 3 files. Hourly accumulation was calculated based on both sampling rates which resulted in a sample size of 253,514. As expected from the comparison of these accumulation pairs the obtained normalized mean bias was close to zero (0.03) while the correlation coefficient was 0.922 and the normalized mean absolute error 0.21.

If we compare different skill scores for 1-hour QPEs in Estonia and Italy, part of the differences in correlation coefficient and normalized mean absolute error can be explained as due to different time sampling. Table 2 below summarizes correlation coefficient and normalized mean absolute error in Estonia and Italy.

Table 2. Verification of the 1-hour accumulation QPE products of Estonia and Italy and differences without ("Difference") and with ("Comp. Diff") compensating the impact of the temporal sampling. CC and NMAE values are obtained from Table 3 and Table 4.

	$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$		$R(Z_H)$	$R(K_{DP})$	$R(Z_H,K_{DP})$
CC (Estonia)	0.679	0.674	0.697	NMAE (Estonia)	0.537	0.868	0.594
CC (Italy)	0.843	0.808	0.870	NMAE (Italy)	0.531	0.514	0.423
Difference	-0.164	-0.134	-0.173	Difference	0.006	0.354	0.171
Comp. Diff.	-0.086	-0.056	-0.095	Comp. Diff.	-0.204	0.144	-0.039

Compensating the values obtained in Estonia for loss of correlation (0.078) and increased NMAE (0.21) due to 15-minutes time sampling with values estimated in Italy, it is visible that CC and NMAE are comparable in Estonia and Italy (last row in Table 2). It is worth noting that after the compensation is applied, QPE estimated by $R(Z_H)$ shows lower NMAE in Estonia. The difference in NMAE of $R(K_{DP})$ and $R(Z_H)$ QPEs might stem from different precipitation regimes (more intense precipitation in Italy).

~~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 mainly from liquid precipitation (hail can also occur) which is required for more reliable rainfall intensity estimation. Possible occurrence of hail was not removed from the data because of the intention to keep additional data processing minimal and allow level comparison of the various QPE methods.~~

~~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 that mountains block most of the radar signal for lowest elevations.~~

~~Radar-based QPEs have been accumulated to 1-hour duration and longer durations have been calculated based on these accumulations. Accumulations were calculated by adding subsequent instantaneous radar QPE values without any space-time interpolation. No missing data for radar or gauges was tolerated to prevent underestimation. A threshold of 0.1 mm was set and applied such that both gauge and radar QPE values must exceed this value to make the pair valid.~~

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

~~Normalized Mean Absolute Error: $NMAE = \frac{\sum_{i=1}^{n}|r_i - g_i|}{\sum_{i=1}^{n} g_i}$, (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 QPE products are compared with single location gauge measurements of selected short periods from Estonia and Italy.~~.~~ This allows ~~to~~for evaluating~~e~~ the performance of the radar QPE against gauge measurements from a time-series viewpoint.

Figure 2 shows one month of precipitation on Jõgeva station location (60 km away from the radar site) in Estonia with 1-~~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. The 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.

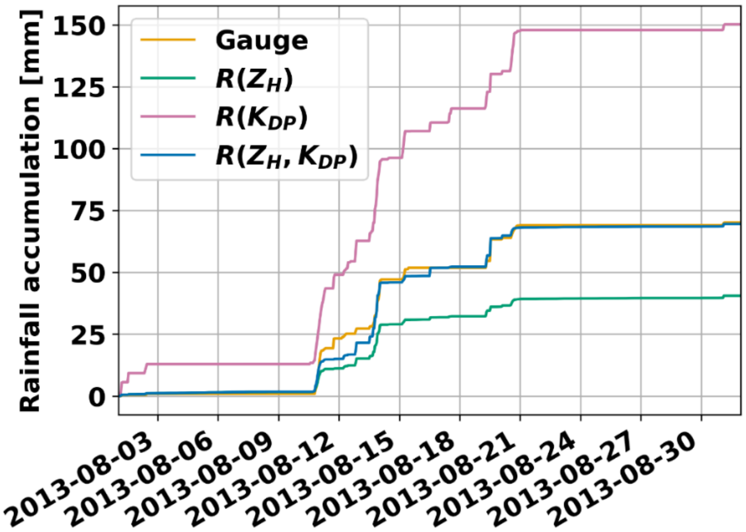


Figure 2. One month 1-hour rainfall cumulative accumulations, Sürgavere radar data, Jõgeva station gauge data.

Gauge and radar accumulations are not always so well correlated as Fig. 3 demonstrates. In this accumulation period, there are rainfall events which show that gauge values can be both under- and overestimated by radar products. Rainfall around 11th of June 2016 is overestimated by all radar QPE products with the smallest overestimation by $R(Z_H)$ and greatest by $R(K_{DP})$ which overestimated the gauge by more than double in this event. In the following days until 21st of June 2016 light to medium precipitation was recorded by the gauge and during this time $R(K_{DP})$ mostly overestimated the gauge accumulations while $R(Z_H)$ underestimated rainfall. On the 21st of June 2016, a convective rainfall event occurred during which 51 mm of rainfall was measured in 2 hours with a gauge. All radar QPE products underestimated the rainfall amount during this event. By the end of the month-long accumulation period $R(Z_H,K_{DP})$ was closest to the gauge value (underestimation by 16.6 mm) while $R(Z_H)$ underestimated even more and $R(K_{DP})$ again overestimated gauge measurements.

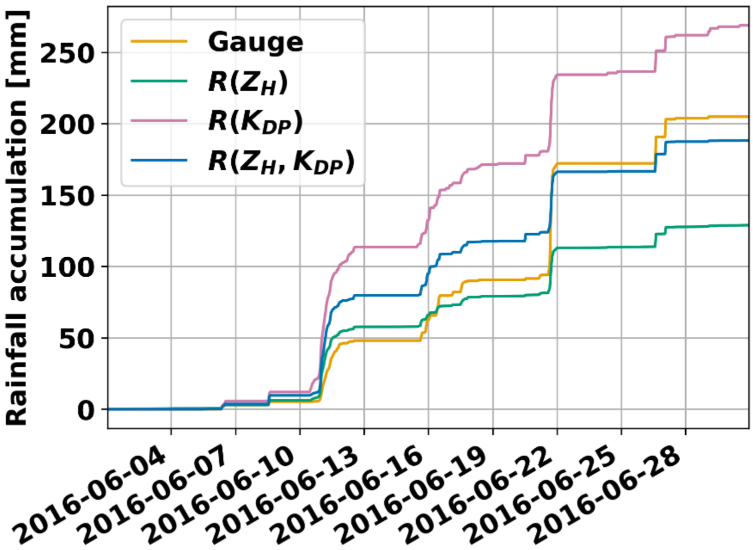


Figure 3. One month 1-hour rainfall cumulative accumulations, Sürgavere radar data, Tartu-Tõravere station gauge data.

Figure 4 illustrates a case from Italy, a comparison of a gauge located within a 30 km distance from the radar to Bric della Croce radar precipitation estimation products. At~~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 a 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. At~~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 a gauge in light precipitation as it was mostly based on reflectivity data, but in the case of more intense precipitation, it was still underestimating compared to gauge data. At~~In~~ the end of the period, the accumulated value for $R(Z_H,K_{DP})$ was 26.7 mm.

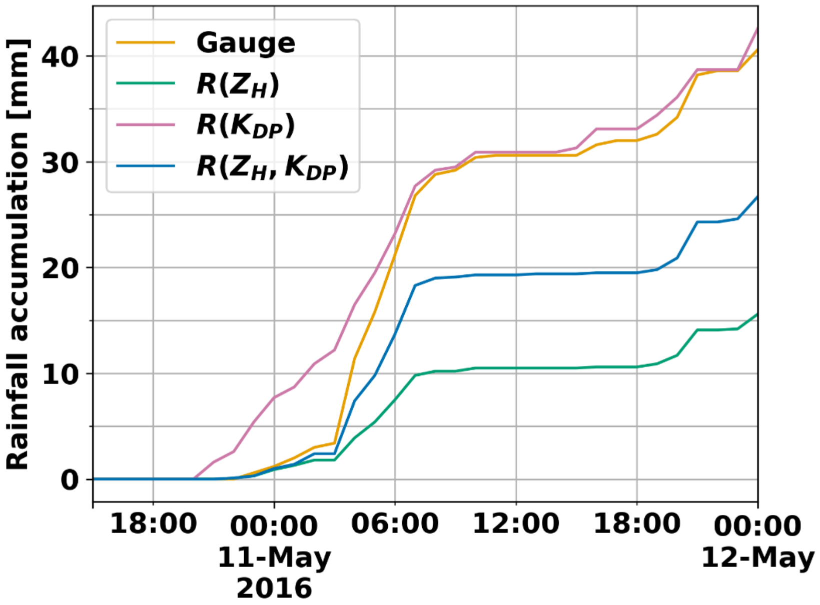


Figure 4. 1-hour rainfall cumulative accumulations from Verolengo gauge, located at 29 km from the radar, and co-located Bric della Croce radar QPE.

In all selected cases the general behaviour of QPEs is similar. Weather radar estimations, even when sampled by 15-minutes interval observations, follow gauge measurements with good agreement. Although the second case from Estonia illustrated well that longer scan interval increases the scatter 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. In~~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. Another cause of differences between the two countries might be differences in the drop size distribution climatologies. Rainfall retrieval relations also entail errors and to keep the comparison as uniform as possible we decided to use the same relations for both Italy and Estonia. These example cases demonstrated that radar can be used for 1-hour accumulations, but systematic errors cannot be excluded. These cases also presented the shortcomings of studies based only on a few cases. The performance of a QPE method depends heavily on a chosen case and it might perform differently on a long-term analysis. ~~In order t~~To find out errors and uncertainties and to see how QPEs compare to gauge measurements on a 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. The ~~I~~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 3~~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
NMAE	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

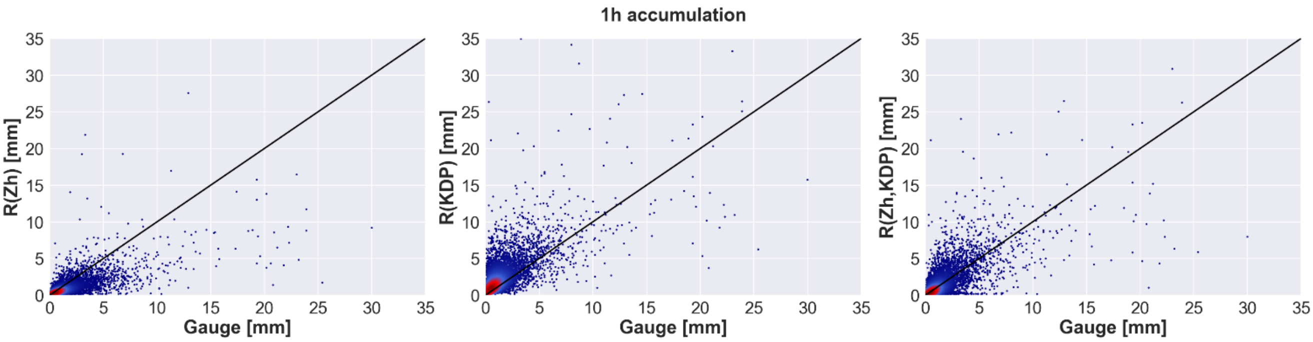


Figure 5. Scatter plots of radar-based rainfall estimates against rain gauge observations for 1-hour accumulation intervals in Estonia 2011-2018. The corresponding verification measures are presented in Table 3~~1~~. The ~~N~~number of radar-gauge data pairs with 8 gauges and accumulations > 0.1 mm is 7,019.

Table 3~~1~~ presents the verification results for the hourly accumulation interval in Estonia. Figure 5 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, NMAE 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 improvement by combining strong aspects of the two methods. 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 scatter in the hourly radar accumulations with all products. Mostly, it can be linked to the low spatial representativeness of the point measurements of rain gauges. This effect is more pronounced on a short time scale and it originates from a scarce gauge network and insufficient radar scan rate. Small scale effects like wind drift might also be more influential on a shorter accumulation period (Lauri et al., 2012). The reason why $R(Z_H)$ might have the best performances when NMAE and RMSE are considered is ~~because~~that 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. 6, it can be seen that the overall behaviour of the radar products is similar to Estonia. Although from Fig. 6 it can be noticed that of the four highest 1-hour accumulations measured by the gauge, three of them have significantly higher radar estimates for $R(Z_H,K_{DP})$ than either $R(Z_H)$ or $R(K_{DP})$. This could be explained by precipitation that was very variable in intensity and also in spatial coverage in these three cases which in turn caused unsteady behaviour of the precipitation estimates. Z_H underestimates high intensities, but with low intensities K_{DP} becomes noisy and the rainfall intensity estimation is not feasible. Finally, to reduce K_{DP} uncertainties range averaging is mandatory, leading to underestimation in case of very localized showers. By blending both $R(Z_H)$ and $R(K_{DP})$, a better rainfall estimation is expected.

Table 4~~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 the more 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 NMAE and NMB while having larger RMSE due to higher rainfall intensities recorded in Italy.

Table 4~~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
NMAE	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

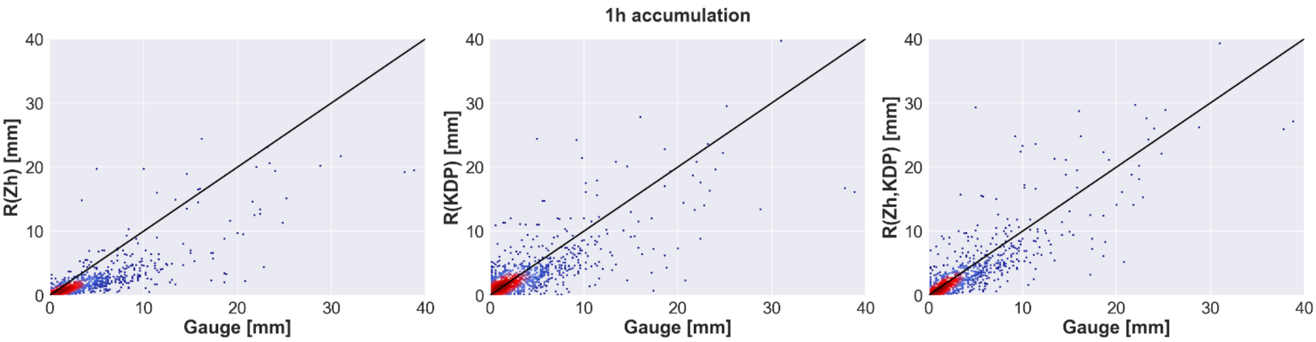


Figure 6. Italy 1-hour accumulations 2012-2016. The corresponding verification measures are presented in Table 4~~2~~. The ~~N~~number of radar-gauge data pairs with 42 gauges and accumulations > 0.1 mm is 1,233.

3.3 Comparison of 24-hours accumulations

Table 5~~3~~ shows the verification results for the daily accumulation interval in Estonia, while Fig. 7 presents the corresponding scatter plots. As expected, much less scatter can be seen than on the daily level but overall, the results are consistent with the hourly interval verification outcomes. Using longer accumulation intervals leads to less severe errors as the longer period compensates for both underestimates and overestimates. Reflectivity based product, $R(Z_H)$, is still underestimating rain depths while the negative bias is considerably smaller than in hourly interval data. By looking at the definition of NMB in Eq. (3~~5~~) it can be seen that in case the same underlying samples are used NMB should be equal on all accumulation lengths. In our study, the underlying samples were different as the 0.1 mm threshold was applied after the accumulation as the~~a~~ last step before calculating the verification metrics. This emphasizes the importance of low-intensity precipitation for total accumulations. $R(K_{DP})$ is the least accurate of the three products also on daily 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 NMAE of 0.438, RMSE of 3.992 mm, and the highest Nash-Sutcliffe Efficiency equal to 0.392. Overall there is noticeably less scatter in the daily radar accumulations compared to the 1-hour interval.

Table 5~~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
NMAE	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

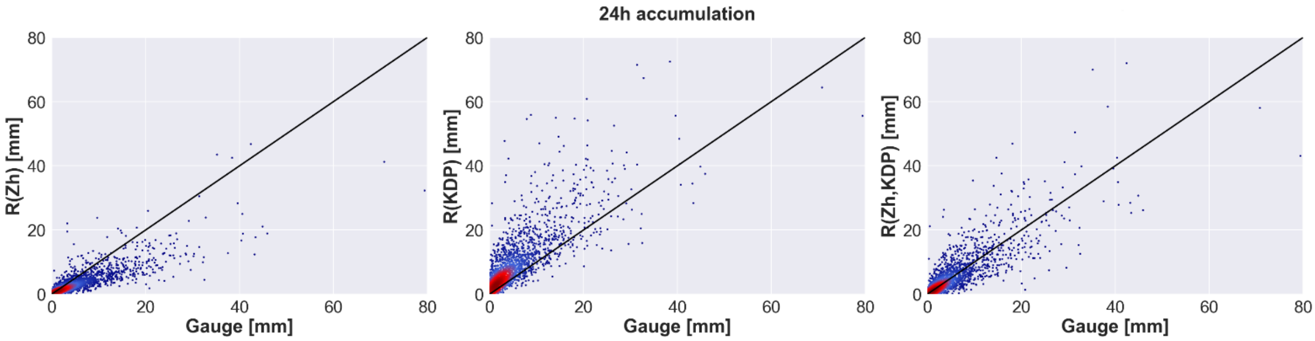


Figure 7. Estonia 24-hours accumulations 2011-2018. The corresponding verification measures are presented in Table 5~~3~~. The ~~N~~number of radar-gauge data pairs with 8 gauges and accumulations > 0.1 mm is 2,148.

Table 6~~4~~ shows the verification results for the daily accumulation interval in Italy, while Fig. 8 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 scatter of radar accumulations cannot be observed compared to the 1-hour level. I~~O~~n Fig 7. two regimes can be observed, and we assume that VPR correction leads to these regimes. Bric della Croce weather radar is located on a top of a hill at 770 m a.s.l. and during the winter season, a vertical profile reflectivity correction (VPR) is applied (Koistinen, 1991). This correction is manually switched on at the beginning of the cold season and it is switched off at the end. In the case of convective precipitation, this correction may lead to rainfall overestimation. On the other hand, stratiform cold precipitation is heavily underestimated when VPR correction is switched off.

Table 6~~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
NMAE	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

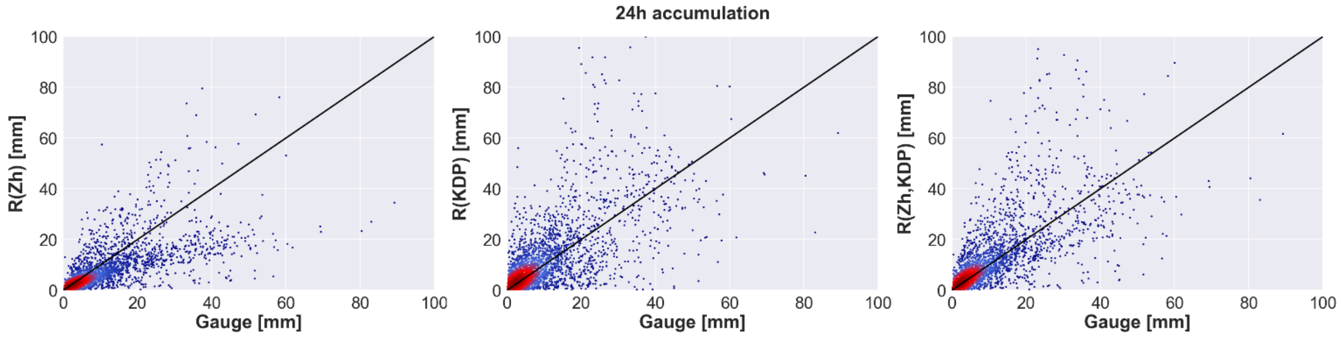


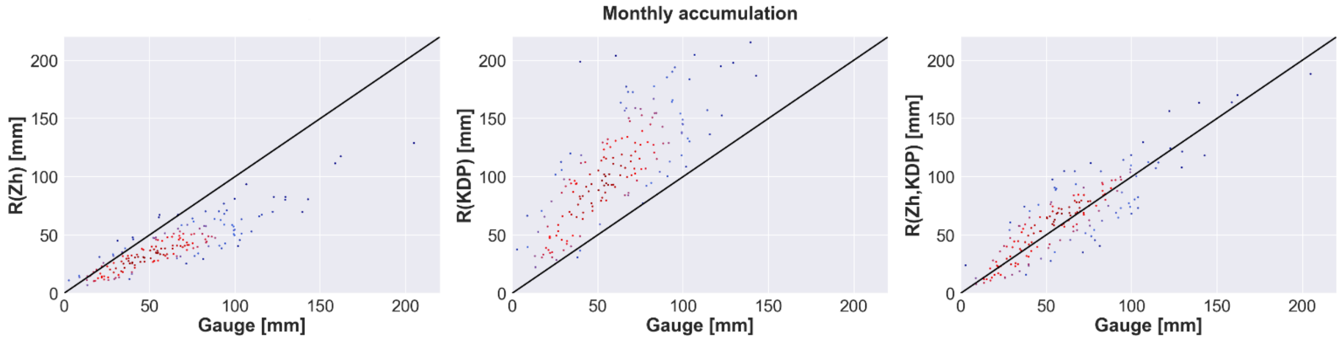
Figure 8. Italy 24-hours accumulations 2012-2016. The corresponding verification measures are presented in Table ~~6~~4. The ~~N~~number of radar-gauge data pairs with 42 gauges and accumulations > 0.1 mm is 3,010.

3.4 Comparison of monthly accumulations

Table ~~5~~7 shows the verification results for the monthly accumulation interval in Estonia, while Fig. 9 presents the corresponding scatter plots. Compared to shorter time scales overall on a monthly scale the correlation of all the products with gauge accumulations is higher. $R(Z_H)$ is underestimating with a larger mean bias (-0.284) than on a daily level but with a smaller normalized mean absolute 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 the 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~~7. 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
NMAE	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



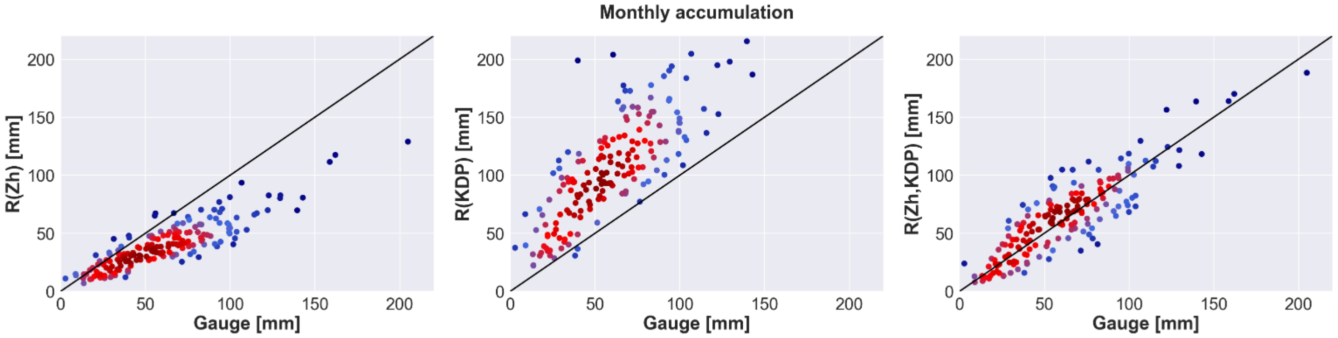


Figure 9. Estonia monthly accumulations 2011-2018. The corresponding verification measures are presented in Table ~~5~~7. The ~~N~~number of radar-gauge data pairs with 8 gauges is 179.

Table 8~~6~~ shows the verification results for the monthly accumulation interval in Italy, while Fig. 10 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 a monthly scale and $R(K_{DP})$ overestimating. $R(Z_H, K_{DP})$ is still overestimating but with a 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 a monthly scale compared to daily intervals. The ~~C~~correlation coefficient is higher and NMAE is lower on all the products when the two timescales are compared.

Table 8~~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
NMAE	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

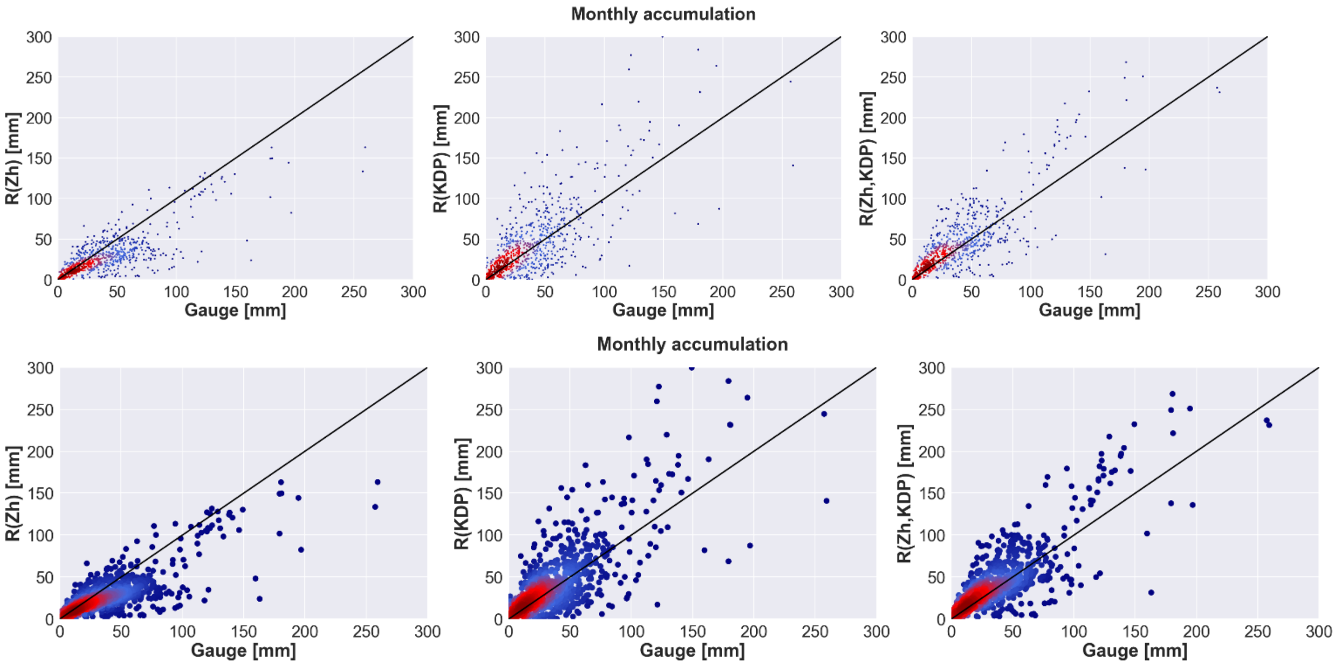


Figure 10. Italy monthly accumulations 2012-2016. The corresponding verification measures are presented in Table ~~6~~8. The ~~N~~number of radar-gauge data pairs with 42 gauges is 675.

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 a long period of multi-year data is used. From Estonia five years of 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 t~~To calculate rainfall from polarimetric variables, the 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~~ scarcer radar data from Estonia had more 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 scattering was visible. The case comparisons revealed also the shortcomings of analysis based only on selected short periods. The performance of the QPE methods then depends on the representativeness of the chosen cases and results can easily be skewed. Using a dataset with a length of at least several years without preselection provides more robust results and allows for evaluating the operational usability of the methods.

When the three products are compared to each other based on the full length of 5 years of data in the 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 the monthly accumulation scale it was performing distinctly better as it had RMSE 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 others clearly on an 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.

Overall the results show that the combined product $R(Z_H,K_{DP})$ performs better on almost all of the verification measures in both countries compared to $R(Z_H)$ and $R(K_{DP})$ as it uses successfully the benefits of each other product and eliminates the weaknesses. $R(Z_H)$ was good at low precipitation intensities but in general, it was underestimating precipitation. It had an average NMB of -0.159 for~~over~~ all ~~the~~ accumulation lengths in ~~case of~~ Estonia and -0.145 in Italy. $R(K_{DP})$ was performing well at higher intensities but in general was overestimating precipitation. It had an average NMB of 1.731 ~~over~~for all the accumulation lengths in ~~case of~~ Estonia and 0.592 in Italy. While the combined product $R(Z_H,K_{DP})$ was slightly overestimating precipitation with an average NMB of 0.250 ~~over~~for all the accumulation lengths in ~~case of~~ Estonia and 0.305 in Italy. In both countries the $R(Z_H,K_{DP})$ product also had the highest average CC over all the accumulation lengths with CC of 0.800 in Estonia and 0.792 in Italy. Generally, the CC was higher the longer the accumulation period was with the highest CC in monthly accumulations ($R(Z_H,K_{DP})$ CC of 0.875 in Estonia and 0.799 in Italy).

In ~~case of~~ Estonia, the overestimation of $R(K_{DP})$ was noticeably higher than in Italy. We hypothesize that this is mostly due to different climatological regimes ~~-~~between Italy and Estonia as high~~er~~-~~-~~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. Overall the results of the study showed that dual polarimetric radar QPE and especially the combined product $R(Z_H,K_{DP})$ show good potential to be used on long-term datasets~~in climate studies~~ if certain limitations are considered.

Synoptic patterns could be used as an additional source for classifying 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 investigate if frequent scans play a 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.

Acknowledgements. This work was partly supported by the project IUT20-11 of the Estonian Ministry of Education and Research, the Estonian Research Council grant PSG202, and~~ by~~ the European Regional Development Fund within National Programme for Addressing Socio-Economic Challenges through R&D (RITA1/02-52-07).

References

Alber, R., Jaagus, J., and Oja, P.: Diurnal cycle of precipitation in Estonia, Estonian J. of Earth Sci., 64, 305-313, https://doi.org/10.3176/earth.2015.36, 2015.

Bringi, V.N., Rico-Ramirez, M.A., and Thurai, M.: Rainfall estimation with an operational polarimetric C-band radar in the United Kingdom: comparison with a gauge network and error analysis, J. Hydrometeorol., 12, 935-954, https://doi.org/10.1175/JHM-D-10-05013.1, 2011.

Cao, Q., Knight, M. and Qi, Y.: Dual-pol radar measurements of Hurricane Irma and comparison of radar QPE to rain gauge data, In Proceed. of the 2018 IEEE Radar Conference, Oklahoma City, OK, USA, 23-27 April 2018, 0496-0501, https://doi.org/10.1109/RADAR.2018.8378609, 2018

Chandrasekar, V. and Cifelli, R.: Concepts and principles of rainfall estimation from radar: Multi sensor environment and data fusion, Indian J. Radio Space Phys., 41, 389-402, 2012.

Chandrasekar, V., Keränen, R., Lim, S. and Moisseev, D.: Recent advances in classification of observations from dual polarization weather radars, Atmos. Res., 119, 97-111, https://doi.org/10.1016/j.atmosres.2011.08.014, 2013

Chang, W.Y., Vivekanandan, J., Ikeda, K. and Lin, P.L.: Quantitative precipitation estimation of the epic 2013 Colorado flood event: Polarization radar-based variational scheme, J. Appl. Meteorol. Climatol., 55, 1477-1495, https://doi.org/10.1175/JAMC-D-15-0222.1, 2016

Chen, H. and Chandrasekar, V.: The quantitative precipitation estimation system for Dallas–Fort Worth (DFW) urban remote sensing network, J. Hydrol., 531, 259-271, https://doi.org/10.1016/j.jhydrol.2015.05.040, 2015.

Cifelli, R., Chandrasekar, V., Lim, S., Kennedy, P.C., Wang, Y., and Rutledge, S.A.: A new dual-polarization radar rainfall algorithm: Application in Colorado precipitation events, J. Atmos. Ocean. Technol., 28, 352-364, https://doi.org/10.1175/2010JTECHA1488.1, 2011.

Cornes, R.C., van der Schrier, G., van den Besselaar, E.J. and Jones, P.D.: An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets, J. Geophys. Res.-Atmos., 123, 9391-9409, https://doi.org/10.1029/2017JD028200, 2018.

Cremonini, R. and Bechini, R.: Heavy rainfall monitoring by polarimetric C-band weather radars, Water, 2, 838–848, https://doi.org/10.3390/w2040838, 2010.

Cremonini, R. and Tiranti, D.: The Weather Radar Observations Applied to Shallow Landslides Prediction: A Case Study From North-Western Italy, Front. Earth Sci., 6, 134, https://doi.org/10.3389/feart.2018.00134, 2018.

Crisologo, I., Vulpiani, G., Abon, C.C., David, C.P.C., Bronstert, A., and Heistermann, M.: Polarimetric rainfall retrieval from a C-Band weather radar in a tropical environment (The Philippines), Asia-Pac. J. Atmos. Sci., 50, 595-607, https://doi.org/10.1007/s13143-014-0049-y, 2014.

Devoli, G., Tiranti, D., Cremonini, R., Sund, M., and Boje, S.: Comparison of landslide forecasting services in Piedmont (Italy) and Norway, illustrated by events in late spring 2013, Nat. Hazards Earth Syst. Sci., 18, 1351–1372, https://doi.org/10.5194/nhess-18-1351-2018, 2018.

Giangrande, S.E., McGraw, R., and Lei, L.: An application of linear programming to polarimetric radar differential phase processing, J. Atmos. Ocean. Technol., 30, 1716-1729, https://doi.org/10.1175/JTECH-D-12-00147.1, 2013.

Giangrande, S.E. and Ryzhkov, A.V.: Estimation of rainfall based on the results of polarimetric echo classification, J. Appl. Meteorol. Climatol., 47, 2445-2462, https://doi.org/10.1175/2008JAMC1753.1, 2008.

Gorgucci, E., Scarchilli, G., and Chandrasekar, V.: Calibration of radars using polarimetric techniques, IEEE Trans. Geosci. Remote Sens., 30, 853-858, http://doi.org/10.1109/36.175319, 1992.

Gorgucci, E., Scarchilli, G., and Chandrasekar, V.: A procedure to calibrate multiparameter weather radar using properties of the rain medium, IEEE Trans. Geosci. Remote Sens., 37, 269-276, https://doi.org/10.1109/36.739161, 1999.

Goudenhoofdt, E. and Delobbe, L.: Generation and verification of rainfall estimates from 10-yr volumetric weather radar measurements, J. Hydrometeorol., 17, 1223-1242, https://doi.org/10.1175/JHM-D-15-0166.1, 2016.

Gourley, J.J., Illingworth, A.J., and Tabary, P.: Absolute calibration of radar reflectivity using redundancy of the polarization observations and implied constraints on drop shapes, J. Atmos. Ocean. Technol., 26, 689-703, https://doi.org/10.1175/2008JTECHA1152.1, 2009.

Gregorč, G., Macpherson, B., Rossa, A., and Haase, G.: Assimilation of radar precipitation data in NWP Models—a review, Phys. Chem. Earth, Part B; Hydrol. Oceans Atmos., 25, 1233-1235, https://doi.org/10.1016/S1464-1909(00)00185-4, 2000.

Helmus, J.J. and Collis, S.M.: The Python ARM Radar Toolkit (Py-ART), a Library for Working with Weather Radar Data in the Python Programming Language, J. Open Res. Softw., 4(1), http://doi.org/10.5334/jors.119, 2016.

Koistinen, J.: Operational correction of radar rainfall errors due to the vertical reflectivity profile, in: Proceedings of the 25th Radar Meteorology Conference, American Meteorological Society, Paris, France, 91–96, 1991.Krajewski, W.F., Villarini, G., and Smith, J.A.: Radar-Rainfall Uncertainties: Where are We after Thirty Years of Effort?, Bull. Am. Meteorol. Soc., 91, 87–94, https://doi.org/10.1175/2009BAMS2747.1, 2010.

Lauri, T., Koistinen, J., and Moisseev, D.: Advection-Based Adjustment of Radar Measurements, Mon. Wea. Rev., 140, 1014–1022, https://doi.org/10.1175/MWR-D-11-00045.1, 2012.

Leinonen, J., Moisseev, D., Leskinen, M., and Petersen, W.A.: A climatology of disdrometer measurements of rainfall in Finland over five years with implications for global radar observations, J. Appl. Meteorol. Climatol., 51, 392-404, https://doi.org/10.1175/JAMC-D-11-056.1, 2012.

MacPherson, B., Lindskog, M., Ducrocq, V., Nuret, M., Gregoric, G., Rossa, A., Haase, G., Holleman, I., and Alberoni, PP.: Assimilation of Radar Data in Numerical Weather Prediction (NWP) Models, Weather Radar – Principles and Advanced Applications. Springer, Berlin, Germany, https://doi.org/10.1007/978-3-662-05202-0_9, 2004.

Montopoli, M., Roberto, N., Adirosi, E., Gorgucci, E., and Baldini, L.: Investigation of Weather Radar Quantitative Precipitation Estimation Methodologies in Complex Orography, Atmosphere, 8, 34, https://doi.org/10.3390/atmos8020034, 2017.

Nash, J.E. and Sutcliffe, J.V.: River flow forecasting through conceptual models part I: A discussion of principles, J. Hydrol., 10, 282-290, https://doi.org/10.1016/0022-1694(70)90255-6, 1970.

Overeem, A., Holleman, I., and Buishand, A.: Derivation of a 10-year radar-based climatology of rainfall, J. Appl. Meteorol. Climatol., 48, 1448-1463, https://doi.org/10.1175/2009JAMC1954.1, 2009.

Petropoulos, G.P. and Islam, T.: Remote Sensing of Hydrometeorological Hazards. CRC Press, Boca Raton FL, USA, 2017.

Ryzhkov, A.V., Diederich, M., Zhang, P., and Simmer, C.: Potential utilization of specific attenuation for rainfall estimation, mitigation of partial beam blockage, and radar networking, J. Atmos. Ocean. Technol., 31, 599-619, https://doi.org/10.1175/JTECH-D-13-00038.1, 2014.

Ryzhkov, A.V., Schuur, T.J., Burgess, D.W., Heinselman, P.L., Giangrande, S.E., and Zrnic, D.S.: The Joint Polarization Experiment: Polarimetric rainfall measurements and hydrometeor classification, Bull. Am. Meteorol. Soc., 86, 809-824, https://doi.org/10.1175/BAMS-86-6-809, 2005.

Ryzhkov, A.V. and Zrnić, D.S.: Comparison of dual-polarization radar estimators of rain, J. Atmos. Ocean. Technol., 12, 249-256, https://doi.org/10.1175/1520-0426(1995)012%3C0249:CODPRE%3E2.0.CO;2, 1995.

Ryzhkov, A.V. and Zrnic, D.S.: Radar Polarimetry for Weather Observations. Springer, Cham, Switzerland, https://doi.org/10.1007/978-3-030-05093-1, 2019.

Saltikoff, E., Friedrich, K., Soderholm, J., Lengfeld, K., Nelson, B., Becker, A., Hollmann, R., Urban, B., Heistermann, M. and Tassone, C.: An Overview of Using Weather Radar for Climatological Studies: Successes, Challenges, and Potential, Bull. Am. Meteorol. Soc., 100, 1739-1752, https://doi.org/10.1175/BAMS-D-18-0166.1, 2019

Schraff, C., Reich, H., Rhodin, A., Schomburg, A., Stephan, K., Periáñez, A., and Potthast, R.: Kilometre-scale ensemble data assimilation for the COSMO model (KENDA), Quart. J. Roy. Meteor. Soc., 142, 1453–1472, https://doi.org/10.1002/qj.2748, 2016.

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., and Hsu, K.L.: A review of global precipitation data sets: data sources, estimation, and intercomparisons, Rev. Geophys., 56, 79-107, https://doi.org/10.1002/2017RG000574, 2018..

Tammets, T. and Jaagus, J.: Climatology of precipitation extremes in Estonia using the method of moving precipitation totals, Theor. Appl. Climatol., 111, 623-639, https://doi.org/10.1007/s00704-012-0691-1, 2013.

Tapiador, F., Marcos, C., Navarro, A., Jiménez-Alcázar, A., Moreno Galdón, R., and Sanz, J.: Decorrelation of satellite precipitation estimates in space and time, Remote Sens., 10, 752, https://doi.org/10.3390/rs10050752, 2018.

Vuerich, E., Monesi, C., Lanza, L., Stagi, L., Lanzinger, E.: WMO Field Intercomparison of Rainfall Intensity Gauges, Vigna di Valle, Italy, October 2007 - April 2009, WMO/TD- No. 1504; IOM Report- No. 99, 2009.

Vulpiani, G. and Baldini, L.: Observations of a severe hail-bearing storm by an operational X-band polarimetric radar in the Mediterranean area, In Proceed. of the 36th AMS Conference on Radar Meteorology, Breckenridge, CO, USA, 16-20 September 2013, 7208, 2013.

Vulpiani, G., Tabary, P., Parent du Chatelet, J. and Marzano, F.S.: Comparison of advanced radar polarimetric techniques for operational attenuation correction at C band, J. Atmos. Ocean. Technol., 25, 1118-1135, https://doi.org/10.1175/2007JTECHA936.1, 2008.

Vulpiani, G., Montopoli, M., Passeri, L.D., Gioia, A.G., Giordano, P., and Marzano, F.S.: On the use of dual-polarized C-band radar for operational rainfall retrieval in mountainous areas, J. Appl. Meteorol. Climatol., 51, 405-425, https://doi.org/10.1175/JAMC-D-10-05024.1, 2012.

Wang, Y. and Chandrasekar, V.: Algorithm for estimation of the specific differential phase, J. Atmos. Ocean. Technol., 26, 2565-2578, https://doi.org/10.1175/2009JTECHA1358.1, 2009.

Wang, Y. and Chandrasekar, V.: Quantitative precipitation estimation in the CASA X-band dual-polarization radar network, J. Atmos. Ocean. Technol., 27, 1665-1676, https://doi.org/10.1175/2010JTECHA1419.1, 2010.

Wang, Y., Zhang, J., Ryzhkov, A.V., and Tang, L.: C-band polarimetric radar QPE based on specific differential propagation phase for extreme typhoon rainfall, J. Atmos. Ocean. Technol., 30, 1354-1370, https://doi.org/10.1175/JTECH-D-12-00083.1, 2013.